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Development and Update of Guidelines to Perform and Report Partial Least Squares Path Modeling in Information Systems Research

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Completed Research Paper

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Abstract

Partial least squares (PLS) path modeling has been widely and dominantly used in the field of Information Systems (IS) during decades. The usage and prescriptions for performing PLS path modeling has been recently examined, debated, and improved, which have generated substantial changes, contributions, and developments (e.g., composite models, confirmatory composite analysis, bootstrap-based test of overall model fit evaluation) on a separate manner that requires a holistic piece of work to guide IS scholars. This paper introduces PLS path modeling to be skilled to perform and report a high quality PLS analysis by following the latest suggested standards. We provide a constructive and illustrative example on a model on business value of social media in companies using data simulated for 300 observations to explain the latest contributions in PLS path modeling. The key contribution of this manuscript is the description, position, explanation, development, and illustration at the user-level, of the when, why, and how to perform a high-quality PLS estimation by following the latest standards suggested in prior methodological literature on PLS path modeling.

Keywords

PLS path modeling, guidelines, empirical IS research.

Introduction

Partial least squares (PLS)-Structural equation modeling (SEM) is a technique that has been popularized in the field of Information Systems (IS) for its ability to evaluate complex research questions by estimating a complex research model, modeling latent variables, and estimating several types of measurement errors. There are two types of SEM techniques: covariance-based SEM and variance-based SEM. Covariance-based SEM estimates model parameters using the empirical variance-covariance matrix. Variance-based SEM first creates proxies as linear combinations of the observed variables, which are used later to estimate the model parameters (Henseler et al. 2016). Partial least squares is the most popular and developed method of estimation among the variance-based SEM technique.

PLS path modeling (i.e., the method of estimation of PLS) has been widely and dominantly used in the field of IS during decades (Marcoulides and Saunders 2006, Pavlou and El Sawy 2006, Benitez and Walczuch 2012, Ringle et al. 2012). IS research usually incorporate research problems and questions that require on the conceptualization, operationalization, and estimation of pure composite models, or models with a combination of composite and reflective constructs. PLS is the unique method of estimation that can estimate successfully this type of models (Henseler et al. 2016).

The usage and prescriptions for performing PLS path modeling has been recently examined, debated, and improved (e.g., Hair et al. 2012a, Hair et al. 2012b). Very recent research has revisited the theoretical foundations (e.g., Rigdon 2012, 2014, Sarstedt et al. 2014), and the strengths and weaknesses of PLS path modeling (Aguirre and Marakas 2013, Ronkko and Evermann 2013, Henseler et al. 2014, Rigdon et al. 2014, Henseler et al. 2016). This examination, heated debate, and revisits have generated substantial changes, contributions, and developments on a separate manner that requires a holistic piece of work to be used by IS scholars. Some of these relevant contributions have been the proposal of the composite models (e.g., Rigdon 2012, Henseler 2015), the introduction of the confirmatory composite analysis and the ways to check for model identification (Henseler et al. 2014), the bootstrap-based test of overall model fit evaluation (Dijkstra and Henseler 2015a), consistent PLS (PLSc) algorithm (Dijkstra and Henseler 2015b), and the heterotrait-monotrait (HTMT) ratio of correlations as criteria to evaluate discriminant validity of factor models (Henseler et al. 2015).

PLS is an effective method to estimate models that combine reflective and composite constructs. PLS is also recommended when the proposed model is purely composite, that is, all the constructs included in the model are composite constructs. Since it is possible to evaluate the overall model fit of a PLS estimation, it is rational to say that PLS can be used now for both confirmatory and exploratory research (Henseler et al. 2016). Although PLSc can be practically and usefully used to estimate factor models, cannot be considered as effective as covariance-based SEM methods of estimation to estimate factor models.

How to perform and report an impactful empirical analysis using PLS path modeling in your best current and future IS research? This is the question this manuscript tries to answer. The changes proposed in the last three years and new developments require of clear and updated guidelines that will guide IS scholars on their empirical analysis and testing. Many recent submissions are being desk rejected in leading IS journals based on the out of date empirical analysis using PLS path modeling. The field of IS requires a clear technical and applied understanding on how to perform a rigorous PLS path modeling with the current standards and advances.

This paper introduces PLS path modeling to be skilled to perform and report a high quality PLS analysis by following the latest suggested standards by means of the statistical software package Advanced Analysis of Composites (ADANCO) 2.0.1 (http://www.composite-modeling.com/) (Henseler and Dijkstra 2015). Based on the latest standards in PLS path modeling, the paper addresses the *when*, *why*, and *how* to perform a high-quality PLS estimation with emphasis in the research topics of IS. A practical example is explained and developed to guide analysts.

Foundations of PLS path modeling

The PLS Path Model and the Algorithm of PLS

In the current consideration, the PLS algorithm is a full-fledged SEM method of estimation that can estimate composite and factors measurement models, estimate recursive and non-recursive structural models, and conduct approximate and exact tests of model fit (Dijkstra and Henseler 2015a, 2015b).

A PLS path model (i.e., the theory that the author team wants to test) is formally defined as two sets of linear equations: the measurement model and the structural model. The measurement model (i.e., the measures of constructs/concepts) specifies the relations between a construct and its observed indicators. The structural model includes the relationships between the constructs that composes the proposed theory to be tested.

PLS path models can contain two types of measurement models: Factor models and composite models (Rigdon 2012, Henseler et al. 2016). Factor models use reflective constructs and assume that the variance of a set of indicators can be perfectly explained by the existence of one unobserved variable and individual random error (Henseler et al. 2014, Dijkstra and Henseler 2015b). Factor models can be used to model behavioral concepts as personality traits, individual behavior, and individual attitude, which appears frequently in the theoretical development of Behavioral Sciences (Henseler et al. 2016).

