# EDITOR'S COMMENTS

## A Critical Look at the Use of PLS-SEM in *MIS Quarterly*

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### *Introduction*

Wold's (1974, 1982) partial least squares structural equation modeling (PLS-SEM) approach and the advanced PLS-SEM algorithms by Lohmöller (1989) have enjoyed steady popularity as a key multivariate analysis method in management information systems (MIS) research (Gefen et al. 2011). Chin's (1998b) scholarly work and technology acceptance model (TAM) applications (e.g., Gefen and Straub 1997) are milestones that helped to reify PLS-SEM in MIS research. In light of the proliferation of SEM techniques, Gefen et al. (2011), updating Gefen et al. (2000), presented a comprehensive, organized, and contemporary summary of the minimum reporting requirements for SEM applications.

Such guidelines are of crucial importance for advancing research for several reasons. First, researchers wishing to apply findings from prior studies or wanting to contribute to original research must comprehend other researchers' decisions in order to understand the robustness of their findings. Likewise, when studies arrive at significantly different results, the natural course is to attempt explaining the differences in terms of the theory or concept employed, the empirical data used, and how the research method was applied. A lack of clarity on these issues, including the methodological applications, contradicts the goals of such studies (Jackson et al. 2009). Even worse, the misapplication of a technique may result in misinterpretations of empirical outcomes and, hence, false conclusions.

Against this background, rigorous research has a long-standing tradition of critically reviewing prior practices of reporting standards and research method use (e.g., Boudreau et al. 2001). While the use of covariance-based SEM (CB-SEM) techniques has been well documented across disciplines (e.g., Medsker et al. 1994; Shook et al. 2004; Steenkamp and Baumgartner 2000), few reviews to date have investigated usage practices specific to PLS-SEM (see, however, Gefen et al. 2000). Previous reviews of such research practices were restricted to strategic management (Hulland 1999) and, more recently, marketing (Hair et al. 2012; Henseler et al. 2009), and accounting (Lee et al. 2011). The question arises as to how authors publishing in top IS journals such as *MIS Quarterly* have used PLS-SEM thus far, given the SEM recommendations of Gefen et al. (2011). By relating Gefen et al.'s (2011) reporting guidelines to actual practice, we attempt to identify potential problematic areas in PLS-SEM use, problems which may explain some of the criticism of how it has been applied (e.g., Marcoulides et al. 2009; Marcoulides and Saunders 2006).

By reviewing previous PLS-SEM research in *MIS Quarterly*, we can hopefully increase awareness of established reporting standards. The results allow researchers to further improve the already good reporting practices that have been established in *MIS Quarterly* and other top journals and thus could become blueprints for conducting PLS-SEM analysis in other disciplines such as strategic management and marketing.

## Review of PLS-SEM Research in MIS Quarterly

Our review examines all empirical studies using PLS-SEM and published in *MIS Quarterly* in the 20-year period from 1992 through 2011.[1] There were 65 studies containing 109 structural equation model estimations deploying the PLS-SEM technique (several studies estimated multiple models using different set-ups and/or different data sets, collected at different points of time). In the analyses below, we use the term *studies* when referring to the 65 journal articles and the term *models* when referring to the 109 PLS-SEM applications in these articles. Figure 1 shows the (cumulative) number of *MIS Quarterly* studies using PLS-SEM between 1992 and 2011.[2]

For one, it is apparent that the use of PLS-SEM has increased over time. Regressing the number of studies on the linear effect of time, in fact, yields a significant model ($F = 44.04$; $p < 0.01$) and a significant time effect ($t = 6.64$; $p < 0.01$).

## Why Did Researchers Choose PLS-SEM?

The choice of PLS-SEM usually includes a discussion of the comprehensive reasoning of the researchers. Nearly three-quarters of all studies address this issue in a single paragraph at the beginning of the data analysis by referring to some specific statistical properties of the PLS-SEM method. The most frequently cited reasons relate to small sample sizes (24 studies, 36.92%), non-normal data (22 studies, 33.85%), and the use of formatively measured latent variables (20 studies, 30.77%). Other substantive reasons for choosing PLS-SEM (e.g., exploratory research objectives and ensuring convergence), as suggested, for example, by Gefen et al. (2011) and Hair et al. (2012), are rarely given (see Table 1).

We address each of the three key reasons mentioned above in more detail in the following sections on model and data characteristics.

## Structural and Measurement Model Characteristics

Descriptive statistics for the key elements of the structural and the measurement models in *MIS Quarterly* reveal an average number of 8.12 latent variables, 27.42 indicators, and 11.38 structural model relationships per model (see Table 2). Researchers seem to appreciate the ability of PLS-SEM to handle model complexity with fewer restrictions compared to CB-SEM. By comparison, in their review of CB-SEM studies, Shah and Goldstein (2006) report an average of 4.7 latent variables and 16.3 indicators per model. Similarly, Baumgartner and Homburg (1996) report lower median values for both model elements (6 and 12, respectively).

A large number of models in *MIS Quarterly* employ only reflectively measured constructs (46 models; 42.20%), followed by about one third of the models employing both reflective and formative measures (see Table 2). PLS-SEM applications that include latent variables with only formative measurement models appear rarely (two models; 1.83%). In the remaining cases (28 models; 25.69%), the researchers did not provide any explanation of the measurement instrument. Interestingly, 23 of these 28 models (82.14%) were published in 2000 or later, a time when the discussion of the epistemic nature of relationships between constructs and their measures was already in full swing (e.g., Chin 1998b; Diamantopoulos and Winklhofer 2001).

