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Structural Equation Modeling in Information Systems Research Using Partial Least Squares

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Abstract:

Empirical studies that use structural equation modeling (SEM) are widespread in information systems research. During the last few years, the component-based approach partial least squares (PLS) for testing structural models has become increasingly popular. At the same time, this approach's limitations have become a greater concern. Some researchers even suggest using alternative approaches that are considered superior to PLS.

However, we believe that PLS is an adequate choice if the research problem meets certain characteristics and the technique is properly used. Thus, the intention of this article is to resolve potential uncertainties that researchers intending to use PLS might have. Consequently, we provide a nontechnical overview of PLS and outline the ongoing discourses on SEM in general and the PLS approach in particular. Furthermore, we present a basic framework for empirical research applying PLS as well as a detailed explanation of the different process steps. Finally, examples of information systems research using PLS are summarized to demonstrate its beneficial application and the appropriateness of the proposed framework.

This article can serve as a helpful guide for inexperienced researchers applying PLS for the first time, but also as a reference guide for researchers with a better understanding of the field.

Keywords: structural equation modeling, partial least squares, information systems research

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I. INTRODUCTION

The information systems (IS) discipline examines socioeconomic systems that are characterized by the interplay between hardware and software on the one hand, as well as individuals, groups, and organizations on the other. For example, technology adoption, acceptance, and success, as well as the conditions under which these can be achieved are typical issues that are addressed by IS research. These research fields are similar in that their investigation requires the researcher to cope with constructs such as the beliefs, perceptions, motivation, attitude, or judgments of the individuals involved. These constructs are usually modeled as latent variables (LVs) that can be measured only through a set of indicators. Structural equation models describe the relationships between several of these LVs. A number of algorithms and software programs are available to estimate their relationships based on a dataset.

Among these algorithms, the partial least squares (PLS) algorithm has become increasingly popular both in IS research and in other disciplines such as marketing (Albers 2010; Henseler et al. 2009) or strategic management (Hulland 1999). However, reminders of this approach's limitations have recently become more prominent. Consequently, researchers opt for a more careful application of PLS. Especially its statistical power at small sample sizes, the overall model fit, as well as the misspecification of measurement models have been the focus of recent discussions. To resolve the uncertainties that researchers intending to use PLS might have, we investigate current discourses on the PLS approach. In the following sections, we:

- demonstrate the increasing popularity of PLS in the IS research community
- outline the PLS approach by providing a nontechnical overview and reflecting on the ongoing discussion on structural equation modeling (SEM) in general and on PLS in particular
- discuss differences between PLS and covariance-based approaches
- present a basic framework for empirical research applying the PLS approach
- provide examples of its beneficial application in IS research

As a result, this paper helps SEM beginners and advanced researchers to make an informed decision about whether to use SEM or other alternative approaches to SEM. Even more, we present up-to-date recommendations on how to apply PLS appropriately.

Section II demonstrates the increasing popularity of PLS for SEM in IS research by conducting a systematic review of literature that appeared in two prestigious IS journals during the last fifteen years. In Section III, we present an introduction to SEM by discussing the common philosophical foundations of research applying SEM, presenting the basic elements of a structural equation model, and exploring different types of indicator sets for latent variables. In Section IV, we explain the basic concept of PLS and compare it to alternative approaches like covariance-based SEM (CBSEM). Furthermore, we delineate the PLS algorithm and provide a brief overview of available software tools. In Section V, we introduce a basic framework for applying PLS and take a closer look at its process steps. Finally, Section VI outlines two articles as examples of typical PLS studies on IS research. In particular, we illustrate how researchers have translated their research question into a set of hypotheses expressed by a structural equation model and how they applied PLS to estimate model parameters with a high degree of reliability and validity. To conclude, we summarize the article's contribution in Section VII.

CONTRIBUTION

This paper makes important contributions especially to information systems research.

It provides a nontechnical overview of the component-based approach partial least squares (PLS) for structural equation modeling (SEM). The ongoing discourses on structural equation modeling in general and on the PLS approach in particular are outlined. The paper summarizes and consolidates arguments in favor of and against PLS culminating in a presentation of possible application scenarios and their constraints. Furthermore, the paper presents a basic framework for empirical research applying PLS as well as a detailed explanation of the different process steps. Examples of information systems research using PLS are summarized to demonstrate its beneficial application and the appropriateness of the proposed framework.

The particular intention of this article is to resolve potential uncertainties that researchers intending to use PLS might have. It is expected to serve as a helpful guide for inexperienced researchers selecting the right approach to SEM and—if PLS is chosen—applying it appropriately. However, this paper may also serve as a reference guide for researchers with a better understanding of the field.

II. APPLICATION OF PLS IN INFORMATION SYSTEMS RESEARCH

We conducted a systematic literature review to demonstrate the increasing popularity of PLS in IS research. To this end, we analyzed all research articles that appeared in probably the two most prestigious international IS journals, namely *Information Systems Research* (ISR) and *Management Information Systems Quarterly* (MISQ) (Ferratt et al. 2007; Lowry et al. 2004; Saunders 2009), during a period of fifteen years (from 1994 until 2008). We selected eighty-five of these articles by conducting a full text search using the keywords “PLS” and “partial least squares.” An in-depth analysis revealed that seventy-eight of the identified articles present empirical studies that used PLS as a means of statistical analysis (see Appendix A). The remaining seven papers are methodological or opinion papers on the use of PLS for SEM (see Appendix B).

The first study using PLS that appeared in the two journals and during the period we investigated was published by Igbaria et al. (1994).[1]. Although there were some articles in the 1990s, the popularity of PLS seems to have largely increased during the last few years. Figure 1 shows the distribution of empirical research articles that used PLS over time.

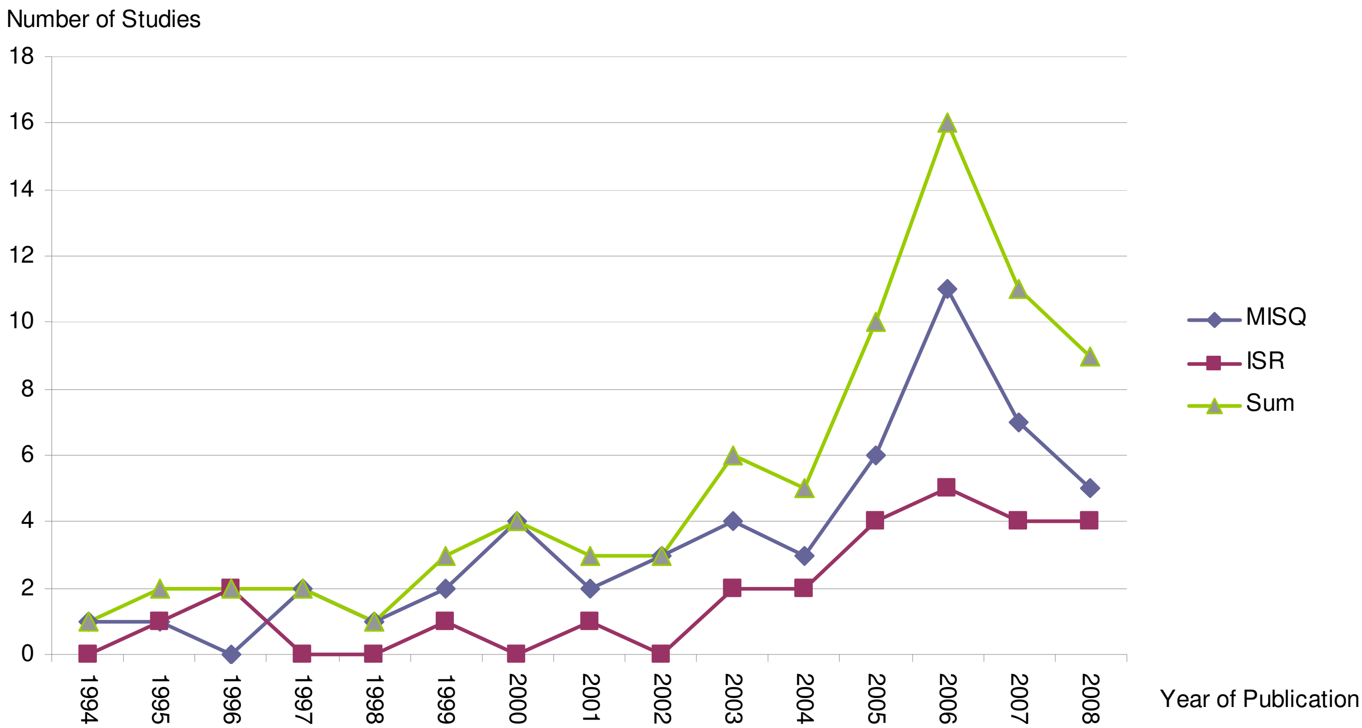

Figure 1: Distribution of studies using PLS over time.

In addition, we contrasted the absolute numbers of articles that used PLS with the total number of articles published in the two journals. Table 1 presents the resulting relative numbers for each year of publication. Furthermore, the numbers are contrasted to the occurrence of studies that apply CBSEM using LISREL, AMOS or EQS (see Figure 2).

[1] To the best of our knowledge, in the two journals that we investigated, the article by Thompson and Higgins (1991) was the first study to ever use PLS for data analysis.

Table 1: Usage of PLS and CBSEM in Research Articles Published in MISQ and ISR					
Year of Publication	**Total Number of Articles**	**Number of PLS Studies**	**Percentage of PLS Studies**	**Number of CBSEM Studies**	**Percentage of CBSEM Studies**
1994	42	1	2.38%	4	9.52%
1995	40	2	5.00%	3	7.50%
1996	51	2	3.92%	1	1.96%
1997	40	2	5.00%	3	7.50%
1998	44	1	2.27%	1	2.27%
1999	47	3	6.38%	2	4.26%
2000	49	4	8.16%	3	6.12%
2001	42	3	7.14%	2	4.76%
2002	45	3	6.67%	6	13.33%
2003	42	6	14.29%	5	11.90%
2004	49	5	10.20%	6	12.24%
2005	53	10	18.87%	5	9.43%
2006	69	16	23.19%	5	7.25%
2007	56	11	19.64%	8	14.29%
2008	59	9	15.25%	12	20.34%
Sum	**728**	**78**	**10.71%**	**66**	**9.07%**

Our analysis' results provide evidence of the increasing popularity of PLS research within the IS community. Furthermore, the numbers indicate that in the empirical studies published in the two journals investigated, PLS has been used even more frequently than the covariance-based approaches. Thus, the results are in line with the findings of Goodhue et al. (2006, p. 2), who discovered that "PLS has been wholeheartedly accepted as an important statistical method in the MIS field."

