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A Comparison of Approaches for the Analysis of Interaction Effects Between Latent Variables Using Partial Least Squares Path Modeling

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In social and business sciences, the importance of the analysis of interaction effects between manifest as well as latent variables steadily increases. Researchers using partial least squares (PLS) to analyze interaction effects between latent variables need an overview of the available approaches as well as their suitability. This article presents 4 PLS-based approaches: a product indicator approach (Chin, Marcolin, & Newsted, 2003), a 2-stage approach (Chin et al., 2003; Henseler & Fassott, in press), a hybrid approach (Wold, 1982), and an orthogonalizing approach (Little, Bovaird, & Widaman, 2006), and contrasts them using data related to a technology acceptance model. By means of a more extensive Monte Carlo experiment, the different approaches are compared in terms of their point estimate accuracy, their statistical power, and their prediction accuracy. Based on the results of the experiment, the use of the orthogonalizing approach is recommendable under most circumstances. Only if the orthogonalizing approach does not find a significant interaction effect, the 2-stage approach should be additionally used for significance test, because it has a higher statistical power. For prediction accuracy, the orthogonalizing and the product indicator approach provide a significantly and substantially more accurate prediction than the other two approaches. Among these two, the orthogonalizing approach should be used in case of small sample size and few indicators per construct. If the sample size or the number of indicators per construct is medium to large, the product indicator approach should be used.

Along with the development of scientific disciplines, the complexity of hypothesized relationships has steadily increased (Cortina, 1993). Moreover, social, psychological, and administrative

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theories are understood to depend on environmental factors, as for instance expressed by contingency theory (see, e.g., Woodward, 1958). Thus, besides the examination of direct effects between constructs, researchers are more and more interested in interaction effects (Carte & Russell, 2003). Researchers who want to use structural equation modeling (SEM) to test complex models with interaction effects of latent variables can basically choose between two techniques: covariance-based SEM, and partial least squares (PLS) path modeling. Although there is a growing body of literature on how interaction effects can be modeled by means of covariance-based SEM (cf. reviews of Li et al., 1998; Marsh, Wen, & Hau, 2004; Lee, Song, & Poon, 2004; Schumacker & Marcoulides, 1998), there is a lack of comprehensive studies that compare existing approaches for the analysis of interaction effects between so-called latent variables using PLS path modeling. Although several approaches have been suggested (cf. Chin, Marcolin, & Newsted, 2003; Henseler & Fassott, in press; Wold, 1982), it remains unclear what the particular strengths and weaknesses of each approach are. When choosing among different approaches for the analysis of interaction effects using PLS path modeling, a researcher addresses three questions to the different approaches: To what extent can each approach recover the true parameter value of the interaction effect and the single effects, respectively? How powerful or conservative is each approach? Finally, if the main objective of the model is to predict rather than to test a theory—which is a typical scenario of PLS path modeling—which approach has the highest prediction accuracy?

The objective of this article is to answer these questions, and to develop a guideline for researchers who would like to apply PLS path modeling to analyze interaction effects between latent variables. The article begins with a detailed presentation of the three approaches that have been suggested so far: the so-called product indicator approach (Chin, Marcolin, & Newsted, 1996, 2003), a two-stage approach (Chin et al., 2003; Henseler & Fassott, in press), and a hybrid approach that is based on an initial proposal by Wold (1982). Moreover, an additional approach for SEM in general, recently suggested by Little, Bovaird and Widaman (2006), is adapted to PLS path modeling. These four approaches are compared in terms of their performance (i.e., point estimate accuracy, power, and prediction accuracy). To illustrate the differences in estimation outcomes, we begin by reanalyzing the data of a technology acceptance study originally conducted by Chin et al. (2003). Additionally, we use a Monte Carlo simulation to systematically examine the behavior of each of these approaches. We then compare and contrast results, draw respective conclusions, and give recommendations for how interaction effects can optimally be modeled by means of PLS path modeling.

APPROACHES FOR THE ANALYSIS OF INTERACTION EFFECTS BETWEEN LATENT VARIABLES USING PLS PATH MODELING

Interaction effects (also called moderating effects) are evoked by variables, the variation of which influences the strength or the direction of a relationship between an independent and a dependent variable (Baron & Kenny, 1986, p. 1174). Such moderator variables can be categorical or metric in nature. Typically, the effect of categorical moderator variables is tested by means of group comparisons. For this purpose, observations are grouped according to their value of the categorical moderator variable. Subsequently, analyses are conducted, and the outcomes are compared across groups. Alternatively, in the case of metric moderator variables, the product of two variables is used to represent the interaction effect. For a structural model, the regression equation would have the following form:

$$\eta = \beta_0 + \beta_1 \cdot \xi + \beta_2 \cdot \mu + \beta_3 \cdot \xi \cdot \mu + \varepsilon \tag{1}$$

Here, η is the endogenous variable that shall be explained by the exogenous variable ξ, the moderator variable μ, and the interaction of the two. The βs represent the regression parameters, where β_0 stands for the constant. The unexplained variance is captured by the error term ε. Note that η, ξ, and μ are latent variables, and thus are supposed to be measured with error. Equation 1 can be rearranged into a different form, representing a regression of η on ξ having the constant as well as the slope of the exogenous variable ξ depending on the level of the latent moderator variable μ (cf. Jaccard & Turrisi, 2003, p. 17):

$$\eta = (\beta_0 + \beta_2 \cdot \mu) + (\beta_1 + \beta_3 \cdot \mu) \cdot \xi + \varepsilon \tag{2}$$

This form provides intuitive appeal to the interpretation of interaction effects: An increase in the moderator variable μ of 1 *SD* implies a change of the effect of ξ on η by β_3. For instance, if μ is standardized and increased from 0 to 1, the slope of ξ changes from β_1 to $\beta_1 + \beta_3$.

In the literature related to PLS path modeling, three approaches for the analysis of interaction effects between variables have been presented so far. First, Chin et al. (1996, 2003) developed the so-called product indicator approach. Second, Henseler and Fassott (in press) and Chin et al. (2003) suggested using a two-stage approach under certain circumstances. Third, based on an initial proposal by Wold (1982), the inventor of PLS, a hybrid approach can be constructed. Finally, we adapt an orthogonalizing approach suggested by Little et al. (2006) for modeling interactions among latent variables to the effect that it can be used with PLS path modeling. We now describe all four approaches in detail.

The Product Indicator Approach

Busemeyer and Jones (1983) as well as Kenny and Judd (1984) introduced an initial approach for the use of SEM methodology to study interaction effects among latent variables. Recently, Marsh et al. (2004) refined this approach and postulated using the unconstrained product of indicators, thereby delivering a full-fledged specification of structural equation models with interactions. All of these authors suggested building product terms using the indicators of the latent independent variable and the indicators of the latent moderator variable. These product terms serve as indicators of the interaction term in the structural model. Chin et al. (1996, 2003) were the first to transfer this approach to PLS path modeling. First, they introduced a new latent variable, the latent interaction term. Further, they suggested creating the so-called product indicators p_{ij}; that is, all possible pairwise products of the centered indicators of the exogenous variable (x_i) and of the moderator variable (m_j):

$$p_{ij} = x_i \cdot m_j \qquad \forall i, j. \tag{3}$$

The product indicators p_{ij} become the indicators of the latent interaction term. If the exogenous latent variable ξ has I indicators and the latent moderator variable μ has J indicators, then the latent interaction variable will have $I \cdot J$ product indicators. Figure 1 shows a simple example of the product indicator approach. Note that Chin et al. (2003) recommended using the centered original indicators to produce the product indicators. Although such a proceeding does not necessarily diminish the multicollinearity resulting from building the product term (see Echambadi & Hess, 2007; contrary to Cohen, 1978; Cronbach, 1987), it does facilitate the interpretation of the interaction model results.

Although this approach has been considerably difficult to implement in a covariance-based SEM context, it was found to be easily implementable in PLS path modeling. One question that is particularly raised in SEM is whether all possible indicator products should be formed and assigned to the interaction term. Jöreskog and Yang (1996) showed that one product term is sufficient to estimate the moderating effect. Jonsson (1998) used several but not all product terms to get a better estimate of the interaction term's standard error. However, this coincides with a stronger bias of the estimates themselves (Jonsson, 1998). As PLS path modeling does not rely on distributional assumptions and therefore does not require any estimate of parameter standard errors, the correct estimation of the interaction term's path coefficient is to be prioritized against the estimation of its standard error. Furthermore, PLS path modeling relies on consistency at large (cf. Schneeweiss, 1993); that is, a large number of indicators per latent variable are needed to get unbiased estimates of the latent variable. Hence, a limitation of the number of product indicators, as discussed by Jöreskog and Yang (1996) in the case of covariance-based SEM, would not be worthwhile. Moreover, due to the character of the PLS estimation, a reduction of product indicators does not greatly facilitate the speed of the estimation process. Thus, the approach by Chin et al. (2003) seems quite promising.