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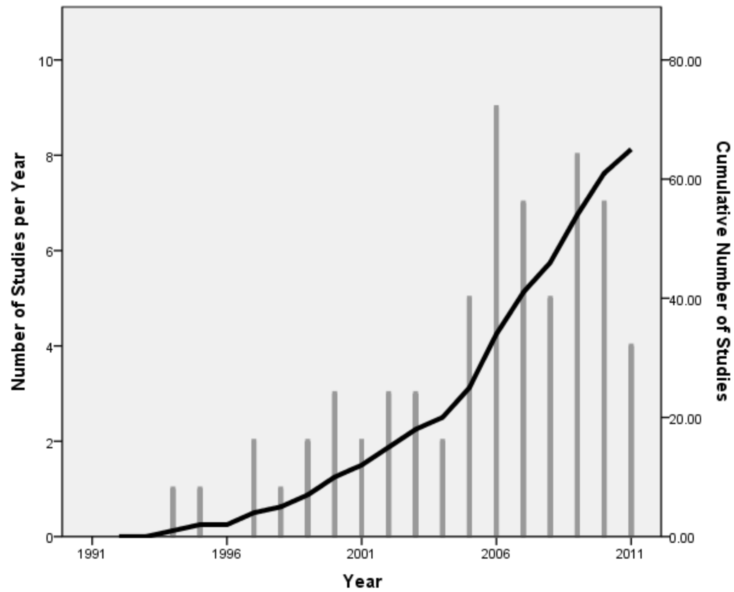
[1]Our data source was the ABI/INFORM Complete, EBSCO Business Source Complete, and JSTOR databases, as well as the journal online archive (http://www.misq.org/archive/), using the keywords *partial least squares* and *PLS* to search full text of the articles. The list of results was then examined independently by two professors proficient in the technique, the purpose being to identify those studies eligible for inclusion in the review. In this process, conceptual papers and simulation studies on methodological aspects (e.g., Qureshi and Compeau 2009; Wetzels et al. 2009) were removed from the search list. In order to avoid the biasing effects of single studies, applications with more than 10 models per study were not considered in this analysis (e.g., Venkatesh et al. 2003). The complete list of studies is available in the Online Supplement to this editorial (http://www.misq.org/supplements/).

[2]To shed further light on the quality of PLS-SEM use and results reporting in *MIS Quarterly*, we benchmarked our results against those obtained from a review of the three marketing journals with the highest journal impact factor according to the Thomson Reuters 2010 journal citation report (i.e., *Journal of Marketing*, *Journal of the Academy of Marketing Science*, and *Journal of Marketing Research*). These marketing journals published 41 empirical studies (with 60 models) using PLS-SEM in the 20-year period between 1992 and 2011. Tables 1 through 8 illustrate these results vis-à-vis those from *MIS Quarterly*.




Legend: The gray lines represent year-by-year totals; the line represents the cumulative numbers of studies.

**Figure 1. The Use of PLS-SEM in *MIS Quarterly* Over Time**

**Table 1. Reasons for Using PLS-SEM**

| | Number of Studies in *MISQ* Reporting (N = 65) | Proportion Reporting (%) | Number of studies in *JM*, *JMR*, and *JAMS* Reporting (N = 60) | Proportion Reporting (%) |
|---|---|---|---|---|
| Total | 46 | 70.77 | 20 | 33.33 |
| *Specific Reasons:* | | | | |
| Small Sample Size | 24 | 36.92 | 15 | 25.00 |
| Non-Normal Data | 22 | 33.85 | 19 | 31.67 |
| Formative Measures | 20 | 30.77 | 19 | 31.67 |
| Focus on Prediction | 10 | 15.38 | 14 | 23.33 |
| Model Complexity | 9 | 13.85 | 6 | 10.00 |
| Exploratory Research | 7 | 10.77 | 1 | 1.67 |
| Theory Development | 6 | 9.23 | 0 | 0.00 |
| Use of Categorical Variables | 4 | 6.15 | 6 | 10.00 |
| Convergence ensured | 2 | 3.08 | 2 | 3.33 |
| Theory Testing | 1 | 1.54 | 5 | 8.33 |
| Interaction Terms | 1 | 1.54 | 5 | 8.33 |

**Table 2. Model Descriptive Statistics**

| Criterion | Number of Models in *MISQ* Reporting (N = 109) | Proportion Reporting (%) | Number of Models in *JM*, *JMR*, and *JAMS* Reporting[†] (N = 60) | Proportion Reporting (%) |
|---|---|---|---|---|
| Number of Latent Variables | | | | |
| Mean[a] | 8.12 | – | 9.35 | – |
| Median | 7 | | 9 | |
| Range | (3; 36) | | (3; 20) | |
| Number of Structural Model Relations | | | | |
| Mean[a] | 11.38 | – | 13.2 | – |
| Median | 8 | | 11 | |
| Range | (2; 64) | | (2; 35) | |
| Mode of Measurement Models | | | | |
| Only Reflective | 46 | 42.20 | 18 | 30.00 |
| Only Formative | 2 | 1.83 | 1 | 1.67 |
| Reflective and Formative | 33 | 30.28 | 32 | 53.33 |
| Not Specified | 28 | 25.69 | 9 | 15.00 |
| Number of Indicators per Reflective Construct [b] | | | | |
| Mean[a] | 3.58 | – | 3.57 | – |
| Median | 3.5 | | 3 | |
| Range | (1; 400) | | (1; 46) | |
| Number of Indicators per Formative Construct [c] | | | | |
| Mean[a] | 3.03 | – | 4.12 | – |
| Median | 3 | | 3.5 | |
| Range | (1; 11) | | (1; 25) | |
| Total Number of Indicators in Models | | | | |
| Mean[a] | 27.42 | – | 34.57 | – |
| Median | 26.5 | | 28.5 | |
| Range | (5; 1,064) | | (10; 103) | |
| Number of Models with Control Variables | 29 | | 28 | |
| Number of Control Variables | | | | |
| Mean | 3.69 | – | 1.82 | – |
| Median | 4 | | 0 | |
| Range | (1; 6) | | (0; 8) | |
| **Criterion** | **Number of Studies in *MISQ* Reporting (N = 65)** | **Proportion Reporting (%)** | **Number of Studies in *JM*, *JMR,* and *JAMS* Reporting (N = 41)** | **Proportion Reporting (%)** |
| Number of Studies with | | | | |
| Single-Item Constructs | 31 | 47.69 | 21 | 51.22 |
| Higher Order Constructs (i.e., Hierarchical Component Analysis) | 15 | 23.08 | 15 | 36.59 |
| Nonlinear Relationships | 3 | 4.62 | 4 | 9.76 |
| Model Modified in the Course of the Analysis | 18 | 27.69 | 8 | 19.51 |
| If yes, Comparison with Initial Model? | 6 | 9.23 | 0 | 0.00 |
| Item Wordings Reported | 58 | 89.23 | 34 | 82.93 |
| Scales Reported | 55 | 84.62 | 34 | 82.93 |
| Scale Means and Standard Deviations Reported | 43 | 66.15 | 27 | 65.85 |
| Correlation/Covariance Matrix | 54 | 83.08 | 29 | 70,73 |

