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Partial Least Square Structural Equation Modelling' use in Information Systems: An Updated Guideline of Practices in Exploratory Settings

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Abstract
The purpose of many studies in the field of Information Systems (IS) research is to analyse causal relationship between variables. Structural Equation Modelling (SEM) is a statistical technique for testing and estimating those causal relationships based on statistical data and qualitative causal assumption. Partial Least Square Structural Equation Modelling (PLS-SEM) is the technique that is mostly used in IS research. It has been subject to many reviews either in confirmatory or exploratory settings. However, it has recently emerged that PLS occupies the middle ground of exploratory and confirmatory settings. Thus, this paper intends to propose an updated guideline for the use of PLS-SEM in Information Systems Research in exploratory settings maintaining interpretability. A systematic literature review of 40 empirical and methodological studies published between 2012 and 2016 in the leading journal of the field guide future empirical work.

Keywords: SEM; PLS-SEM; Information Systems; Confirmatory; Exploratory; Guideline

1. Introduction

The purpose of many studies in the field of Information Systems (IS) research is to analyse causal relationship between variables. Several techniques allow researchers to evaluate their models such as regression, structural equation modelling (SEM). SEM is a statistical technique for testing and estimating those causal relationship based on statistical data and qualitative causal assumption (Urbach & Ahlemann, 2010). Contrary to the first generation statistical tools such as regression, SEM enables researchers to answer a set of an interrelated research question in a: a) single, b) systematic, and comprehensive analysis by modelling the relationship between multiple independent and dependent constructs simultaneously. This capability for simultaneous analysis differs greatly from most first generation regression models such as linear regression, LOGIT, ANOVA, and MANOVA, which can analyse only

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one layer of linkages between independent and dependent variables at a time (Gefen, Straub, & Boudreau, 2000).

SEM is highly recommended and used in the field of IS research. Quantitative research in Information System (IS) frequently uses structural equation modelling, allowing researchers to represent latent constructs, observations and their relationship in a single statistical model (Evermann & Tate, 2014). SEM has two major techniques: The Partial Least Squares (PLS) and the Covariance Based (CB). CB-SEM requires a sound theory base and confirmatory research while PLS does not need a sound theory base and support a confirmatory or exploratory research (Hair, Ringle, & Sarstedt, 2011).

Partial Least Square Structural Equation Modelling (PLS-SEM) is the most SEM technique used in IS research. PLS is regarded as the most fully developed and general system (Jörg Henseler, Hubona, & Ash, 2016). IS was identified as the primary user of PLS (Evermann & Tate, 2014).

Rönkkö et al. (2012) argue that the use of partial least squares path modelling as a tool for theory testing has been increasing in the late 90's and PLS is currently one of the most common quantitative data analysis methods in the top IS journals. However, they emphasise that reliance on PLS method has possibly resulted in producing and publishing a large number of studies, whose results are invalid. These critics have been addressed by the literature (J. Henseler et al., 2014).

The technique has been subject to many reviews (Evermann & Tate, 2012; Jörg Henseler et al., 2016; Rouse & Corbitt, 2008; Urbach & Ahlemann, 2010). That has resulted in the production of guidelines for the use of PLS-SEM in IS research. Most of these guidelines focus on either explanatory (confirmatory) or exploratory research. For instance, Henseler et al. (2016) propose an updated guideline for the use of PLS in IS research in confirmatory settings. On the other hand, Urbach & Ahlemann (2010) come up with a guideline for the utilisation of the technique in exploratory contexts.

The literature provides three purposes of any research: exploratory, descriptive or explanatory (confirmatory). An exploratory study is a valuable means of finding out what is going on; to look for new insights; to ask questions and to evaluate phenomena in a new light (Saunders, Lewis, & Thornhill, 2009). Exploratory research goes with a predictive model (Evermann & Tate, 2014).The object of descriptive research is to portray an accurate profile of persons, events or situations (Saunders et al., 2009). Studies that establish causal relationships between variables may be termed explanatory research (Saunders et al., 2009). Explanatory research goes with the causal model (confirmatory) model (Kante, Oboko, & Chepken, 2017).