Usually, the path coefficient of the interaction term (i.e., the latent variable with the product indicators) is immediately used to quantify the interaction effect and interpreted like the

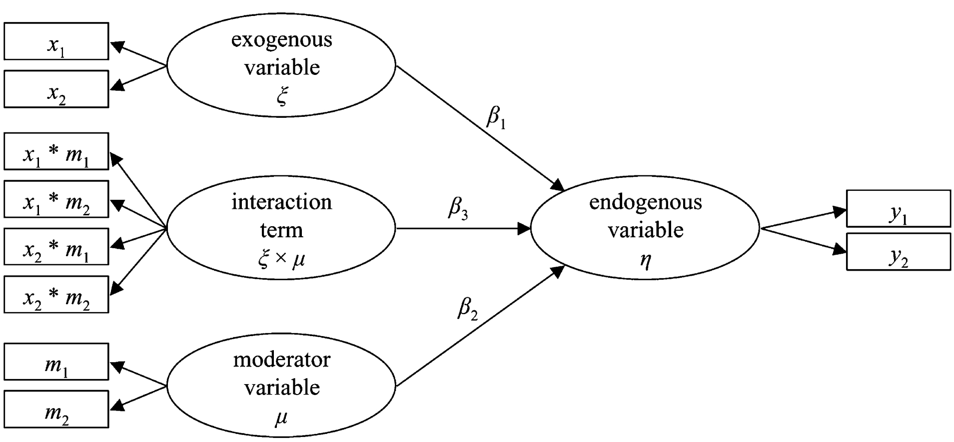


FIGURE 1 Product indicator approach.

parameter estimate of a product term in multiple regression (the β_3 in Equation 1). We would like to emphasize that this is not feasible,[1] due to a special characteristic of PLS. PLS calculates path coefficients from standardized latent variable scores; that is, for the structural model Equation (1) is not estimated, but a regression in which all predictors, including the interaction term, are standardized. The regression equation of the structural model as estimated by PLS takes the following form:

$$\eta = \beta_1 \cdot \xi + \beta_2 \cdot \mu + \beta_3^* \cdot \frac{(\xi \cdot \mu) - \overline{(\xi \cdot \mu)}}{s_{(\xi \cdot \mu)}} + \varepsilon \tag{4}$$

In general, if the product of two standardized variables does not equal the standardized product of these variables, the value β_3^* will be different from the value β_3 in Equation 1. To make β_3^* interpretable, we suggest adjusting the standard deviation of the interaction term's latent variable score prior to calculating the structural model regression with the interaction term. Concretely, the latent variable scores of the interaction term should be multiplied by the weighted average of the standard deviations of the product indicators, using the respective loadings of the product indicators as weights. As neither Chin et al. (2003) nor any other researchers applying the product indicator approach (e.g., Pavlou & Gefen, 2005) raise the issue of standardized interaction terms, it remains unclear whether an adjustment has ever been made. The fact that PLS internally works with standardized latent factor scores implies that the constant of the structural model equation equals zero. In contrast to covariance-based SEM (see Marsh et al., 2004), the PLS product indicator approach does not require explicit modeling of the means structure. However, if the indicator means and standard deviations are meaningful, an external post hoc calculation of nonstandardized model parameters seems to be worthwhile.

The Two-Stage Approach

The idea of the two-stage approach was initially suggested by Chin et al. (2003) and elaborated by Henseler and Fassott (in press). These authors recognized that if the exogenous variable or the moderator variable are formative, the pairwise multiplication of indicators is not feasible. "Since formative indicators are not assumed to reflect the same underlying construct (i.e., can be independent of one another and measuring different factors), the product indicators between two sets of formative indicators will not necessarily tap into the same underlying interaction effect" (Chin et al., 2003, Appendix D). Instead of using the product indicator approach, Henseler and Fassott (in press) similarly articulated the two-stage PLS approach for estimating moderating effects in particular when formative constructs are involved. The two-stage approach makes use of PLS path modeling's advantage of explicitly estimating latent variable scores. The two stages are built up as follows:

[1]This phenomenon can best be observed at an interaction model with one indicator per latent variable. Usually, the path coefficient β_3 as estimated by the product indicator approach will not equal the regression parameter β_3 of the product term in a multiple regression between the indicators unless indicators are standardized.

Stage 1: In the first stage, the main effect PLS path model is run to obtain estimates for the latent variable scores. The latent variable scores are calculated and saved for further analysis.

Stage 2: In the second stage, the interaction term $\xi \cdot \mu$ is built up as the element-wise product of the latent variable scores of the exogenous variable ξ and the moderator variable μ. This interaction term as well as the latent variable scores of ξ and μ are used as independent variables in a multiple linear regression on the latent variable scores of the endogenous variable η.

Figure 2 illustrates the two-stage approach. Note that although the latent variable scores of ξ and μ are standardized, the interaction term is not—and should not be. If the interaction term were standardized, it would become difficult to quantify an interaction effect, because an interpretation as illustrated at the basis of Equation 2 would not be feasible any more.

Although the latent variable scores are estimated in the first stage, they are used in the second stage to determine the coefficients of the regression function in the form of Equation 1. The second stage can be realized by multiple linear regression or be implemented within PLS path modeling by means of single-indicator measurement models. Although Chin et al. (2003)

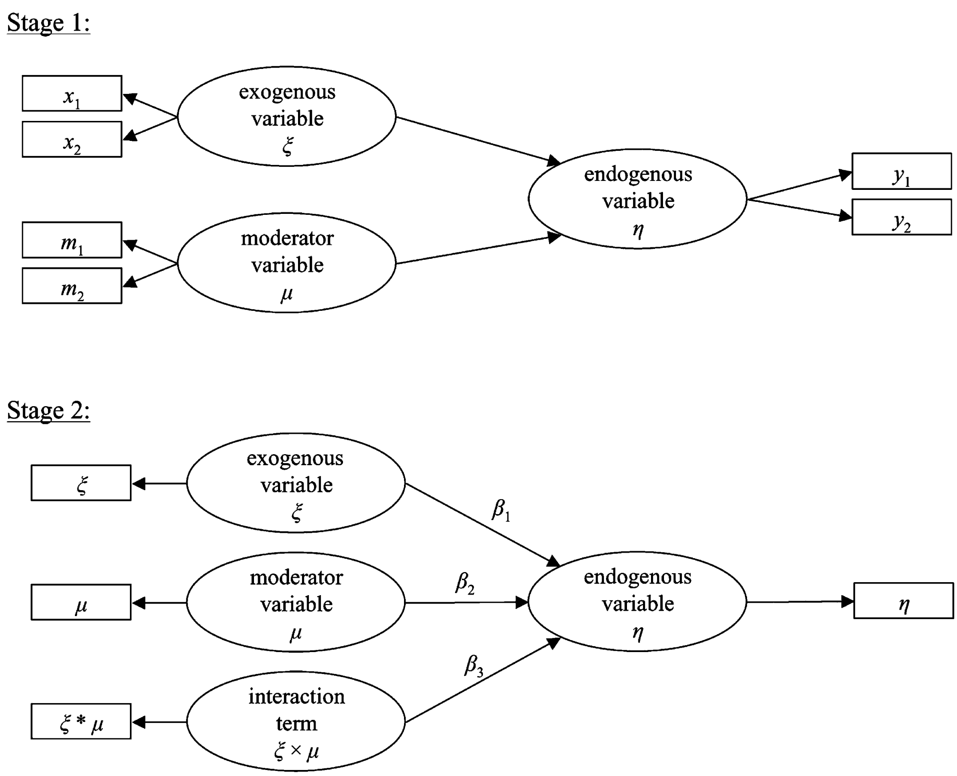


FIGURE 2 Two-stage approach.

as well as Henseler and Fassott (in press) limited the usage of the two-stage approach to cases when the exogenous or the moderator variable or both are formative, this limitation is not mandatory. It can also be applied to models with interaction effects among latent variables with reflective measurement models. However, a clear disadvantage of the two-stage approach is that the moderating effect is not taken into account when estimating the latent variable scores. The fact that the two-stage approach is a limited-information approach was a key reason for Chin et al. (2003) to prefer the product indicator approach.

The Hybrid Approach

Wold (1982), the inventor of PLS, presented a simple device for the PLS estimation of path models with nonlinearities in the structural model. Although he considered in depth only a model with a quadratic term, the approach is generalizable to other nonlinear relations between latent variables, in particular encompassing interaction effects. Wold's approach combines the advantages of the two prior methods. First, it takes the structural model into account when estimating the latent variable scores. Second, the interaction term's scores are guaranteed to coincide with the product of the interacting latent variables' scores. Wold's approach combines elements of the two-stage approach and the product indicator approach, making it a hybrid approach. Like in the two-stage approach, the element-wise product of the latent variable scores of the independent and the moderator variable serves as an interaction term; also as in the product indicator approach, the interaction term is updated during the algorithm runtime and used to estimate the latent variable scores. To illustrate the working principle of the hybrid approach, we draw on Tenenhaus, Vinzi, Chatelin, and Lauro's (2005) description of the PLS algorithm, and extend it where necessary (in italics). The PLS algorithm delivers estimates for the latent variable scores by means of an iterative process that basically consists of four steps:

1. *Outer estimation of the latent variable scores:* Outer estimates of the latent variables, $\hat{\xi}_n^o$ and $\hat{\eta}_n^o$, are calculated as linear combinations of their respective indicators. These outer estimates are standardized (i.e., $M = 0, SD = 1$). The weights of the linear combinations result from Step 4 of the previous iteration. When the algorithm is initialized, and no weights are yet available, any arbitrary nontrivial linear combination of indicators can serve as an outer estimation of a latent variable. *The first step is extended so that after computing the outer estimates of all latent variables, an interaction term proxy is calculated as the element-wise product of the respective outer estimates.*
2. *Estimation of the inner weights:* For each latent variable, inner weights are calculated to reflect how strongly the other latent variables are connected to it. There are three schemes available for determining the inner weights. Wold (1982) originally proposed the centroid scheme. Later, Lohmöller (1989) developed the factor weighting scheme and the path weighting scheme. The centroid scheme uses the sign of the correlations between a latent variable[2] and its adjacent latent variables, and the factor scheme uses the very correlations. The path weighting scheme pays tribute to the arrow orientations in the path model. The weights of those latent variables that explain the focal latent variable are set to the regression coefficients yielded from a regression of the focal latent

[2]More precisely, the outer estimate.

variable on its explaining latent variables. The weights of those latent variables that are explained by the focal latent variable are determined as in the factor weighting scheme. Independent of the weighting scheme, a weight of zero is assigned to all nonadjacent latent variables. *In the second step, inner weights for the interaction term proxy are also determined.*

3. *Inner estimation of the latent variable scores:* Inner estimates of the latent variables, $\hat{\xi}_n^i$ and $\hat{\eta}_n^i$, are calculated as linear combinations of the outer estimates of their respective adjacent latent variables, using the previously determined inner weights. *In this step, the interaction term proxy is also used to estimate the latent variable scores of the endogenous variable.*
4. *Estimation of the outer weights:* The outer weights are calculated either as the covariances between the inner estimates of each latent variable and its indicators (in Mode A) or as the regression weights resulting from the ordinary least squares regression of the inner estimates of each latent variable on its indicators (in Mode B). *In this step, there are no changes necessary for the hybrid approach, because the interaction term does not have any indicators assigned.*

These four steps are iterated until the change in outer weights between two iterations goes below a predefined limit. The algorithm terminates after Step 1, delivering estimates of latent variable scores for all latent variables including the interaction term. The path coefficients result from a regression of the endogenous variable's scores on the other variables' scores (including the interaction term).