[†]Please see footnote 2 for details on how this column was generated.
[a]Estimate for 5% trimmed mean.
[b]Includes only models that have been marked as including reflective indicators (N = 79 for MISQ and N = 50 for JM, JMR and JAMS).
[c]Includes only models that have been marked as including formative indicators (N = 35 for MISQ and N = 50 for JM, JMR and JAMS).

Finally, it is noteworthy that *MIS Quarterly* has established a high level of transparency through detailed standard reporting practices with respect to measurement models. More than 80% of the studies mention item wordings, report item scales, and include the correlation or covariance matrix (see Table 2) as called for by Gefen et al. (2011). Two-thirds of all studies report scale means and standard deviations. Even though these reporting practices are satisfactory, they still leave room for improvement.

### Imprudent Use of Formative Measurement Models

A key argument for employing PLS-SEM relates to the use of formative measurement models since PLS-SEM readily handles both reflective and formative measures. Technically and implicitly, researchers accept the underlying assumptions of the PLS-SEM method (e.g., predictor specification; Lohmöller 1989; Wold 1982), which allow for the possibility of formative measurement models. However, automatically relying on PLS-SEM when using formative measures is not without its own problems, particularly because PLS-SEM is restricted to estimating formative constructs *sans* error terms (Diamantopoulos 2011). In practice, this circumstance is hard to defend because scholars cannot really be certain that all possible causes related to the latent variable are accounted for by the indicators (Diamantopoulos 2006). This is why establishing an acceptable level of measurement validity before analysis of the structural relationships is essential in PLS-SEM studies (e.g., by establishing external validity via a redundancy analysis; Chin 1998b).

Our review indicates that the average number of indicators is significantly smaller in formative than in reflective constructs (3.03 versus 3.58; $p < 0.01$). In that formative constructs should represent the entire population of indicators (Diamantopoulos et al. 2008), one would generally expect formative measurement models to be more capacious than reflective ones. So this is a puzzle.

### The Curse and Blessing of Single-Item Constructs

A much debated subject across disciplines is the use of single-item measures (e.g., Bergkvist and Rossiter 2007; Drolet and Morrison 2001; Wanous et al. 1997). Since PLS-SEM allows for the unrestricted use of single item constructs, it is not surprising that many models (31 models, 47.69%) deploy them, as shown in Table 2.

Single-item constructs have practical advantages (e.g., Fuchs and Diamantopoulos 2009) and there are circumstances in which researchers may have no other choice than to use single item constructs (Straub et al. 2004) and, thus, be criticized for mono-operationalization bias (Cook and Campbell 1979). However, single-item constructs do not offer more for less (Sarstedt and Wilczynski 2009). In terms of psychometric properties, recent research shows that only under very specific conditions do single items perform as well as multi-item scales (Diamantopoulos et al. 2012). As Diamantopoulos et al. (2012, forthcoming) point out, "opting for single item measures in most empirical settings is a risky decision as the set of circumstances that would favor their use is unlikely to be frequently encountered in practice."

This conclusion holds even more so for PLS-SEM since the utilization of a small number of items for construct measurement (in the extreme, the use of a single item) works against PLS-SEM's tendency to bias estimates (i.e., an overestimation of the measurement model relations and an underestimation of the structural model relations) when the number of indicators and/or the number of observations increase (i.e., consistency at large; Lohmöller 1989; Wold 1982). Despite their ease of implementation in PLS-SEM, researchers should follow Diamantopoulos et al.'s (2012) guideline and only consider single items (rather than a multi-item scale) when (1) small sample sizes are present (i.e., $N < 50$), *and* (2) effect sizes of 0.30 and lower are expected, *and* (3) the items of the originating multi-item scale are highly homogeneous (i.e., Cronbach's alpha>0.90), *and* (4) the items are semantically redundant.

## *Sampling Characteristics*

The most prominent argument for choosing PLS-SEM in *MIS Quarterly* is the use of small sample sizes. This issue has been passionately debated over the last years (e.g., Goodhue et al. 2006; Marcoulides and Saunders 2006) with Gefen et al. (2011, p. iii) noting that there is an "apparent misuse of perceived leniencies such as assumptions about minimum sample sizes."

Prior studies appearing in scholarly journals (e.g., Reinartz et al. 2009)—including those more critical of the PLS-SEM method (e.g., Lu et al. 2011)—indicate that PLS-SEM overcomes problematic model identification issues and that it is a powerful method to analyze complex models using smaller samples. Nevertheless, like any other statistical technique, PLS-SEM is not immune to threats from data inadequacies and researchers should make every effort to provide support for its statistical power in the research setting at hand. If commonly known standards of collecting adequate sets of empirical data have been met (e.g., the identification and treatment of outliers and other influential observations or the handling of missing values), PLS-SEM can indeed be a "silver bullet" in certain research situations (e.g., when models are relatively complex and representative sets of data are rather small; Hair et al. 2011; Reinartz et al. 2009).

As shown in Table 3, about a quarter of all models having fewer than 100 observations and six models (5.50%) fail the commonly suggested rule of ten (Hair et al. 2011), which is admittedly only a rough guideline regarding minimum sample size requirements. It is important to note that this practice cannot supplant additional power analyses (Chin 1998a), which as few as three studies (4.62%) carried out in an effort to provide further support for the adequacy of the resulting sample size. To address this, researchers could have used power tables from regression (e.g., Cohen 1992) to determine minimum sample size requirements (Chin 2010). Other important sampling characteristics have also been little analyzed or satisfactorily presented. While about one-third of the studies address non-response bias, only ten studies (15.38%) report the exact treatment of missing values and four studies (6.15%) broach the issue of detecting influential observations (e.g., outliers) and their treatment while only two studies (3.08%) use a holdout sample to validate their findings (see Table 3).