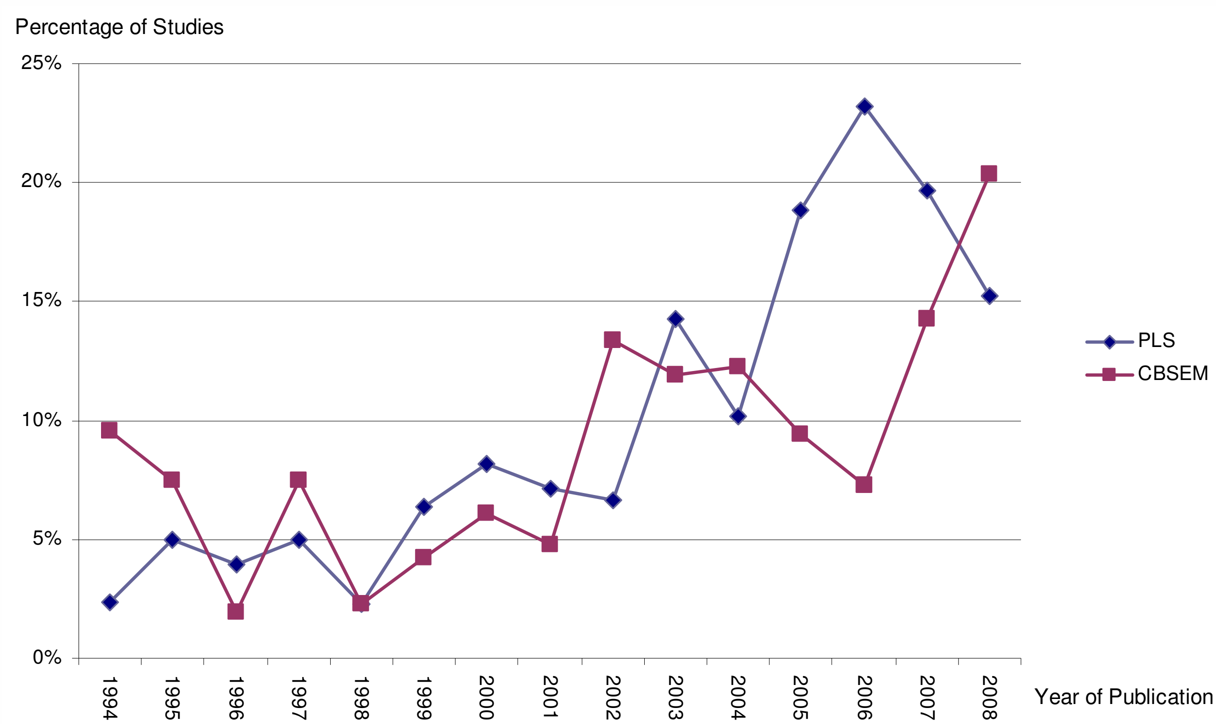

Figure 2: Relative numbers of studies using PLS and CBSEM.

Following Henseler et al.'s (2009) approach, we analyzed the empirical studies with regard to the main motivation for using PLS (see Appendix A). Most of the researchers argue that their studies' objectives are in line with PLS's particular strengths. We summarize the researchers' arguments for choosing PLS as the statistical means for testing structural equation models as follows:

- PLS makes fewer demands regarding sample size than other methods.
- PLS does not require normal-distributed input data.
- PLS can be applied to complex structural equation models with a large number of constructs.
- PLS is able to handle both reflective and formative constructs.
- PLS is better suited for theory development than for theory testing.
- PLS is especially useful for prediction

In fact, the stated advantages reflect most of PLS's strengths. However, an increasing number of articles advising a more careful application of PLS have recently been published (see Appendix B). Accordingly, some of the characteristics above have to be treated with caution as we further elaborate on in the subsequent sections. Surprisingly, some arguments are even wrong and neither reflect PLS's nor CBSEM's capabilities correctly. This underlines the necessity to clarify the characteristics, advantages, and disadvantages of these two approaches.

III. INTRODUCTION TO STRUCTURAL EQUATION MODELING

SEM is a statistical technique for simultaneously testing and estimating causal relationships among multiple independent and dependent constructs (Gefen et al. 2000). Before introducing the PLS approach and discussing its characteristics, we briefly expose the underlying philosophical assumptions of research that applies SEM, present the basic properties of a structural equation model, and explore the different types of indicator sets for latent variables.

Philosophical Foundations

IS research is characterized by a wealth of different philosophical positions ranging from strictly positivist to interpretive and constructivist epistemological beliefs. Since the aptness of one's position cannot be ultimately determined, researchers are free to make their own choices. However, deciding on a philosophical position is not arbitrary; it has a significant impact on the research design and the nature of the insights that the researcher can acquire. For instance, scholars recommend not using different research methods with conflicting underlying philosophical assumptions. Although recent voices favor a differentiated perspective on this incommensurability thesis, researchers need to carefully analyze whether their multi-methods approach may lead to severe ontological or epistemological problems (Mingers 2001).

Research that applies SEM usually follows a positivist epistemological belief. According to the work of Orlikowski and Baroudi (1991), as well as Dubé and Paré (2003), a set of characteristics classifies research as positivist. Ontologically, positivist research assumes an objective, physical, and social world that exists independently of humans. Furthermore, the nature of this world can be relatively easily apprehended, characterized, and measured. The researcher plays a passive, neutral role and does not intervene in the phenomenon of interest. Epistemologically, the positivist perspective is concerned with the empirical testability of theories. In other words, these theories are either confirmed or rejected. They are premised on the existence of *a priori* fixed relationships within phenomena that can be identified and tested through hypothetico-deductive logic and analysis. The relationship between theory and practice is considered as primarily technical. In contrast with the position adopted by the interpretive and critical philosophies, researchers can objectively evaluate or predict actions or processes, but cannot become involved in moral judgments or subjective opinions.

Nature of Structural Equation Models

The purpose of many research projects is to analyze causal relationships between variables. SEM is a statistical technique for testing and estimating those causal relationships based on statistical data and qualitative causal assumptions. SEM techniques can be considered the second generation of multivariate analysis (Fornell 1987). In contrast to first-generation techniques, such as factor analysis, discriminant analysis, or multiple regression, SEM allows the researcher to simultaneously consider relationships among multiple independent and dependent constructs. Thus, SEM answers a set of interrelated research questions in a single, systematic, and comprehensive analysis (Gefen et al. 2000). An additional asset of a structural equation model is that it supports latent variables (LVs). LVs can be considered "hypothetical constructs invented by a scientist for the purpose of understanding a research area" (Bentler 1980, p. 420). Since LVs are unobservable and cannot be directly measured, researchers use observable and empirically measurable indicator variables (also referred to as manifest variables (MVs)) to estimate LVs in the model. Thus, the relationships can be analyzed between theoretical constructs, such as intentions, perceptions, satisfaction, or benefits, which are important to almost every discipline. Consequently, the use of LVs has the potential to model theoretical constructs that are hard or impossible to measure directly.

A structural equation model consists of different sub-models. The *structural model* (or inner model) comprises the relationships between the LVs, which has to be derived from theoretical considerations. The independent LVs are also referred to as exogenous variables and the dependent LVs as endogenous variables. For each of the LVs within the structural equation model, a *measurement model* (or outer model) has to be defined. These models embody the relationship between the empirically observable indicator variables and the LVs. The measurement model itself needs to be grounded on an auxiliary theory. Citing Blalock (1971), Edwards and Bagozzi (2000, p. 115) noted that, "without this auxiliary theory, the mapping of theoretic constructs onto empirical phenomena is ambiguous, and theories cannot be empirically tested."

The combination of structural model and measurement models leads to a complete structural equation model. An example of a simple model is illustrated in Figure 3. It consists of one exogenous (ξ_i) and two endogenous variables (η_i). The LVs are operationalized through the measurable indicator variables x_i and y_i. The relationships between the variables are quantified by path coefficients. The path coefficients λ_i within the measurement models are either determined by weights—for formative constructs—or loadings—for reflective constructs. The path coefficients between latent endogenous variables are labeled β_i, whereas the path coefficients between exogenous and endogenous variables are referred to as γ_i.

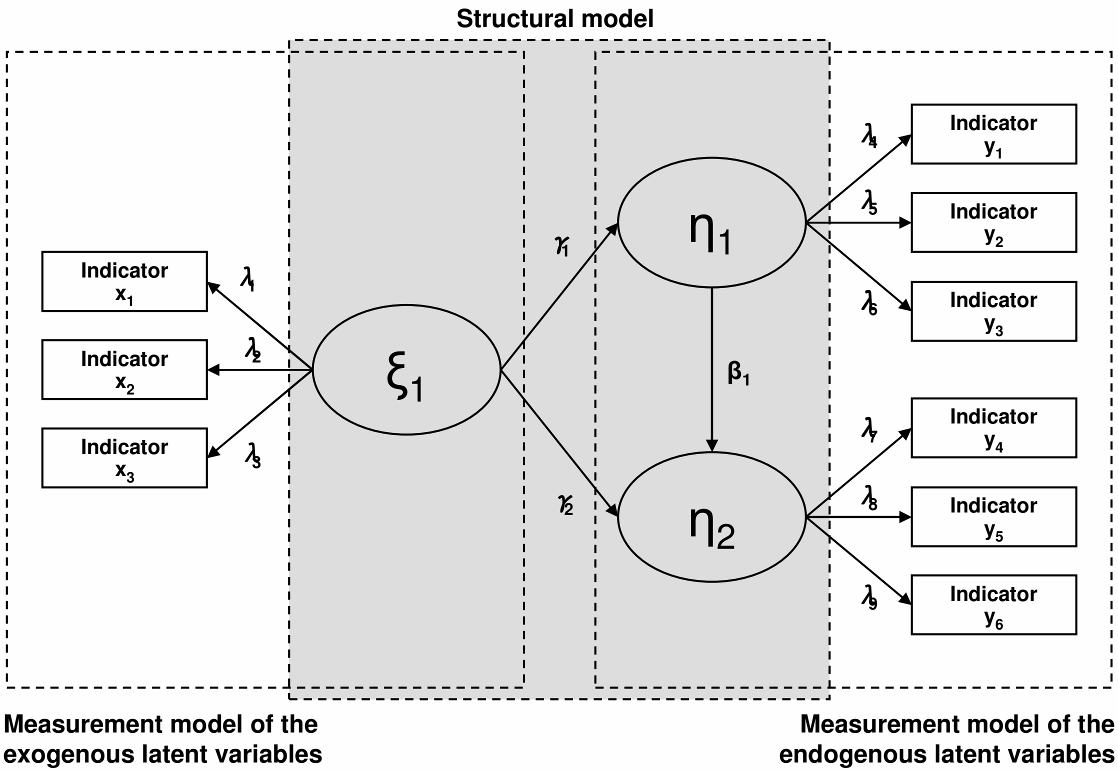

Figure 3: Example of a structural equation model (adapted from Backhaus et al. 2000).

The primary statistical problem of analyzing the structural equation model is the optimal estimation of the model's parameters as well as the determination of the model's goodness-of-fit to the sample data on the measured variables. SEM usually assumes that there are linear relationships between variables. If it does not adequately fit the data, the proposed model has to be rejected as a possible candidate for the observed variables' causal structure. However, the causal structure can be considered plausible if the model cannot be statistically rejected (Bentler 1980).