As shown, the hybrid approach requires a modification of the PLS algorithm. However, as up to now it has not been implemented in any of the leading PLS software distributions,[3] the approach has not been available for applied research yet.

The Orthogonalizing Approach

Little et al. (2006) recently suggested an orthogonalizing approach for modeling interactions among latent variables. Although this approach was applied to covariance-based SEM, it is easily transferable to PLS path modeling. Basically, the orthogonalizing approach is an extension of the use of residual centering for moderated multiple regressions as described by Lance (1988). The underlying idea of residual centering is that "[i]deally, an interaction term is uncorrelated with (orthogonal to) its first-order effect terms" (Little et al., 2006, p. 499). One way to achieve this goal is mean-centering the variables that are multiplied to form the interaction term. However, more often than not, a certain degree of correlation between the interaction term and the original variables remains. To eliminate this remaining correlation, residual centering can be used:

> Residual centering, as originally suggested by Lance (1988), is essentially a two-stage OLS procedure in which a product term [...] is regressed onto its respective first-order effect[s]. The

[3] We considered the following software distributions (author in parenthesis): LVPLS (Lohmöller, 1984) including later graphical extensions, PLS-Graph (Chin, 1993–2003), SmartPLS (Ringle et al., 2005), and SPAD-PLS (DECISIA, 2003).

> residuals of this regression are then used to represent the interaction [...] effect. The variance of this new orthogonalized interaction term contains the unique variance that fully represents the interaction effect, independent of the first-order effect variance (as well as general error or unreliability). (Little et al., 2006, p. 500)

As a consequence of the orthogonality of the interaction term, the parameter estimates of the single effects in a model with interaction term are identical to the parameter estimates of the direct effects in a model without interaction. Furthermore, residual centering yields a regression coefficient for the orthogonalized cross-product term that can directly be interpreted as the effect of the interaction on the dependent variable (Lance, 1988, p. 164) and thus replace the assessment of the increase in the coefficient of determination due to the inclusion of the interaction term. Little et al. (2006) seized these advantages to SEM by introducing a modification to the product indicator approach. Like in the latter one, product indicators are first created as element-wise products of the indicators of the independent and the moderator variables. For two latent variables, ξ and μ, with two indicators each, say x_1 and x_2, and m_1 and m_2, respectively, the following preliminary product indicators p_1 to p_4 will be created:

$$p_{11} = x_1 \cdot m_1 \tag{5}$$

$$p_{12} = x_1 \cdot m_2 \tag{6}$$

$$p_{21} = x_2 \cdot m_1 \tag{7}$$

$$p_{22} = x_2 \cdot m_2 \tag{8}$$

Each of the four preliminary product indicators is then regressed on all indicators of the exogenous and the moderator variable:

$$p_{11} = b_{0,11} + b_{1,11}x_1 + b_{2,11}x_2 + b_{3,11}m_1 + b_{4,11}m_2 + e_{11} \tag{9}$$

$$p_{12} = b_{0,12} + b_{1,12}x_1 + b_{2,12}x_2 + b_{3,12}m_1 + b_{4,12}m_2 + e_{12} \tag{10}$$

$$p_{21} = b_{0,21} + b_{1,21}x_1 + b_{2,21}x_2 + b_{3,21}m_1 + b_{4,21}m_2 + e_{21} \tag{11}$$

$$p_{22} = b_{0,22} + b_{1,22}x_1 + b_{2,22}x_2 + b_{3,22}m_1 + b_{4,22}m_2 + e_{22} \tag{12}$$

The residuals of these regressions, in this case e_{11} to e_{22}, are then used as indicators of the interaction term, in analogy to the product indicator approach. That way, it is ensured that the indicators of the interaction term do not share any variance with any of the indicators of the exogenous as well as the moderator variable. From the fact that PLS calculates the latent variable scores as linear combinations of the respective indicators, it can be derived that the interaction term is orthogonal to its constituting latent variables.

The orthogonalizing approach as described by Little et al. (2006) has a correlated error structure that is required to provide unbiased estimates. In contrast to covariance-based SEM, PLS path modeling does not and cannot impose constraints onto error covariances. Releasing constraints is therefore neither necessary nor possible.[4]

SOFTWARE IMPLEMENTATION

To illustrate the four approaches, and to compare them in terms of their performance, it was necessary to use adequate PLS software. Although three of the four approaches—the product indicator approach, the two-stage approach, and the orthogonalizing approach—could have been executed by means of available software, one approach, the hybrid approach, needs a manipulation of the standard PLS algorithm. As none of the available PLS software packages allows for manipulations of the PLS algorithm itself,[5] we created our own implementation of the PLS algorithm applying the algorithm in vector form following the detailed description of Tenenhaus et al. (2005). As an extension to the PLS algorithm, the hybrid approach was implemented as described in the previous section. We used R 2.3.1 (R Development Core Team, 2006) as programming language. Besides the thorough compliance with the algebraic terms as formulated by Tenenhaus et al. (2005), the correctness of the PLS code was further verified by contrasting the results of two data analyses conducted with our implementation against the results of the PLS path modeling implementations PLS-Graph 3.0 (Chin, 1993–2003) and SmartPLS 2.0 M2 (Ringle, Wende, & Will, 2005). Except for obvious rounding inaccuracies, the results were identical. Further evidence of the correctness of our PLS implementation is provided by reanalyzing the data that underlay the second study of Chin et al. (2003), which is illustrated in the following section.

ANALYZING AN EXAMPLE FROM MANAGEMENT INFORMATION SYSTEMS RESEARCH: A MODIFIED TECHNOLOGY ACCEPTANCE MODEL

To illustrate the different approaches for the analysis of interaction effects between latent variables using PLS path modeling, we chose a particular technology acceptance model (TAM), mainly for two reasons: First, PLS has become a method of choice for statistical analysis in TAM studies (cf. Gefen & Straub, 1997). Second, moderating effects play a prominent role in the TAM literature (cf. Bhattacherjee & Sanford, 2006; Brown & Venkatesh, 2005). Drawing on Davis (1989), Chin et al. (2003) identified perceived usefulness and enjoyment as direct antecedents of information technology adoption intentions. Moreover, they tested an interaction effect of enjoyment on the perceived usefulness–intention relation by means of the PLS product indicator approach. The structural model can be expressed by the following equation:

$$\begin{aligned} \text{adoption intention} = {} & \beta_1 \cdot \text{usefulness} + \beta_2 \cdot \text{enjoyment} \\ & + \beta_3 \cdot \text{usefulness} \cdot \text{enjoyment} + \varepsilon \end{aligned} \tag{13}$$

[4]We thank an anonymous reviewer for this observation.

[5]SmartPLS, as Java-based software, principally allows for plug-ins. However, this functionality had not yet been provided by the programmers when this article was written.

TABLE 1
Different Model Results for the Technology Acceptance Model

		Parameter Estimate β (Bootstrap t Value)				
Analyzer	*Approach*	*Perceived Usefulness*	*Enjoyment*	*Interaction*	R^2	f^2
Chin, Marcolin, & Newsted (2003)	Main effects model	0.517	0.269		0.465	
	Product indicator	0.449	0.227	−0.209	0.500	0.070
Own calculations	Main effects model	0.5165 (8.2575)	0.2687 (5.3682)		0.4649	
	Product indicator	0.4486 (7.4094)	0.2262 (5.2924)	−0.2092 (−4.1534)	0.4995	0.0691
	Two-stage	0.4447 (7.2649)	0.2269 (5.2639)	−0.1413 (−4.3531)	0.5003	0.0708
	Hybrid	0.4446 (7.0779)	0.2267 (4.9759)	−0.1413 (−4.1218)	0.5001	0.0704
	Orthogonalizing	0.5165 (8.8435)	0.2686 (5.8844)	−0.1848 (−1.9472)	0.4988	0.0676
	Orthogonalizing (adjusted)	0.5165	0.2686	−0.1537	0.4988	0.0676
	Product indicator (adjusted)	0.4470	0.2257	−0.1516	0.4994	0.0689

We reanalyzed the data from Chin et al.[6] using all four approaches for the analysis of interaction effects between latent variables using PLS path modeling. Furthermore, we adjusted the parameter estimates of the product indicator approach as well as the orthogonalizing approach. Table 1 presents the outcomes we gained by means of the different approaches and contrasts them to the original results of Chin et al. (2003).