Similarly, authors motivate their choice of PLS-SEM with distributional considerations in one-third of the studies, but only four studies (6.15%) specifically analyze the normality of their data. Given that highly skewed data inflate bootstrap standard errors (Hair et al. 2012) and the well-known tendency of PLS-SEM to slightly underestimate structural model relationships (Dijkstra 1983), one needs to pay close attention to the data distributional characteristics, especially when using relatively small Ns. In this context, it is important to note that even though PLS-SEM provides precise estimates in situations with extremely non-normal data (Cassel et al. 1999; Reinartz et al. 2009), motivating the use of PLS-SEM primarily on the grounds of distributional considerations is not advisable in light of the multitude of robust covariance-based estimator options available (Gefen et al. 2011; Reinartz et al. 2009).

## *Empirical Analysis and Results Reporting*

### Reporting Algorithmic Options

Reported computational settings leave some room for improvement (see Table 4). For example, while almost every study mentions the use of resampling methods for significance testing (e.g., bootstrapping and jackknifing), only about one-third of the studies share their algorithmic parameter settings (e.g., the number of bootstrap samples/cases and selected sign change option). Reporting the precise settings is important, however, because a poor choice of options can lead to significantly biased standard error estimates (e.g., Efron and Tibshirani 1986). Bootstrap estimates also serve as the basis for confidence intervals allowing an assessment of parameter stability. Reporting (bias corrected) bootstrap confidence intervals has only recently been proposed for PLS-SEM (Gudergan et al. 2008; Sarstedt, Henseler, and Ringle 2011); their use should be more strongly considered in future studies (i.e., no study in our review made use of this useful significance reporting option). Finally, only 38 studies (58.46%) report the software used for the PLS-SEM analysis (see Table 4)—as required by most license agreements. Providing this information is important, however, since software applications differ in their default settings (e.g., bootstrapping standard errors differ depending on the software-specific scheme for selecting initial outer weights to start the PLS-SEM algorithm and the applied bootstrapping sign change option).

### Formative Measurement Model Evaluation

In the case of formative measurement models, the aforementioned issues continue to be important with respect to evaluating results of PLS-SEM studies in *MIS Quarterly*. Even though there are numerous guidelines for validating formative measurement models (Diamantopoulos and Winklhofer 2001; Hair et al. 2012; MacKenzie et al. 2011; Petter et al. 2007), *MIS Quarterly* authors have restricted themselves to reporting indicator weights (24 of 35 models using formative measures, 68.57%) and their p-value testing outcomes (20 models, 57.14%) (see Table 5). An even smaller number of models addressed indicator multicollinearity (9 models, 25.71%), which is an important desideratum for interpreting results. Moreover, we note the surprising finding that 5 of 35 models (14.29%) inappropriately evaluated formative measurement models by using reflective evaluation criteria in spite of well-cited articles such as Petter et al. (2007) that have been raising awareness of the dangers of misspecified models.

Formative constructs have a place in research but their meaningful use is much more demanding (Bagozzi 2011). Future research in *MIS Quarterly* should improve the validation of formative constructs by more closely following the recommendations given by scholars such as Diamantopoulos and Winklhofer (2001), Hair et al. (2012), MacKenzie et al. (2011), and Petter et al. (2007). For example, when using a formative measurement instrument, multiple indicator multiple cause (MIMIC) models, or in PLS-SEM, a redundancy analysis (Chin 1998b), permit the testing of formative construct validity, which should be cross-validated on a fresh set of data and replicated in subsequent research (Diamantopoulos and Winklhofer 2001).

### Reflective Measurement Model Evaluation

Whereas the evaluation of formative measurement models gives rise to concern, our review reveals that PLS-SEM studies in *MIS Quarterly* usually build on satisfactory evaluations that ensure the reliability and validity of the reflective measurement model construct

| **Table 3. Sampling Characteristics** | | | | |
|---|---|---|---|---|
| | **Number of Models in *MISQ* Reporting (N = 109)** | **Proportion Reporting (%)** | **Number of Models in *JM*, *JMR,* and *JAMS* Reporting (N = 60)** | **Proportion Reporting (%)** |
| Sample Size | | | | |
| Mean [a] | 238.12 | | 210.88 | |
| Median | 198 | | 160 | |
| Range | (17; 1,449) | | (39; 2,990) | |
| Less than 100 Observations | 25 | 22.94 | 11 | 18.33 |
| Ten Times Rule of Thumb Not Met | 6 | 5.50 | 8 | 13.33 |
| If not met, to what extent (in percentages) was the sample size *below* the required N according to the ten times rule ? | 22.51% | | 24.87% | |
| | **Number of Studies in *MISQ* Reporting (N = 65)** | **Proportion Reporting (%)** | **Number of Studies in *JM*, *JMR*, and *JAMS* Reporting (N = 41)** | **Proportion Reporting (%)** |
| Nonresponse Bias | 24 | 36.92 | 16 | 39.02 |
| Holdout Sample Used | 2 | 3.08 | 0 | 0.00 |
| Missing Values Reported | 10 | 15.38 | 5 | 12.20 |
| Treatment of Influential Observations (e.g., Outliers) Reported | 4 | 6.15 | 3 | 7.32 |
| Non-Normality Reported (e.g., Skewness, K-S test) | 4 | 6.15 | 2 | 4.88 |

[a]Estimate for 5% trimmed mean.