In contrast, composite models/constructs are formed as linear combinations of their respective indicators. A composite construct serves as proxy for the concept under investigation (i.e., the recipe) that is composed of a mix of indicators (i.e., the ingredients) (Henseler 2015). As an example, consider bread. Bread is constituted from wheat, water, salt, and yeast. If we were to examine the correlations between the amount of wheat, water, salt, and yeast in a sample of loaf of bread, the correlations are likely to be high. However, such correlations do not mean that bread is a reflective construct and that bread causes wheat, water, salt, and yeast. Rather, bread is a composite construct where wheat, water, salt, and yeast are the simple entities (i.e., the ingredients) which are combined to form the composite concept we call bread. Clearly, the temporal precedence of the ingredients also suggests that bread cannot be the common cause of the ingredients. The composite model does not impose any restrictions on the co-variances among indicators of the same construct, thereby relaxing the assumption that all the covariation among a block of indicators is explained by a common factor. Composite constructs can be employed to conceptualize, operationalize, and estimate emergent, strong, complex, and "man-made" (or "firm-made") concepts (Henseler et al. 2016). Composite constructs are concepts created by the man or a firm that have a high level of abstraction and complexity.

For example, the construct information technology (IT) infrastructure capability refers to the firm's ability to use and leverage the IT resource infrastructure of the firm for business activities (e.g., Benitez and Walczuch 2012, Chen et al. 2015, Ajamieh et al. 2016). IT infrastructure capability is a "man/firm-made" concept that should be modelled as a composite construct (Benitez and Ray 2012, Ajamieh et al. 2016). There is not only one recipe for conceptualizing and estimating a concept. Like different bakeries can produce different types of bread, different scholars can produce different recipes for a same concept. For example, based on Melville et al. (2004) work, Ajamieh et al. (2016) consider the recipe "IT infrastructure capability" as composed by IT technological infrastructure capability, IT managerial infrastructure capability, and IT technical infrastructure capability. IT capability i.e. a similar construct to IT infrastructure capability is, for example, considered by prior IS research (Bharadwaj 2000, Santhanam and Hartono 2003) as composed of IT technical infrastructure, human IT resources, and IT-enabled intangibles. Both reflective and composite constructs are proxies of the concept under investigation. Considering that a significant portion of concepts in IS research are emergent, strong, and man/firm-made, composite models are expected to be the dominant conceptualization in IS research. As composite models are less restrictive than factor models, they usually have a greater overall model fit (Landis et al. 2000).

The structural model contains the hypothesized relationships included in the proposed theory that wants to be tested. These relationships thus included exogenous and endogenous variables. Exogenous variables are assumed to derive from outside the model, that is, they do not receive the influence (arrow) from any other variable. Differently, endogenous variables are partially explained by other variables in the model and they receive at least one arrow in the structural model from other variables in the model. The structural relationships are assumed to be linear. The estimation of the value and significance of the beta coefficients is the key aspect to test whether the hypothesized relationships included in the proposed theory are supported by the data.

The estimation of PLS path model parameters happens in four steps: first, an iterative PLS algorithm that determines composite scores for each construct, that is, it creates a proxy as a linear combination of the observed indicators per each construct (Henseler et al. 2016). Second, a correction for attenuation is required for those constructs that are modeled as factors. As factors contain measurement error they are proxies. Proxy correlations are underestimations of the real factor correlations, and factors should be corrected for attenuation by using PLSc, which means that proxy correlations are divided by the square root of its reliability (Dijkstra and Henseler 2015b). The main output of the second step is a consistent construct correlation matrix. In the third step, the model parameters (e.g., weights, loadings, beta coefficients) are estimated based on this consistent construct correlation matrix (Benitez et al. 2016a). Ordinary least squares can be used to estimate the beta coefficients in this step if the model does not include bidirectional relationships nor potentially suffer of omitted variables (i.e., there is no suspicion of endogeneity)[1]. However, if the scholars want/need to check for endogeneity, two-stage least squares should be used instead of ordinary least squares (Benitez and Ray 2012, Dijkstra and Henseler 2015a, Benitez et al. 2016a). Finally, bootstrapping is applied to obtain the level of significance of the model parameters.

Looking at the Research Problem

PLS is an effective method to estimate composite models or models that combine reflective and composite reflective constructs. We additionally argue that the method of estimation can also be selected based on the type of research problem to be solved in the research. This introduces the type of research problem to the criteria to decide the method to be used in the empirical analysis. PLS appears to be a useful method of estimation to examine and address research problems that include emergent, strong, complex, and "man/firm-made" concepts as well as to test interesting theories that have the potential to provide a good answer to an important research problem in a timely way.

[1] See Benitez et al. (2016a) for a description of how to address endogeneity in a PLS path modeling.

Statistically talking, covariance-based SEM methods of estimation can be more efficient to estimate factor models than PLS path modeling. However, PLSc could be used rationally to also estimate purely factors models because PLS path modeling and its associated statistical software package have been proven to be especially useful and agile to test theories. In this sense, PLSc path modeling could be useful to test in an agile way interesting theories that includes factors to solve novel research problems. To stop urgently a patient's blood hemorrhage, a surgeon can do it following a well-established protocol or in a useful and agile way. While fulfilling the protocol will be the optimal way to proceed in the most of situations, some patients may need of a more agile solution to avoid dying. We should not kill or delay interesting theories that address important novel research problems because we only want to follow the protocol per se.