In a first step, we estimated the main effects model. We came to the same results as Chin et al. (2003). Perceived usefulness (parameter estimate 0.5165) and enjoyment (parameter estimate 0.2687) explain 46.49% of the variance in adoption intention. In a second step, we tested a perceived usefulness–enjoyment interaction by means of the four approaches. The product indicator approach reproduced Chin et al.'s (2003) estimates for the single effects ($\beta_1 = 0.4486$ and $\beta_2 = 0.2622$) as well as for the interaction effect ($\beta_3 = -0.2092$), increasing the explained variance to 0.4995. The results of the two-stage approach and the hybrid approach are almost identical to those of the product indicator approach, with one exception: the interaction term's path coefficient for both approaches. Both the two-stage approach and the hybrid approach yield an estimate for β_3 of −0.1413, which is a decrease in absolute terms of more than 32%. Overall,

[6]"The data were obtained from a single organization that had recently installed electronic mail. A total of 60 questions relating to a recent introduction of electronic mail were presented. Of the 575 questionnaires distributed, 250 usable responses were analyzed representing 43.5 percent of those surveyed. On average, the respondents had been using electronic mail for 9 months, sent 2.53 messages per day (s.d. = 2.36) and received 4.79 messages per day (s.d. = 3.49). Respondents were on average 39 years old (s.d. = 9.28) and had worked for the company an average of 11 years (s.d. = 6.9). Sixty percent of the respondents were male. The respondents came from various levels in the organization, 13 percent were managers, 12 percent were engineers, 38 percent were technicians, and the remaining 37 percent were clerical workers" (Chin et al., 2003, online appendix, p. 9).

the results of the two-stage approach and the hybrid approach differ only marginally. In contrast, the results of the orthogonalizing approach differ substantially. Obviously, the parameters of the single effects equal those of the main effects model. The parameter of the interaction effect has an intermediate value. For all approaches, bootstrapping with 500 bootstrap resamples was performed. Whereas for the single effects, the bootstrap t values do not differ strongly across approaches and warrant a $p < .001$ significance level, the interaction effect bootstrap t value of the orthogonalizing approach is much lower than the respective value of the other approaches, and does not signal significance at a 5% level.

Furthermore, Table 1 presents the results of the product indicator approach with the interaction term's standard deviation adjusted prior to calculating the structural model regression. The same was done for the orthogonalizing approach. The adjustments resulted in smaller path coefficients of the interaction effect, coming closer to the values of the two-stage and the hybrid approach. At the same time, the other path coefficients as well as the proportion of explained variance remain almost unchanged.

As the results reveal, there are some differences across the four approaches. However, it remains unclear which of the approaches delivers estimates most proximate to the true underlying population parameters, and in particular, whether the interaction effect can be considered significant on a predefined significance level like, for example, $\alpha = .05$. Furthermore, there might or might not be a ranking of the approaches in terms of their prediction accuracy. Although in this study, there were almost no differences in variance explanation (R^2s varied for only 0.3%), this does not necessarily imply that in general, all four approaches have the same prediction accuracy. To find generalizable patterns and to investigate the appropriateness of the four approaches presented, we conducted a Monte Carlo simulation.

A MONTE CARLO EXPERIMENT

The goal of this experiment is to elucidate the performance of the different approaches for the analysis of interaction effects between latent variables using PLS path modeling. We compare the point estimate accuracy, the power, and the prediction accuracy of the four considered approaches at different numbers of indicators per construct and different numbers of observations. The steps of the Monte Carlo experiment are as follows: First, we define an underlying true model and determine the factor attributes. Second, we generate random data that emerge from the model parameters. Third, given the random data, we let each PLS approach estimate the model under each factor combination.

The choice of the underlying model is crucial for the simulation outcomes. We define an underlying true model that is as simple as possible, consisting of one exogenous latent variable, one latent moderator variable, and one endogenous latent variable. As true path coefficients, 0.3 for the moderated path (β_1), 0.5 for the second single effect (β_2), and 0.3 for the interaction effect (β_3) were chosen. The simulation model is depicted in Figure 3. We opted for a mixed design, in which the four different approaches are fixed factors, and the number of indicators per latent variable as well as the number of observations serve as random factors. As possible numbers of indicators per latent variable, six different levels were used: 2, 4, 6, 8, 10, or 12 indicators. As representative numbers of observations for PLS path models with interaction

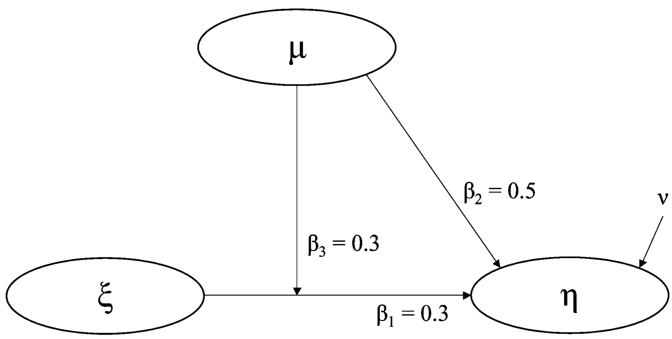


FIGURE 3 Simulation model.

effects, five different levels were selected: 50, 100, 150, 200, and 500 observations.[7] We chose a full-factorial design to have the possibility of capturing eventual interaction effects between the factors. Hence, 30 (six levels of indicators times five levels of observations) conditions emerged.

Under each of the 30 conditions, 500 Monte Carlo runs were intended. For each run, standard-normal latent variable scores were created for the exogenous, the endogenous, and the moderator variable, building the basis for the calculation of indicator scores. Loadings of all indicators were set to 0.7. Not only does the value of 0.7 allow for comparisons with existing Monte Carlo studies (mainly Chin et al., 2003), it also makes the measurement models touch conventional acceptance thresholds of reliability and validity, where internal consistency (reliability) as represented by Cronbach's alpha ranges from 0.658 (for 2 indicators) to 0.920 (for 12 indicators) and Dillon-Goldstein's rho ranges from 0.794 to 0.993 respectively, for indicator reliability of 0.49 (meeting Hulland's [1999] threshold of 0.4), and convergence validity as represented by an average variance extracted of 0.49 (coming close to Fornell and Larcker's [1981] threshold of 0.50). The values x_{ij} of the ith indicator of each latent variable ξ_j were created as a linear combination of the respective latent variable scores and a normal-distributed random vector:

$$x_{ij} = 0.7 \cdot \xi_j + \sqrt{1 - 0.7^2} \cdot N(0, 1) \tag{14}$$

Furthermore, all indicators x_{ij} were standardized, having a mean of zero and a standard deviation of one. As additional input for the product indicator approach, the product indicators were calculated following Equation 3. For the orthogonalizing approach, like in Equations 9 to 12, regressions were applied and their residuals saved as indicators of the interaction term.

For each run in each condition, all four approaches for the analysis of interaction effects between latent variables using PLS path modeling were used to estimate the model. We selected the path weighting scheme as inner weighting scheme, because it is the only scheme that

[7] Chin, Marcolin, and Newsted (2003) also investigated the case of 20 observations. However, taking into account that in the orthogonalizing approach, the indicators of the interaction term are regressed on all indicators of the exogenous variables, several conditions would have led to singularities. For instance, having 10 indicators per construct, a regression with 20 independent variables would have to be estimated by means of 20 observations.

takes into account the causal order of the constructs (Lohmöller, 1989). Furthermore, within all approaches, all latent variables were estimated with Mode A, which usually represents reflective measurement models (cf. Chin, 1998). Each estimation was accompanied by 500 bootstrap calculations to assess the significance of the estimates, thereby following Mooney and Duval's (1993) recommendation of 500 resamples when applying bootstrapping to estimate a parameter using a single sample. For each bootstrap sample, the product indicators as well as the orthogonalized product indicators were recalculated.[8] The following PLS estimation outcomes were measured for each run:

- Path coefficient estimates for the single effects and the interaction effect.
- Bootstrap t values for all effects.
- The squared correlation between the predicted latent variable scores of the endogenous variable and its true scores.

In the following sections, we report and discuss the simulation outcomes for parameter accuracy, statistical power, and prediction accuracy.

Parameter Accuracy

To compare the different parameters, we examined to what extent the parameter estimates deviated from the true values. At first, we assessed the mean relative bias (MRB). The MRB is the mean over the deviations from the true value, and is algebraically defined as (Reinartz, Echambadi, & Chin, 2002, p. 237):

$$MRB = \frac{1}{t}\sum_{i=1}^{t}\frac{\hat{X}_i - X_i}{X_i} \qquad (15)$$

Positive MRBs indicate an overestimation of the true parameter, negative MRBs an underestimation. Table 2 gives an overview of the MRB of each approach under all conditions for the three path coefficients. The overall picture gives mixed evidence: Whereas the two-stage approach and the orthogonalizing approach yield the most accurate estimates of the single effects, the product indicator approach together with the orthogonalizing approach perform best for the estimation of the interaction effect. To verify this rather qualitative evaluation, we conducted a series of analyses of variance (ANOVAs).[9] Box's test of equality of covariance matrices was significant, $F(714, 365748823) = 136.889$, $p < .001$, indicating that the covariance matrices vary among conditions. However, potential biases in significance are remedied by means of the balanced design of our experiment.

Table 3 contains the F tests resulting from the three ANOVAs. Although there are no significant three-way interactions among the independent variables, there are significant two-

[8] We thank an anonymous reviewer for this hint. It must be stated, though, that until now, existing implementations of the bootstrap in PLS software do not allow inclusion of this recalculation.

[9] Although we encountered significant sphericity, with Bartlett's test indicating a $\chi^2(3)$ of 1135.473, we decided against a multivariate analysis of variance (MANOVA), because MANOVA does not allow for random factors, and—albeit significant—correlations between the relative biases of the three path coefficients were well below 0.1, thus not substantial.