| **Table 4. Technical Reporting** | | | | |
|---|---|---|---|---|
| | **Number of Studies in *MISQ* Reporting (N = 65)** | **Proportion Reporting (%)** | **Number of Studies in *JM*, *JMR*, and *JAMS* Reporting (N = 41)** | **Proportion Reporting (%)** |
| *Software Used* | | | | |
| PLS Graph (Chin 2003) | 35 | 53.85 | 11 | 26.83 |
| SmartPLS (Ringle et al. 2005) | 2 | 3.08 | 7 | 17.07 |
| LVPLS (Lohmöller 1987) | 1 | 1.54 | 2 | 4.88 |
| Not Reported | 27 | 41.54 | 21 | 51.22 |
| *Resampling Method (e.g., Bootstrapping)* | | | | |
| Use Mentioned | 61 | 93.85 | 25 | 60.98 |
| Algorithmic Options | 24 | 36.92 | 16 | 39.02 |

| **Table 5. Reported Formative Measurement Model Statistics** | | | | | |
|---|---|---|---|---|---|
| **Empirical Test Criterion in PLS-SEM** | | **Number of Models Reporting in *MISQ* (N = 35)** | **Proportion Reporting (%)** | **Number of Models Reporting in *JM*, *JMR*, and *JAMS* (N = 33)** | **Proportion Reporting (%)** |
| Reflective Criteria Used to Evaluate Formative Constructs | | 5 | 14.29 | 5 | 15.15 |
| Absolute Indicator Contribution to the Construct | Indicator Weights | 24 | 68.57 | 17 | 51.52 |
| Significance of Weights | Standard Errors, Significance Levels, t-Values/ p-Values for Indicator Weights | 20 | 57.14 | 8 | 24.24 |
| Multicollinearity | Only VIF/ Tolerance | 9 | 25.71 | 9 | 27.27 |
| | Only Condition Index | 0 | 0.00 | 0 | 0.00 |
| | Both | 0 | 0.00 | 0 | 0.00 |

scores. In particular, most studies report indicator loadings (70 of 79 models, 88.61%) and measures of internal consistency by reporting Cronbach's alpha (8 models, 10.13%), composite reliability (45 models, 56.96%), or both (22 models, 27.85%). All studies provide evidence of convergent validity and most models assess discriminant validity (see Table 6), using approaches as described in, for example, Straub et al. (2004) or Gefen and Straub (2005).

Even though the handling of reflective measures suggests that researchers are following good practice, future PLS-SEM studies should continue to further improve measurement validation (Boudreau et al. 2001; Straub 1989). Moreover, while researchers frequently use confirmatory factor analyses (CFA) prior to the model evaluation (26 models, 32.91%), it would actually be preferable to avoid this practice. Considering that the parameter estimates depend on the specific set-up of the analyzed model, it is more appropriate to evaluate these measures via PLS-SEM statistics.

### Structural Model Evaluation

A common argument for using PLS-SEM is that the technique excels at prediction and almost all model estimations use the coefficient of determination $R^2$ values) to characterize the ability of the model to explain and predict the endogenous latent variables (see Table 7). However, only 13 models (11.93%) use Cohen's (1988) pseudo F-test ($f^2$ effect size), which allows a scholar to evaluate the independent variable's incremental explanation of a dependent variable. In that PLS-SEM is strong on prediction, it is disconcerting to see that none of the studies uses Stone's (1974) and Geisser's (1974) cross-validated redundancy measure $Q^2$, which allows for assessing the model predictive relevance (Wold 1982). In addition, changes in $Q^2$ allow assessing the relative impact of the structural model for predicting the observed measures of an endogenous latent variable by the $q^2$ effect size (Chin 1998b).

In light of our results, we urge researchers to use statistical criteria such as $f^2$, $Q^2$, and $q^2$ more frequently (Chin 1998b; Hair et al. 2011; Henseler et al. 2009) to make a stronger case for model predictive capabilities. Likewise, researchers should compare the theoretical model with the saturated model, which includes all possible paths "in order to (1) verify that the significant paths in the theoretical model also remain significant in the saturated model, and (2) that adding the paths via the saturated model does not significantly increase the $f^2$" (Gefen et al. 2011, p. viii). None of the *MIS Quarterly* studies we examined applied this analysis. Similarly, the estimation of alternative models (Gefen et al. 2011) is the exception, with 18 studies (27.69%) engaging in model modifications, and 6 studies (9.23%) providing a comparison with the initial model. In this context, and as emphasized by Rigdon, Preacher et al. (2011), researchers should think more broadly in terms of the different relationships in the structural model and the measurement models (e.g., linear versus nonlinear relationships; Henseler et al. 2012). Methodological research should, therefore, make greater efforts to develop ways to explore different model set-ups in this respect.

PLS-SEM studies in *MIS Quarterly* address, to some extent, additional hypothesized complexity in the model set-up (see Table 2 and Table 8) by, for instance, mediator analysis (15 studies, 23.08%) and hierarchical component models (15 studies, 23.08%). Only three studies (4.62%) examine nonlinear relationships, even though this kind of analysis can easily be carried out in PLS-SEM (Rigdon et al. 2010). Group analyses by means of continuous or categorical moderators are considered in 24 studies (36.92%), often without conveying any details on the methods deployed. For instance, alternative approaches to moderator analyses perform differently in PLS-SEM (Henseler and Chin 2010) and the limitations of conventional statistical tests in multigroup comparisons have been reported in the literature (Rigdon et al. 2010; Sarstedt, Henseler, and Ringle 2011). Moreover, only three studies (4.62%) address the issue of measurement model invariance in the context of multigroup analyses.

Finally, it is noteworthy that far too few of the PLS-SEM studies in *MIS Quarterly* conducted supplementary analyses (see Table 8), most of which have been summarized in the recommendations by Gefen et al. (2011) and Hair et al. (2012). For example, none of the studies addresses the critical issue of unobserved heterogeneity—carried out by using, for example, FIMIX-PLS (Sarstedt, Becker et al. 2011; Sarstedt and Ringle 2010)—that, if not handled properly, can seriously compromise the results, interpretation, and conclusions (Rigdon et al. 2010; Rigdon, Ringle et al. 2011; Ringle et al. 2010).