A constructive and illustrative example

Description of the Example

We provide a constructive and illustrative IS example to explain the latest contributions in PLS path modeling. Figure 1 presents the proposed theory to be tested on a sample of 300 observations that come from data simulated only for the purposes of this example and manuscript. Firm level is the unit of the analysis in the example. Social executive behavior is the positive/negative behavior of the firm's top managers towards the firm's usage of social media for business activities. Social employee behavior is the positive/negative behavior of the firm's employees towards the firm's usage of social media for business activities. Social media capability refers to the firm's ability to purposely use and leverage external social media platforms to execute business activities (Braojos et al. 2015a, 2015b, Benitez et al. 2016b). Business process performance is the firm's relative performance in the key business processes as compared with its key competitors (e.g., Tallon and Pinsonneault 2011). Based on recent IS research on social media in organizations (e.g., Aral et al. 2013, Benitez et al. 2016b), the conceptual model argues that social executive behavior and social employee behavior positively affects the development of a firm's social media capability, which in turn influences positively firm's business processes performance. This conceptual model includes the following three hypotheses to be tested:

Hypothesis 1 (H1): There is a positive relationship between social executive behavior and social media capability.

Hypothesis 2 (H2): There is a positive relationship between social employee behavior and social media capability.

Hypothesis 3 (H3): There is a positive relationship between social media capability and business process performance.

Reflective constructs can be used to model behavioral concepts as personality traits, individual behavior, and individual attitude (Henseler et al. 2016). Considering social executive behavior and social employee behavior refer to individual behavior and attitude, these constructs were specified as reflective. Social executive behavior was measured with four reflective indicators (SEXB1-SEXB4). Social employee behavior was measured with four reflective indicators (SEMB1-SEMB4). These constructs were specified and estimated by using mode A consistent (Dijkstra and Henseler 2015b).

A composite construct serves as proxy for the concept under investigation (i.e., the recipe) that is composed of a mix of indicators (i.e., the ingredients) (Henseler 2015). Composite constructs can be employed to conceptualize, operationalize, and estimate emergent, strong, complex, and "firm-made" concepts (Henseler et al. 2016). Social media capability and business process performance (i.e., two recipes) were specified as composite constructs. Facebook, Twitter, corporate blog(s), and LinkedIn are our ingredients to be combined to shape the construct social media capability (Braojos et al. 2015a). Supplier relations, product and service enhancement, production and operations, marketing and sales, and customer relations are the ingredients used to execute the recipe of the construct business process performance (Tallon and Pinnsoneault 2011). These constructs were estimated by using the regression weights (mode B). The usage of mode B should be the starting point in weighting scheme for estimating composite constructs because the estimation of these weights is consistent (Dijkstra 2010). As correlation weights (mode A) are more stable, mode A should be used in combination with mode B or in isolation (for all composite constructs) after having tried the estimation with mode B in presence of negative or nor significant indicator weights.

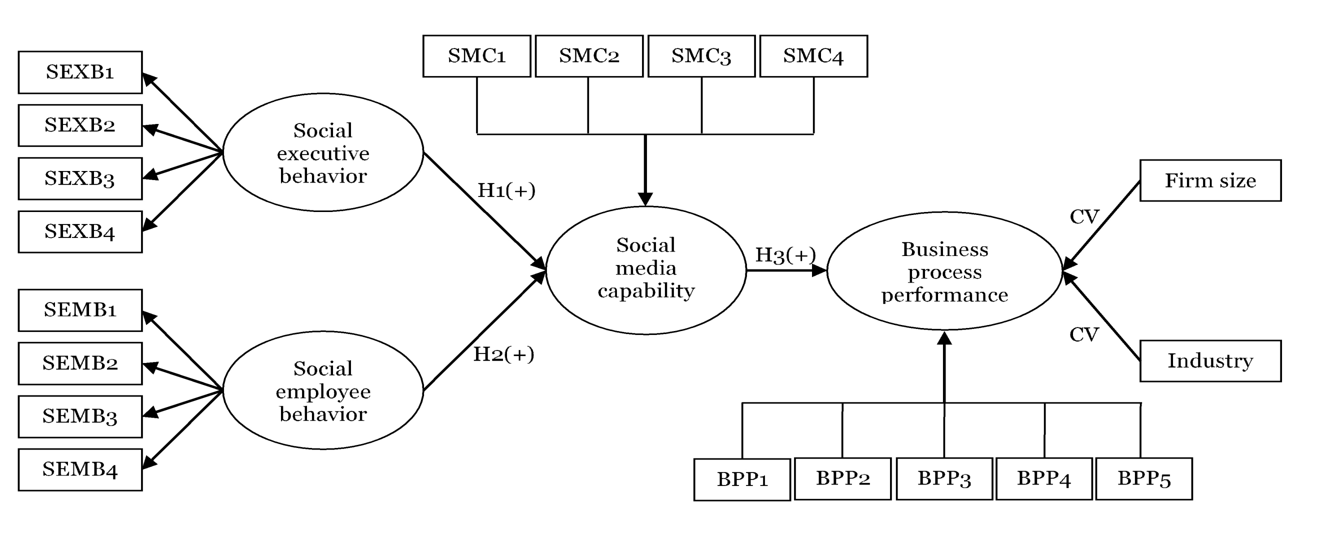

Figure 1. Conceptual Model (CV = Control Variables)

Confirmatory Analysis and Measurement Model Evaluation

ADANCO 2.0.1 Professional for Windows (http://www.composite-modeling.com/) (Henseler and Dijkstra 2015) was used for the explanation and illustration of the empirical analysis of the example. ADANCO is modern software for variance-based SEM. It models composites, common factors, and single-indicator constructs, and facilitates causal and predictive modeling.

