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Partial Least Squares Structural Equation Modeling

in Human Resource Management Research

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PARTIAL LEAST SQUARES STRUCTURAL EQUATION MODELING IN HUMAN RESOURCE MANAGEMENT RESEARCH

ABSTRACT

Partial least squares structural equation modeling (PLS-SEM) has become a key multivariate analysis technique that human resource management (HRM) researchers frequently use. While most disciplines undertake regular critical reflections on the use of important methods to ensure rigorous research and publication practices, the use of PLS-SEM in HRM has not been analyzed so far. To address this gap in HRM literature, this paper presents a critical review of PLS-SEM use in 77 HRM studies published over a 30-year period in leading journals. By contrasting the review results with state-of-the-art guidelines for use of the method, we identify several areas that offer room of improvement when applying PLS-SEM in HRM studies. Our findings offer important guidance for future use of the PLS-SEM method in HRM and related fields.

Keywords: partial least squares, structural equation modeling, PLS-SEM, human resource management, guidelines, review

INTRODUCTION

In recent years, human resource management (HRM) scholars have increasingly turned their attention to understanding the complex interrelationships that constitute the HRM black box (also see Banks and Kepes, 2015, Chowhan, 2016). The emergence of progressively more complex models in HRM underlines the critical importance of developing advanced analytical methods (e.g., Wright, Gardner, Moynihan and Allen, 2005). Structural equation modeling (SEM) has become a widely used method when investigating such models' relationships, for example, those that determine the impact of HRM practices on attitudinal and behavioral HR outcomes, as well as on organizational performance (e.g., Baluch, Salge and Piening, 2013, Buonocore and Russo, 2013). SEM's ability to simultaneously estimate the direct, indirect (e.g., mediating), and moderating effects of multiple constructs while accounting for measurement error has enabled researchers to examine relationships that would otherwise be difficult to disentangle and study.

Partial least squares SEM (PLS-SEM) is often used across different management disciplines, including organization research (Sosik, Kahai and Piovoso, 2009) and strategic management (Hair, Sarstedt, Pieper and Ringle, 2012a). PLS-SEM estimates the parameters of a set of equations in a structural equation model by combining principal components analysis and regression-based path analysis (Mateos-Aparicio, 2011). The method offers various advantages for researchers using cause-effect relationship models to explain, or predict, a particular construct, such as job satisfaction (e.g., Buonocore and Russo, 2013), turnover intentions (e.g., Brunetto, Teo, Shacklock and Farr-Wharton, 2012), and expatriation behavior (Schlägel and Sarstedt, 2016). These advantages include its ability to (1) handle very complex models with many indicators and constructs, (2) estimate formatively specified constructs, (3) handle small sample sizes with the required level of care, and (4) derive determinate latent variable scores, which can be applied in subsequent analyses (Richter, Cepeda Carrión, Roldán and Ringle, 2016). PLS-SEM thus overcomes several of covariance-based SEM's (CB-SEM; Jöreskog, 1978) well-known limitations, particularly in research settings characterized by complex research models and limited data.

The growing number of articles using PLS-SEM in business research (Hair, Sarstedt, Hopkins and Kuppelwieser, 2014) and the controversy regarding its advantages and limitations (e.g., Goodhue, Lewis and Thompson, 2012, Marcoulides, Chin and Saunders, 2012, Rönkkö and Evermann, 2013, Sarstedt, Hair, Ringle, Thiele and Gudergan, 2016) call for a critical review of the way the method is used in the HRM field. Reflecting critically on the use of PLS-SEM is crucial, as this could reveal important avenues for improvement, thereby helping authors develop and complete their studies, as well as helping them evaluate the work of others (e.g., Sanders, Cogin and Bainbridge, 2014, Rosopa and Kim, 2017). The ensuing implications are not only relevant for HRM researchers, but extend to other fields of business research that increasingly use the PLS-SEM method (e.g., Nitzl, 2016).

This is the first paper to systematically examine how PLS-SEM has been applied in HRM research, with the aim of providing important guidance and, where applicable, opportunities for course correction in future applications. We first discuss PLS-SEM's utility for HRM research across universal, contingency, configurational, and contextual modes of theorizing. Next, we offer a set of guidelines for the appropriate application of PLS-SEM. We then use these guidelines to assess how PLS-SEM is used in the top journals for HRM and employment relations research. Our review of 77 studies published over a 30-year period, from 1985 to 2014, reveals that there is considerable variation in the way PLS-SEM is applied in HRM research. The review also highlights several areas that offer room for improvement in future HRM studies.

THEORIZING IN HRM AND PLS-SEM

Reference to empirical HRM research being "seriously under-theorized" is relatively consistent (Fleetwood and Hesketh, 2008, p. 126). HRM literature generally draws on four dominant theorizing modes that differ regarding the complexity characterizing the resultant models (Delery and Doty, 1996, Martín-Alcázar, Romero-Fernandez and Sánchez-Gardey, 2005), namely a universalistic, contingency, contextual, and configurational mode. HRM models following the universalistic perspective are the simplest in terms of the model complexity. These models infer that the relationships between independent and dependent variables are universal across the population of employees and independent of any other contextual factors. PLS-SEM is appropriate for assessing such universalistic associations within the HRM context.