Auxiliary Measurement Theories: Reflective and Formative Models

As outlined above, one attractive characteristic of SEM is its ability to cope with LVs that cannot be measured directly but that require measurement models consisting of one or many indicators. In general, two different types of indicators can be distinguished:

(1) Reflective indicators are considered "effects" of the LVs. In other words, the LVs cause or form the indicators (Chin 1998b). All reflective indicators measure the same underlying phenomenon, namely the LV. Whenever the LV changes, all reflective indicators should change accordingly, which refers to internal consistency (Bollen 1984). Consequently, all reflective indicators should correlate positively.

(2) In contrast, formative indicators cause or form the LV by definition (Chin 1998b). These indicators are viewed as the cause variables that reflect the conditions under which the LV is realized. Since there is no direct causal relationship between the LV and the indicators (but vice versa), formative indicators may even be inversely related to each other. In other words, formative indicators of the same LV do not necessarily have to correlate (Bollen 1984; Rossiter 2002).

Table 2 provides a comprehensive comparison of formative and reflective models.

Table 2: Comparison of Formative and Reflective Measurement Models (Jarvis et al. 2003)

Criteria	Formative Model	Reflective Model
1. Direction of causality from construct to measure implied by the conceptual definition	*Direction of causality is from items to construct.*	*Direction of causality is from construct to items.*
Are the indicators (items) (a) defining characteristics or (b) manifestations of the construct?	Indicators are defining characteristics of the construct.	Indicators are manifestations of the construct.
Would changes in the indicators/items cause changes in the construct or not?	Changes in the indicators should cause changes in the construct.	Changes in the indicator should not cause changes in the construct.
Would changes in the construct cause changes in the indicators?	Changes in the construct do not cause changes in the indicators.	Changes in the construct do cause changes in the indicators.
2. Interchangeability of the indicators/items	*Indicators need not be interchangeable.*	*Indicators should be interchangeable.*
Should the indicators have the same or similar content? Do the indicators share a common theme?	Indicators need not have the same or similar content/indicators need not share a common theme.	Indicators should have the same or similar content/indicators should share a common theme.
Would dropping one of the indicators alter the conceptual domain of the construct?	Dropping an indicator may alter the conceptual domain of the construct.	Dropping an indicator should not alter the conceptual domain of the construct.
3. Covariation among the indicators	*Not necessary for indicators to covary with each other*	*Indicators are expected to covary with each other.*
Should a change in one of the indicators be associated with changes in the other indicators?	Not necessarily	Yes
4. Nomological net of the construct indicators	*Nomological net of the indicators may differ.*	*Nomological net of the indicators should not differ.*
Are the indicators/items expected to have the same antecedents and consequences?	Indicators are not required to have the same antecedents and consequences.	Indicators are required to have the same antecedents and consequences.

Generally, reflective indicators are widespread and only a small proportion of SEM-based studies have applied formative measurement models. The use of reflective measurement models was considered the norm and researchers did not question those that they applied. This led to a significant number of past studies with misspecified measurement models, mostly those using a reflective model with formative indicators. A study by Petter et al. (2007) showed that 30 percent of analyzed structural equation models in leading IS journals were subject to such misspecifications. Other authors like Diamantopoulos and Winklhofer (2001) and Jarvis et al. (2003) support this view.

Consequently, there has been an ongoing discourse on the characteristics of both model types and especially on the limitations of formative indicators (Bagozzi 2007; Bollen 1984; Bollen 2007; Howell et al. 2007a; Howell et al. 2007b). Some researchers opt for the exclusive usage of reflective indicators for theory testing, since formative constructs seem to have epistemological, logical, and statistical problems (e.g., Wilcox et al. 2008). Bagozzi (2007, p. 236) concludes that "Formative measurement can be done, but only for a limited range of cases and under restrictive assumptions. Yet, even here problems in interpretation may arise." Nevertheless, researchers should carefully design their measurement models so that a block of indicators is either completely formative or completely reflective. Moreover, validity indicators need to correspond with the chosen mode. A comprehensive overview on the thoughtful application of formative measurement models has been published by Diamantopoulos et al. (2008). If there is a real choice between applying formative or reflective measurement, we recommend using the latter due to its less problematic epistemological assumptions and the wealth of validity measures available.

IV. THE PLS APPROACH

Partial least squares (PLS) is a component-based approach for testing structural equation models. In the following, we present the basic concept of PLS, compare PLS to alternative approaches for estimating parameters of structural equation models, outline the PLS algorithm, and provide a brief overview of available PLS software tools.

Basic Concept

The PLS algorithm dates back to Wold's (1966) early work on the principal component analysis. It was first completely formalized in 1979 (Wold 1979), with his main reference to PLS in 1985 (Wold 1985). Several researchers have built on Wold's work, developing it further and refining the algorithm (Chin 1998b; Chin and Newsted 1999; Chin and Todd 1995; Lohmöller 1984; Lohmöller 1989). PLS is based on the idea of having two iterative procedures using least squares estimation for single and multi-component models. By applying these procedures, the algorithm aims at minimizing the variance of all the dependent variables (Chin 1998b). Accordingly, the cause-and-effect directions between all the variables need to be clearly defined (Huber et al. 2007). The model quality improves as more indicators are used to explain the LVs, since a larger number of indicators can better explain an LV's variance ("consistency at large") (Huber et al. 2007; Lyttkens 1973). In general, two applications of PLS are possible (Chin 1998b): It can either be used for theory confirmation or theory development. In the latter case, PLS is used to develop propositions by exploring the relationships between variables.

The PLS approach has several characteristics making it attractive to researchers: First of all, it is "distribution-free." Consequently, there are no assumptions regarding the distributional form of measured variables (Chin 1998b). Moreover, PLS will neither produce inadmissible solutions nor suffer factor indeterminacy (Fornell and Bookstein 1982). Under certain conditions, it works with relatively small sample sizes (Cassel et al. 1999). Furthermore, PLS generates LV estimates for all cases in the data set. Finally, there is no need for independent observations (Wold 1980) or identical distributions of residuals (Chin and Newsted 1999; Lohmöller 1989).

In contrast, some scholars have pointed out that the LVs are estimated as the aggregates of the corresponding indicator variables, in which measurement errors occur. This may lead to inconsistencies, since the PLS estimates are very close to the empirical data (Chin and Newsted 1999; Fornell and Cha 1994; Huber et al. 2007). In addition, parameter estimates for the structural model are frequently inferior to those produced by alternative approaches. Furthermore, it is not possible to perform significance tests of model parameters with PLS.[2] And although it is often stated that PLS is the only method that can handle both reflective and formative constructs, concurrent techniques like Linear Structural Relationship (LISREL) also have this ability (Jarvis et al. 2003).

Selecting PLS or Covariance-based SEM Approaches

Currently, there are two general approaches to SEM: (1) covariance-based structural equation modeling (CBSEM) as implemented in LISREL, AMOS, EQS, SEPATH, and RAMONA and (2) the component-based approach PLS. These approaches differ in their analyses' objectives, their underlying statistical assumptions, and the nature of the fit statistics they produce (Gefen et al. 2000). The covariance analysis is based on the developments of Joreskög (1973), Keesling (1972), and Wiley (1973). It typically uses a maximum likelihood (ML) function to minimize the difference between the sample covariance and those predicted by the theoretical model. Consequently, the estimated parameters attempt to reproduce the observed values' covariance matrix. If the ML function is applied, the observed variables have to follow a normal distribution. In contrast, the PLS algorithm minimizes the variance of all the dependent variables instead of explaining the covariation. Consequently, PLS makes lower demands on measurement scales, sample size, and residual distributions (Wold 1985). In addition, PLS avoids inadmissible

[2] However, these tests can be carried out by using resampling techniques such as bootstrapping (Efron 1979; Efron and Tibshirani 1993) or jackknifing (Miller 1974).

solutions and factor indeterminacy (Fornell and Bookstein 1982). However, according to several authors, such as Goodhue et al. (2006; 2007) or Marcoulides and Saunders (2006), the supposed advantages of PLS over covariance-based methods have to be handled with care. Table 3 summarizes the characteristics of the PLS approach and compares it with CBSEM.

Table 3: Comparison of PLS and CBSEM (adapted from Chin and Newsted 1999)

Criteria	PLS	CBSEM
Objective	Prediction-oriented	Parameter-oriented
Approach	Variance-based	Covariance-based
Assumption	Predictor specification (nonparametric)	Typically multivariate normal distribution and independent observations (parametric)
Parameter estimates	Consistent as indicators and sample size increase (i.e., consistency at large)	Consistent
Latent variable scores	Explicitly estimated	Indeterminate
Epistemic relationship between an LV and its measures	Can be modeled in either formative or reflective mode	Typically only with reflective indicators. However, the formative mode is also supported.
Implications	Optimal for prediction accuracy	Optimal for parameter accuracy
Model complexity	Large complexity (e.g., 100 constructs and 1,000 indicators)	Small to moderate complexity (e.g., less than 100 indicators)
Sample size	Power analysis based on the portion of the model with the largest number of predictors. Minimal recommendations range from 30 to 100 cases.	Ideally based on power analysis of specific model—minimal recommendations range from 200 to 800.
Type of optimization	Locally iterative	Globally iterative
Significance tests	Only by means of simulations; restricted validity	Available
Availability of global Goodness of Fit (GoF) metrics	Are currently being developed and discussed	Established GoF metrics available

The philosophical distinction between the two SEM approaches is whether to use CBSEM for theory testing, or PLS for theory development and predictive applications (Henseler et al. 2009). Whereas CBSEM is theory-oriented, and emphasizes the transition from exploratory to confirmatory analysis, PLS is primarily intended for causal predictive analysis in situations of high complexity but low theoretical information (Jöreskog and Wold 1982). If CBSEM premises such as distributional assumptions, acceptable sample size, or maximal model complexity are violated, PLS is a reasonable alternative for theory testing. However, the lack of established global goodness-of-fit (GoF) criteria limits its use (Henseler et al. 2009).

Overall, PLS can be an adequate alternative to CBSEM if the problem has the following characteristics (Chin 1998b; Chin and Newsted 1999):

- The phenomenon to be investigated is relatively new and measurement models need to be newly developed,
- The structural equation model is complex with a large number of LVs and indicator variables,
- Relationships between the indicators and LVs have to be modeled in different modes (i.e., formative and reflective measurement models),[3]
- The conditions relating to sample size, independence, or normal distribution are not met, and/or
- Prediction is more important than parameter estimation.

[3] LISREL can also handle both reflective and formative constructs, but the handling is relatively complicated.

On the other side, covariance-based approaches to SEM have to be taken into consideration when established constructs and reflective measurement models are available, when the study is confirmative to a large extent and the structural model is of low-to-medium complexity. Researchers should also be aware of the fact that CBSEM is a more established approach with recognized GoF metrics and better parameter accuracy and thus being more frequently accepted for rigorous model validation purposes (Figure 4).