Analysts can set the dominant indicator of each multi-indicator construct. ADANCO allows to select an indicator which is dominant over the others, in this choice one should select the indicator in which one has the largest confidence that the correlation between the indicator and the construct is positive. This can be done based on the results obtained in prior literature. As we prepared an illustrative example based on simulated data, we did not set any indicator as dominant.

Because the example does not include multidimensional constructs, the measurement and the structural models can be estimated and evaluated simultaneously. Firm size and industry were included as control variables (e.g., Chen et al. 2015). Firm size was estimated as the natural logarithm of simulated data of the number of employees to avoid a high variability between this measure for each observation (Benitez and Ray 2012, Henseler et al. 2016). Industry was measured as a composite construct shaped by three indicators created as follows. Industries of the simulated observations were classified in four groups determining one of these groups (industry group 4) as the group reference. For each observation three dummy indicators (industry group 1, industry group 2, industry group 3) were created (0: No, 1: Yes) in comparison with the industry group 4. Finally, industry is operationalized as a composite first-order construct shaped by industry group 1, industry group 2, and industry group 3. This way of operationalization provides equidistant measures (Henseler et al. 2016). Figure 2 illustrates how industry was operationalized. IS scholars can use the dominant or most important industry as the reference group.

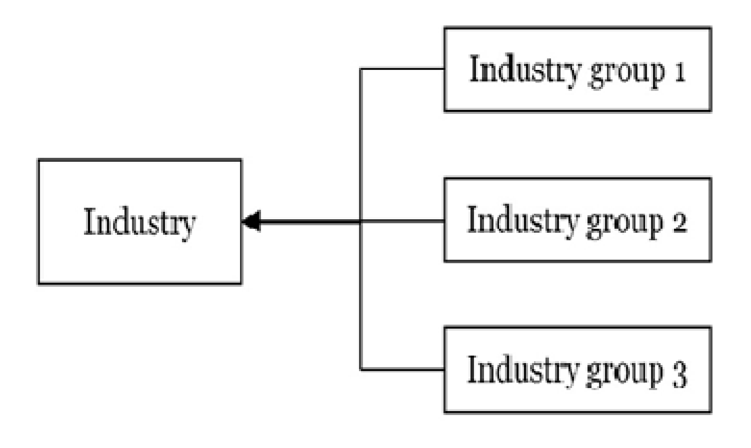

Figure 2. Operationalization of Industry

Note: Industry group 4 is the reference group.

The evaluation of the measurement model should start with a confirmatory factor/composite analysis (Henseler et al. 2014). This analysis consists in evaluating the overall fit of the saturated model (the model that enables free correlation between the constructs included in the proposed model). Confirmatory factor/composite analysis checks the adequacy of the factor and composite models by comparing the empirical correlation matrix with the model-implied correlation matrix[2] by examining the standardized root mean squared residual (SRMR), unweighted least squares (ULS) discrepancy (d_{ULS}), and geodesic discrepancy (d_G) for the saturated model (Henseler et al. 2014). The confirmatory analysis will answer the following question: Do the data give support to the factor model? Does it make sense to create this composite model? SRMR is an approximate measure of the overall model fit. d_{ULS} and d_G are exact measures of the overall model fit. This analysis can detect errors in assignment of indicators to constructs or in number of constructs (i.e., model misspecification) (Henseler et al. 2014). This measure of goodness of fit evaluates the discrepancy between the empirical correlation matrix and the model-implied correlation matrix (Henseler 2015). The lower the values, the better the fit between the proposed model and the data (Henseler and Dijkstra 2015). Overall, the SRMR value should be lower than 0.080 to accept the fit between the proposed model and the data. All discrepancies should be below the 95%-quantile of the bootstrap discrepancies (Henseler et al. 2014). As the SRMR value of the measurement model was 0.030 and all discrepancies were below the 95%-quantile of the bootstrap discrepancies (HI_{95}), the measurement model should not be rejected based on the alpha level of 0.05, which suggests very good measurement model fit (see Table 1)[3]. Bootstrapping was conducted with 4999 subsamples, with appears to be the most accepted standard now. These results suggest empirical support for this structure of factors and composites of the proposed model. This means that the data are coherent with the combination of factors and composites in the measurement model. Next step should be evaluating the reliability and validity of the reflective and composite constructs.

Table 1. Results of the Confirmatory Composite Analysis

Discrepancy	**Overall saturated model fit evaluation**		
	Value	**HI_{95}**	**Conclusion**
SRMR	0.030	0.049	Supported
d_{ULS}	0.210	0.546	Supported
d_G	0.049	0.221	Supported

[2] The empirical correlation matrix contains the correlations between all indicators. It refers to the "real data". The model-implied correlation matrix contains the correlations which we would find between the indicators if the corporate world functioned (was created) per the proposed theory.

[3] If some of the discrepancies was above the 95%-quantile of the bootstrap discrepancies, d_G seems to be the prevalent measure of the discrepancies. If none of the discrepancies was below HI_{95}, analysts can evaluate whether at least the discrepancies are below the 99%-quantile of the bootstrap discrepancies (HI_{99}) before to reject the model.

Scholars should ensure the content validity of the constructs by examining carefully how the constructs were measured and operationalized in prior research. However, in the case of composite constructs, it is possible and desirable that modifications in the measure scheme, number, and content of indicators may happen, that is, scholars should have some flexibility to modify the ingredients and/or the recipe to study a concept.