Nevertheless, Evermann & Tate (2014) argue that the causal and predictive modelling are dualities. Rather, there is a middle-ground between the two extreme positions. It is easier for decision makers and others to easily accept a predictive model if it is plausibly interpreted (Evermann & Tate, 2014). Further, they state that it may be simpler to determine the prediction boundaries, i.e. determine what situations the model will hold and under what situations the model will break, when a plausible substantive interpretation is available. Users of predictive models have more trust in its results, especially for unexpected or counterintuitive predictions, when there is a plausible interpretation possible (ibid.). In contrast to explanatory modelling, the plausible interpretations in this context do not entail a rigorous formal statistical testing of all posited relationships and model constraints as in causal- explanatory modelling (Evermann & Tate, 2014).

PLS path modelling was developed to occupy this middle ground and to straddle the traditional divide between causal-explanatory and predictive modelling at the extremes. It aims to maintain interpretability while engaging in predictive modelling (Evermann & Tate, 2014). Therefore, it is needed to review the guidelines of exploratory research by taking into account the middle ground. That justifies the purpose of this paper.

This article aims to update the guideline for the use of PLS-SEM in Information Systems Research in exploratory settings maintaining interpretability. It updated the paper of Urbach & Ahlemann (2010) that is mainly for exploratory settings.

2. Material and Methods

This section describes the methods that were used to conduct the study.

To efficiently perform the systematic literature, search criterion for inclusion in the dataset were defined. Table 1 provides the criterion.

Table 1: Criterion for inclusion/exclusion in the dataset

Inclusion	Criteria
Time of publication	Published between 2012 and 2016
Appropriate source	Researchgate.com, aisnet.org, webofscience.com, google scholar
Search terms	Information Systems, Information System, Information System research, Use of Structural Equation Modelling, Use of Partial Least Square Equation Modelling, Use of PLS-SEM, Guidelines for the use of PLS-SEM, PLS-SEM use in IS, Research methods using PLS-SEM

We had papers from proceedings and journals. Management Information Systems Quarterly (MISQ), Information Systems Research (ISR), Journal of Management Information Systems (JMIS) and Journal of the Association of Information Systems (JAIS) were identified as the four leading journals in the field of IS (Evermann & Tate, 2010). This paper is restrained to MISQ as it is recognised as the leading journal. We had for 26 research papers from MISQ:

- Eight papers in 2012: two empirical studies and six methodological papers

- Five papers in 2013: four empirical papers and one methodological study.
- Three papers in 2014: all of them were empirical studies.
- Six studies in 2015: one methodological paper and five empirical studies.
- One empirical study in 2016.

On the proceeding papers, we selected four papers from the conferences that were hosted or organised by the Association for Information Systems and its affiliated organisations. In conclusion, the data set was a sample size of 40 studies. From the data set, it was extracted: 1) reason for choosing PLS-SEM, 2) research epistemology, 3) research approach, 4) research strategy, 5) Model characteristics and 6) Model evaluation.

3. Results and Discussion

This section presents the in-depth analyses of the papers.

3.1 The Reasons for choosing PLS

Urbach & Ahlemann (2010) argue that overall, PLS can be an adequate alternative to CBSEM if the problem has the following characteristics:

- 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 modelled in different modes (i.e., formative and reflective measurement models).
- The conditions relating to sample size, independence, or normal distribution are not met, and. CB requires a large sample size while PLS does not require large sample size. If the sample size is small, PLS is recommended in Information System research (Evermann & Tate, 2014), in Marketing research (Hair et al., 2011).

Table 2 gives an overview of the reason that underlines studies from our dataset to choose PLS.

Table 2. Reason for choosing PLS-SEM

Reason	Authors	Years
Small sample sizes	(Bartelt & Dennis, 2014; Ifinedo, 2015; Wang, Tai, & Grover, 2013)	2013; 2014; 2015
Non normality	(Ifinedo, 2015; Park, Sharman, & Rao, 2015; Wang et al., 2013; Xu, Benbasat, & Cenfetelli, 2014)	2013; 2014; 2015
Exploratory research objective/ predictive purposes	(Fang et al., 2014; Johnston, Warkentin, & Siponen, 2015; Park et al., 2015)	2014; 2015

Analyse formative and reflective constructs	(Han, Ada, Sharman, & Rao, 2015a; Majchrzak, Wagner, & Yates, 2013)	2013; 2015
Analyse formative constructs	(Kankanhalli, Ye, & Teo, 2015)	2015
Number of interaction terms	(Venkatesh, Thong, & Xu, 2012)	2012
Mediated Models	(Bartelt & Dennis, 2014)	2014