## *How to Improve the Use of PLS-SEM in Future*

Our review substantiates that PLS-SEM has become a key data analysis tool for publications in *MIS Quarterly*. Most PLS-SEM studies published in this journal meet a reasonable proportion of the requirements set forth by Gefen et al. (2011). Nevertheless, more can and should be done to meet the highest standards of PLS-SEM use. Specifically, based on our review, the following issues warrant attention to improve PLS-SEM applications in this journal: (1) The reasons why PLS-SEM was employed (i.e., researchers should match the

| Table 6. Reported Reflective Measurement Model Statistics | | | | | |
|---|---|---|---|---|---|
| **Empirical Test Criterion in PLS-SEM[a]** | | **Number of Models in *MISQ* Reporting (N = 79)** | **Proportion Reporting (%)** | **Number of Models in *JM*, *JMR*, and *JAMS* Reporting (N = 50)** | **Proportion Reporting (%)** |
| Indicator Reliability | Indicator Loadings | 70 | 88.61 | 27 | 54.00 |
| Internal Consistency Reliability | Only Composite Reliability | 45 | 56.96 | 16 | 32.00 |
| | Only Cronbach's Alpha | 8 | 10.13 | 5 | 10.00 |
| | Both | 22 | 27.85 | 10 | 20.00 |
| Convergent Validity | AVE1 | 70 | 88.61 | 28 | 56.00 |
| | Other | 9 | 11.39 | 1 | 2.00 |
| Discriminant Validity | Only Fornell-Larcker Criterion | 29 | 36.71 | 20 | 40.00 |
| | Only Cross-Loadings | 7 | 8.86 | 3 | 6.00 |
| | Both | 33 | 41.77 | 10 | 20.00 |
| | Other | 3 | 3.80 | 1 | 2.00 |

[a]Single item constructs were excluded from this analysis.

| Table 7. Reported Structural Model Statistics | | | | | |
|---|---|---|---|---|---|
| **Criterion** | **Empirical Test Criterion in PLS-SEM** | **Number of Models in *MISQ* Reporting (N = 109)** | **Proportion reporting (%)** | **Number of Models in *JM*, *JMR,* and *JAMS* Reporting (N = 60)** | **Proportion Reporting (%)** |
| Coefficient of Determination | $R^2$ | 105 | 96.33 | 56 | 93.33 |
| | $f^2$ Effect Size | 13 | 11.93 | 3 | 5.00 |
| Predictive Relevance | Cross-Validated Redundancy $Q^2$ | 0 | 0.00 | 5 | 8.33 |
| | $q^2$ Effect Size | 0 | 0.00 | 0 | 0.00 |
| Path Coefficients | Absolute Values | 107 | 98.17 | 57 | 95.00 |
| Significance of Path Coefficients | Standard Errors, Significance Levels, t-Values, p-Values | 107 | 98.17 | 55 | 91.67 |
| Confidence Intervals | – | 0 | 0.00 | 0 | 0.00 |
| Total Effects | – | 4 | 3.67 | 3 | 5.00 |

| Table 8. Additional Considerations and Supplementary Analyses | | | | |
|---|---|---|---|---|
| **Criterion** | **Number of Studies in *MISQ* Reporting (N = 65)** | **Proportion Reporting (%)** | **Number of Models in *JM*, *JMR,* and *JAMS* Reporting (N = 41)** | **Proportion Reporting (%)** |
| Common Method Variance | 26 | 40.00 | 12 | 29.27 |
| Mediator Analysis | 15 | 23.08 | 14 | 34.15 |
| Multigroup Analysis | | | | 0.00 |
| Continuous Moderator Analysis | 8 | 12.31 | 7 | 17.07 |
| Categorical, Observed (Multigroup Comparison) | 16 | 24.62 | 5 | 12.20 |
| Categorical, Unobserved (Model-Based Segmentation Techniques; e.g., FIMIX-PLS) | 0 | 0.00 | 0 | 0.00 |
| Measurement Model Invariance | 3 | 4.62 | 3 | 7.32 |
| Tetrad Analysis | 1 | 1.54 | 0 | 0.00 |

goals of their research with the PLS-SEM capabilities, that is, use PLS-SEM primarily for exploratory work and for prediction), (2) the suitability of the data used and reporting of sampling and other statistics (e.g., distributions and statistical power calculations), (3) the use of formative measures and their evaluation, (4) the inclusion of additional structural model evaluation criteria in compliance with the PLS-SEM prediction-oriented goals, and (5) the reporting of the particular procedures employed, and the algorithmic options employed.

## Conclusion

Every SEM approach has certain strengths but also exhibits clear constraints, constraints which limit its utility in certain research situations—as discussed and shown by authors such as Jöreskog and Wold (1982) and Reinartz et al. (2009) in their comparisons of CB-SEM and PLS-SEM.[3] We thus call for a more informed and rigorous use of PLS-SEM. Much of the criticism found currently in the literature may be less related to PLS-SEM itself than to misuses of the method or the belief that a given analytical technique can overcome any challenge researchers face (e.g., the realized N). If correctly applied, PLS-SEM can indeed be a "silver bullet" for estimating causal models in many model and data situations (Hair et al. 2011), especially when complex models and secondary data are involved. Secondary data, whose use is becoming more and more common in business research, is typically collected without the benefit of a theoretical framework and is often not a good match for CB-SEM analysis. In light of the need in CB-SEM for high-quality and specially developed manifest variables, PLS-SEM may often be the better choice for structural modeling of secondary data (Rigdon 2012).

PLS-SEM is still catching up with the methodological advances that have been carried out on CB-SEM over more than the last 25 years. Researchers must improve the method further and provide guidance on appropriate techniques to extend PLS-SEM analyses and their correct applications. For instance, about a quarter of all studies considered the inclusion of hierarchical component models but about half of these studies explain exactly how they were conducted (see Table 2). Thus, knowledge of the use of the different types of hierarchical component models in PLS-SEM (e.g., the formative–formative type) remains scant (for additional results on this technique and on how to apply it, see the Online Supplement to this editorial). Researchers should continue to make every possible effort to follow the many avenues for improving and extending the PLS-SEM method in order to make its use even more valuable for empirical researchers.