The validity of factors and composite models should be evaluated in a different way. Reliability and convergent validity of the reflective constructs (social executive behavior and social employee behavior) should be evaluated by checking the Dijkstra and Henseler's rho (p_A), average variance extracted (AVE), factor loading values and level of significance (Dijkstra and Henseler 2015b, Henseler et al. 2016). A p_A value greater than 0.707 means that the construct scores are reliable (Nunnally and Bernstein 1994). AVE is the most accepted measure of convergent validity for factor models. An AVE greater than 0.500 means that reflective constructs are unidimensional (Fornell and Larcker 1981). Factor loadings should be greater than 0.707 and significant at 95%. p_A values for social executive behavior and social employee behavior were 0.938 and 0.913[4]. Their factor loadings ranged from 0.769^{***} to 0.912^{***} which suggests these measures are reliable. Their AVE values were 0.788 and 0.716 which indicates that these constructs are unidimensional (see Table 2).

Discriminant validity indicates that two constructs are theoretically different. To be theoretically different, these constructs should be statistically different. After the latest contributions, IS scholars can check the discriminant validity of the reflective constructs through the Fornell-Larcker criterion (Fornell and Larcker 1981), the HTMT ratio of correlations (Henseler et al. 2015), and cross-loadings evaluation. The Fornell-Larcker criterion indicates that a factor should have a correlation with other factors of the model lower than the square root of the AVE (Fornell and Larcker 1981). In our example, 0.104 was lower than 0.888 and 0.846, which suggests that based on this criterion, there is discriminant validity between social executive behavior and social employee behavior (Table 3). As per the HTMT ratio of correlations criterion, a factor has discriminant validity when its HTMT ratio of correlations is lower than 0.850 or being greater than 0.850, the HTMT value is significantly different to 1 (Henseler et al. 2015). In the example, the HTMT value between social executive behavior and social employee behavior was 0.322 well below 0.850. The upper 95% quantile of the HTMT was 0.416, which indicates with 95% probability the HTMT value between social executive behavior and social employee behavior was smaller than 0.416 (statistically different to 1)[5]. Cross-loadings should be evaluated by checking that each indicator loading has a greater correlation with its constructs than with other constructs. This enable analysts to analyze whether indicators are correctly assigned to its factor (Henseler et al. 2016). In the example, all indicators of social executive behavior had a greater correlation with its factor than with social employee behavior. The same was observed for the indicators of social employee behavior. All these analyses provide evidence of content validity, reliability and convergent validity, and discriminant validity for the reflective constructs of the example.

Composite constructs require of a unique evaluation of their measurement properties. Once the analyst has found support to the structure of composites in the confirmatory composite analysis and content validity has been ensured by creating the composite partially or totally based on prior literature, multicollinearity, weights and loadings should be evaluated (Cenfetelli and Bassellier 2009, Benitez and Ray 2012). Multicollinearity can be evaluated by examining the variance inflation factor (VIF) values. VIF values greater than 10 indicates multicollinearity can be serious concern in the data[6]. Weights measure the relative contribution of an indicator to its construct. Loadings refer to the bivariate correlation and measure the absolute contribution of an indicator to its construct (Cenfetelli

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[4] In evaluating the construct reliability, analysts can also examine and report the Dillon-Goldstein p_c and the Cronbach's alpha, which both should be greater than 0.707 (Henseler et al. 2016). In our example, p_c of social executive behavior and social employee behavior were 0.937 and 0.910. Cronbach's alpha values for these constructs were 0.937 and 0.908 respectively.

[5] ADANCO provides two HTMT values. The first value refers to the HTMT value and is presented in the PLS section under the label "Discriminant Validity Heterotr" in the Excel report. The second value refers to the upper 95% quantile of the HTMT and it is presented in the bootstrapping section with the label "HTMT" in the Excel report.

[6] VIF values may be irrelevant for the composite scores, and the weighting scheme used hardly matters for highly correlated indicators (i.e., mode A, mode B, or sum score) (Dana and Dawe 2004). If analysts face to indicators with high multicollinearity we recommend using the correlation weights (mode A) instead of the regression weights (mode B) to increase stability (Dijkstra and Henseler 2011).

and Bassellier 2009). In this sense, weights show the degree of importance of each indicator (ingredient) to the composite construct (the recipe). Analysts should check whether all indicator weights are significant. For those indicators with non-significant weights, it should be checked if loadings are significant. Scholars should reconsider dropping those indicators for which neither the weights nor loadings are significant. However, the author panel can keep composite indicators with neither non-significant weights nor loadings to preserve content validity, that is, to save their conceptualization and understanding of the concept.