However, HRM scholars are moving from universalistic to more multifaceted HRM models, such as those based on the contingency, contextual, and configurational perspectives (Martín-Alcázar, Romero-Fernández and Sánchez-Gardey, 2008). Contingency approaches usually result in more complex models, because they consider interactions rather than the simple direct relationships that characterize universalistic models (Van de Ven and Drazin, 1985). An example of contingency reasoning is the extent to which line management development conditions the impact that strategic HRM partners have on high performance work system implementation (Buonocore and Russo, 2013). While PLS-SEM can assess contingency arguments—either through moderation analysis, or the use of multigroup analysis—it is important to understand such contingency's nature. Boyd, Takacs Haynes, Hitt, Bergh and Ketchen (2012) point out that, when the contingency argument concerns the slope of the difference, the appropriate modeling approach is to analyze the moderating effect. Whereas factor indeterminacy limits factor-based SEM's usefulness for moderation analyses (Hair, Black, Babin and Anderson, 2010), PLS-SEM is particularly suitable, as the method has practically no limitations when integrating one or more interaction term(s) into the path model. However, when running a moderation analysis, researchers must carefully choose a suitable approach to compute the interaction term (Henseler and Chin, 2010) and employ bias-corrected and accelerated (BCa) confidence intervals when interpreting their results (Aguirre-Urreta and Rönkkö, 2018).

When the focus of the argument concerns differences in the strength of an association conditional on a certain contingency variable, a suitable modeling procedure compares groups that differ in respect of a specific contingency variable. PLS-SEM enables such comparisons by combining measurement invariance testing (Henseler, Ringle and Sarstedt, 2016b) and various types of multigroup analysis, such as Chin and Dibbern's (2010) permutation test, or Henseler, Ringle and Sinkovics' (2009) bootstrap-based approach.

Similar to contingency approaches, contextual perspectives imply that environmental factors influence HRM practices. A contextual approach highlights, for example, the relevance of social, cultural, and institutional influences for HRM decisions and effects (Martín-Alcázar et al., 2005). While much research in this area employs qualitative methods, there have been calls to use more advanced quantitative techniques when studying contextual effects (Martín-Alcázar et al., 2005). For example, research on HRM practices has used SEM to investigate the impact of context on cultural factors, such as hierarchical distance (Triguero-Sánchez, Peña-Vinces and Sánchez-Apellániz, 2013), and on socio-political factors, such as unionization (Thommes and Weiland, 2010, Innocenti, Pilati and Peluso, 2011). With its capacity to undertake moderation and multigroup analyses, PLS-SEM offers the means to employ this contextual analysis approach in HRM. Furthermore, PLS-SEM allows for estimating models that researchers hypothesize as having (multiple) mediating effects, either in isolation, or in combination with moderators in mediated moderation, or moderated mediation, models (Nitzl, Roldán and Cepeda Carrión, 2016). For example, Brunetto et al. (2012) apply PLS-SEM to research the mediating effect of affective commitment on the relationship between employee engagement and turnover intentions.

The configurational mode of HRM theorizing involves patterns of factors that jointly relate to certain other factors in more complex models. The configurations of a range of HRM practices can embody synergistic effects and higher-order interactions that cannot be easily represented in traditional contingency models (Doty and Glick, 1994). Similar to the universalistic perspective, a simple configurational argument implies that one configuration of HRM practices, which is always independent of contextual contingencies, will produce a certain outcome (Marler, 2012). In contrast, aligned with the contingency perspective, an extended configurational conceptualization implies that, for example, depending on a particular industry type, a certain bundle of HRM practices will enhance organizational performance (Subramony, 2009). Owing to its flexibility regarding model specification, PLS-SEM proves suitable to assess configurations' impact on HRM practices. By adopting methods, such as the formation of indices, to proxy a range of practices (e.g., Shaw, Dineen, Fang and Vellella, 2009) previous measures could only inadequately take a configurational approach in HRM research. More recent studies have adopted the use of formative measures to depict bundles of HRM practices (e.g., Triguero-Sánchez et al., 2013, Bello-Pintado, 2015). PLS-SEM is particularly suitable in this regard, because it allows for the estimation of formatively specified measurement models without limitations (Becker, Rai and Rigdon, 2013a), which have become increasingly popular in the social sciences.[1] Furthermore, higher-order constructs—as frequently used in PLS-SEM studies in other fields (e.g., Ringle, Sarstedt and Straub, 2012)—allow for the simultaneous modeling of constructs on different levels of abstraction. For example, in Konradt, Warszta, and Ellwart's

[1] Note that there are also controversies regarding the nature and usefulness of formative measurement (e.g., Bollen and Diamantopoulos, 2017).

(2013) examination of the influence that the process fairness has on applicants' pursuit intentions, recommendation intentions, and intentions to reapply, they consider process fairness as a higher-order construct formed by three lower-order components: formal characteristics, explanation, and interpersonal treatment.