None of the studies used the small sample sizes criterion to justify the use of PLS-SEM. Instead, each one had another argument to justify their use of the technique. The use of small sample size for PLS-SEM is not recommended. For instance, Oodhue, Ewis, Hompson, Marcoulides, & Chin (2012) argue that when determining the minimum sample size to obtain adequate power, use Cohen's approach (regardless of the technique to be used). Do not rely on the rule of 10 (or the rule of 5) for PLS (ibid.). In addition, Kline (2013) argues that a "typical" sample size in studies where SEM was used is about 200 cases. Moreover, Garson (2016) quoting (Chin & Newsted, 1999) argues that sample sizes equivalent to those commonly found in SEM (ex., 150-200) are needed. Therefore, we conclude that a sample size of 200 or above is the right sample size for using PLS-SEM.

3.2 Research Epistemology

Many philosophical positions characterise information System research. Saunders et al. (2009) draw a comparison of the four research philosophies, which can be applied in information management research (Positivism, realism, interpretivism and pragmatism).

In Information System research, Urbach & Ahlemann (2010) argue that the investigation that applies SEM follows a positivist epistemological belief. Furthermore, they report that the positivist researcher does not intervene in the inquiry and thus plays a neutral roleEpistemologically, the positivist perspective is concerned with the empirical testability of theories (Urbach & Ahlemann, 2010). In other words, these theories are either confirmed or rejected. None of the paper that we reviewed had addressed the philosophical point of view. Therefore, we are consistent with Urbach & Ahlemann (2010) who argue that research that applies SEM (including PLS) follows a positivist epistemological belief.

3.3 Research Approach

The extent to which the researcher is evident about the theory at the beginning of his/her research raises an important question concerning the design of the research project (Saunders et al., 2009). That is whether his/her research should use the deductive approach, in which the researcher develops a theory and hypothesis (or hypotheses) and design a research strategy to test the hypothesis, or the inductive approach, in which he/she would collect data and develop a theory as a result of the data analysis (ibid.). None of the paper that we reviewed had reported their research approach. Nevertheless, the purpose of the empirical studies we reviewed was to gather data and test their hypotheses. That is a deductive approach, and thus, we conclude that studies using PLS-SEM apply a deductive approach. This research approach was not provided by the guidelines of Urbach & Ahlemann (2010).

3.4 Research Strategy

Saunders et al. (2009) argued that survey is a popular and shared strategy in business and management research and is most frequently used to answer who, what, where, how much and how many questions. It, therefore, tends to be used for exploratory and descriptive research. Our data set reveals that PLS-SEM studies applied survey as a strategy. That was also consistent as these studies were mainly done in exploratory settings.

3.5 Model Characteristics

A Structural equation model consists of two models. The structural inner model contains the relationship between the latent variables, which has to be derived from theoretical considerations. The second model is called the measurement model (or outer). This model deal with "how do you measure your latent variables?"