Table 2. Measurement Model Evaluation

Code	Construct/indicator	ρ_A	AVE	VIF	Weight	Loading
Social executive behavior (1: Strongly disagree, 5: Strongly agree) (reflective)		0.938	0.788			
SEXB1	The behavior of top business executives towards the adoption of social media is positive			4.014	0.278^{***}	0.905^{***}
SEXB2	Top business executives are positive in adopting social media for business activities			3.459	0.269^{***}	0.877^{***}
SEXB3	Top business executives support the adoption of social media for business activities			3.122	0.263^{***}	0.856^{***}
SEXB4	Top business executives are willing to support the adoption of social media in the firm			4.167	0.280^{***}	0.912^{***}
Social employee behavior (1: Strongly disagree, 5: Strongly agree) (reflective)		0.913	0.716			
SEMB1	The behavior of employees towards the adoption of social media is positive			3.486	0.301^{***}	0.901^{***}
SEMB2	Employees are positive to adopt social media in the firm			2.553	0.274^{***}	0.820^{***}
SEMB3	Employees support the adoption of social media in the firm			2.165	0.257^{***}	0.769^{***}
SEMB4	Employees are willing to support the adoption of social media in the firm			3.323	0.296^{***}	0.888^{***}
Social media capability: My firm has purposely used and leveraged... for business activities (1: Strongly disagree, 5: Strongly agree) (composite)						
SMC1	Facebook			1.037	0.229^{***}	0.397^{***}
SMC2	Twitter			1.032	0.489^{***}	0.627^{***}
SMC3	Corporate blog(s)			1.059	0.601^{***}	0.751^{***}
SMC4	LinkedIn			1.020	0.333^{***}	0.455^{***}
Business process performance: Relative to your key competitors, what has been your performance in last three years in the following business processes (1: Significantly worse, 5: Significantly better than my key competitors) (composite)						
BPP1	Supplier relations			1.022	0.285^{**}	0.397^{**}
BPP2	Product and service enhancement			1.134	0.553^{***}	0.307^{**}
BPP3	Production and operations			1.105	0.108	$0.203^{\dagger}$
BPP4	Marketing and sales			1.064	0.609^{***}	0.531^{***}
BPP5	Customer relations			1.063	0.629^{***}	0.591^{***}

Note: $^{\dagger}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$, one-tailed test.

Table 3. Discriminant Validity Evaluation based on the Fornell-Larcker Criterion

	Social executive behavior	Social employee behavior
Social executive behavior	**0.888**	
Social employee behavior	0.104	**0.846**

Note: Diagonal row presents the square roof of the AVE.

VIF values for the composite indicators of the example ranged from 1.020 to 1.134 which suggests multicollinearity is not a problem in our data. All the composite indicator weights and loadings are significant at 95% except one (production and operations of the construct business process performance). The weight of this indicator is 0.108 and its loading is $0.203^{\dagger}$ (close to be significant).

Considering production and operations may include some of the key business processes of a firm, we decided to keep this indicator in the empirical analysis to preserve content validity[7]. Overall, the measurement properties of both reflective and composite constructs of the example had good measurement properties. After all these analyses at the measurement model level, analysts can proceed with the evaluation of the structural model.

Table 4. Discriminant Validity based on Cross-loading Evaluation

	Social executive behavior	Social employee behavior
SEXB1	**0.905**	0.291
SEXB2	**0.877**	0.282
SEXB3	**0.856**	0.276
SEXB4	**0.912**	0.294
SEMB1	0.290	**0.901**
SEMB2	0.264	**0.820**
SEMB3	0.248	**0.769**
SEMB4	0.286	**0.888**

Structural Model Evaluation

In the evaluation of the structural model, the analyst should examine the beta coefficients and their level of significance, R^2 and/or adjusted R^2, overall fit of the estimated model, and effect size (f^2) for each relationship (Henseler et al. 2016). Beta coefficients should be greater than 0.200 and significant at 95% level to be economically and statistically significant (Benitez and Ray 2012). The beta coefficients for the hypothesized relationships included in the example ranged from 0.396^{***} to 0.515^{***}, which provides support for the proposed model[8]. R^2 values refer to explained variance of an endogenous variable in the proposed theory. These values are relevant in explanatory research of non-recursive models, that is, in estimations that use ordinary least squares in the PLS path modeling. We recommend to both report R^2 and adjusted R^2 values. Adjusted R^2 values consider for model complexity and sample size, and are thus helpful to compare different models or the explanatory of a model across different data sets (Henseler et al. 2016). R^2 values for social media capability and business process performance in the example were 0.443 and 0.267. Adjusted R^2 values for these constructs were 0.439 and 0.259.

After that, analysts should evaluate the overall fit of the estimated model in a similar way as we explained in the confirmatory analysis. The estimated model refers to a combination of the measurement and structural model. All discrepancies were below the 95%-quantile of the bootstrap discrepancies (HI_{95}), the estimated model should not be rejected based on the alpha level of 0.05, which suggests very good overall fit for the proposed theory (see Table 5). This means that this theory is useful to explain how the corporate world and IS domain function.

Finally, we urge analysts to examine and report effect sizes for each relationship included in the model. f^2 values refer to the incremental contribution of an exogenous variable to an endogenous variable represented graphically by an arrow. f^2 values of 0.020, 0.150, and 0.350 indicates weak, medium, or large effect size (Cohen 1988). In a similar way, all actors in a movie cannot perform a leading role, it is unusual and unlikely that most of constructs have a large effect size (leading role) in the proposed theory (the movie). f^2 values for the hypothesized relationships included in our example ranged from 0.252 to 0.363 (medium to large). Overall, the proposed theory in the exampled is well supported by

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[7] In this type of situation, analysts can also repeat the analysis by dropping the questioned indicators to explore whether the decision of keeping vs. dropping the questioned indicators affect the results. We dropped BPP3 and repeated the empirical analysis. The results obtained were qualitatively identical which suggests this decision does not affect the findings of the investigation.

[8] A beta coefficient is significant when its p-value is below 0.05 or when zero is not included in the 95% confidence interval. The 95% confidence interval can be extracted from the ADANCO Excel report from the 2.5% and 97.5% values.

the data. Table 6 presents the correlation matrix. Figure 3 represents a summary of the test of hypotheses.