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[3]This notion holds for every approach to SEM, including the recently proposed generalized structured component analysis (GSCA; Hwang et al. 2010; Hwang and Takane 2005). Henseler (2012) shows that the prominently proposed advantages of GSCA do not hold true when the method is correctly applied and evaluated.

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# EDITOR'S COMMENTS – SUPPLEMENT

## A Critical Look at the Use of PLS-SEM in *MIS Quarterly*

### *Appendix A: PLS-SEM Studies in MIS Quarterly (1992–2011)*

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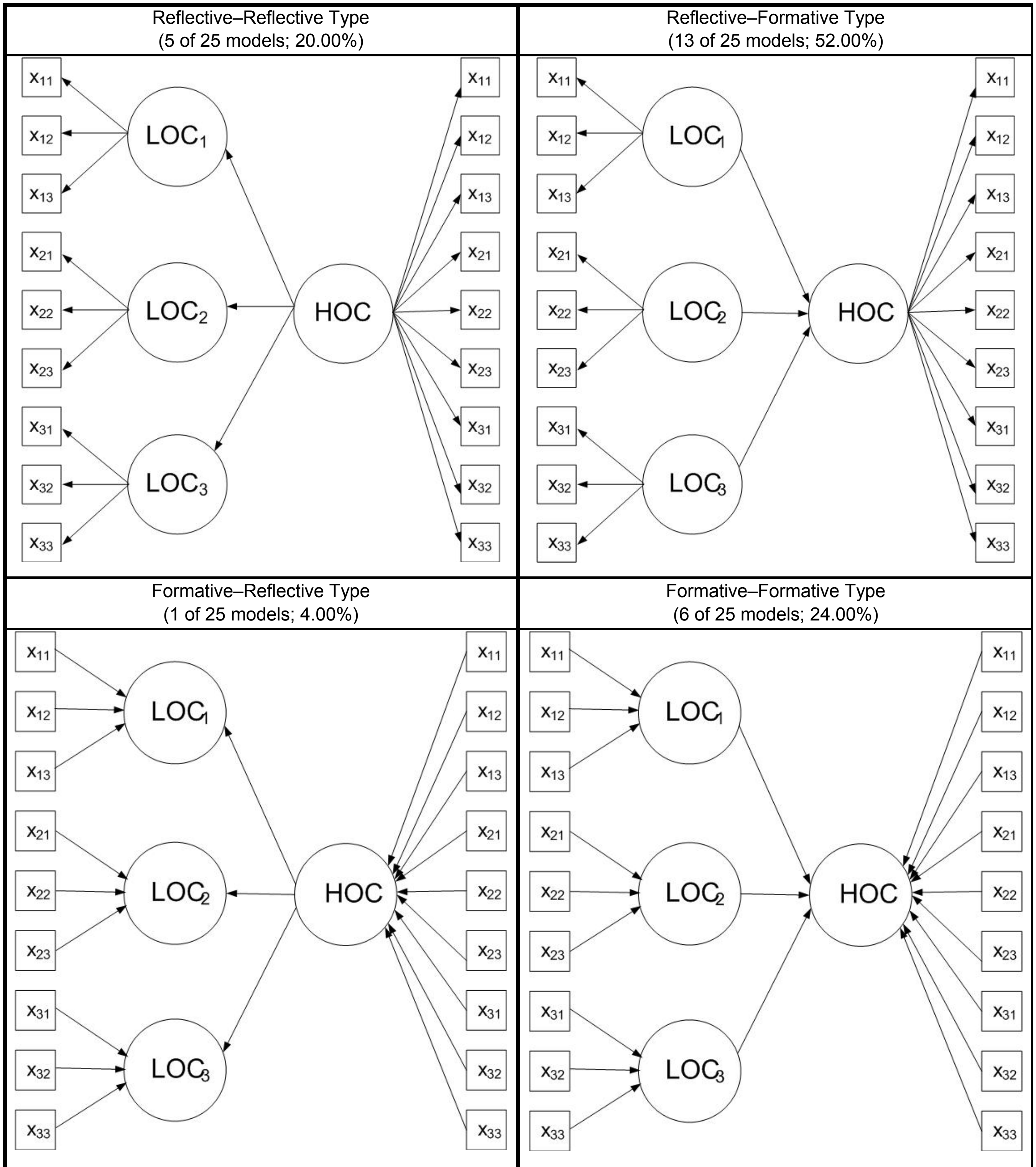
## *Appendix B: Hierarchical Component Models*

In total, 15 studies (23.08%) included 25 hierarchical component models. Only 7 of these 15 studies (46.67%) state exactly how the hierarchical component analysis, which researchers often call second-order construct analysis, was carried out. While two studies used factor scores, the authors of the other five studies stated that they applied the indicator reuse technique that Wold (1982) proposed for this kind of analysis. The majority of studies (8 of 15 studies, 53.33%) provide no detailed information on how the analysis was carried out. Thus, more specific knowledge about the use of hierarchical component models in PLS-SEM remains scant.

When using the PLS-SEM method for model estimation, all latent variables—which includes higher order components—must have a measurement model with at least one indicator. Technically, Lohmöller (1989) showed that the indicator reuse approach is suitable for the analysis of hierarchical component models in PLS-SEM (i.e., the higher order component uses all indicators of the lower order components; Figure B1). This approach works best when all lower order components have the same number of indicators. Otherwise, the interpretation of the relationships between the lower and the higher order components must account for the bias of unequal numbers of indicators in the lower order components. Even though some of the five studies that apply the indicator reuse technique have highly unbalanced numbers of indicators in their lower order components, none of them accounts for this important issue when interpreting the path coefficients. A potential solution to this problem is the computation and comparison of total effects between the lower order component indicators and the higher order component.