PLS-SEM GUIDELINES FOR HRM

When using PLS-SEM, researchers need to be conversant with the method and its appropriate application. Prior research has produced several guidelines and recommendations on how to use PLS-SEM (e.g., Haenlein and Kaplan, 2004, Gefen and Straub, 2005, Chin, 2010, Lowry and Gaskin, 2014, Henseler, Hubona and Ray, 2016a, Sarstedt, Ringle and Hair, 2017b), including several edited volumes (e.g., Esposito Vinzi, Chin, Henseler and Wang, 2010, Abdi, Chin, Esposito Vinzi, Russolillo and Trinchera, 2016, Latan and Noonan, 2017, Avkiran and Ringle, 2018), and textbooks on the method (e.g., Garson, 2016, Ramayah, Cheah, Chuah, Ting and Memon, 2016, Hair, Hult, Ringle and Sarstedt, 2017b, Hair, Sarstedt, Ringle and Gudergan, 2018). The set of guidelines presented in this section is aimed at helping HRM researchers use PLS-SEM better when assessing data and evaluating estimation results. The guidelines were derived by merging PLS-SEM fundamentals with findings from recent PLS-SEM methodological improvements (e.g., Hair et al., 2018) and with best practice in other fields using this method (e.g., Peng and Lai, 2012, Kaufmann and Gaeckler, 2015, Nitzl, 2016, Ali, Rasoolimanesh, Sarstedt, Ringle and Ryu, 2018). Our guidelines are based on four aspects of a structured PLS-SEM analysis process (Figure 1) that prior research on the use of PLS-SEM identified as relevant: (1) determining the research goal, (2) structural model specification, (3) measurement model specification, and (4) results evaluation.

=== INSERT FIGURE 1 HERE ===

When following these guidelines, HRM researchers, however, need to be aware of the recent controversies surrounding the method: Some researchers oppose the method, arguing that PLS-SEM is not a (factor-based) latent variable method, lacks goodness-of-fit measures, and produces biased parameter estimates (e.g., Rönkkö and Evermann, 2013, Rönkkö, McIntosh and Antonakis, 2015, Rönkkö, Antonakis, McIntosh and Edwards, 2016). However, this view has been criticized for ignoring PLS-SEM's measurement philosophy and analytical goals, which differ fundamentally from those of CB-SEM (Rigdon, 2012, Sarstedt et al., 2016, Rigdon, Becker and Sarstedt, 2017a), thus rendering any comparison of the two SEM types as "comparing apples with oranges" (Marcoulides et al., 2012, p. 725). In estimating the construct measures, CB-SEM follows a common factor model approach. The underlying statistical assumption is that the variance of a set of indicators can be perfectly explained by the existence of one unobserved variable (the common factor) and individual random error. PLS-SEM on the other hand follows a composite model approach in linear combinations of indicators define composites, which represent that conceptual variable of interest in the statistical model (Sarstedt et al., 2016, Rigdon, Sarstedt and Ringle, 2017b). Henseler et al. (2014, p. 184) note that defining factor-based results obtained from CB-SEM as true, but composite-based PLS-SEM results as universally false, is a "very restrictive view of SEM." Recent research echoes this objection, calling for a more holistic understanding of the interplay between measurement conceptualization, operationalization, modeling, and estimation (e.g., Sarstedt et al., 2016, Hair, Hollingsworth, Randolph and Chong, 2017a, Nitzl and Chin, 2017). Nevertheless, to preempt potential criticism, HRM researchers should take this debate and the different positions into consideration when choosing an appropriate SEM method.

Determining the Research Goal

Early in the research process, HRM researchers develop an understanding of the type of model they will be investigating and the purpose of this investigation. PLS-SEM was initially designed to allow the exploration of models in an effort to develop theory. Wold (1985, pp. 590) envisioned a discovery-oriented process, “a dialogue between the investigator and the computer.” In other words, instead of following a deductive approach of creating and testing a specific model, the researchers would critically review the initial results and improve the model further by means of an inductive approach. The inductive improvement process, deductively tested in several iterations, leads to a final model that better matches the theory with the data than the earlier models.

PLS-SEM enables researchers to address a broad range of research questions by (1) allowing for estimating formatively specified measurement models (Sarstedt et al., 2016), (2) handling non-normal data (Cassel, Hackl and Westlund, 1999), and (3) working effectively with a wide range of sample sizes (Hair, Hult, Ringle, Sarstedt and Thiele, 2017c), which is often an issue in HRM research (e.g., Vermeeren et al., 2014). Hence, HRM research endeavoring to assess complex theories and incorporate models with an explanatory and/or predictive focus should employ PLS-SEM (Rigdon, 2016).

Structural Model Specification

In the structural model, researchers establish links between constructs through a set of paths, which usually reflects the hypotheses. The relationships between constructs can capture direct, indirect (mediated), and interaction (moderated) effects. For example, the path between employee performance (Y_4) and turnover (Y_7) in Figure 2 exemplifies a direct relationship. The link between employee performance (Y_4) and turnover (Y_7) through commitment (Y_6) is an example of an indirect relationship. Here, changes in commitment potentially mediate employee performance’s effect on turnover. A moderation effect occurs when a construct affects the strength, or the direction, of the relationship between two other constructs. We could argue, for example, that rewards (Y_5) moderate the relationship between employee performance (Y_4) and commitment (Y_6). This effect is modeled via an interaction term (Y_4 x Y_5), which is similar to a contingency logic. When considering mediation and moderation simultaneously in this example, the researcher creates a moderated mediation model (Nitzl et al., 2016).

PLS-SEM is also capable of investigating higher-order models, which have become increasingly relevant in HRM studies (Teo, Le Clerc and Galang, 2011), particularly in configurational models. For example, in Figure 2, the construct employee performance (Y_4) represents a higher-order construct formed by three lower-order components, which, in this case, are: ability (Y_1), motivation (Y_2), and opportunity (Y_3). Higher-order constructs improve the model parsimony and allow for a more nuanced analysis of dimension-specific effects on subsequent constructs (e.g., Edwards, 2001). Importantly, HRM researchers need to explicitly justify that using a higher-order model is appropriate in their study, and to clearly conceptualize the higher- and lower-order components.