TABLE 2
Mean Relative Bias of the Path Coefficients

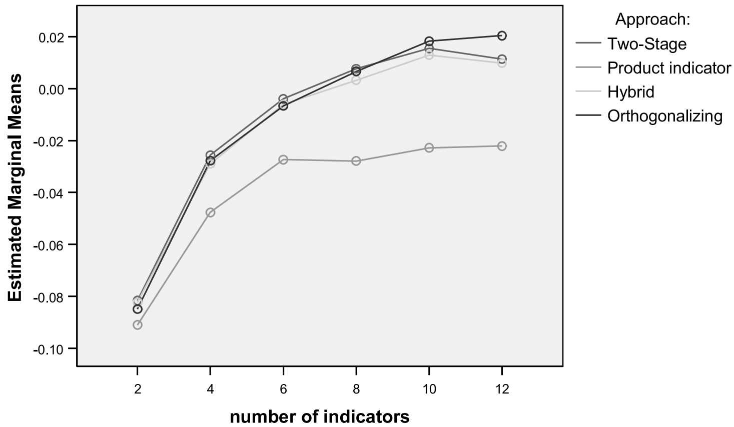
			No. of Indicators					
Parameter	*No. of Observations*	*Approach*	*2*	*4*	*6*	*8*	*10*	*12*
β_1	50	Two-stage	**−0.0816**	**−0.0256**	**−0.0040**	0.0076	0.0154	0.0113
		Product indicator adjusted	−0.0910	−0.0477	−0.0274	−0.0279	−0.0228	−0.0221
		Hybrid	−0.0823	−0.0290	−0.0061	**0.0032**	**0.0129**	**0.0098**
		Orthogonalizing	−0.0849	−0.0278	−0.0067	0.0066	0.0182	0.0203
	100	Two-stage	−0.0880	−0.0439	**−0.0201**	−0.0090	−0.0056	−0.0043
		Product indicator adjusted	−0.0931	−0.0520	−0.0306	−0.0225	−0.0183	−0.0176
		Hybrid	−0.0890	−0.0452	−0.0215	−0.0105	−0.0071	−0.0059
		Orthogonalizing	**−0.0870**	**−0.0397**	−0.0205	**−0.0072**	**−0.0040**	**0.0018**
	150	Two-stage	**−0.0898**	−0.0480	−0.0308	−0.0194	−0.0179	−0.0059
		Product indicator adjusted	−0.0921	−0.0529	−0.0362	−0.0261	−0.0251	−0.0130
		Hybrid	−0.0901	−0.0488	−0.0317	−0.0203	−0.0189	−0.0068
		Orthogonalizing	−0.0913	**−0.0474**	**−0.0297**	**−0.0182**	**−0.0155**	**−0.0054**
	200	Two-stage	−0.1010	−0.0478	−0.0343	−0.0287	−0.0190	**−0.0166**
		Product indicator adjusted	−0.1029	−0.0511	−0.0384	−0.0329	−0.0238	−0.0214
		Hybrid	−0.1014	−0.0485	−0.0349	−0.0294	−0.0196	−0.0174
		Orthogonalizing	**−0.0995**	**−0.0474**	**−0.0330**	**−0.0276**	**−0.0180**	**−0.0170**
	500	Two-stage	−0.1018	−0.0572	−0.0369	−0.0270	−0.0240	−0.0213
		Product indicator adjusted	−0.1025	−0.0583	−0.0383	−0.0286	−0.0257	−0.0232
		Hybrid	−0.1020	−0.0574	−0.0372	−0.0273	−0.0243	−0.0216
		Orthogonalizing	**−0.1007**	**−0.0565**	**−0.0361**	**−0.0268**	**−0.0235**	**−0.0210**
β_2	50	Two-stage	**−0.1496**	−0.0722	**−0.0394**	**−0.0308**	**−0.0198**	−0.0092
		Product indicator adjusted	−0.1650	−0.1046	−0.0863	−0.0841	−0.0755	−0.0670
		Hybrid	−0.1509	−0.0747	−0.0428	−0.0345	−0.0236	−0.0131
		Orthogonalizing	−0.1545	**−0.0720**	−0.0419	−0.0387	−0.0218	**−0.0091**
	100	Two-stage	**−0.1597**	**−0.0862**	**−0.0588**	**−0.0392**	**−0.0348**	**−0.0238**
		Product indicator adjusted	−0.1658	−0.0991	−0.0779	−0.0625	−0.0570	−0.0469
		Hybrid	−0.1604	−0.0876	−0.0610	−0.0413	−0.0370	−0.0264
		Orthogonalizing	−0.1617	−0.0899	−0.0599	−0.0433	−0.0356	−0.0240
	150	Two-stage	−0.1648	−0.0935	−0.0676	**−0.0478**	−0.0346	−0.0333
		Product indicator adjusted	−0.1697	−0.1020	−0.0787	−0.0602	−0.0482	−0.0472
		Hybrid	−0.1655	−0.0946	−0.0690	−0.0494	−0.0363	−0.0349
		Orthogonalizing	**−0.1638**	**−0.0932**	**−0.0666**	−0.0501	**−0.0353**	**−0.0331**
	200	Two-stage	−0.1657	−0.0954	**−0.0639**	**−0.0488**	**−0.0375**	−0.0310
		Product indicator adjusted	−0.1685	−0.1015	−0.0714	−0.0575	−0.0472	−0.0407
		Hybrid	−0.1660	−0.0962	−0.0649	−0.0499	−0.0386	−0.0322
		Orthogonalizing	**−0.1653**	**−0.0946**	−0.0643	−0.0496	−0.0377	**−0.0308**
	500	Two-stage	−0.1690	**−0.1014**	**−0.0692**	**−0.0540**	−0.0451	**−0.0370**
		Product indicator adjusted	−0.1700	−0.1036	−0.0720	−0.0570	−0.0485	−0.0404
		Hybrid	−0.1693	−0.1018	−0.0696	−0.0545	−0.0456	−0.0375
		Orthogonalizing	**−0.1683**	−0.1025	−0.0700	−0.0554	**−0.0439**	−0.0378
β_3	50	Two-stage	−0.1687	−0.1017	−0.0907	−0.0776	−0.0587	−0.0617
		Product indicator adjusted	−0.1255	−0.0233	**0.0035**	0.0417	0.0342	0.0458
		Hybrid	−0.1626	−0.0947	−0.0818	−0.0685	−0.0490	−0.0510
		Orthogonalizing	**−0.1094**	**−0.0033**	0.0197	**0.0204**	**0.0271**	**0.0075**
	100	Two-stage	−0.1489	−0.0887	−0.0726	−0.0659	−0.0456	−0.0370
		Product indicator adjusted	−0.1135	−0.0350	−0.0151	**−0.0032**	0.0170	0.0243
		Hybrid	−0.1466	−0.0836	−0.0676	−0.0604	−0.0400	−0.0312
		Orthogonalizing	**−0.1107**	**−0.0276**	**−0.0108**	−0.0056	**0.0091**	**0.0122**
	150	Two-stage	−0.1437	−0.0959	−0.0663	−0.0545	−0.0450	−0.0430
		Product indicator adjusted	−0.1139	**−0.0549**	**−0.0243**	**−0.0096**	**0.0000**	**−0.0001**
		Hybrid	−0.1414	−0.0928	−0.0628	−0.0505	−0.0410	−0.0390
		Orthogonalizing	**−0.1138**	−0.0553	−0.0266	−0.0186	−0.0134	−0.0118
	200	Two-stage	−0.1452	−0.0959	−0.0719	−0.0539	−0.0456	−0.0393
		Product indicator adjusted	−0.1261	**−0.0658**	**−0.0396**	**−0.0216**	**−0.0123**	**−0.0046**
		Hybrid	−0.1435	−0.0934	−0.0692	−0.0509	−0.0426	−0.0361
		Orthogonalizing	**−0.1240**	−0.0670	−0.0426	−0.0286	−0.0224	−0.0171
	500	Two-stage	−0.1396	−0.0894	−0.0664	−0.0497	−0.0435	−0.0354
		Product indicator adjusted	**−0.1323**	**−0.0773**	**−0.0540**	**−0.0375**	**−0.0309**	**−0.0222**
		Hybrid	−0.1390	−0.0883	−0.0652	−0.0485	−0.0422	−0.0342
		Orthogonalizing	−0.1325	−0.0787	−0.0562	−0.0412	−0.0353	−0.0274

Note. Best performing approach per condition is marked in bold.

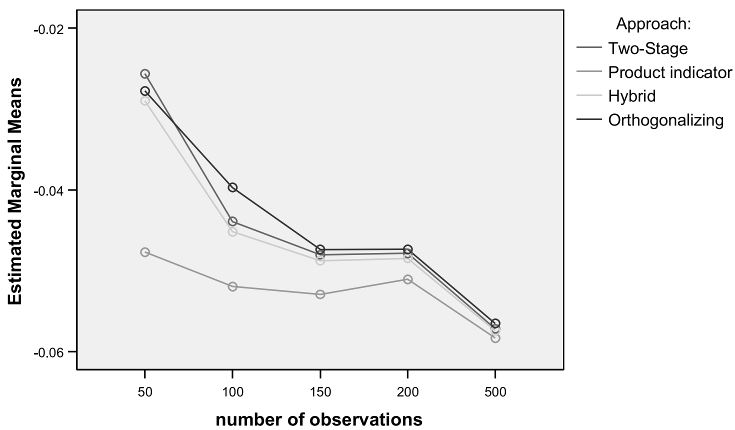
TABLE 3
F Test Over the Relative Biases

Relative Bias of the Effect	Determinant	Mean Square		Degrees of Freedom			
		MS_{Hyp}	MS_{Err}	df_{Hyp}	df_{Err}	*F*	*Significance*
$RB(\beta_1)$	Intercept	73.285	11.142	1	6	6.577	.042
	Approach	0.359	0.081	3	14	4.422	.022
	Indicators	9.982	0.025	5	26	396.500	.000
	Observations	1.179	0.091	4	17	12.996	.000
	Approach × Indicators	0.009	0.003	15	60	2.839	.002
	Approach × Observations	0.075	0.003	12	60	22.451	.000
	Indicators × Observations	0.019	0.003	20	60	5.689	.000
	3-way interaction	0.003	0.006	60	59,878	0.530	.999
$RB(\beta_2)$	Intercept	330.221	24.129	1	5	13.686	.013
	Approach	0.915	0.197	3	14	4.644	.018
	Indicators	23.794	0.031	5	22	772.843	.000
	Observations	0.348	0.188	4	13	1.852	.179
	Approach × Indicators	0.023	0.005	15	60	4.341	.000
	Approach × Observations	0.180	0.005	12	60	34.529	.000
	Indicators × Observations	0.013	0.005	20	60	2.576	.003
	3-way interaction	0.005	0.005	60	59,878	1.131	.228
$RB(\beta_3)$	Intercept	182.556	19.006	1	5	9.605	.024
	Approach	8.754	0.860	3	14	10.184	.001
	Indicators	18.308	0.127	5	26	144.285	.000
	Observations	0.765	0.852	4	14	0.898	.492
	Approach × Indicators	0.075	0.016	15	60	4.732	.000
	Approach × Observations	0.800	0.016	12	60	50.501	.000
	Indicators × Observations	0.068	0.016	20	60	4.274	.000
	3-way interaction	0.016	0.014	60	59,878	1.167	.177