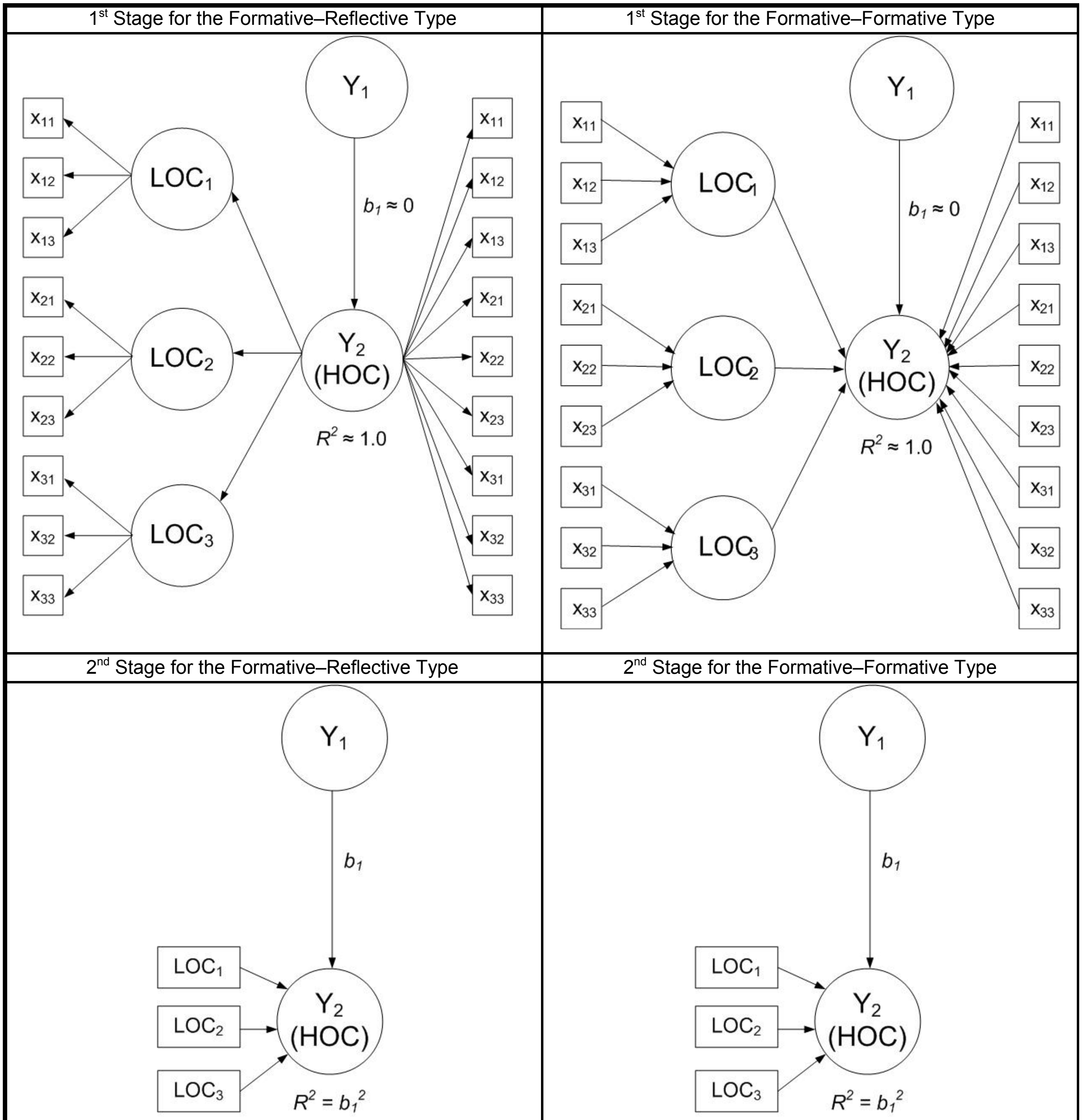
Generally, four types of hierarchical component models (Figure B1) appear in the extant literature, with their naming differing largely (Wetzels et al. 2009). While the formative–reflective type has only been used in a single case, reflective–formative hierarchical component models represent the most popular type in *MIS Quarterly* PLS-SEM applications.

With two exceptions, the majority of studies (13 of 15 studies, 86.67%) relate the higher order component to other latent variables in the nomological net that are not part of the hierarchical component model—as required by Chin (1998). In three studies (20%), the higher order component is endogenous (i.e., it has at least one latent variable as a predecessor in the structural model which is not an element of the hierarchical component model), while, in contrast, the higher order component explains other latent variables in five studies (33.33%). In the remaining five studies (33.33%), the higher order component has other latent variables in the structural model as both predecessors and successors.




*Legend*: LOC = lower order component; HOC = higher order component

**Figure B1. Hierarchical Component Models in PLS-SEM**




*Legend*: LOC = lower order component; HOC = higher order component; $Y_1$ = exogenous latent variable in the structural model (its measurement model is not further specified in this illustration); $Y_2$ = endogenous latent variable in the structural model; $b_1$ = standardized path coefficient for the structural model relationship between the latent variables $Y_1$ and $Y_2$.

**Figure B2. Two-Stage Approach for the Hierarchical Component Analysis**

In half of the formative–formative type and in a quarter of the reflective–formative type of hierarchical component model applications, the higher order component is endogenous. These model set-ups require particular attention when the repeated indicators approach is used since almost all variance of the higher order component is explained by its lower order components ($R^2 \approx 1.0$; Figure B2). As a consequence, the path relationship from the latent variable (predecessor) to the endogenous higher order component is always approximately zero and nonsignificant.

In this kind of situation, a mixture of the repeated indicators approach and the use of latent variable scores in a two-stage approach—which is similar to the two-stage approach in moderator analyses in PLS-SEM (Henseler and Chin 2010)—is appropriate. In the first stage, one uses the repeated indicators approach to obtain the latent variable scores for the lower order components which then, in the second stage, serve as manifest variables in the measurement model of the higher order component (Figure B2). Thereby, the higher order component is embedded in the nomological net in a way that allows other latent variables as predecessors to explain some of its variance, which may result in significant path relationships.

Even though these explications further substantiate the use of hierarchical component models in PLS-SEM from a technical perspective, more knowledge is needed to integrate the theoretical and technical underpinnings. Future research on the appropriate use of formative measurement models in PLS-SEM must also address the use of formative–reflective, reflective–formative, and formative–formative types of hierarchical component models.

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