=== INSERT FIGURE 2 HERE ===

Measurement Model Specification

In addition to the structural model, HRM researchers need to detail the measurement models. An important step in this regard is deciding on the measurement mode (e.g., Diamantopoulos and Winklhofer, 2001). One of PLS-SEM's strengths when doing so is its capacity to handle formatively specified measurement models without limitation (Cenfetelli and Bassellier, 2009, Becker et al., 2013a). As noted in our discussion of configurational HRM models above, many management studies use reflective indicators, but for a range of HRM constructs, such as bundles of HRM practices, formative measures may be more appropriate. For example, in Figure 2, commitment (Y_6) is measured by using reflective indicators constituting the consequences of employees' commitment; the following are examples of the scale items: "I would be very happy to spend the rest of my career with this organization," or "I feel a strong sense of belonging to this organization." Conversely, the rewards construct (Y_5) is measured by using formative indicators representing different aspects of rewards, such as salary increments, annual bonuses, and promotions. Given the considerable biases that result from measurement model misspecifications (e.g., Diamantopoulos and Siguaw, 2006), HRM researchers need to verify whether each construct within the model requires a reflectively or formatively specified measurement model.

PLS-SEM also allows for the use of nominal, ordinal, and interval-scaled measures in predictor constructs (e.g., Haenlein and Kaplan, 2004) and for incorporating single-item measures. However, single items exhibit significantly lower levels of predictive validity than multi-item scales (e.g., Diamantopoulos, Sarstedt, Fuchs, Wilczynski and Kaiser, 2012), which is particularly problematic when using a prediction-based method such as PLS-SEM. HRM researchers using PLS-SEM should therefore generally opt for multi-item scales.

Determining valid construct measures—taking decisions concerning higher-order, formative measures rather than reflective ones into account, as well as single-item measures rather than multi-item ones—complements specifying the path model. Once the path model has been specified, researchers turn their attention to the criteria related to the model evaluation.

Results Evaluation

A two-stage approach is used to evaluate PLS-SEM results (Henseler et al., 2009)—see Figure 3. Stage 1 relates to the measurement model evaluation, whereas Stage 2 deals with the structural model evaluation.

=== INSERT FIGURE 3 HERE ===

Stage 1: Evaluating Measurement Models

When evaluating measurement models, researchers need to distinguish between reflectively and formatively specified constructs. An initial assessment to help distinguish between the formative and reflective modes can draw on PLS-SEM's confirmatory tetrad analyses. If a researcher has used reflectively measured constructs, the indicator loadings should be examined. Standardized loadings over 0.70 are desirable (Chin, 2010). HRM researchers can subsequently investigate the internal consistency reliability by ensuring that Cronbach's α, ρ_A, and the composite reliability are more than 0.70 and below 0.95 (Hair et al., 2017b; Chapter 4). However, the results of these three reliability assessments usually differ, with Cronbach's α representing the most conservative criterion, the composite reliability the most liberal one, and the ρ_A an approximately exact reliability measure of the PLS-SEM composites. Researchers should also assess the convergent validity. The average variance extracted (AVE) is a suitable criterion for this purpose. If the AVE is above 0.50, the construct explains an average of at least 50 percent of its items' variance (Chin, 1998). Finally, HRM researchers are advised to assess discriminant validity. Much research relies on the Fornell-Larcker criterion and cross loadings when investigating discriminant validity (e.g., Hair, Sarstedt, Ringle and Mena, 2012b), but Henseler, Ringle and Sarstedt (2015) have shown that these criteria perform poorly in terms of disclosing discriminant validity problems. Instead, researchers should use the HTMT criterion, which is defined as the mean value of the indicator correlations across constructs (i.e., the heterotrait-heteromethod correlations) relative to the (geometric) mean of the average correlations of the indicators measuring the same construct. High HTMT values indicate a problem with discriminant validity. Based on simulation and previous research, Henseler et al. (2015) recommend that HTMT values should not exceed 0.90 if the path model includes constructs that are conceptually similar (e.g., cognitive job satisfaction and affective job satisfaction). When the constructs are conceptually more distinct, a more conservative, threshold value of 0.85 is recommended. Finally, researchers should use a bootstrapping procedure to determine whether the HTMT value is statistically significantly lower than one.

Measurement models with formative indicators require a different approach to measurement evaluation. The first step involves carrying out a redundancy analysis to test the convergent validity of the formatively measured construct. Second, HRM researchers need to assess the collinearity between the indicators, which is the source of well-known issues in regression-based analyses, like those carried out by PLS-SEM (e.g., Mason and Perreault, 1991). Collinearity assessment usually involves computing each item's variance inflation factor (VIF). There are different standards of acceptable VIF values, such as 10.00 (e.g., Sarstedt and Mooi, 2014; Chapter 7), with lower values being better. However, until future PLS-SEM research identifies a suitable VIF threshold, researchers should adhere to the more conservative rules of thumb, such as 3.33 (Diamantopoulos and Siguaw, 2006), or 5 (Hair, Ringle and Sarstedt, 2011).