way interactions; that is, the influence of the approach used is not independent from the number of indicators and the number of observations. However, contrasting the mean square of the direct effects with that of the interaction effects, the contribution of the interaction effects is rather small. Furthermore, profile plots were generated to detect possible crossover interactions. Figure 4 contains six pithy profile plots visualizing the shaded cells of Table 2. These exemplary profile plots reveal that crossover interactions play only a minor role. We thus proceed to the assessment of direct effects. As Table 3 reveals, all factors have significant direct effects on the relative bias of the estimate. To identify differences among the four approaches, we conducted post hoc tests over the approach factor. We applied Tamhane T2, Dunnett T3, and Dunnett C, because they do not assume covariances to be equal across cells. All three tests provide a coherent pattern (see Table 4): Concerning the relative bias of the single effects estimates, the product indicator approach provides significantly worse results than the other approaches, which together build a rather homogenous subset. Concerning the relative bias of the interaction effect estimates, the product indicator and the orthogonalizing approach do not differ significantly, and the hybrid approach and the two-stage approach deliver significantly more inaccurate estimates. Thus, for the estimation of both the single effects and the interaction effect, the orthogonalizing approach belongs to the best performing subset.



(1a) Estimated Marginal Means of relative bias of single effect of ξ at number of observations = 50

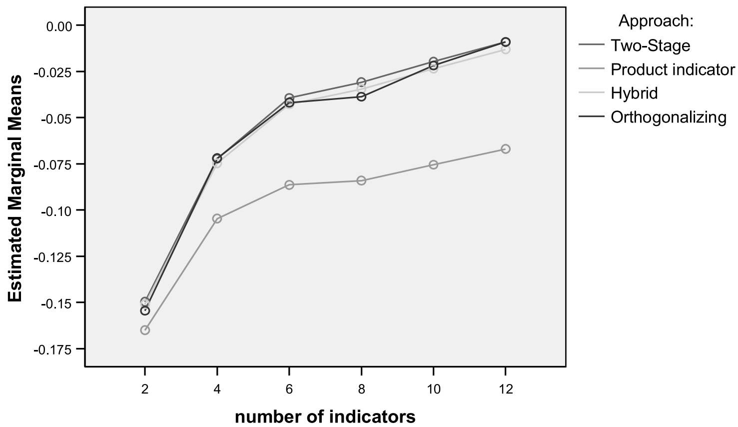


(1b) Estimated Marginal Means of relative bias of single effect of ξ at number of indicators = 4

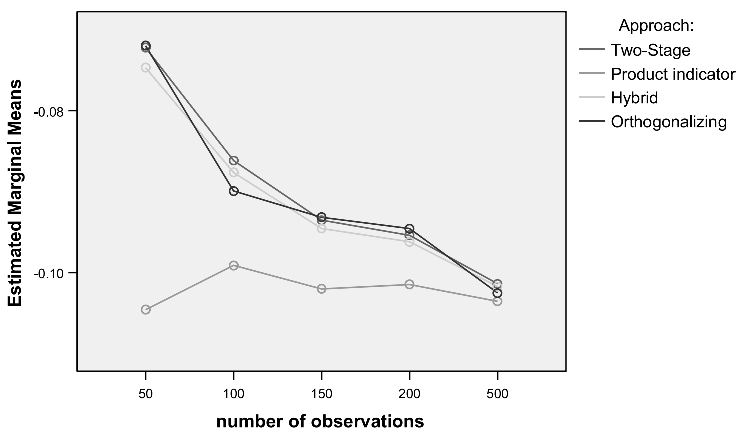
FIGURE 4 Estimated Marginal Means of relative biases with cross-over interactions. (*continued*)

Statistical Power

A researcher intending to make a conclusion about the existence of an interaction effect would want to avoid two errors: (a) concluding that there is an interaction effect although in reality there is none (Type I error), and (b) concluding that there is no interaction effect although there is one in reality (Type II error). To avoid Type I errors, one uses a predefined significance criterion (e.g., $\alpha = .05$) when rejecting the null hypothesis; to avoid Type II errors, one has to apply a statistical test with satisfactory statistical power. "The power of a statistical test of a null hypothesis is the probability that it will lead to the rejection of the null hypothesis, i.e., the probability that it will result in the conclusion that the phenomenon exists" (Cohen, 1988,



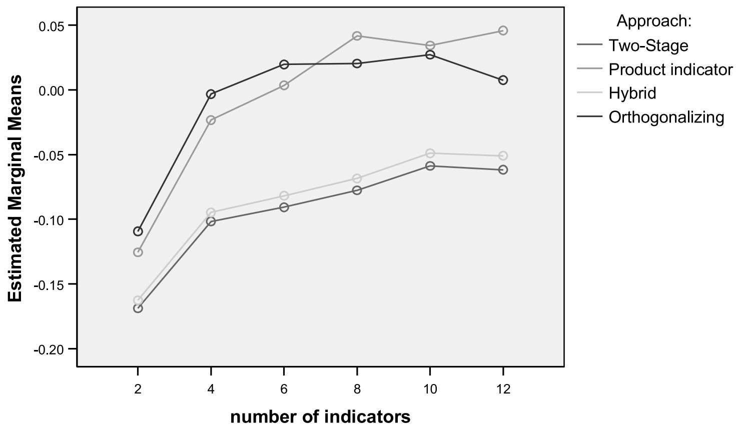
(2a) Estimated Marginal Means of relative bias of single effect of μ at number of observations = 50



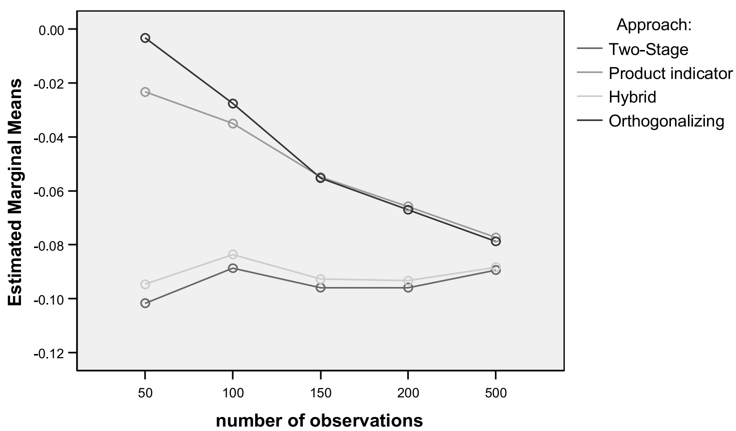
(2b) Estimated Marginal Means of relative bias of single effect of μ at number of indicators = 4

FIGURE 4 (*Continued*).

p. 4). Often, a power of one minus four times the significance level is advocated, thus 80% for a significance criterion of .05, implying that a Type I error is regarded as four times as serious as a Type II error. The power of a statistical test depends on several factors, namely the statistical significance criterion used in the test, the effect size in the population, the sample size, and the measurement reliability. In the Monte Carlo experiment, we kept the effect size in the population constant—the interaction effect of the true model as presented in Figure 3 has an effect size of about 0.136. Moreover, we used a constant significance criterion of .05 throughout the experiment. We evaluated the bootstrap t values, and estimated the power of each approach per experimental condition as the proportion of the Monte Carlo runs that yielded a significant interaction effect.



(3a) Estimated Marginal Means of relative bias of interaction effect $\xi \times \mu$ at number of observations = 50



(3b) Estimated Marginal Means of relative bias of interaction effect $\xi \times \mu$ at number of indicators = 4

FIGURE 4 (*Continued*).

Figure 5 depicts the estimated marginal means of the power of each approach when the model has 2, 4, 6, 8, 10, or 12 indicators per latent variable, and there are 50, 100, 150, 200, and 500 observations. On the face of Figure 5, the two-stage approach and the hybrid approach excel under almost all conditions. Only if there are very few indicators the orthogonalizing approach seems to be the most powerful of the approaches. To corroborate these findings, an ANOVA was conducted, similar to the one for parameter accuracy. Again, the covariance matrices across the 30 experimental conditions varied significantly, as documented by Levene's test, $F(119, 59857) = 581.818$, $p < .001$, which again is not harmful to the between-subject tests because of the balanced design. The results of the tests of between-subject effects are

TABLE 4
Multiple Comparisons Over the Relative Biases

Approaches Under Comparison	Significance of Differences in RB(ξ)			Significance of Differences in RB(μ)			Significance of Differences in RB(interaction)		
	Tamhane	*Dunnett T3*	*Games-Howell*	*Tamhane*	*Dunnett T3*	*Games-Howell*	*Tamhane*	*Dunnett T3*	*Games-Howell*
Two-stage vs. product indicator	.000	.010	.000	.000	.010	.000	.000	.000	.000
Two-stage vs. hybrid	.847	.848	.686	.490	.495	.369	.000	.010	.000
Two-stage vs. orthogonalizing	.897	.898	.748	.845	.847	.684	.000	.008	.000
Product indicator vs. hybrid	.000	.010	.000	.000	.010	.000	.000	.000	.000
Product indicator vs. orthogonalizing	.000	.009	.000	.000	.010	.000	.209	.208	.162
Hybrid vs. orthogonalizing	.199	.206	.155	.997	.997	.960	.000	.008	.000

TABLE 5
F Test Over the Statistical Power

Determinant	*Mean Square*		*Degrees of Freedom*				
	MS_{Hyp}	MS_{Err}	df_{Hyp}	df_{Err}	*F*	*Significance*	*Partial* η^2
Intercept	28,943.379	1,088.428	1	5	26.592	.004	.843
Approach	83.507	8.462	3	19	9.869	.000	.615
Indicators	127.015	10.602	5	27	11.980	.000	.687
Observations	969.876	14.104	4	29	68.767	.000	.905
Approach × Indicators	2.821	0.682	15	60	4.135	.000	.508
Approach × Observations	6.323	0.682	12	60	9.266	.000	.650
Indicators × Observations	8.463	0.682	20	60	12.403	.000	.805
3-way interaction	0.682	0.127	60	59,857	5.357	.000	.005

presented in Table 5. All three two-way interactions as well as the three-way interaction of approach, number of indicators, and number of observations are significant. These interactions become most obvious in plate (1a) of Figure 5.