Table 5. Structural Model Evaluation		
Relationship	**Beta coefficient**	
Social executive behavior → Social media capability (H1)	0.422*** (8.830) [0.327, 0.512]	
Social employee behavior → Social media capability (H2)	0.396*** (8.052) [0.300, 0.490]	
Social media capability → Business process performance (H3)	0.515*** (11.231) [0.426, 0.609]	
Firm size → Business process performance (control variable)	0.022 (0.304) [-0.129, 0.159]	
Industry → Business process performance (control variable)	0.030 (0.312) [-0.161, 0.174]	
Endogenous variable	**R^2**	**Adjusted R^2**
Social media capability	0.443	0.439
Business process performance	0.267	0.259
SRMR value	0.032	
SRMR HI_{95}	0.049	
d_{ULS} value	0.232	
d_{ULS} HI_{95}	0.558	
d_G value	0.052	
d_G HI_{95}	0.222	
f^2		
Social executive behavior → Social media capability (H1)	0.286	
Social employee behavior → Social media capability (H2)	0.252	
Social media capability → Business process performance (H3)	0.363	
Firm size → Business process performance (control variable)	0.001	
Industry → Business process performance (control variable)	0.002	

Note: t-values are presented in parentheses. Confidence intervals are presented in brackets.

Table 6. Correlation Matrix[9]

	1	2	3	4	5	6
1. Social executive behavior	1.000					
2. Social employee behavior	0.298***	1.000				
3. Social media capability	0.532***	0.508***	1.000			
4. Business process performance	0.209***	0.295***	0.515***	1.000		
5. Firm size	-0.024	-0.046	-0.014	0.016	1.000	
6. Industry	0.066	0.070	0.010	0.036	0.038	1.000

[9] Review panels of top IS journals ask often authors to include the level of significance of inter-construct correlations. ADANCO software package does not provide this level of significance. Analysts can use the latent variables scores from the ADANCO Excel report and regress the constructs in Excel or SPSS to acquire and report the level of significance of the inter-construct correlations. IBM SPSS 20 for Windows statistical software package was used for this goal in our example.

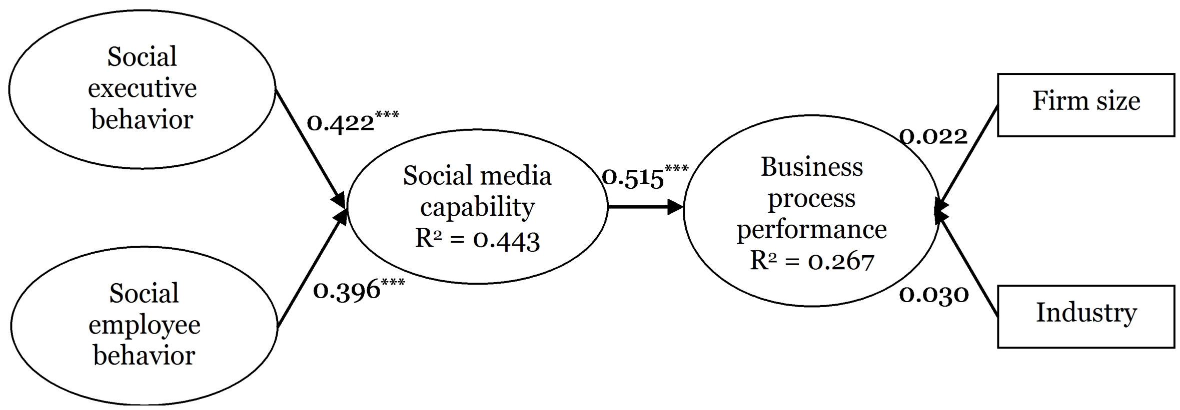

Figure 3. Results of the Test of Hypotheses

Test of Robustness

In recent debate on PLS path modeling, some works (e.g., Ronkko et al. 2016) have argued that weights may capitalize on chance. This means that if the analysts let the data calculate indicator weights (using mode B or mode A) weights may capitalize on chance, which in turn may affect the results. However, these works have not said how scholars can check and demonstrate that their analysis is not subject to capitalization on chance. Analysts may perform a test of robustness to check for absence on capitalization on chance in two ways. First, analysts can change to sum score (unit weight) the weighting scheme of their composite constructs and check the behavior of new weights as well that this change does not affect the results. By using sum score analysts are fixing weights to unit instead of enabling the data to show the relative contribution of each weight to the construct (all indicator weights will have the same value). Tables 7-9 present the results of this first additional analysis. Using unit weights yielded qualitatively identical results[10]. Second, by keeping the previously established weighting scheme in the proposed model, analysts can try alternative model configurations to examine whether the weight value and behavior keep the same. We explored a different configuration by estimating a model where we assumed that business process performance affects social media capability, keeping other specification and relationships the same. The measurement model evaluation of this alternative model yielded similar results. Both models (i.e., our proposed model and this alternative model) showed good measurement model fit, being the values essentially the same. The indicator weights and their level of significance of composite constructs for both models also presented similar results, ranging from 0.108 to 0.629*** for our proposed model, and from 0.111 to 0.621*** for the alternative model. Similarly, the indicators loadings and their level of significance of composite constructs for both models were very similar, ranging from 0.203† to 0.751*** for our proposed model, and from 0.206* to 0.763*** for the alternative model. In the example, this test of robustness suggested that capitalization on chance did not seem to be a problem in our empirical analysis.

Discussion and conclusions

PLS path modeling has been widely and dominantly used in the field of IS during the last decades (e.g., Marcoulides and Saunders 2006, Ringle et al. 2012). The usage and prescriptions for performing PLS path modeling has been recently examined, debated, and improved in last three years (e.g., Hair et al. 2012a, Hair et al. 2012b). This examination, heated debate, and revisits have generated substantial changes, contributions, and developments on a separate manner that requires a holistic piece of work to guide future works in the field of IS. Based on the latest standards in PLS path modeling, this manuscript addresses the *when*, *why*, and *how* to perform a high-quality PLS estimation in IS research. This manuscript thus provides a development and update on PLS path modeling in IS field.