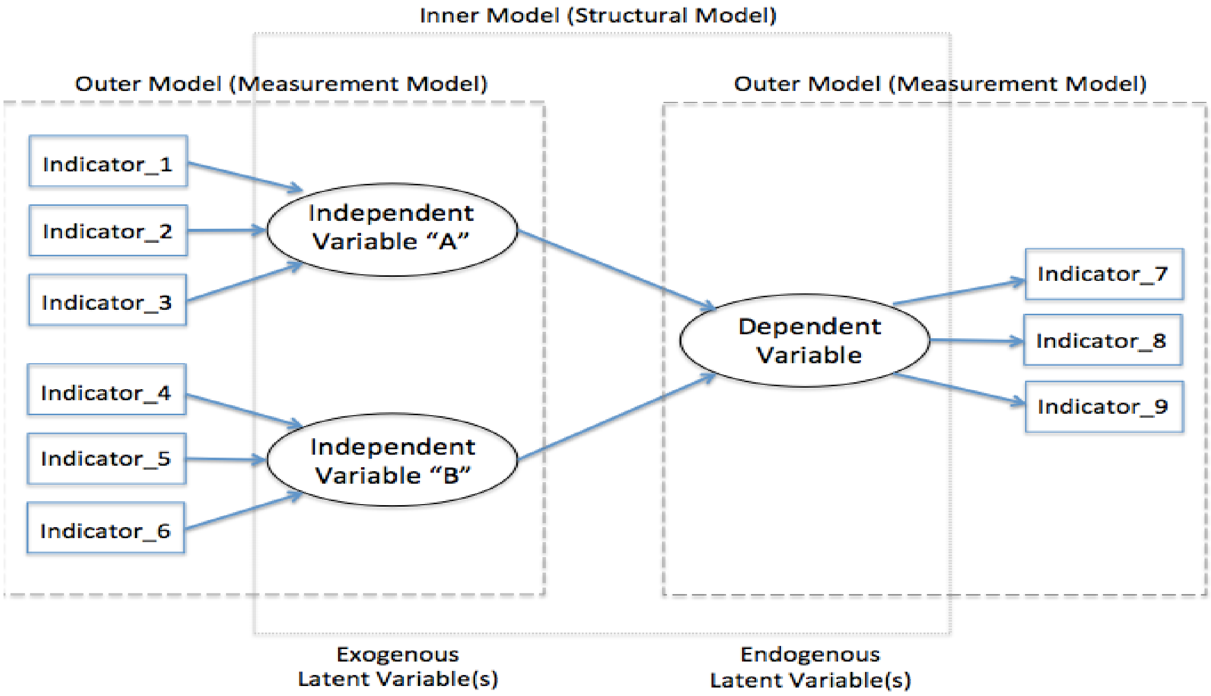

Figure 1. Inner vs Outer Model in a SEM Diagram
Source: Wong (2014)

3.5.1. Outer Model

Measurement model specification requires the consideration of the nature of the relationship between constructs and measures. Latent variable measurement concerns the process of ensuring that local independence is satisfied for a selected set of observed variables or indicators and this can be done via the use of a model such as a common factor model (Oodhue et al., 2012). There are two types of measurement models: reflective and formative (Figure 2) (Hreats, Becker, & Ringle, 2013). Formative and reflective are thus the two currently accepted ways of specifying the relationship between latent constructs and observed variables that are causally related to them (Aguirre-urreta & Marakas, 2012).

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.

Figure 2. Overview of reflective/formative models
Source: adapted from Urbach & Ahlemann (2010)

In reflective measures, changes in the construct are reflected in shifts in all of its indicators, and the direction of causality is from the construct to the indicators (Garson, 2016). Reflective indicators are assessed regarding their loadings, which entails the simple correlation between the indicator and the construct (Hreats et al., 2013). The reflective model were reported by some reviewed empirical studies (Bartelt & Dennis, 2014; Fang et al., 2014; Han, Ada, Sharman, & Rao, 2015; Johnston et al., 2015; Kankanhalli et al., 2015; Marsh, Morin, Parker, & Kaur, 2014; Setia, Ventkatesh, & Joglekar, 2013; Xu et al., 2014).

In formative measures, the indicators do not reflect the underlying construct but are combined to form it without any assumptions about the intercorrelation patterns among them (Garson, 2016). The direction of causality is from the indicators to the construct, and the weights of formative indicators represent the importance of each indicator in explaining the variance of the construct (Hreats et al., 2013). Reviewed empirical studies reported the use of formative model (Han et al., 2015; Jarvis, Mackenzie, & Podsakoff, 2012; Kankanhalli et al., 2015; Majchrzak et al., 2013; Marett, Otondo, & Taylor, 2013; Schmitz, Teng, & Webb, 2016; Setia et al., 2013; Venkatesh et al., 2012; Wang et al., 2013; Wu, Straub, & Liang, 2015).