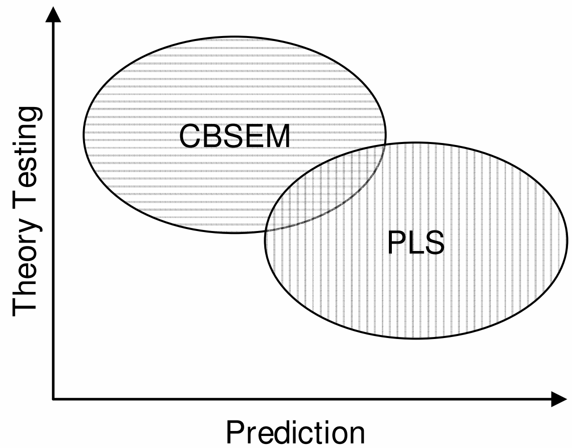

Figure 4: CBSEM vs. PLS (according to Henseler et al. 2009).

A clear and unequivocal recommendation for one of the two approaches is neither possible nor reasonable. Both approaches have their specific advantages and disadvantages that qualify them for specific settings better than for others. Consequently, researchers should carefully analyze the design of the study and the characteristics of the sample before they opt for one of them. Sometimes it may also be possible to apply both PLS and CBSEM and in most cases results are—not surprisingly—very similar. When both approaches can be applied according to the above-mentioned preconditions, we recommend using CBSEM then due to the higher degree of validity of its results. This is mainly due to the bias resulting from a low number of observations/variables and the bias resulting from PLS's manner to confound measurement errors and variable variances (Scholderer and Balderjahn 2006).

Algorithm

Since this article aims at giving a nontechnical overview of PLS, we will present only the main features of the algorithm. More detailed explanations are offered by Chin (1998b) and Huber et al. (2007). The PLS algorithm consists of a preparatory phase, an iterative main procedure, and a final phase. During the first phase, all variables are normalized so that results can be interpreted easily and the main procedure can apply simplified computations.

The main procedure consists of two steps. The first step is called *outside approximation* and estimates all LVs in the form of weighted aggregates of the MVs. In a first iteration, this estimation is achieved by allocating equal weights to each block of indicators. Using these weights, LV scores are calculated for each of the cases. Further iterations calculate more appropriate weights, which are based on the empirical data and the proxies for all LVs obtained from the next step. The calculation of the weights is done by means of regression. The second step is called *inside approximation* and creates proxies for each endogenous LV based on this LV's association with other, neighboring LVs. Once more, regression is used. The results of this regression are new LV proxies for the next iteration of this pair of outside and inside approximations. The algorithm stops applying a stopping rule when, for instance, the previous iteration has not led to a significant improvement of the LV estimates. During the last phase of the algorithm, factor loadings, path coefficients, as well as validation measures, are computed. PLS is called *partial,* since only a subset of the model parameters is estimated at each of the algorithm's procedural steps. Through the algorithm, the user obtains weights for all the formative indicators, loadings for all reflective indicators, and coefficients (standardized regression coefficients) for all paths between LVs. In addition, most programs automatically calculate basic validation measures.

Software Tools

With the growing interest in SEM using PLS in various disciplines, PLS software's availability has also increased—quite considerably. Currently, several tools are available; the researcher has to choose one that fits his/her preferences best. The most established software tools for PLS path modeling are LVPLS (Lohmöller 1984; Lohmöller 1987), PLS-Graph (Chin 2001), PLS-GUI (Li 2005), SmartPLS (Ringle et al. 2005), SPAD PLS Path Modeling (SPAD 2009), and VisualPLS (Fu 2006).

Various criteria, such as usability, methodological capability, statistical accuracy, documentation, and availability have to be taken into account when choosing an adequate software solution for analyzing structural equation models. Temme et al. (2005; 2006) have conducted a comprehensive comparison of various PLS software tools. In their analysis, the programs' strengths and weaknesses are identified to help the user make an informed selection. The results indicate that the different tools are very similar regarding their ease of use. However, the analysis of simulated data reveals that the algebraic signs of the weights/factor loadings and path coefficients can vary across the different programs. Although these sign changes are not an issue from a statistical point of view, researchers should treat the interpretation of their results with caution.

V. A FRAMEWORK FOR APPLYING PLS IN STRUCTURAL EQUATION MODELING

In this section, we provide an overview of typical SEM-based research by presenting a generic process model and pointing out the activities required within each process step and the results produced (Figure 5). To make it more understandable, the model suggests a linear process flow. However, the reader should be aware that SEM studies are seldom that straightforward. In many cases, researchers decide to return to previous steps in order to revise decisions made, either because intermediate results render this necessary or the researchers may want to compare alternative model variants or data analysis approaches. Besides the model validation phase, most of the framework’s characteristics are not exclusively PLS-specific but applicable to SEM in general. Thus, we especially emphasize the model validation phase and describe the necessary steps in detail.

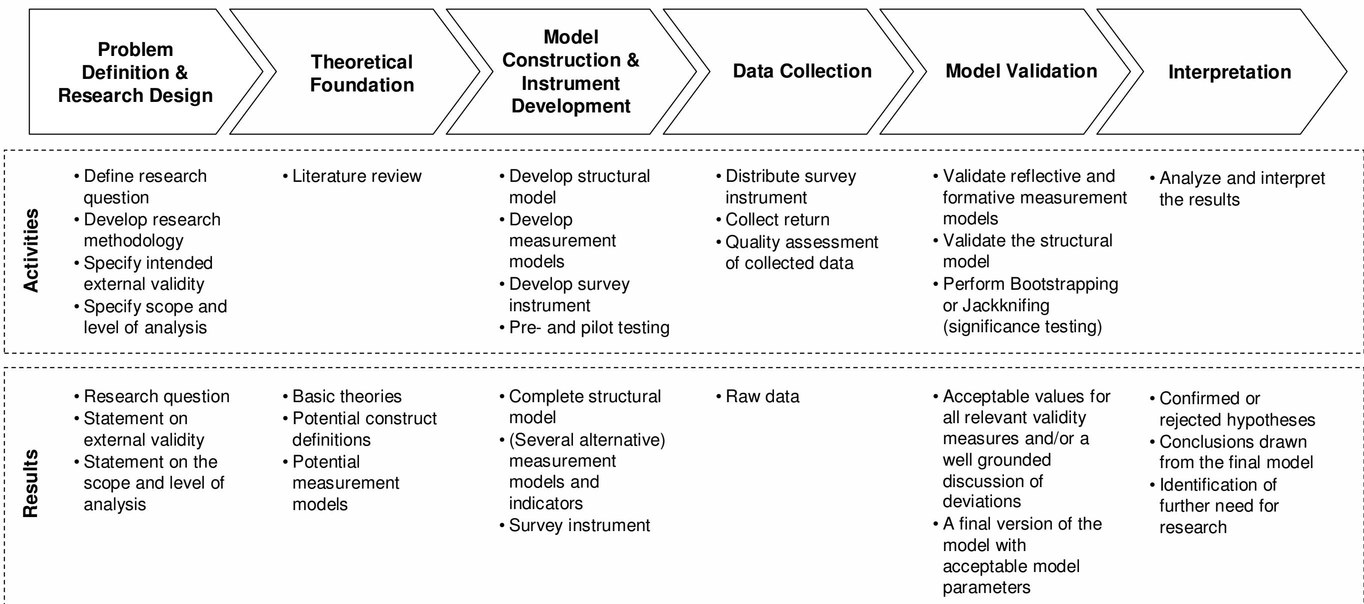

Figure 5: Framework for applying PLS in structural equation modeling.

Problem Definition and Research Design

As with the majority of research endeavors, the first research phase requires researchers to define their research question and design their research methodology accordingly. In this case, the focus is on SEM/PLS research, and, therefore, the following questions regarding the appropriateness of this approach need to be answered (Bortz and Döring 2006; Saunders et al. 2007):

- Are the positivist philosophical foundations acceptable, and are the assumptions suitable?
- Is the phenomenon sufficiently understood so that the construction of a structural equation model is promising?
- Will it be possible to collect data of the required quality?
- Is there enough SEM/PLS competency in the research team or can the required level of expertise be acquired?

If researchers can answer these questions positively, it is worth considering SEM/PLS research as a viable approach. In a next step, it is necessary to define the problem domain. This definition is a solid basis for clearly understanding the final research results' external validity. In particular, the intended external validity will determine the sampling strategy during the data collection phase. The definition of the problem domain also includes a clear specification of the level of analysis: Do the research questions address organizations or individuals (Lewis et al. 2005)? It will be easier to develop clear measurement models and a suitable survey instrument if the answer to this fundamental question is absolutely unambiguous.

Theoretical Foundation

In advanced multivariate analyses like SEM/PLS, the theoretical foundation is particularly relevant. The constructs, the measurement models, and the structural model, should all be based on strong theory. If not, the researcher could construct theories generated by data that do not reflect causal relationships between variables but accidental correlations. Accordingly, this research phase aims to identify (1) theories that may serve as a starting point for the researcher's own model development as well as (2) useful construct definitions and measurement models in literature. These objectives are mainly achieved by means of structured literature reviews (Fettke 2006; Webster and Watson 2002), which may apply techniques such as content analysis (Weber 1990). Scholars suggest both deductive (Lewis et al. 2005; Petter et al. 2007) and inductive approaches to construct development (Lewis et al. 2005). In the latter case, open-ended interviews, questionnaires, or case studies may be applied. Nevertheless, using existing construct definitions and measurement models whenever possible is recommended, as this reduces the effort required for the model development and allows a more effective comparison of the results. Typical SEM/PLS study shortcomings resulting from this phase are the inadequate analysis of the antecedent theories' premises and, thus, the developed hypotheses' lack of theoretical foundation.

Model Construction and Instrument Development

Even though a thorough literature review may provide researchers with a number of building blocks for their model construction, it is very likely that certain constructs will require new measurement approaches. In addition, a structural model needs to be developed—a process influenced by existing theories, presuppositions deduced from exploratory research and/or the researcher's creativity. Researchers often overemphasize the development of the structural model, while neglecting the measurement models (Petter et al. 2007), even though they are equally important.

To date, the literature offers little guidance for the development of structural models. Nevertheless, several researchers have suggested possible ways of developing measurement models. Some focus only on the model construction, while others also include the research process's early and late phases in their methodology (Bollen 1989; Diamantopoulos and Winklhofer 2001; Lewis et al. 2005; Rossiter 2002). In general, the researcher should be aware of a number of general design considerations. Sometimes, it is useful to have alternative blocks of indicators for the same LV (e.g., one reflective and one formative block). This allows researchers to leave the decision of the type of measurement model open until the model validation phase. Researchers are also urged to use a significant number of indicators. Increasing the block size does not only lead to better estimates, but also lowers the standard errors (Chin 1998b). In addition, a larger number of indicators enable the substitution of indicators at a later stage; or, in general, a large number of indicators allow more degrees of freedom during the cyclic process of model validation and optimization (Churchill 1979; Homburg and Giering 1996). It is also important to make a clear and conscious decision regarding the nature of the measurement models; misspecifications of measurement models could have a severe negative impact on the overall quality of the research results, which cannot easily be fixed at a later stage. Since reflective indicators are currently predominant in SEM/PLS studies, the researcher should be especially vigilant when constructing formative measurement models.