[10] Some authors (e.g., Wold 1982) have discussed that mode B should be used for exogenous and mode A for endogenous constructs. We repeated the analysis by estimating business process performance with mode A. This analysis yielded similar measurement and structural results.

Table 7. Test of Robustness: Unit Weights: Results of the Confirmatory Composite Analysis			
Discrepancy	**Overall saturated model fit evaluation**		
	Value	**HI_{95}**	**Conclusion**
SRMR	0.041	0.052	Supported
d_{ULS}	0.389	0.628	Supported
d_G	0.071	0.245	Supported

Table 8. Test of Robustness: Unit Weights: Measurement Model Evaluation						
Code	**Construct/indicator**	**p_A**	**AVE**	**VIF**	**Weight**	**Loading**
	Social executive behavior (reflective)	0.938	0.788			
SEXB1	The behavior of top business executives towards the adoption of social media is positive			4.014	0.278***	0.905***
SEXB2	Top business executives are positive in adopting social media for business activities			3.459	0.269***	0.877***
SEXB3	Top business executives support the adoption of social media for business activities			3.122	0.263***	0.856***
SEXB4	Top business executives are willing to support the adoption of social media in the firm			4.167	0.280***	0.912***
	Social employee behavior (reflective)	0.913	0.716			
SEMB1	The behavior of employees towards the adoption of social media is positive			3.486	0.301***	0.901***
SEMB2	Employees are positive to adopt social media in the firm			2.553	0.274***	0.820***
SEMB3	Employees support the adoption of social media in the firm			2.165	0.257***	0.769***
SEMB4	Employees are willing to support the adoption of social media in the firm			3.323	0.296***	0.888***
	Social media capability (composite)					
SMC1	Facebook			1.037	0.433***	0.577***
SMC2	Twitter			1.032	0. 433***	0.567***
SMC3	Corporate blog(s)			1.059	0. 433***	0.618***
SMC4	LinkedIn			1.020	0. 433***	0.551***
Business process performance (composite)						
BPP1	Supplier relations			1.022	0.450***	0.557***
BPP2	Product and service enhancement			1.134	0.450***	0.199***
BPP3	Production and operations			1.105	0.450***	0.522***
BPP4	Marketing and sales			1.064	0.450***	0.447***
BPP5	Customer relations			1.063	0.450***	0.500***

PLS is a full-fledged SEM method of estimation that can estimate composite and factors measurement models, estimate recursive and non-recursive structural models, and conduct approximate and exact tests of model fit (Dijkstra and Henseler 2015a, 2015b). In this sense, PLS path modeling appears to be a method of estimation effective to examine and address research problems that include emergent, strong, complex, and "man/firm-made" concepts (composite models). PLS path modeling is also a useful method of estimation to test agilely interesting theories that include factors that have the potential to provide good and timely answers to an important and emergent research problem. We urge to reduce the radicalness in the selection of methods to resolve research problems.

Table 9. Test of Robustness: Unit Weights: Structural Model Evaluation

Relationship	**Beta coefficient**	
Social executive behavior → Social media capability (H1)	0.407*** (8.373) [0.309, 0.497]	
Social employee behavior → Social media capability (H2)	0.382*** (7.340) [0.280, 0.481]	
Social media capability → Business process performance (H3)	0.455*** (9.133) [0.354, 0.550]	
Firm size → Business process performance (control variable)	-0.018 (-0.353) [-0.121, 0.083]	
Industry → Business process performance (control variable)	0.047 (0.924) [-0.056, 0.083]	
Endogenous variable	**R^2**	**Adjusted R^2**
Social media capability	0.441	0.407
Business process performance	0.209	0.201
SRMR value	0.042	
SRMR HI_{95}	0.053	
d_{ULS} value	0.402	
d_{ULS} HI_{95}	0.653	
d_G value	0.075	
d_G HI_{95}	0.249	
f^2		
Social executive behavior → Social media capability (H1)	0.252	
Social employee behavior → Social media capability (H2)	0.222	
Social media capability → Business process performance (H3)	0.261	
Firm size → Business process performance (control variable)	0.000	
Industry → Business process performance (control variable)	0.003	

We provide a constructive and illustrative IS example with data simulated for 300 observations to explain the latest contributions in PLS path modeling. The example is based on a model on business value of social media in companies. The key contribution of this manuscript is the description, position, explanation, development, and illustration at the very user-level, of the *when*, *why*, and *how* to perform a high-quality PLS estimation by following the latest standards suggested in prior methodological literature on PLS path modeling. This is particularly useful as some editors have recently called for desk rejecting papers that use PLS path modeling. The example is set at first-order construct level and combines two reflective with two composite constructs. We describe the notion of factor versus composite models with the constructs of the example. After that, we summarize and illustrate how to evaluate a measurement model with reflective and composite constructs, including the execution of a confirmatory factor/composite analysis (Henseler et al. 2014). Finally, we provide guidelines to evaluate the structural model including the overall fit evaluation of the estimated model, and the execution of a test of robustness to examine capitalization on chance.

Although the manuscript is limited to PLS estimation for explanatory research with first-order constructs, we are confident of the usefulness and potential to guide IS scholars in performing empirical research through the usage of PLS path modeling. A further guidelines manuscript is also required on the updating of the moderation analysis, the estimation of second-order constructs, and comparison of nested models with PLS path modeling. We call for papers providing a development and update of guidelines on these methodological aspects in the IS domain.

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