Finally, researchers should investigate the indicator weights' significance and relevance, using bootstrapping to derive the *p* values as well as BCa confidence intervals (Aguirre-Urreta and Rönkkö, 2018). When running bootstrapping, researchers need to (1) use the no sign change option (e.g., Streukens and Leroi-Werelds, 2016) and (2) draw a sufficiently high number of bootstrap samples, which must be at least as large as the sample size. Although an initial assessment of 500 bootstrap samples suffices, the final analysis should draw on 5,000, or preferably 10,000, bootstrap samples (Streukens and Leroi-Werelds, 2016). Depending on whether the indicator weights are significant, researchers also need to examine the indicator loadings—see Cenfetelli and Bassellier (2009) and Hair et al. (2017b; Chapter 5) for more detailed guidelines on formative measurement model evaluation.

Stage 2: Evaluating Structural Models

Once HRM researchers have assessed that the measurement model is satisfactory, Stage 2 involves the structural model's evaluation. A useful first step in this assessment is to analyze the path coefficients; the evaluation is similar to that of the regression coefficients. Analogous to the indicator weight analysis, the use of bootstrapping techniques allows for assessing each coefficient's significance (Tenenhaus, Esposito Vinzi, Chatelin and Lauro, 2005). HRM researchers should, as part of this assessment, also evaluate the total effects; that is, the summative effects of the direct and indirect relationships on a specific endogenous construct (Albers, 2010). When following this step, researchers should assess the R^2 values of all the endogenous constructs as a measure of the model's in-sample predictive power. A rough rule of thumb is that R^2 values of 0.25, 0.50, and 0.75 are respectively weak, moderate, and strong (Hair et al., 2011). In a third step, researchers should evaluate the model's predictive power further by means of the Q^2 value. This value is obtained by means of the blindfolding procedure, which omits a part of the data matrix, estimates the model parameters, and predicts the omitted part by using the previously computed estimates. The smaller the difference between the predicted and the original values, the greater the Q^2 value and, thus, the model's predictive accuracy (Chin, 1998). Since the sample structure remains largely intact, the Q^2 measure can only be partly considered a measure of an out-of-sample prediction (Rigdon, 2012); "Fundamental to a proper predictive procedure is the ability to predict measurable information of new cases" (Shmueli, Ray, Velasquez Estrada and Chatla, 2016, p. 4553). As a remedy, Shmueli et al. (2016) developed the PLSpredict procedure for generating holdout sample-based point predictions on an item, or construct, level, which HRM researchers should use in future PLS-SEM studies

Research has introduced goodness-of-fit measures for PLS-SEM, such as the standardized root mean square residual (SRMR), the root mean square residual covariance (RMS_{theta}), the normed fit index (NFI; also referred to as the Bentler-Bonett index), the non-normed fit index (NNFI; also referred to as the Tucker-Lewis index), and the exact model fit test (Lohmöller, 1989, Henseler et al., 2014, Dijkstra and Henseler, 2015). However, contrary to CB-SEM, whose users rely heavily on goodness-of-fit measures (Cliff, 1983), PLS-SEM constitutes a prediction-oriented approach to SEM, which emphasizes the predictive accuracy of models grounded in well-developed causal explanations. Jöreskog and Wold (1982, p. 270) refer to this interplay when labeling PLS-SEM "causal-predictive," meaning that when the structural theory is strong, the path relationships can be interpreted as causal. Against this background, Sarstedt et al. (2017b) conclude that "validation using goodness-of-fit measures is also relevant in a PLS-SEM context but less so compared to factor-based SEM. Instead, researchers should primarily rely on criteria that assess the model's predictive performance."

Finally, the assessment of the data structure's heterogeneity is an important issue that HRM researchers need to address when evaluating PLS-SEM results (Ratzmann, Gudergan and Bouncken, 2016). Multigroup (e.g., Matthews, 2018) and moderator analyses (e.g., Henseler and Fassott, 2010) allow for analyzing known or assumed sources of heterogeneity (i.e., analysis of observed heterogeneity). Nevertheless, researchers also need to address the issue of possibly unknown and unobserved heterogeneity. In the presence of critical levels of unobserved heterogeneity, the PLS-SEM results can be highly misleading on the aggregate data level (Becker, Rai, Ringle and Völckner, 2013b). PLS-SEM-based latent class methods, such as finite mixture PLS (Hahn, Johnson, Herrmann and Huber, 2002), help the researcher detect and treat critical levels of unobserved heterogeneity. Peng and Lai (2012), Kaufmann and Gaeckler (2015), Hair et al. (2018; Chapters 4 and 5) explain in detail how to systematically analyze observed and unobserved heterogeneity in PLS-SEM analyses.

REVIEW OF PLS-SEM RESEARCH IN HRM

Approach

Our review includes all HRM and employment relations articles published between 1985 and 2014 in journals appearing on the 2007 and 2010 versions of the Association of Business Schools (ABS) list (Harvey, Kelly, Morris and Rowlinson, 2010). We used the ABS list as the basis for our review coverage, because it is the only internationally recognized journal list that categorizes journals as HRM, or employment relations, types. Earlier research also used this list as the basis for reviewing HRM research (e.g., Almond and Gonzalez Menendez, 2012). We included all HRM and employment relations journals with an ABS quality rating of 2, 3, or 4, because their articles are fully refereed according to recognized standards and conventions. We also included relevant articles in similar journals dedicated to organizational studies, management, and psychology, which a panel of seven HRM researchers considered as falling within the HRM field. Table OA1 in the Online Appendix shows the journals included in this initial list. While not presented as a census of all relevant HRM-related research, the resulting publication list amply reflects mainstream HRM research.