Even if, from a validation and model development perspective, a large number of indicator blocks and indicators are preferable, data collection instruments usually restrict the number of acceptable indicators. Consequently, many authors propose developing the data collection instrument (mostly a questionnaire for a survey) in a cyclic fashion, starting with a large number of indicators and concluding with the most relevant ones. Since this article is not focused on questionnaire development (see Dillmann [2008] for guidance), we concentrate on general deductive and empirical procedures to refine measurement models (Lewis et al. 2005). Several of these procedures are available:

1. Pre-tests allow the researcher to receive empirical feedback from a controlled sample. The subjects involved should be knowledgeable in the specific problem domain. They are asked to complete the survey instrument and give feedback on its quality. The subjects offer advice on improving the instrument in terms of one or more design perspectives, such as the format, content, understandability, terminology, ease of use, or speed of completion.

2. Pilot tests evaluate the survey instrument with a larger but still small sample. Again, the participants may provide feedback on the instrument's quality. In particular, the researcher may validate his/her model by applying validation measures as discussed in the following sections.
3. If several alternative blocks of indicators or alternative indicators within one block are used, the researcher may apply one or several item screening methods to choose the most appropriate blocks or items. For example, Lawshe (1975) suggests that experts should rate the alternative indicators and that a quantitative metric (content validity ratio, CVR) should be calculated and tested for significance in order to determine the most appropriate indicators. Other approaches include card-sorting and item-ranking techniques (Davis et al. 1989; Kankanhalli et al. 2005; Moore and Benbasat 1991), or expert panels combined with Q-sorting (Boudreau et al. 2001).

Having successfully conducted these validation steps, the researcher can assume that the *content validity* of the measurement models analyzed has been established. In this context, content validity refers to "the degree to which items in an instrument reflect the content universe to which the instrument will be generalized" (Straub et al. 2004, p. 424). Generally, content validity is not easy to assess, since the commonly employed evaluation of this validity is judgmental and highly subjective (Straub et al. 2004). Accordingly, content validity has been controversial since it was first referred to (Sireci 1998).

Data Collection

With the survey instrument at hand, the researchers can begin collecting empirical data. As Bentler (1980) states, it is "necessary to assure that the conditions for data gathering are theoretically appropriate and statistically adequate." A central topic that is particularly relevant to PLS-based research is sample size. One advantage of the PLS approach that is often invoked is its ability to work well with small sample sizes (e.g., Falk and Miller 1992). This entails a number of voices calling for a more differentiated view of sample size requirements (Goodhue et al. 2006; Marcoulides et al. 2009; Marcoulides and Saunders 2006). An often-cited rule of thumb, developed by Barclay et al. (1995) and postulated by Chin (1998b), is based on the idea that the sample size depends on the number of predictors that are involved in the multiple regressions in the inside and outside approximation. Consequently, researchers should (a) identify the block with the largest number of formative indicators and count them, (b) identify the LV with the largest number of independent LVs and count them, and (c) take the maximum of both figures and multiply this by ten to obtain the minimum sample size. However, the situation is more complicated: For instance, small sample sizes (e.g., $n = 20$) do not allow the detection or confirmation of structural paths with small coefficients (Chin and Newsted 1999). In such cases, sample sizes are required that are similar to those necessary for covariance-based approaches ($n > 150$). In general, resampling methods, such as bootstrapping (Efron 1979; Efron and Tibshirani 1993) or jackknifing (Miller 1974), should be used to evaluate the precision of the estimates and the standard errors.

Before starting with the model validation, the quality of empirical data gathered during the data collection phase needs to be verified (e.g., Lewis et al. 2005). A typical subject of analysis is the response rate. It is difficult to recommend an acceptable response rate, since this will be strongly dependent on the study's population, context, and data collection methods. Sivo et al. (2006) have discussed the issue of low response rates in IS research. Although surveys with lower response rates do not necessarily yield less accurate measurements than surveys with higher response rates (Visser et al. 1996), high response rates usually reflect a study's rigor in the eyes of editors, reviewers, and readers (Van der Stede et al. 2005). If the desired response rate is not achieved in the first round of collecting data, follow-up procedures should be employed. Follow-ups can effectively improve response rates and help bring the more resistant respondents into the study (Dillman 2008; Van der Stede et al. 2005).

Moreover, the researcher should check for nonresponse bias. Nonresponse bias generally occurs when some of the target respondents do not participate in the survey and, thus, cause an unreliable representation of the selected sample. Even with a large number of responses and high response rates, strong hypothetical differences in the nonresponse group can produce misleading conclusions that do not generalize the entire target group and, consequently, limit a study's external validity. Therefore, it is necessary to address the issue of nonresponse before, during, and after data collection (King and He 2005; Van der Stede et al. 2005). To minimize nonresponse before and during the data collection, Rogelberg and Stanton (2007) recommend, among others, the prenotification of participants, providing incentives, and sending out reminder notes. After the data collection, nonresponse bias can be assessed by verifying that the responses of early and late respondents do not differ significantly. The idea behind this approach is that late respondents are more likely to resemble non-respondents than early respondents (Armstrong and Overton 1977). Additionally, it may be reasonable to search for outliers and analyze whether they can be regarded as acceptable cases.

In a further step, possible common method bias should be assessed. Common method bias occurs when a significant amount of spurious covariance shared among variables is attributable to the common method used for collecting data (Buckley 1990; Malhotra et al. 2006). The most widespread approach for evaluating possible common method bias is probably Harman's single-factor test (Malhotra et al. 2006; Podsakoff et al. 2003). Therefore, all items used in the study are subject to an exploratory factor analysis. The unrotated factor solution is investigated to determine the number of factors that are necessary to account for the variance in the items. Common method bias is assumed to exist, if "(1) a single factor emerges from unrotated factor solutions," or "(2) a first factor explains the majority of the variance in the variables" (Malhotra et al. 2006, p. 1867). Despite its popularity and simplicity, Harman's single-factor test offers some limitations. Therefore, alternative approaches have been proposed for assessing common method bias (Lindell and Whitney 2001; Malhotra et al. 2006; Podsakoff et al. 2003; Sharma et al. 2009).

Model Validation

After the data quality has been evaluated, the researcher can run the PLS algorithm to calculate the model parameter's estimates. Model validation denotes the process of systematically evaluating whether the hypotheses expressed by the structural model are supported by the data or not. In general, the model validation is an attempt to determine whether the measurement models as well as the structural model fulfill the quality criteria for empirical work. PLS does not provide an established global goodness-of-fit criterion. However, there are several criteria for assessing partial model structures. In practice, a certain model validation process has been found to be reasonable. In general, a systematic application of the different criteria is carried out in a two-step process, encompassing (1) the assessment of the measurement models and (2) the assessment of the structural model. To assess the measurement models, we have to distinguish between reflective and formative models.

Assessment of Reflective Measurement Models

Following the validation guidelines of Straub et al. (2004) and Lewis et al. (2005), we suggest testing the reflective measurement models for at least unidimensionality, internal consistency reliability, indicator reliability, convergent validity, and discriminant validity by applying standard decision rules.

Unidimensionality refers to an LV having each of its measurement items relate to it better than to any others (Gerbing and Anderson 1988). In contrast to LISREL (Gefen 2003), unidimensionality cannot be directly measured with PLS, but can be assessed using an exploratory factor analysis (EFA). EFA's objective is to establish whether the measurement items converge to the corresponding constructs (factors), whether each item loads with a high coefficient on only one factor, and that this factor is the same for all items that are supposed to measure it. The number of selected factors is determined by the numbers of factors with an Eigenvalue exceeding 1.0. An item loading is usually considered high if the loading coefficient is above .600 and considered low if the coefficient is below .400 (Gefen and Straub 2005).

The traditional criterion for assessing *internal consistency reliability* is Cronbach's alpha (CA), whereas a high alpha value assumes that the scores of all items with one construct have the same range and meaning (Cronbach 1951). An alternative measure to Cronbach's alpha is the composite reliability (CR) (Werts et al. 1974). Chin (1998b) recommends composite reliability as a measure, since it overcomes some of CA's deficiencies. Cronbach's alpha assumes that all indicators are equally reliable; therefore, it tends to severely underestimate the internal consistency reliability of LVs in PLS structural equation models. In contrast, composite reliability takes into account that indicators have different loadings (Henseler et al. 2009). Regardless of which coefficient is used for assessing internal consistency, values above .700 are desirable for exploratory research and values above .800 or .900 in more advanced stages of research, whereas values below .600 indicate a lack of reliability (Nunnally and Bernstein 1994). However, levels above .950 "are more suspect than those in the middle alpha ranges" (Straub et al. 2004, p. 401), indicating potential common method bias.

Indicator reliability describes the extent to which a variable or set of variables is consistent regarding what it intends to measure. The reliability of one construct is independent of and calculated separately from that of other constructs. The researcher can monitor reflective indicators' loadings to assess indicator reliability. Generally, it is postulated that an LV should explain at least 50 percent of each indicator's variance. Accordingly, indicator loadings should be significant at least at the .050 level and greater than .707 ($\approx \sqrt{.500}$) (Chin 1998b). An exception is exploratory research designs, where authors recommend lower threshold values like .500 (Straub 1989), .450 (Lewis et al. 1995), or .300 (Lederer and Sethi 1992). The significance of the indicator loadings can be tested using resampling methods, such as bootstrapping (Efron 1979; Efron and Tibshirani 1993) or jackknifing (Miller 1974). There may be various reasons for these requirements not being fulfilled: (1) The item is simply unreliable; (2) the item may be influenced by additional factors, such as a method effect (Podsakoff et al. 2003); or (3) the construct itself is multidimensional in character and thus items are capturing different issues (Chin 1998b). In any of these cases, the measurement model needs to be adjusted and the PLS algorithm initiated once more in order to obtain new results.

Convergent validity involves the degree to which individual items reflecting a construct converge in comparison to items measuring different constructs. A commonly applied criterion of convergent validity is the average variance extracted (AVE) proposed by Fornell and Larcker (1981). An AVE value of at least .500 indicates that an LV is on average able to explain more than half of the variance of its indicators and, thus, demonstrates sufficient convergent validity.

Finally, *discriminant validity* concerns the degree to which the measures of different constructs differ from one another. Whereas convergent validity tests whether a particular item measures the construct it is supposed to measure, discriminant validity tests whether the items do not unintentionally measure something else. In SEM using PLS, two measures of discriminant validity are commonly used. For the first measure, cross-loadings are obtained by correlating each LV's component scores with all the other items (Chin 1998b). If each indicator's loading is higher for its designated construct than for any of the other constructs, and each of the constructs loads highest with its assigned items, it can be inferred that the different constructs' indicators are not interchangeable. The second measure, the Fornell-Larcker criterion (Fornell and Larcker 1981), requires an LV to share more variance with its assigned indicators than with any other LV. Accordingly, the AVE of each LV should be greater than the LV's highest squared correlation with any other LV.