Despite the crossover interaction, all direct effects are significant as well. In particular, the statistical power differs per approach, $F(3, 19) = 9.869$, $p < .001$. To further examine these differences, we look at the post hoc tests presented in Table 6. As we cannot assume cell covariances to be equal, we behold the Tamhane T2, Dunnett T3, and Games-Howell tests, which all lead to coherent conclusions. The two-stage approach and the hybrid approach can be considered as a homogenous subset, which has the highest statistical power. The orthogonalizing approach has a significantly weaker statistical power, but is still significantly more powerful than the product indicator approach.

Prediction Accuracy

A researcher who wants to include interaction effects in a model for prediction purposes would be interested in the different approaches' ability to predict an endogenous latent variable. To

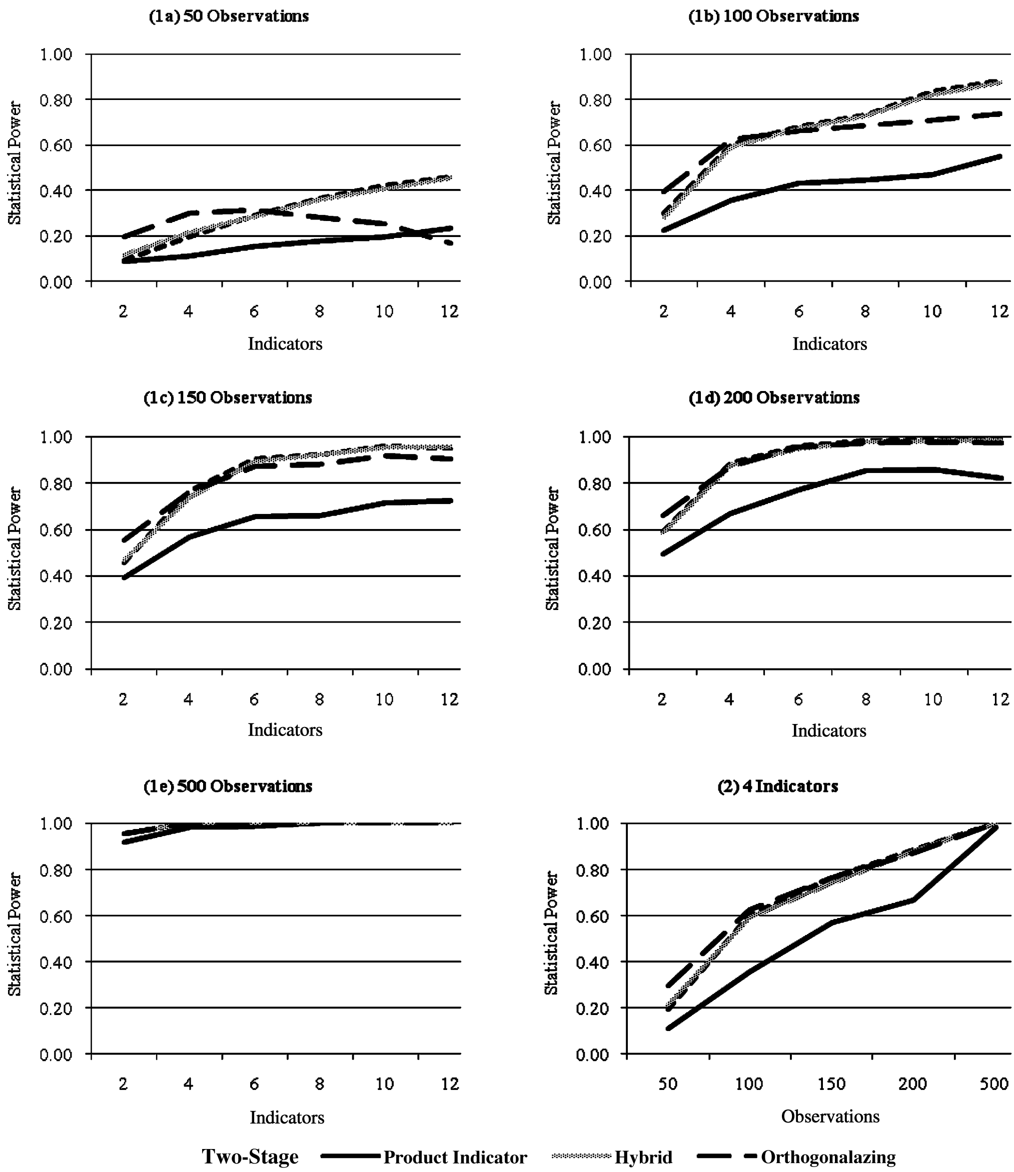


FIGURE 5 Statistical power of the four approaches to detect the interaction effect.

examine the prediction accuracy, we look at the proportion of the true endogenous variable's variance that can be explained by each approach. Again, we consider the 30 predefined conditions. Table 7 exhibits the average (over 500 Monte Carlo samples) squared correlations (r^2) between the predicted and the true values of the endogenous latent variable. It can quickly be seen that depending on the number of indicators and observations, the highest

TABLE 6
Multiple Comparisons Over the Statistical Power

Approaches Under Comparison	*Significance of Differences in Interaction Term's Statistical Power*		
	Tamhane T2	*Dunnett T3*	*Games-Howell*
Two-stage vs. product indicator	.000	.009	.000
Two-stage vs. hybrid	.994	.994	.944
Two-stage vs. orthogonalizing	.001	.011	.001
Product indicator vs. hybrid	.000	.009	.000
Product indicator vs. orthogonalizing	.000	.009	.000
Hybrid vs. orthogonalizing	.007	.017	.007

TABLE 7
Squared Correlations (r^2) Between the Predicted and the True Values of the Endogenous Latent Variable

No. of Observations	*Approach*	*No. of Indicators*						*Average*
		2	*4*	*6*	*8*	*10*	*12*	
50	Two-stage	.2874	.3776	.4104	.4175	.4438	.4550	.4221
	Product indicator adjusted	.3015	.4087	.4539	.4750	.4995	**.5134**	
	Hybrid	.2874	.3777	.4107	.4178	.4442	.4559	
	Orthogonalizing	**.3094**	**.4208**	**.4672**	**.4820**	**.5042**	.5088	
100	Two-stage	.2744	.3547	.3799	.3956	.4131	.4230	.3850
	Product indicator adjusted	.2825	.3740	.4047	**.4245**	**.4441**	**.4533**	
	Hybrid	.2743	.3547	.3799	.3957	.4132	.4231	
	Orthogonalizing	**.2854**	**.3770**	**.4053**	.4224	.4387	.4453	
150	Two-stage	.2742	.3420	.3708	.3888	.4025	.4094	.3719
	Product indicator adjusted	.2801	.3552	**.3873**	**.4081**	**.4227**	**.4303**	
	Hybrid	.2742	.3421	.3709	.3888	.4026	.4095	
	Orthogonalizing	**.2813**	**.3562**	.3864	.4035	.4162	.4228	
200	Two-stage	.2655	.3387	.3704	.3823	.3967	.4035	.3650
	Product indicator adjusted	.2697	.3486	**.3832**	**.3962**	**.4117**	**.4193**	
	Hybrid	.2656	.3387	.3704	.3823	.3968	.4036	
	Orthogonalizing	**.2707**	**.3490**	.3822	.3940	.4072	.4131	
500	Two-stage	.2669	.3310	.3624	.3768	.3890	.3962	.3558
	Product indicator adjusted	.2686	**.3353**	**.3674**	**.3823**	**.3948**	**.4022**	
	Hybrid	.2669	.3310	.3624	.3768	.3890	.3962	
	Orthogonalizing	**.2689**	.3351	.3666	.3809	.3929	.3996	
Average		.2777	.3574	.3896	.4046	.4211	.4292	.3799

Note. The best performing approach per condition is marked in bold.

prediction accuracy is achieved either by the orthogonalizing or the product indicator approach.

Again, we chose a balanced mixed factorial design with the approach as a fixed factor and the number of indicators and observations as random factors. From the ANOVA, all interaction terms emanate as significant. Whereas the two-way interactions—the interaction of approach with number of indicators, $F(15, 60000) = 6.003$, $p < .001$, $\eta_p^2 = 0.600$; the interaction of number of indicators with number of observations, $F(12, 60000) = 43.048$, $p < .001$, $\eta_p^2 = 0.896$; and the interaction of approach with number of observations, $F(20, 60000) = 19.577$, $p < .001$, $\eta_p^2 = 0.867$, are significant and substantial, the three-way interaction of approach with number of indicators and number of observations, $F(60, 59878) = 1.464$, $p = .011$, $\eta_p^2 = 0.001$, lacks substantiality. Furthermore, we found a significant main effect of the PLS interaction approach, $F(3, 14721) = 6.341$, $p = .006$, $\eta_p^2 = 0.564$. The number of indicators, $F(5, 27995) = 198.944$, $p < .001$, $\eta_p^2 = 0.973$, and the number of observations, $F(4, 21875) = 20.157$, $p < .001$, $\eta_p^2 = 0.787$, turned out to be significant determinants of prediction accuracy as well. As post hoc analyses, Tamhane's T2 and Tukey's honestly significant difference (HSD) test came to very proximate results. Furthermore, Tukey's HSD revealed two homogenous subsets of approaches. The first subset contains the two-stage and the hybrid approach, both showing an average explained variance of 37%. The second subset consists of the orthogonalizing and the product indicator approach, both explaining about 39% of the true endogenous variable's variance. In conclusion, the orthogonalizing and the product indicator approach provide a significantly and substantially more accurate prediction than the other two approaches. Among these two, the orthogonalizing approach should be used in case of small sample size and few indicators per construct. If the sample size or the number of indicators per construct is medium to large, the product indicator approach should be used.[10] Looking at the two-stage and the hybrid approach we find again that there is no notable difference between them. Interestingly, the advantages of the orthogonalizing and the product indicator approach over the other two approaches in terms of prediction accuracy could not be validly derived from the empirical R^2 values of the TAM example presented earlier.