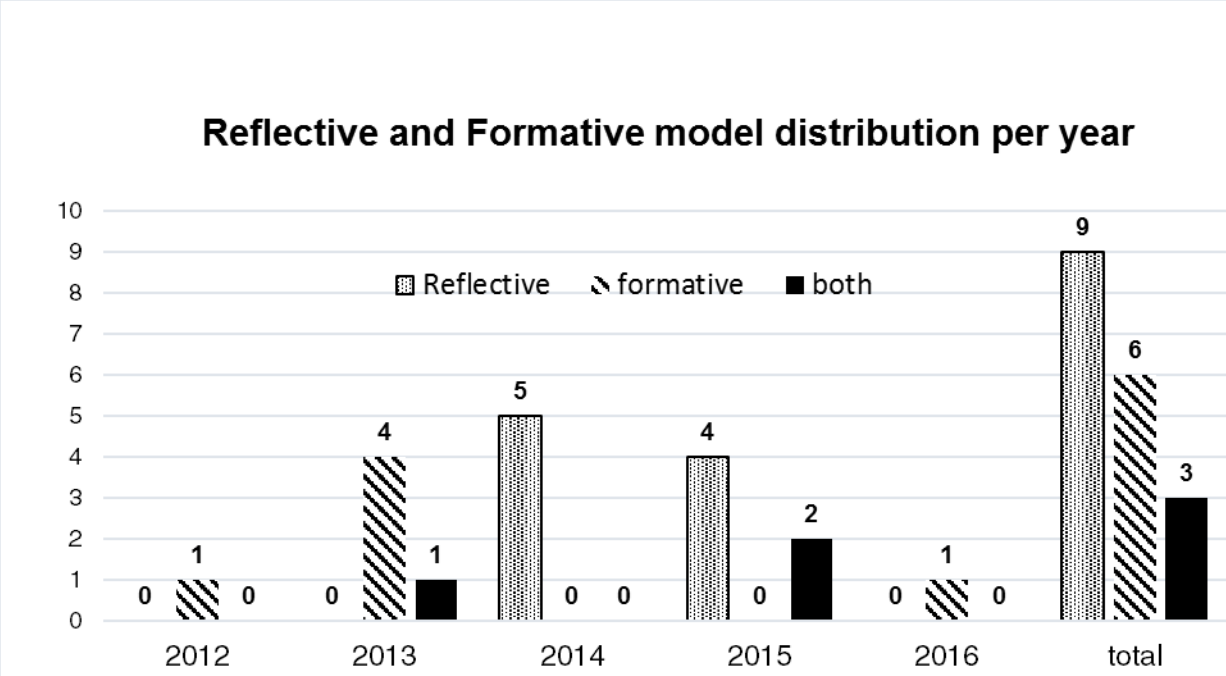

Figure 3. Model distribution per year

3.5.2 Inner Model or Structural Model

The inner model (structural model) has also two types of variables: Exogenous and Endogenous (see figure 1). A latent variable is exogenous if it is not an effect of any other latent variable in the model (there are no-incoming arrows from other latent variables) (Garson, 2016). A latent variable is endogenous if it is an effect of at least one other latent variable (there is at least one incoming arrow from another latent variable) (Garson, 2016).

The inner model can also have other variables such as moderating variable, mediating variable and controlling variable. A moderator is a qualitative (e.g., sex, race, class) or quantitative (e.g., level of reward) variable that affects the direction and/or strength of the relation between an independent or predictor variable and a dependent or criterion variable (Baron & Kenny, 1986). They further argue that the relationship between two variables changes as a function of the moderator variable. In other words, moderator effect = interaction effect.

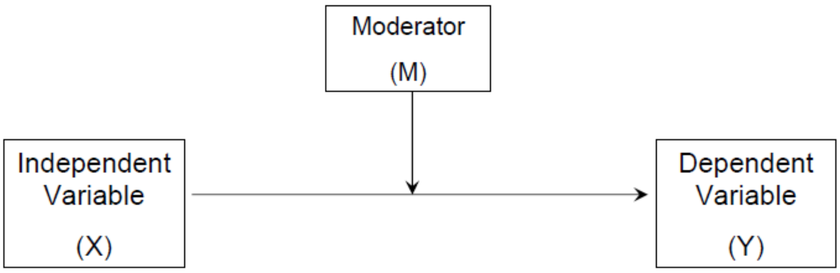

Figure 4. Conceptual diagram for moderating variable
Source: adapted from Chin (2006)

A mediator (or mediating variable) accounts for the relationship between the predictor and the criterion (Baron & Kenny, 1986). It is an intervening variable (Garson, 2016).
An intervening variable (mediator) transmits the effect of an independent variable to a dependent variable (Chin, 2006).

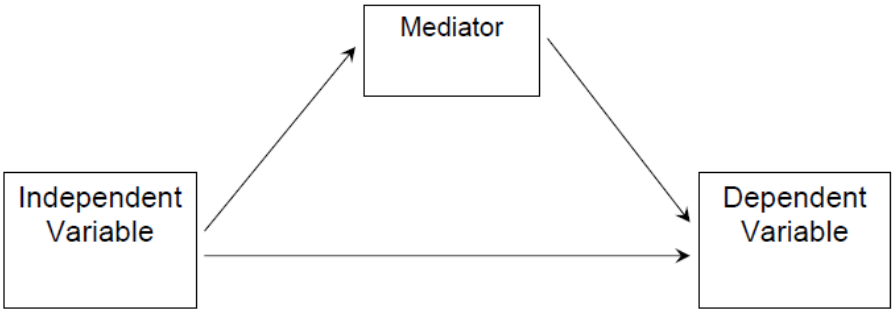

Figure 5. Conceptual diagram for mediating variable
Source: adapted from Chin (2006)