Initially, we filtered the papers in our list of selected journals to identify those using PLS-SEM. Following prior PLS-SEM reviews in related business research disciplines (e.g., Peng and

Lai, 2012, Kaufmann and Gaeckler, 2015, Nitzl, 2016), we carried out a full text search in the EBSCO Business Source Premier, ProQuest ABI/INFORM, JSTOR, and SciVerse SCOPUS databases, using the search terms "partial least squares" and "PLS." In addition, we searched each journal's online library. This search ensured that we had identified all the journal articles that met the two selection criteria. Since some of the organizational studies, management, and psychology journals are interdisciplinary and therefore cover functional areas outside the HRM field, a panel of HRM experts screened the articles from these journals to ensure that only those that fit within the HRM discipline were included. The panel comprised seven academics from Australasia, Europe, and the USA who identified themselves as HRM researchers. Articles were only included if at least three panel members identified them as falling within the HRM field. Table OA2 in the Online Appendix shows all the HRM studies included in our review.

We evaluated 77 studies with a total of 114 PLS path models against the five key elements that underpin the guidelines outlined above according to the: (1) reasons for using PLS-SEM, (2) data characteristics, (3) model characteristics, (4) results evaluation, and (5) reporting (e.g., Hair et al., 2012a, Hair et al., 2012b, Nitzl, 2016).[2] Two researchers with a strong background in PLS-SEM research and with prior experience of PLS-SEM assessment, coded each article with more than 80 percent agreement. Where there was disagreement, a third researcher's input was sought to arrive at an agreement.

Reasons for Using PLS-SEM

Of the 77 studies, a total of 65 (84.4 percent) offered arguments for choosing PLS-SEM in their analysis (Table OA3 in the Online Appendix). The key reasons are: small sample size (51

[2] Throughout this article, we use the term "studies" when we discuss the 77 journal articles and use the term "models" when discussing the 114 PLS path models estimated in these papers.

studies, 66.2 percent), non-normal data (33 studies, 42.9 percent), theory development (20 studies, 26.0 percent), and use of categorical variables (15 studies, 19.5 percent). Especially with regard to the latter two main arguments, HRM research differs from other business research disciplines, in which these aspects are far less emphasized (e.g., Hair et al., 2012b).

In many instances, PLS-SEM works efficiently with small sample sizes when other methods fail (Rigdon, 2016), but numerous studies have long called such analyses' legitimacy into question (Marcoulides and Saunders, 2006). For example, using common factor model data, Goodhue et al. (2012) have shown that PLS-SEM suffers from increased standard deviations, decreased statistical power, and reduced accuracy (also see Marcoulides et al., 2012). More recently, Hair et al. (2017c), using composite model data, have confirmed these results, but only with regard to measurement model estimates. In the structural model, biases are generally marginal, quickly converging to zero as the sample size increases. As with any other statistical method, PLS-SEM's performance depends on the nature of the population (e.g., with regard to the survey variables' variance) and the quality of the sample. Even the most sophisticated statistical methods cannot offset badly designed samples (Sarstedt, Bengart, Shaltoni and Lehmann, 2017a). Similarly, recent research has critically commented on non-normal data as the sole argument for using PLS-SEM (e.g., Reinartz, Haenlein and Henseler, 2009, Goodhue et al., 2012, Rigdon, 2016), because CB-SEM offers a wide range of estimators whose distributional requirements range from strict to weak to almost none. Furthermore, standard maximum likelihood estimation—as commonly used in CB-SEM—has proven extremely robust regarding violations of its underlying distributional assumptions (e.g., Reinartz et al., 2009).

To summarize, choosing PLS-SEM mainly for sample size and data distribution reasons is not justified (Rigdon, 2016). Researchers should instead underline their model's and analyses' predictive focus (Rigdon, 2012), or the data's composite-model-based nature (Sarstedt et al., 2016)—if applicable.

Data Characteristics

HRM PLS-SEM studies have a mean sample size of 142.5 (Table OA4 in the Online Appendix), which is lower than in other business research disciplines, such as hospitality management (mean=332; Ali et al., 2018), management information systems (mean=238.1; Ringle et al., 2012), marketing (mean=211.3; Hair et al., 2012b), operations management (mean=246; Peng and Lai, 2012), strategic management (mean=154.9; Hair et al., 2012a), and supply chain management (mean=274.4; Kaufmann and Gaeckler, 2015). This finding is a cause for concern given the recent calls to abandon the small sample size argument (Goodhue et al., 2012, Rigdon, 2016). Most models (102; 89.5 percent) meet the "ten-times" rule to determine the minimum sample size requirements for estimating a PLS path model. On average, the 12 models (10.5 percent) that did not meet this criterion fell 52.8 percent short of the recommended sample size. Although the "ten-times" rule allows researchers to gauge the minimum requirements for a PLS-SEM sample (Hair et al., 2011), it neglects important issues related to statistical power. Researchers should run power analyses that account for model structure, expected effect sizes, and significance level to determine the necessary sample size (e.g. Marcoulides and Chin, 2013). Alternatively, Kock and Hadaya (2017) suggest the use of the inverse square root method and the gamma-exponential method to determine the minimum sample size. These approaches' recommended sample sizes are typically higher than those implied by the "ten times" rule.