Table 4: Assessment of Reflective Measurement Models

Validity Type	Criterion	Description	Literature
Unidimen-sionality	Exploratory factor analysis (EFA)	Measurement items should converge in the corresponding factor so that each item loads with a high coefficient on only one factor, and this factor is the same for all items that are supposed to measure it. The number of selected factors is determined by the numbers of factors with an Eigenvalue exceeding 1.0. An item loading is usually considered high if the loading coefficient is above .600 and considered low if the coefficient is below .400.	Gefen and Straub (2005), Gerbing and Anderson (1988)
Internal consistency reliability	Cronbach's alpha (CA)	Measures the degree to which the MVs load simultaneously when the LV increases. Alpha values ranges from 0 (completely unreliable) to 1 (perfectly reliable). Proposed threshold value for confirmative (explorative) research: CA > .800 or .900 (0.700). Values must not be lower than .600.	Cronbach (1951), Nunally and Bernstein (1994)
Internal consistency reliability	Composite reliability (CR)	Attempts to measure the sum of an LV's factor loadings relative to the sum of the factor loadings plus error variance. Leads to values between 0 (completely unreliable) and 1 (perfectly reliable). Alternative to Cronbach's Alpha, allows indicators to not be equally weighted. Proposed threshold value for confirmative (explorative) research: CA > .800 or .900 (0.700). Values must not be lower than .600.	Werts et al. (1974), Nunally and Bernstein (1994)
Indicator reliability	Indicator loadings	Measures how much of the indicators variance is explained by the corresponding LV. Values should be significant at the .050 level and higher than .700. For exploratory research designs, lower thresholds are acceptable. The significance can be tested using bootstrapping or jackknifing.	Chin (1998b)
Convergent validity	Average variance extracted (AVE)	Attempts to measure the amount of variance that an LV component captures from its indicators relative to the amount due to measurement error. Proposed threshold value: AVE > 0.500.	Fornell and Larcker (1981)
Discriminant validity	Cross-loadings	Cross-loadings are obtained by correlating the component scores of each latent variable with all other items. If the loading of each indicator is higher for its designated construct than for any of the other constructs, and each of the constructs loads highest with its own items, it can be inferred that the models' constructs differ sufficiently from one another.	Chin (1998b)
Discriminant validity	Fornell-Larcker criterion	Requires an LV to share more variance with its assigned indicators than with any other LV. Accordingly, the AVE of each LV should be greater than the LV's highest squared correlation with any other LV.	Fornell and Larcker (1981)

Table 4 summarizes all the criteria that a reliable and valid reflective measurement model should meet. If this does not happen, the researcher may drop certain items from the measurement model and/or reallocate items to the structural model's LVs.

Assessment of Formative Measurement Models

The validation of formative measurement models requires a different approach than the one applied for reflective models. Conventional validity assessments do not apply to formative measurement models, and the concepts of reliability and construct validity are not meaningful when employing such models (Bollen 1984; 1989). Whereas reliability becomes an irrelevant criterion for assessing formative measurement, the examination of validity becomes crucial (Diamantopoulos 2006). Accordingly, Henseler et al. (2009) suggest assessing the validity of formative constructs on two levels: the indicator and the construct levels.

To assess *indicator validity*, the researcher should monitor the significance of the indicator weights by means of bootstrapping (Efron 1979; Efron and Tibshirani 1993) or jackknifing (Miller 1974). A significance level of at least .050 suggests that an indicator is relevant for the construction of the formative index and, thus, demonstrates a sufficient level of validity. Some authors also recommend path coefficients greater than .100 (Lohmöller 1989) or .200 (Chin 1998b). In addition, the degree of multicollinearity among the formative indicators should be assessed by calculating the variance inflation factor (VIF) (Cassel and Hackl 2000; Fornell and Bookstein 1982). The VIF indicates how much of an indicator's variance is explained by the other indicators of the same construct. Values below the commonly accepted threshold of 10 indicate that multicollinearity is not an issue (Diamantopoulos and Siguaw 2006; Gujarati 2003).

The first step for assessing *construct validity* could be a test for nomological validity. In this context, nomological validity means that, within a net of hypotheses, the formative construct behaves as expected. Accordingly, those relationships between the formative construct and other models' constructs, which have been sufficiently referred to in prior literature, should be strong and significant (Henseler et al. 2009; Peter 1981; Straub et al. 2004). We further propose assessing construct validity by checking discriminant validity. Therefore, MacKenzie et al. (2005) suggest testing the interconstruct correlations between formative constructs as well. Correlations between formative and all other constructs of less than .700 indicate sufficient discriminant validity (Bruhn et al. 2008).

Table 5: Assessment of Formative Measurement Models

Validity Type	Criterion	Description	Literature
Indicator validity	Indicator weights	Significance at the .050 level suggests that an indicator is relevant for the construction of the formative index and, thus, demonstrates a sufficient level of validity. Some authors also recommend path coefficients greater than .100 or .200.	Chin (1998b), Lohmöller (1989)
Indicator validity	Variance inflation factor (VIF)	Indicates how much of an indicator's variance is explained by the other constructs' indicators and, thus, indicates how redundant the indicator's information is. Acceptable values are below 10.	Cassel and Hackl (2000), Diamanto-poulos and Siguaw (2006), Fornell and Bookstein (1982), Gujarati (2003)
Construct validity	Nomological validity	Means that, within a net of hypotheses, the formative construct behaves as expected. Relationships between the formative construct and other models' constructs, which have been sufficiently referred to in prior literature, should be strong and significant.	Henseler et al. (2009), Peter (1981), Straub et al. (2004)
Construct validity	Interconstruct correlations	If the correlations between the formative and all the other constructs are less than .700, the constructs differ sufficiently from one another.	Mackenzie et al. (2005), Bruhn et al. (2008)

The different criteria for assessing formative measurement models are summarized in Table 5. However, in contrast to reflective measurement models, a subsequent modification of formative measurement models only on the basis of statistical outcomes is inadmissible. Discarding a formative model's item would omit a unique part of the composite latent construct and, thus, change the meaning of the variable (Jarvis et al. 2003). Accordingly, both significant and insignificant formative indicators should be kept in the measurement model as long as this is conceptually justified (Henseler et al. 2009).

Assessment of the Structural Model

After the measurement models have been successfully validated, the structural model can be analyzed. The first essential criterion for the assessment of the PLS structural equation model is each endogenous LV's coefficient of determination (R^2). R^2 measures the relationship of an LV's explained variance to its total variance. The values should be sufficiently high for the model to have a minimum level of explanatory power. Chin (1998b) considers values of approximately .670 substantial, values around .333 average, and values of .190 and lower weak.

The next step of the structural model's assessment comprises the evaluation of the path coefficients between the model's LVs. Therefore, the researcher should check the path coefficient's algebraic sign, magnitude, and significance. Paths, whose signs are contrary to the theoretically assumed relationship, do not support the pre-postulated hypotheses. A path coefficient's magnitude indicates the strength of the relationship between two LVs. Some authors argue that path coefficients should exceed .100 to account for a certain impact within the model (e.g., Huber et al. 2007). Furthermore, path coefficients should be significant at least at the .050 level. In order to determine the significance, resampling techniques such as bootstrapping (Efron 1979; Efron and Tibshirani 1993) or jackknifing (Miller 1974) should be used. Established GoF indices are not yet available for PLS, even if first steps into this directions have been made (e.g., Tenenhaus et al. 2005). In contrast, CBSEM offers a set of GoF indices with corresponding significance tests to analyze the quality of the structural model.

The researcher can evaluate the effect size of each path in the structural equation model by means of Cohen's f^2 (Cohen 1988). The effect size measures if an independent LV has a substantial impact on a dependent LV. It is calculated as the increase in R^2 of the LV to which the path is connected, relative to the LV's proportion of unexplained variance (Chin 1998b). Values for f^2 between .020 and .150, between .150 and .350, and exceeding .350 indicate that an exogenous LV has a small, medium, or large effect on an endogenous LV (Chin 1998b; Cohen 1988; Gefen et al. 2000).

Finally, the structural model's predictive relevance can be assessed with a nonparametric Stone-Geisser test (Geisser 1975; Stone 1974). This test uses a blindfolding procedure (e.g., Tenenhaus et al. 2005) to create estimates of residual variances. By systematically assuming that a certain number of cases are missing from the sample, the model parameters are estimated and used to predict the omitted values. Q^2 measures the extent to which this prediction is successful. Positive Q^2 values confirm the model's predictive relevance in respect of a particular construct. Furthermore, the better the tested model's predictive relevance, the greater Q^2 becomes (Fornell and Cha 1994). In line with the effect size f^2, the predictive relevance's relative impact can be assessed by means of the measure q^2.

Table 6: Assessment of the Structural Model

Validity Type	Criterion	Description	Literature
Model validity	Coefficient of determination (R^2)	Attempts to measure the explained variance of an LV relative to its total variance. Values of approximately .670 are considered substantial, values around .333 moderate, and values around .190 weak.	Chin (1998b), Ringle (2004)
Model validity	Path coefficients	Path coefficients between the LVs should be analyzed in terms of their algebraic sign, magnitude, and significance.	Huber et al. (2007)
Model validity	Effect size (f^2)	Measures if an independent LV has a substantial impact on a dependent LV. Values of .020, .150, .350 indicate the predictor variable's low, medium, or large effect in the structural model.	Cohen (1988), Chin (1998b), Ringle (2004)
Model validity	Predictive relevance (Q^2)	The Q^2 statistic is a measure of the predictive relevance of a block of manifest variables. A tested model has more predictive relevance the higher Q^2 is, and modifications to a model may be evaluated by comparing the Q^2 values. The proposed threshold value is $Q^2 > 0$. The predictive relevance's relative impact can be assessed by means of the measure q^2.	Stone (1974), Geisser (1975), Fornell and Cha (1994)

The different criteria for assessing a PLS model on the structural level are summarized in Table 6. Having confirmed the validity of the structural model, the results can be evaluated to test the research hypotheses.

Interpretation

The interpretation of the results generated by the PLS algorithm is possible only if the previous model validation has been successfully accomplished. All relevant validation measures should have produced acceptable results. If this is the case, the parameter estimates, or possibly even the LV estimates for the cases, can be interpreted on the basis of the structural equation model's theoretical foundation. Consequently, the hypotheses expressed by the structural model can be regarded as either confirmed or rejected. Based on the final model confirmed by the empirical analysis, the researcher can answer his/her research questions, draw conclusions, and derive implications for both theory and practice. Finally, the need for further research can be identified.

VI. EXAMPLES OF PLS-BASED IS RESEARCH

In order to illustrate the PLS approach's functionality for IS scholars, we outline two articles published in international IS journals. In respect of each study, we briefly elaborate on how the researchers have translated their hypotheses into structural equation models and how they estimated the model parameters by using PLS. To summarize, both examples fundamentally follow the same research process. Although there might be studies that do not fit into our proposed scheme, we believe that the majority of comparable studies' approaches are captured within our framework.