RECOMMENDATIONS

Based on the results of the Monte Carlo simulation, it is possible to give recommendations to researchers who want to analyze interaction effects between latent variables by means of PLS path modeling. The differences in estimation outcomes depending on the selected approach make it necessary for a researcher to make a well-based decision on which approach to use for the modeling of interaction effects by means of PLS path modeling. As the outcomes reveal, none of the approaches excels in all criteria. Instead, each approach has a number of strengths and weaknesses, which make it suitable for one application but less for another. The choice of approaches should therefore mainly be based on the researcher's objectives. Is the model aimed at detecting interaction effects; that is, shall the question be answered whether the interaction delivers a significant additional explanation of the endogenous variable (first case)?

[10]If prediction is the only purpose of the moderated path analysis, any adjustment of the interaction term's standard deviation is arbitrary, and can thus be ignored.

Or is the model meant for finding an estimate for the true parameter of an interaction effect, thus describing the relations (second case)? Or is it the objective of the interaction model to give a better prediction of the endogenous latent variable (third case)?

In the first case, when a researcher is mainly interested in the significance of an interaction effect, an approach that needs a minimal amount of observations given a particular significance level (Type-I-error), power (Type-II-error), and effect size is preferable. As the Monte Carlo simulation revealed, both the two-stage and the hybrid approach have a high level of statistical power compared with the orthogonalizing and especially the product indicator approach. Only in the case of few indicators and few observations, the orthogonalizing approach seems to be advantageous. Recognizing the easy use of the two-stage approach on the one hand, and the lack of freely available software implementation of the hybrid approach on the other hand, it appears recommendable to apply the two-stage approach to assess the significance of an interaction effect.

In the second case, when the model is meant for finding an estimate for the true parameter of an interaction effect, at first the product indicator approach might catch one's eye, because it provides the least biased estimates for the interaction effect for medium to large sample sizes. Still, the orthogonalizing approach is not significantly worse than the product indicator approach in point accuracy, and delivers the most accurate estimates of the interaction effects for small sample sizes. However, one must recognize that the product indicator approach's higher point accuracy of interaction effects comes at a cost, namely the downward biased estimation of the single effects. As the orthogonalizing approach does not share this disadvantage, the general use of the orthogonalizing approach to estimate the path coefficients of interaction effects should be advocated. As long as both the exogenous and the moderator variable are centered, and the interaction term is either nonstandardized or ex post adjusted, the path coefficient of the interaction term tells how much the path coefficient of the moderated relation changes for an observation whose value of the moderator variable is 1 *SD* above zero. Going back to our technology acceptance example and using the estimates from the orthogonalizing approach (see Table 1), the adoption intention of an individual perceiving enjoyment 1 *SD* higher than the average is influenced by 0.3628 (= 0.5165 − 0.1537) times perceived usefulness and 0.2686 times enjoyment. It must be noted, though, that whereas the path coefficient of the interaction effect might serve as a first entry to interpretation, Carte and Russell (2003) emphasized that the interaction's regression coefficient should not form the basis for assessing the strength of the interaction effect. Instead, Cohen's (1988) f^2 effect size measure for hierarchical multiple regression can be applied. It is defined as:

$$f^2 = \frac{R^2_{incl} - R^2_{excl}}{1 - R^2_{incl}} \tag{16}$$

where R^2_{excl} is the variance accounted for by the independent and the moderator variable as such, and R^2_{incl} is the combined variance accounted for by the independent and the moderator variable and their interaction.[11] By convention, f^2 effect sizes of 0.02, 0.15, and 0.35 are regarded as small, medium, and large, respectively (Cohen, 1988).

[11] Note that Chin et al. (2003, p. 211) mistakenly labeled R^2_{excl} instead of R^2_{incl} in the denominator of this formula, thereby provoking an underestimation of f^2.

TABLE 8
Recommendations for the Use of the Approaches

		Condition			
		Few Indicators		*Many Indicators*	
Objective	*Approach*	*Few Observations*	*Many Observations*	*Few Observations*	*Many Observations*
Explanation	Product indicator	−	o	−	+
	Two-stage	o	++	+	++
	Hybrid	o	++	+	++
	Orthogonalizing	−	+	−	++
Description of single effects	Product indicator	o	o	o	o
	Two-stage	+	o	+	o
	Hybrid	+	o	+	o
	Orthogonalizing	+	o	+	o
Description of interaction effect	Product indicator	+	o	+	+
	Two-stage	−	−	o	o
	Hybrid	−	−	o	o
	Orthogonalizing	++	o	++	o
Prediction	Product indicator	+	+	++	+
	Two-stage	o	o	+	+
	Hybrid	o	o	+	+
	Orthogonalizing	++	+	++	+

Note. ++ = highly recommendable; + = recommendable; o = acceptable; − = not recommendable.

In the third case, when a researcher wants to achieve as precise a prediction as possible of the endogenous latent variable, the situation is clearer. Either the product indicator or the orthogonalizing approach should be chosen. Both yield higher prediction accuracy than the other two approaches.

Table 8 sums up the partial recommendations that can be derived from the Monte Carlo experiment. Overall, we recommend using the orthogonalizing approach. Among the four presented approaches, it delivers the best point accurate estimates for interaction effect as well as for the single effects. Moreover, it has a high prediction accuracy, which is of focal interest for studies using PLS path models mainly for predication purposes, like customer satisfaction indexes (e.g., Fornell, 1992) and many technology acceptance studies. The major disadvantage of the orthogonalizing approach is its somewhat lower statistical power compared to other approaches. This is unproblematic as long as an interaction effect is found to be significant. However, if an interaction effect has been found to be nonsignificant by the orthogonalizing approach, there remains some ambiguity in the reason for that finding: Is it because there is no interaction effect in reality, or is it because the approach did not have enough statistical power to find it? In such a case, we propose using additionally the more powerful two-stage approach to test whether an interaction effect is significant or not.

LIMITATIONS AND FURTHER RESEARCH

It was our aim to compare the suitability of several PLS-based approaches for the analysis of interaction effects between latent variables. As we limited our study to PLS-based approaches, other SEM techniques like LISREL or regressions of summated scales were not considered. For direct effects, a comparison of biases in PLS estimates with biases in estimates of covariance-structure-based SEM has already been carried out elsewhere (cf. Cassel, Hackl, & Westlund, 1999). However, it might be fruitful to extend such research to incorporate PLS and LISREL approaches alike to model interaction effects.

Not only beyond PLS but also within the domain of PLS path modeling, there are promising terrains for extensions of our research. Being aware that our research is focused on the analysis of interaction effects of continuous (latent) variables, we recognize that there are at least two fields that are strongly related: multigroup analysis and polynomial terms. Multigroup comparisons are a special case of analysis of moderated relationships, and interaction effects themselves are a special case of nonlinear effects.

Multigroup comparisons can be regarded as analyses of interaction effects having a categorical moderator variable. In principle, all categorical moderator variables could be transformed into dummy variables, and used in combination with each of the four presented approaches. However, it remains unclear how well the four approaches perform compared with approaches that are customized for multigroup analyses, as, for example, the one by Dibbern and Chin (2005). Another important issue in multigroup comparisons is measurement invariance. In our study, we assumed the measurement models to be invariant across different levels of the latent moderator variable. Future research could also address this issue and examine the behavior of the four approaches in the light of moderated measurement models.

In many cases, particularly when the independent variable correlates highly with the moderator variable, interaction effects might be confounded with quadratic effects. Carte and Russell (2003) strongly recommended adding quadratic terms in regression equations to avoid biased estimates of the interaction effect. In our analyses, we focused on the interaction term alone, and did not include quadratic terms. Although quadratic terms have already been included in PLS path models (cf. Pavlou & Gefen, 2005), it remains unclear for researchers how this should be done. Originally, all four approaches for the analysis of interaction effects between latent variables using PLS path modeling have been designed to cope with nonlinear effects in general. Thus, it appears likely that the findings of our study can also be generalized to other nonlinear effects including quadratic and cubic effects. However, final evidence of the behavior of such extensions of PLS path models should be given by means of customized Monte Carlo simulations.

As we only used reflective measurement models throughout our contribution, it also remains unclear whether our findings about the PLS-based analysis of interaction effects can be generalized to PLS path models and formative measurement models. Whereas the product indicator approach and its advancement, the orthogonalizing approach, are restricted to reflective measurement models, both the hybrid and the two-stage approach can handle formative measurement models. In light of the increasing popularity of formative measurement models, mainly in business success factor research, there is a need for approaches that can analyze interactions among formative constructs. Furthermore, our item measures were all set at the same reliability. How each method stacks up under conditions of heterogeneous items should be tested in the future.

Finally, it is surprising that the hybrid approach, which has its roots in Wold's (1982) original proposal for the inclusion of nonlinear effects, does not excel in any of the examined categories (i.e., parameter accuracy, statistical power, and prediction accuracy). More evidence on its performance should be gathered to decide whether its implementation and its use in business and social sciences are of any value at all.

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