None of the studies reports skewed data, or kurtosis, or other criteria that corroborate the non-normality of data arguments. This finding is surprising, since the non-normality of data is the second most prevalent cited reason for using PLS-SEM (42.9 percent of all studies). Moreover, only eight studies (7.01 percent) provide information about missing values, but, except for two studies, do not indicate the missing data treatment used. Finally, none of the studies uses holdout samples, even though this procedure helps substantiate the stability and generalizability of the model estimates (Cepeda Carrión, Henseler, Ringle and Roldán, 2016, Shmueli et al., 2016). These results indicate that, in PLS-SEM-based HRM research, there is potential to improve the descriptive statistics' presentation and the data characteristics' analysis.

Model Characteristics

Table 1 depicts the reviewed path models' characteristics. Almost half of the models used reflectively and formatively specified measurement models (49 models; 43.0 percent). While no model used only formative measures, many only used reflective measures (47 models; 41.2 percent). Eighteen models (15.8 percent) did not provide any information about the measurement mode employed, which is problematic given the vast differences between reflective and formative measurement models' evaluation.

=== INSERT TABLE 1 HERE ===

On average, the path models include 7.8 latent variables, which is comparable to the number of path models found in PLS-SEM reviews in related disciplines (e.g., Hair et al., 2012a, Kaufmann and Gaeckler, 2015, Ali et al., 2018), but much higher than the number of latent variables found in publications using factor-based SEM (e.g., Shah and Goldstein, 2006). Similarly, PLS path models employ a relatively large number of structural model path relations (mean = 8.8) and include a greater average number of indicators across all measurement models (mean = 35.0). Reflectively specified measurement models include, on average, 4.5 indicators, whereas formatively specified measurement models include 4.3. This finding is surprising given that formatively specified measurement models should represent the entire population of indicators relevant for measuring the construct and therefore normally comprise more indicators. As such, the finding casts doubt on whether the measurement models used in many PLS-SEM-based HRM studies cover the entire scope of the conceptual variables' content domain. Finally, 87 of 114 PLS path models (76.3 percent) used single-item constructs. This finding is alarming, because studies using single items may have weak predictive validity (e.g., Diamantopoulos et al., 2012). HRM researchers consequently often sacrifice predictive power for simplistic measurements, which is particularly problematic in a PLS-SEM context. Since PLS-SEM constitutes a prediction-oriented approach to SEM, lower predictive power fosters type II errors in the structural model evaluation.

Results Evaluation

Measurement model evaluation

The results of our review imply that there is some room for improvement in terms of evaluating reflective measures, as not all models report their measures of reliability and validity (Table 2; Panel A). Specifically, 73 models (76.0 percent) address indicator reliability, 80 models (83.3 percent) provide internal consistency reliability results, and 77 models (80.2 percent) evaluate convergent validity. Finally, only 61 models (63.5 percent) assess discriminant validity. Future PLS-SEM studies should specifically consider the HTMT criterion (Henseler et al., 2015) to assess discriminant validity, which had not been proposed when the reviewed studies were carried out.

=== INSERT TABLE 2 HERE ===

Models investigating formative measures (Table 2; Panel B) focus on the relevance of the indicator weights (9 models; 18.4 percent), their significance (10 models; 20.4 percent), and the collinearity (8 models; 16.3 percent). Our review reveals that HRM researchers usually overlook fundamental guidelines and fail to assess formative measures adequately. In particular, none of the studies used redundancy analysis to examine the convergent validity of the formatively measured constructs. In addition, it is concerning that, in 32 models (65.3 percent), researchers used criteria proposed for reflective measurement model assessment to evaluate formative measures. Finally, none of the studies made use of confirmatory tetrad analysis (Gudergan, Ringle, Wende and Will, 2008) to test the mode of measurement. In light of these findings, HRM researchers should pay greater attention to established guidelines for evaluating formatively specified measurement models (e.g., Cenfetelli and Bassellier, 2009, Hair et al., 2017b; Chapter 5).

Structural model evaluation

Table 3 summarizes the review results of the structural model evaluations in HRM studies. Eight models (7.0 percent) report Tenenhaus et al.'s (2005) goodness-of-fit index, which, however, offers no indication of the model fit (Henseler and Sarstedt, 2013). Other goodness-of-fit measures, such as SRMR, or NFI, were not used. Criteria used to assess the models' predictive quality include the R^2 (94 models; 82.5 percent), the f^2 effect size (6 models; 5.3 percent), the predictive relevance Q^2 (8 models; 7.0 percent), and the q^2 effect size (0 models; 0.0 percent). Our findings suggest that, in HRM studies, there is room for improving the assessment of models' predictive quality. While researchers routinely consider in-sample predictive power, they pay little attention to out-of-sample predictive power proxy assessment that uses the Q^2 statistic. Given that researchers commonly seek to generalize their results beyond the sample, this statistic, just like Shmueli et al.'s (2016) PLSpredict procedure, should become part of every HRM researcher's toolkit when working with PLS-SEM.

=== INSERT TABLE 3 ===

Before assessing the structural model's predictive power, researchers typically examine the standardized path coefficients to assess the extent to which the data reflect the hypothesized relationships. Almost all of the investigated models (113; 99.1 percent) report *t* or *p* values in their assessment of the path coefficients' significances. Future HRM PLS-SEM studies should also consider bootstrap confidence intervals, as these offer additional information on a coefficient estimate's stability. Hair et al. (2017b) suggest using bias-corrected and accelerated (BCa) bootstrap confidence intervals (also see Aguirre-Urreta and Rönkkö, 2018). Despite their usefulness for gaining a more complete picture of the relevance of a construct's antecedents (Albers, 2010), only a very few researchers considered the total effects in their analyses (6 models; 5.3 percent).