Control variable (controlling) is a variable that is not the focus or planned as part of a research study but its existence has certain impact over Dependent Variable (DV) that cannot be ignored in which it is included in the research model testing together with other Independent Variables (IVs) (Fung, 2015). Hence it is called control variable, i.e. it is kept under "controlled", "monitored" or "constant" to observe whether it has minimal impact on the relationships between the independent variable and dependent variable (Fung, 2015). Usually, the control variable is not included as part of a hypothesis statement.

3.6 Model Evaluation

The model evaluation requires the assessment of the two inter-related models: measurement model (outer model) and structural model (inner model).

3.6.1 Outer Model Fit Evaluation

a. Reflective outer model fit evaluation

The measurement model should be tested for least internal consistency reliability, indicator reliability, convergent validity, and discriminant validity by applying standard decision rules from the IS research literature.

Urbach & Ahlemann (2010) argued that 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). However, Garson (2016) argued that Composite reliability is a preferred alternative to Cronbach's alpha as a test of convergent validity in a reflective model. Compared to Cronbach's alpha, composite reliability may lead to higher estimates of true reliability. Regardless of which coefficient is used for assessing internal consistency, values above .700 are desirable for exploratory research (Urbach & Ahlemann, 2010).

Convergent validity entails the degree to which individual items reflecting a construct converge in comparison to items measuring different constructs. Urbach & Ahlemann (2010) argued that a commonly applied criterion of convergent validity is the average variance extracted (AVE) proposed by Fornell and Larcker (1981). It measures the percent of variance captured by a construct by showing the ratio of the sum of the variance captured by the construct and measurement variance (Gefen et al., 2000). 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 (Garson, 2016; Urbach & Ahlemann, 2010).

Finally, discriminant validity involves 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 (Urbach & Ahlemann, 2010). In SEM using PLS, two measures of discriminant validity are commonly used: Cross loading criterion and Fornell–Larcker (Urbach & Ahlemann, 2010). However, simulation studies demonstrated that the lack of discriminant validity is better detected by the heterotrait-monotrait (HTMT) (Jörg Henseler, Ringle, & Sarstedt, 2014). Moreover, in Information System research, it was argued that Discriminant validity should be assessed by the Heterotrait-Menotrait Ration (HTMT) (Jörg Henseler et al., 2016). Its ratio is the geometric mean of the heterotrait-heteromethod correlations (i.e., the correlations of indicators across constructs measuring different phenomena) divided by the average of the monotrait-heteromethod correlations (i.e., the correlations of indicators within the same construct) (Garson, 2016). Table 3 summarises the measurement model assessment.

Table 3. Reflective measurement model assessment

Validity type	Criterion	Description	Literature
Indicator reliability	Indicator loading > .600	Loadings represent the absolute contribution of the indicator to the definition of its latent variable.	(Fang et al., 2014; Han et al., 2015b; Setia et al., 2013; Urbach & Ahlemann, 2010; Wang et al., 2013)
Internal consistency reliability	Cronbach's α > 0.6	Measures the degree to which the MVs load simultaneously when the LV increases.	(Fang et al., 2014; Garson, 2016; Han et al., 2015b; Urbach & Ahlemann, 2010; Wang et al., 2013)
Internal consistency reliability	Composite reliability > 0.6	Attempts to measure the sum of an LV's factor loadings relative to the sum of the factor loadings plus error variance. Leads to	(Fang et al., 2014; Garson, 2016; Han et al., 2015b; Urbach & Ahlemann, 2010;