Example 1: IS Outsourcing

Our first example is the article titled "Outsourcing of Information Systems Functions in Small and Medium Sized Enterprises: A Test of a Multi-Theoretical Model" by Dibbern and Heinzl (2009), published in *Business & Information Systems Engineering.* The authors examine IS outsourcing in small and medium-sized enterprises (SMEs) in the manufacturing sector. The following two central research questions are addressed:

(1) *To what extent are individual IS functions outsourced by SMEs in Germany?*

(2) *Which determinants are responsible for explaining the variation in the extent to which particular IS functions are outsourced in SMEs?*

Based on transaction cost economic theory, resource-based theory, and power theory, the authors deduce the determinants of IS outsourcing and summarize them as well as their hypothesized relations in a causal model. Each of the model's constructs is operationalized with a set of measurement items, either in reflective or formative mode. Accordingly, a questionnaire was developed that had been pretested with high-level executives. Empirical data were collected when the authors conducted a survey of top managers of 281 SMEs of whom only thirty-four returned the questionnaires. The data analysis was performed using PLS. The first research question is answered by the study's descriptive results. According to these results, the degree of IS outsourcing in SEMs can be considered moderate. To answer the second research question, the structural equation model is tested. The results indicate that internal performance and the know-how deficits against external service providers are key determinants in explaining why different IS functions are outsourced to varying degrees in SMEs. In contrast, transaction costs and the strategic significance of the IS functions seem to play a subordinate role. The summary presented in Table 7 demonstrates how this study fits in our proposed framework.

Example 2: Open Source Development

The second example is Stewart and Gosain's (2006) article titled "The Impact of Ideology on Effectiveness in Open Source Development Teams," published in *MIS Quarterly.* In order to fully understand the concept of open source software (OSS), the authors aim at answering the research question: *What leads to effectiveness in OSS development teams in the absence of formal controls?* To answer this question, a survey-based research design was chosen. Based on existing knowledge of OSS ideology and team effectiveness, the authors developed a framework of the OSS community ideology (including specific norms, beliefs, and values) and a causal model to show how adherence to components of the ideology impacts effectiveness in OSS teams. The hypotheses that needed to be evaluated were developed accordingly. The causal model's constructs are mainly operationalized by adapting items from earlier studies. If there were no prior empirical investigations upon which to draw, new items were created. Empirical data were collected from two surveys and from an OSS website. The authors analyze the data by performing a factor analysis, and they test the hypotheses by using the PLS approach. The analysis's results support the main thesis that OSS team members' adherence to the tenets of the OSS community ideology impacts OSS team effectiveness and reveals that different components impact effectiveness in different ways. The study is summarized according to our framework structure in Table 8.

Table 7: Example 1—IS Outsourcing	
Phase	**Activities and Results**
Problem Definition and Research Design	**Research questions** • To what extent are individual IS functions outsourced by SMEs in Germany? • Which determinants are responsible for explaining the variation in the extent to which particular IS functions are outsourced in SMEs? **Research design** • Development of theoretical framework of IS outsourcing • Transformation into structural equation model • Empirical testing applying survey-based research
Theoretical Foundation	**Literature review** • Transaction cost economic theory • Resource-based theory • Power theory
Model Construction and Instrument Development	**Structural model** • Deduction of determinants of IS outsourcing based on theories reviewed • Combination of determinants and hypothesized relationships to causal model **Measurement models** • Development of new measurement items • Operationalization of variables either in reflective or formative mode **Instrument:** Questionnaire **Pre-/pilot test:** Pre-test with high level executives
Data Collection	**Target** • 281 German SMEs of the same industrial sector • Addressing of top management **Return:** 34 questionnaires (return rate 12%) **Quality assessment:** Test for potential non-response bias
Model Validation	**Validation of measurement models:** Assessment of indicator and construct reliability **Validation of structural model** • Calculation of R^2 • Evaluation of path coefficients
Interpretation	**Discussion** • Evaluation of hypotheses • Drawing conclusions (answering research questions) • Elaboration on limitations and future research opportunities

VII. SUMMARY AND OUTLOOK

In this article, we have reflected the discourse on the component-based procedure of SEM "partial least squares," which has become increasingly popular within the IS research community. We have outlined the current state of discussion on PLS' advantages, disadvantages, and usage scenarios, and have presented a framework for empirical research that applies PLS. Differences between PLS and covariance-based approaches to SEM have been discussed and contrasted. Finally, we have provided a few comprehensible examples of IS research using PLS in order to demonstrate its beneficial application and the appropriateness of the proposed framework.

Empirical research that uses SEM is widespread in the information systems community. More so than other disciplines, the information systems discipline relies heavily on PLS to test structural equation models (Goodhue et al. 2006; Marcoulides et al. 2009). At the same time, claims that remind of this approach's limitations have recently become more prominent in the literature. Although the application of PLS has several advantages when testing causal relationships that other methods don't have, researchers have to be aware that PLS is neither a "magic bullet for achieving adequate statistical power at small sample sizes" (Goodhue et al. 2006, p. 10), nor a "silver bullet to be used with samples of any size" (Marcoulides and Saunders 2006, p. viii). However, with this article, we illustrated that, treating its assumed advantages with caution and keeping its limitations in mind, PLS can be an adequate choice if the research problem meets certain characteristics and the technique is properly used.

Table 8: Example 2—Open Source Development

Phase	Activities and Results
Problem Definition and Research Design	**Research question:** What leads to effectiveness in OSS development teams in the absence of formal controls? **Research design** • Development of theoretical framework of OSS community ideology and effectiveness • Transformation into structural equation model • Empirical testing applying survey-based research
Theoretical Foundation	**Literature review** • OSS ideology • Effectiveness in OSS development teams
Model Construction and Instrument Development	**Structural model** • Deduction of antecedents of OSS effectiveness on theories reviewed • Combination of determinants and hypothesized relationships to causal model **Measurement models** • Development of new measurement items and adaption of items from previous studies • Operationalization of variables in reflective mode **Instrument:** Two questionnaires **Pre-/pilot test:** With subset of sample (second survey)
Data Collection	**Target** • 48 Sourceforge administrators (first survey) • 150 open source project administrators (second survey) **Return** • 18 questionnaires in first survey (response rate 37.5%) • 67 questionnaires in second survey (response rate 44.7%) **Quality assessment:** Test for potential common method bias
Model Validation	**Validation of measurement models** • Assessment of convergent and divergent validity (factor analysis) • Assessment of divergent validity (AVE) and composite reliability **Validation of structural model** • Calculation of R^2 • Evaluation of path coefficients
Interpretation	**Discussion** • Evaluation of hypotheses • Drawing conclusions (answering research questions) • Elaboration on limitations and future research opportunities

With PLS, the barriers to conducting research that analyzes structural equation models are relatively low. Easy-to-use software tools are available that allow researchers to concentrate on their research questions and hide statistics from their users as far as possible. Furthermore, with an increasing number of introductory books and papers, literature on SEM and PLS is becoming more readily available. This article contributes to this growing body of knowledge by serving as a helpful guide for inexperienced researchers applying PLS for the first time, but also as a reference guide for researchers with a better knowledge of the specific field.

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APPENDIX A: STUDIES IN IS RESEARCH USING PLS

Publication	Motivation for Using PLS
Agarwal and Karahanna (2000, MISQ)	”[PLS] places minimal demands on sample size and residual distributions” (p. 678).
Ahuja et al. (2007, MISQ)	"PLS was chosen over LISREL because of the complexity of the model to be tested (i.e., the number of constructs and links)" (p. 8).
Ahuja and Thatcher (2005, MISQ)	“PLS is particularly useful for our study because it is robust to relatively lean sample sizes and non-normal distribution of the data” (p. 441).
Ang and Straub (1998, MISQ)	Not explicitly stated
Armstrong and Sambamurthy (1999, ISR)	"PLS is considered to be particularly robust for such sample sizes and, therefore, appropriate as an analytic approach" (p. 314).
Au et al. (2008, MISQ)	“The research model was tested using the partial least squares (PLS) method of structural equation modeling (PLS-Graph version 3) in view of PLS method’s ability to handle formative constructs and highly complex predictive models” (p. 51).
Banker et al. (2006, ISR)	“We explored partial least squares (PLS) estimation because PLS allow us to model both formative and reflective constructs and provide consistent estimates for small sample data” (p. 365).
Basselier and Benbasat (2004, MISQ)	“PLS supports the testing of higher-order models, using the hierarchical component model” (p. 686).
Benaroch et al. (2006, MISQ)	"PLS has the ability to handle relatively small sample sizes, making it appropriate for our data set" (p. 845).
Bhattacherjee and Premkuma (2004,MISQ)	"Unlike covariance-based structural equation modeling approaches such as LISREL, the variance-based PLS approach does not impose sample size restrictions or require multivariate normality distribution for the underlying data.… Given our small sample ... and the inherent difficulties with establishing multivariate normality with small samples, PLS was deemed more appropriate than LISREL" (p. 237).
Bhattacherjee and Sanford (2006, MISQ)	“The variance-based PLS approach was preferred over covariance-based structural equation modeling approaches such as LISREL because PLS does not impose sample size restrictions and is distribution-free” (p. 815).
Biros et al. (2002, MISQ)	Not explicitly stated
Bock et al. (2005, MISQ)	“PLS was used as it allows latent constructs to be modeled either as formative or reflective indicators as was the case with our data, and it makes minimal demands in terms of sample size to validate a model compared to alternative structural equation modeling techniques” (p. 95).
Brown and Venkatesh (2005, MISQ)	Not explicitly stated
Burton-Jones and Straub (2006, ISR)	"PLS was used in preference to LISREL software because LISREL is not suited to testing higher-order molar constructs in the presence of only one DV" (p. 238).
Cenfetelli et al. (2008, ISR)	Not explicitly stated
Chatterjee et al. (2002, MISQ)	"As we have both formative ... and reflective ... indicators for constructs in the model, we used partial least squares (PLS).… PLS is also recommended for small sample size models, like ours" (p. 77).
Chidambaram and Tung (2005, ISR)	"Given the minimal assumptions of PLS about the distribution of data and its appropriateness in testing a path model such as the one presented in this study, this technique was chosen over other analytical techniques" (p. 159).
Choudhury and Karahanna (2008, MISQ)	"PLS was chosen because ... some of our constructs are formative, and LISREL is not well-suited to modeling such constructs" (p. 189).
Chwelos et al. (2001, ISR)	"PLS is better suited when the focus is on theory development.… PLS, being components based, can incorporate both formative and reflective indicators" (p. 311).