		values between 0 (completely unreliable) and 1 (perfectly reliable).	Wang et al., 2013)
Convergent validity	Average variance Extracted (AVE) > 0.5	It involves the degree to which individual items reflecting a construct converge in comparison to items measuring different constructs.	(Bartelt & Dennis, 2014; Garson, 2016; Han et al., 2015a, 2015b; Jörg Henseler et al., 2016; Kankanhalli et al., 2015; Majchrzak et al., 2013; Setia et al., 2013; Urbach & Ahlemann, 2010; Venkatesh et al., 2012; Wang et al., 2013)
Discriminant validity	Cross-loadings	requires that the loadings of each indicator on its construct are higher than the cross loadings on other constructs	(Gefen et al., 2000; Urbach & Ahlemann, 2010; Wang et al., 2013)
Discriminant validity	Fornell-Larcker	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.	(Bartelt & Dennis, 2014; Fang et al., 2014; Han et al., 2015b; Ifinedo, 2015; Kankanhalli et al., 2015; Urbach & Ahlemann, 2010; Venkatesh et al., 2012; Xu et al., 2014)
Discriminant validity	Heterotrait-Menotrait Ration (HTMT)	Its ratio is the geometric mean of the heterotrait-heteromethod correlations (i.e., the correlations of indicators across constructs measuring different phenomena) divided by the average of the monotrait-hetero-method correlations (i.e., the correlations of indicators within the same construct) (Garson, 2016).	HTMT < 1 (Garson, 2016)

Source: adapted from Urbach & Ahlemann (2010) *b. Formative outer model fit evaluation*

The Evaluation of formative measurement models needs a different approach than that applied for reflective models (Urbach & Ahlemann, 2010). Because the indicators represent different dimensions, the researcher would not expect that the indicators would correlate highly, implying that composite reliability and Cronbach's alpha might not be high (Garson, 2016). 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. Whereas reliability becomes an irrelevant criterion for assessing formative measurement, the examination of validity becomes crucial (Diamantopoulos 2006). Accordingly, Urbach & Ahlemann (2010) quoting Henseler et al. (2009) argue that the indicator and the construct levels are the two measure to assess in evaluating formative constructs.

To assess indicator validity, the researcher should monitor the significance of the indicator weights using bootstrapping (Garson, 2016; Urbach & Ahlemann, 2010; Venkatesh et al., 2012). Outer model weights are the focus in formative models, representing the paths from the constituent indicator variables to the composite factor (Garson, 2016). 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 degree of validity (Urbach & Ahlemann, 2010). Weights vary from 0 to an absolute maximum lower than 1 (Garson, 2016). Also, the degree of multicollinearity among the formative indicators should be assessed by calculating the variance inflation factor (VIF). The VIF indicates how much of an indicator's variance is explained by the other indicators of the same construct (Garson, 2016; Jörg Henseler et al., 2016; Urbach & Ahlemann, 2010). That said, Urbach & Ahlemann (2010) report that 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 (Urbach & Ahlemann, 2010). In this context, nomological validity means that, within a set 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 robust and significant (Henseler et al. 2009; Peter 1981; Straub et al. 2004). Urbach & Ahlemann (2010) further propose assessing construct validity by checking discriminant validity. Correlations between formative and all other constructs of less than .700 indicate sufficient discriminant validity (Urbach & Ahlemann, 2010).

Table 4. Formative measurement model assessment

Validity type	**Criterion**	**Description**	**Literature**
Indicator validity	Indicator weights	Significance at the .050 level suggests that an indicator is relevant for the	(Han et al., 2015b; Marett et al., 2013; Urbach &

		construction of the formative index and, thus, demonstrates a sufficient degree of validity. Some authors also recommend path coefficients greater than .100 or .200.	Ahlemann, 2010; Venkatesh et al., 2012; Wu et al., 2015)
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.	(Garson, 2016; Han et al., 2015b; Kankanhalli et al., 2015; Schmitz et al., 2016; Urbach & Ahlemann, 2010; Venkatesh et al., 2012)
Construct validity	Nomo logical validity	Means that, within a set 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	(Urbach & Ahlemann, 2010; Wu et al., 2015)
Construct validity	Inter-construct correlations	If the correlations between the formative and all the other constructs are less than .700, the constructs differ sufficiently from one another.	(Urbach & Ahlemann, 2010)

Source: adapted from Urbach & Ahlemann (2010)

3.6.2 Inner model fit evaluation

Once the reliability and validity of the outer models established, several steps need to be taken to evaluate the hypothesised relationships within the inner model. The assessment of the model's quality is based on its ability to predict the endogenous constructs. The following criteria facilitate this evaluation: Coefficient of determination (R^2) (Urbach & Ahlemann, 2010), predictive relevance (Q^2) (Evermann & Tate, 2014), and path coefficients (Garson, 2016).

Evermann & Tate (2012) argue that while in traditional regression models the R^2 proportion of explained variance is an indicator of the predictive strength of the model, researchers have recently advocated the use of blindfolding for assessing the predictive strength of structural equation models (Chin, 2010; Ringle et al., 2012). Garson (2016) reports that Blindfolding utilises a cross-validation strategy and reports cross-validated communality and cross-validated redundancy for constructs as well as indicators. He further argued that the purpose is to calculate cross-validated measures of model predictive accuracy (reliability), of which there are four: Construct cross-validated redundancy, Construct cross-validated communality, Indicator cross-validated redundancy and Indicator cross-validated communality.

However, in IS research, Evermann & Tate (2012) quoting Chin (2010) recommend to use redundancy-based blindfolding to assess the predictive relevance of one's "theoretical/structural model" and suggests that a value of $Q^2 > 0.5$ indicates a a predictive model.

R^2 is the measure of the proportion of the variance of the dependent variable about its mean that is explained by the independent variable(s) (Gefen et al., 2000). Urbach & Ahlemann (2010) quoting Chin (1998b) considers values of approximately .670 substantial, values around .333 average, and values of .190 and lower weak. Nevertheless, the "significan value" of R^2 depends on fielding (Garson, 2016). The path coefficients should also be assessed. Urbach & Ahlemann (2010) reports that the R^2 should be above .100. The paths coefficient significance test and p value should be done using the bootstrapping technique.

Finally, the model fitness should be assessed. Henseler et al. (2016) argued that currently, the only approximate model fit criterion implemented for PLS path modelling is the standardised root mean square residual (SRMR). They further claimed that as can be derived from its name, the SRMR is the square root of the sum of the squared differences between the model-implied and the empirical correlation matrix, i.e. the Euclidean distance between the two matrices. By convention, a model has a good fit when SRMR is less than .08 (Hu & Bentler, 1998). Some use the more lenient cut-off of less than .10 (Garson, 2016). Table 5 gives an overview of the assessment of formative models. Four papers report the use of indicator weights to assess indicator validity while five reports the VIF for the same purpose. Only one paper reports the formative construct validity assessment.

Table 5. Structural model assessment

Validity type	Criterion	Description	Literature
Model Predictability	Predictive relevance $Q^2 > 0.05$	By systematically assuming that a certain number of cases are missing from the sample, the model parameters are estimated and used to	(Garson, 2016; Jörg Henseler et al., 2016; Urbach & Ahlemann, 2010)

		predict the omitted values. Q^2 measures the extent to which this prediction is successful.	
Model validity	Effect size (f^2)	Measures of 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.	(Fang et al., 2014; Garson, 2016; Johnston et al., 2015; Schmitz et al., 2016; Urbach & Ahlemann, 2010; Venkatesh et al., 2012; Xu et al., 2014)
Model validity	Model fit SRMR < 0.08	SRMR is a measure of close fit of the researcher's model.	(Garson, 2016; Jörg Henseler et al., 2016)
Model validity	$R^2 > 0.100$	Coefficient of determination	(Bartelt & Dennis, 2014; Fang et al., 2014; Garson, 2016; Hsieh & Petter, 2012; Ifinedo, 2015; Kankanhalli et al., 2015; Majchrzak et al., 2013; Marett et al., 2013; Park et al., 2015; Schmitz et al., 2016; Setia et al., 2013; Urbach & Ahlemann, 2010; Wang et al., 2013; Xu et al., 2014)
Model validity	Path coefficients Critical t-values for a two-tailed test are 1.65 (significance level = 10 percent), 1.96 (significance level = 5 percent), and 2.58 (significance level = 1 percent).	Structural path coefficients are the path weights connecting the factors to each other.	(Bartelt & Dennis, 2014; Fang et al., 2014; Garson, 2016; Hsieh & Petter, 2012; Ifinedo, 2015; Kankanhalli et al., 2015; Majchrzak et al., 2013; Marett et al., 2013; Park et al., 2015; Schmitz et al., 2016; Setia et al., 2013; Urbach & Ahlemann, 2010; Wang et al., 2013; Xu et al., 2014)

Source: adapted from Urbach & Ahlemann (2010)

4. Conclusion

Partial Least Square Structural Equation Modelling has been applied in the field of Information Systems and is characterised as the primary user of that technical statistic. Nevertheless, its use is subject to critics. This review has updated the guidelines for the use of PLS-SEM in IS settings by integrating new criterion for assessing the measurement and the structural model. Nevertheless, this update is a non-technical point of view. The further inquiry could be taken to show how to reports the results of these provided criterions.

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