Publication	Motivation for Using PLS
Compeau et al. (1999, MISQ)	"PLS was preferred to LISREL for this study since the interest in this study was to assess the predictive validity ..., making a focus on the paths rather than the model appropriate.… In addition, PLS does not require distributional assumptions regarding the underlying data" (p. 152).
Compeau and Higgins (1995a, ISR)	Not explicitly stated
Compeau and Higgins (1995b, MISQ)	Not explicitly stated
Enns et al. (2003, MISQ)	"PLS does not impose normality requirements on the data,… .PLS can handle both reflective and formative scales, both of which are used in this study" (p. 87).
Gefen and Straub (1997, MISQ)	"A partial least squares (PLS) analysis using PLS-Graph was performed, in keeping with other TAM studies" (p. 395).
Hsieh et al. (2008, MISQ)	"Partial least squares (PLS) ... does not require multivariate normality of the data, and is less demanding on sample size" (p. 106).
Igbaria et al. (1994, MISQ)	"Of particular relevance to this study is the fact that PLS does not depend on having multivariate normally distributed data (distribution-free),… [PLS] can be used with noninterval-scaled data and importantly, with small samples" (p. 183).
Igbaria et al. (1997, MISQ)	Not explicitly stated
Jarvenpaa et al. (2004, ISR)	Not explicitly stated
Jiang and Benbasat (2007b, ISR)	"PLS was been chosen over LISREL due to its ability to model latent constructs under conditions of non-normality and with small to medium sample sizes" (p. 461).
Jiang and Benbasat (2007a, MISQ)	Not explicitly stated
Kamis (2008, MISQ)	Not explicitly stated
Kanawattanachai and Yoo (2007, MISQ)	"PLS not only generates estimates of standardized regression coefficients for the model's paths, but also takes measurement errors into account, which can then be used to measure the relationship between latent variables,… Additionally, the assumptions of normality and the interval scale data are not necessary,… Based on the features mentioned above, PLS is most suitable during the early stage of theory development because it works well with small sample sizes and complex models" (p. 797).
Karahanna et al. (2006, MISQ)	"[PLS] places minimal demands on sample size and residual distributions" (p. 792).
Karahanna et al. (1999, MISQ)	"[PLS] places minimal demands on sample size and residual distributions" (p. 194).
Karimi et al. (2004, ISR)	Not explicitly stated
Keil et al. (2000, MISQ)	"[PLS] is not contingent upon data having multivariate normal distributions and interval nature.… [PLS] is appropriate for testing theories in the early stages of development" (p. 309).
Ko et al. (2005, MISQ)	"PLS has the ability to handle relatively small sample sizes, making it an appropriate choice for testing the research model" (p. 70).
Komiak and Benbasat (2006, MISQ)	"PLS was chosen over LISREL because this study aims at theory development instead of theory testing,… Whereas LISREL requires a sound theory base, PLS supports exploratory research" (p. 951).
Lewis et al. (2003, MISQ)	"PLS uses a component-based approach to estimation that places minimal demands on sample size and residual distributions,… It also permits simultaneous analysis of both the measurement model and the structural model" (p. 665).
Liang et al. (2007, MISQ)	"Since our research model contains both reflective and formative constructs, and we have a relatively small sample size, partial least square was chosen for data analysis" (p. 70).
Limayem et al. (2007, MISQ)	"Due to the formative nature of some of our measures and non-normality of the data, LISREL analysis was less appropriate,… Equally important, PLS is better suited than CMSEM techniques for the testing of moderation effects" (p. 723).

Publication	Motivation for Using PLS
Ma and Agarwal (2007, ISR)	"PLS is widely accepted as a method for testing theory in early stages, while LISREL is usually used for theory confirmation,… LISREL cannot handle formative constructs as conceptualized for some of the study's variables,… PLS places minimal demands on variable distributions" (p. 54).
Majchrzak et al. (2005, MISQ)	"PLS is able to obtain robust estimates even with small sample sizes" (p. 660).
Malhotra et al. (2007, ISR)	"PLS has an advantage over other structural modeling (SEM) methodologies in that it does not require distributions be normal or known,… Another advantage of using PLS is that it has less stringent sample size requirements" (p. 270).
Miranda and Saunders (2003, ISR)	"PLS makes no assumptions regarding distributional normality, and was chosen over other structural modeling techniques for its lack of sensitivity to sample size" (p. 96).
Moores and Chang (2006, MISQ)	"PLS is preferred to LISREL because our purpose is to ... predict…. PLS does not require normal distribution for the manifest variables" (p. 172).
Nadkarni and Gupta (2007, MISQ)	"PLS is particularly useful for our study because it is robust to non-normal data distribution" (p. 512).
Nicolaou and McKnight (2006, ISR)	"The PLS method applies best to such nascent theories and complex models as this study embodies" (p. 342).
Pavlou and Dimoka (2006, ISR)	"PLS ... is best suited for complex models by placing minimal demands on sample size and residual distributions" (p. 404).
Pavlou and Fygenson (2006, MISQ)	"PLS can handle formative factors, unlike LISREL,… PLS places minimal restrictions on measurement scales, sample size, and residual distributions…. PLS was thus chosen to accommodate the presence of formative factors and the large number of constructs" (p. 127).
Pavlou and Gefen (2005, ISR)	[PLS] can readily handle formative factors… PLS also places minimal restrictions on the sample size and residual distributions,… PLS is better suited for explaining complex relationships as it avoids two problems: inadmissible solutions and factor indeterminacy,… In large, complex models with latent variables PLS is virtually without competition…. We ... chose PLS to accommodate the presence of a large number of variables, formative factors, and moderating effects" (p. 386).
Pavlou et al (2007, MISQ)	"PLS employs a component-based approach for estimation, and it places minimal restrictions on sample size and residual distributions…. PLS is best suited for testing complex relationships by avoiding inadmissible solutions and factor indeterminacy…. Hence, we chose PLS to accommodate the presence of a large number of variables, relationships, and moderating effects" (pp. 121–122).
Pavlou and Sawy (2006, ISR)	"Because of the large number of variables relative to the sample size and the existence of second-order formative factors and moderating effects, PLS was deemed more appropriate than other SEM techniques such as LISREL and EQS" (p. 213).
Rai et al. (2006, MISQ)	"[PLS] is generally recommended for predictive research models where the emphasis is on theory development, whereas LISREL is recommended for confirmatory analysis and requires a more stringent adherence to distributional assumptions…. The ability of PLS to model formative as well as reflective constructs makes it suitable for our purposes" (p. 233).
Ravichandran and Rai (2000, MISQ)	"In PLS, latent constructs can be modeled as either formative or reflective constructs" (p. 396).
Robert Jr. et al. (2008, ISR)	"With PLS no assumptions are made regarding the joint distribution of the indicators or the independence of sample cases…. The ability of PLS to model both formative as well as reflective constructs makes it suitable for our purposes" (p. 326).
Rustagi et al. (2008, ISR)	Not explicitly stated
Saraf et al. (2007, ISR)	"The research model was tested using partial least squares ... because of the lower requirement for sample size, unlike in other structural equation modeling (SEM) techniques such as LISREL" (p. 331).
Srite and Karahanna (2006, MISQ)	Not explicitly stated
Stewart and Gosain (2006, MISQ)	"PLS was used because it is more appropriate than altematives, such as LISREL, when sample sizes are small and models are complex, the goal of the research is explaining variance, and measures are not well established" (p. 301).

Publication	Motivation for Using PLS
Subramani (2004, MISQ)	""PLS ... provides the ability to model latent constructs even under conditions of non-normality and small- to medium-size sample" (p. 59).
Teo et al. (2003, MISQ)	"PLS ... was chosen and used for hypotheses testing primarily because it allows latent constructs to be modeled as either formative or reflective indicators…. PLS has an added advantage over LISREL in that it follows a components-based strategy and thus does not depend on having multivariate normal distributions, interval scales, or a large sample size…. Given the prediction-oriented nature of this study and the use of non-interval scales, PLS was the preferred technique for testing the structural model" (p. 30).
Thatcher and Perrewé (2002, MISQ)	Not explicitly stated
Thong et al. (1996, ISR)	"[PLS] does not depend on having multivariate normal distributions (distribution-free), interval scales, or large sample size…. PLS is also considered more appropriate in earlier stages of theory development…. Given the early stage of theory development ... and the relatively small sample size, PLS was the preferred technique for data analysis in this study" (pp. 258–259).
Vandenbosch and Higgins (1995, ISR)	"PLS is a theory-based approach to conceptualization that has been designed to integrate theory and data, and hence, provides a better platform than traditional multivariate techniques from which to construct and verify theory" (p. 206).
Venkatesh et al. (2008, MISQ)	Not explicitly stated
Venkatesh and Morris (2000, MISQ)	Not explicitly stated
Venkatesh et al. (2003, MISQ)	Not explicitly stated
Venkatesh and Ramesh (2006, MISQ)	Not explicitly stated
Wakefield et al. (2008, ISR)	"The major benefits of [PLS] include robustness for small to medium sample sizes and fewer constraints on the data (e.g., normality assumptions) compared to covariance-based methods" (p. 445).
Wasko and Faraj (2005, MISQ)	Not explicitly stated
Wixom and Todd (2005, ISR)	"PLS was most appropriate given the large number of constructs" (p. 92).
Wixom and Watson (2001, MISQ)	"PLS has several strengths that made it appropriate for this study, including its ability to handle formative constructs and its small sample size requirements" (pp. 27–28).
Yi and Davis (2003, ISR)	"PLS uses a least squares estimation procedure, allowing the flexibility to represent both formative and reflective latent constructs, while placing minimal demands on measurement scales, sample size, and distributional assumptions" (p. 157).
Yoo and Alavi (2001, MISQ)	"We chose PLS among several structural equation modeling tools, including EQS, AMOS, and LISREL because, unlike other tools, PLS does not require a large sample size…. PLS is more suitable when the objective is causalpredictive testing, rather than testing an entire theory" (p. 378).
Zhu and Kraemer (2005, ISR)	"We chose PLS because our research is still at an early stage and the proposed model has not been tested in the literature…. PLS is appropriate for handling both reflective and formative constructs and constructs with mixed scales" (p. 75).
Zhu et al. (2006, MISQ)	"While several methods can be used to analyze the data, we chose PLS for two reasons…. First, our model has formative constructs; PLS uses components-based algorithms and can estimate formative constructs…. Second, PLS is more appropriate when the research model is in an early stage of development and has not been tested extensively" (p. 528).

APPENDIX B: METHODOLOGICAL AND OPINION PAPER

Publication	Title
Boudreau et al. (2001, MISQ)	Validation in Information Systems Research: A State-of-the-Art Assessment
Carte and Russell (2003, MISQ)	In Pursuit of Moderation: Nine Common Errors and their Solutions
Chin (1998a, MISQ)	Issues and Opinion on Structural Equation Modeling
Chin et al. (2003, ISR)	A Partial Least Squares Latent Variable Modeling Approach for Measuring Interaction Effects: Results from a Monte Carlo Simulation Study and an Electronic-Mail Emotion/Adoption Study
Chin and Todd (1995, MISQ)	On the Use, Usefulness, and Ease of Use of Structural Equation Modeling in MIS Research: A Note of Caution
Goodhue et al. (2007, ISR)	Statistical Power in Analyzing Interaction Effects: Questioning the Advantage of PLS with Product Indicators
Marcoulides and Saunders (2006, MISQ)	PLS: A Silver Bullet?

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