Finally, researchers should check for heterogeneity, which, if not considered, can compromise PLS-SEM results' validity (Becker et al., 2013b). The results in Table 3 show that only a few studies (19 studies; 24.7 percent) account for observed heterogeneity by undertaking multigroup analyses, while none assesses unobserved heterogeneity by using finite mixture PLS (Hahn et al., 2002), or other latent class procedures (Ringle, Sarstedt, Schlittgen and Taylor, 2013, Ringle, Sarstedt and Schlittgen, 2014). We expect researchers to address heterogeneity's validity threats by making more use of multigroup (Sarstedt, Henseler and Ringle, 2011) and moderator analyses (Henseler and Fassott, 2010), supplemented by measurement invariance assessment, which has only recently been proposed in a PLS-SEM context (Henseler et al., 2016b). Moreover, we expect examining unobserved heterogeneity to be a standard assessment procedure in PLS-SEM studies.

Reporting

A critical issue for PLS-SEM applications relates to decisions regarding computational options, which can significantly impact the results. The reporting practices in current HRM research reveal scope for improvement in several respects (Table OA5 in the Online Appendix). For instance, none of the studies provided information on the PLS-SEM algorithm's settings (e.g., weighting scheme, stop criterion, sampling weights). Moreover, while researchers reported determining the significance of path coefficients by carrying out resampling techniques in almost every study, only 51 of the 77 studies (66.2 percent) stated the method used (e.g., bootstrapping, or jackknifing), and only 15 studies (19.5 percent) reported the exact parameter settings (e.g., number of bootstrap samples, sign change options, confidence interval type).

Researchers also should report the software they used to estimate the path model, which only 42 of the 77 studies (54.5 percent) did. A total of 20 papers reported that they used PLS Graph (Chin, 2003), while 19 mentioned the use of SmartPLS (Ringle, Wende and Will, 2005, Ringle, Wende and Becker, 2015), and only three reported using either PLS-GUI, VisualPLS, or XLSTAT.

Finally, reporting must include the covariance/correlation matrix of the indicator variables and constructs to allow readers to validate the study findings. In 68 of the 77 studies (88.3 percent), researchers did so, which is an excellent outcome compared to other fields (e.g., Hair et al., 2012a). However, HRM researchers should improve their reporting practice by routinely including both matrices in an (online) appendix.

CONCLUSION

PLS-SEM allows HRM researchers to estimate and assess complex models, while imposing relatively few restrictions in terms of data (e.g., Gefen, Rigdon and Straub, 2011). Our review of

77 studies published in a 30-year period not only confirms the high relevance of the PLS-SEM method for HRM studies, it also reveals that there is variation in the way PLS-SEM is applied in HRM research, which offers scope for improvement. In particular, HRM researchers using PLS-SEM should improve the results reporting and the assessment of formative measurement models, which have become increasingly important in social science research and are well-aligned with certain configurational approaches in HRM research. The assessment of formative measurement models should not only center on potential collinearity issues and the significance of weights, but should also consider more recently developed practices, such as establishing convergent validity, or analyzing formative indicators' loadings (Cenfetelli and Bassellier, 2009).

Similarly, HRM researchers should account for the most recent developments in PLS-SEM-related methodological research. A recent research stream explores the interplay of measurement theory and model estimation in PLS-SEM vis-à-vis CB-SEM (e.g., Sarstedt et al., 2016, Henseler, 2017, Rigdon et al., 2017b). We expect these efforts, as called for by Rigdon (2012), to further PLS-SEM's emancipation from CB-SEM. Another stream deals with the development of novel methods for dealing with measurement invariance (Henseler et al., 2016a), estimating and evaluating higher-order models (van Riel, Henseler, Kemény and Sasovova, 2017), using fit measures (Henseler et al., 2014), and assessing PLS-SEM results based on newly developed predictive performance criteria (Shmueli et al., 2016). These advanced techniques allow HRM researchers a more nuanced modeling of theoretical concepts and their complex relationships.

Future research should address extensions of the PLS-SEM method that allow for exploring longitudinal, panel, and multilevel data structures, which are particularly relevant for HRM researchers (Shen, 2016, Saridakis, Lai and Cooper, 2017). These extensions could employ the latent variable scores obtained from PLS-SEM as variables in longitudinal studies or multilevel models. In addition, future research could consider PLS-SEM's predictive abilities in combination with simulation models. Initial research in this direction has introduced new predictive evaluation criteria (Shmueli et al., 2016, Sharma, Sarstedt, Shmueli, Thiele and Kim, 2017) and uses PLS-SEM outcomes to initialize agent-based simulations (Schubring, Lorscheid, Meyer and Ringle, 2016).

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FIGURES

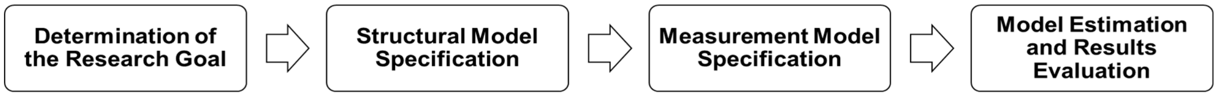
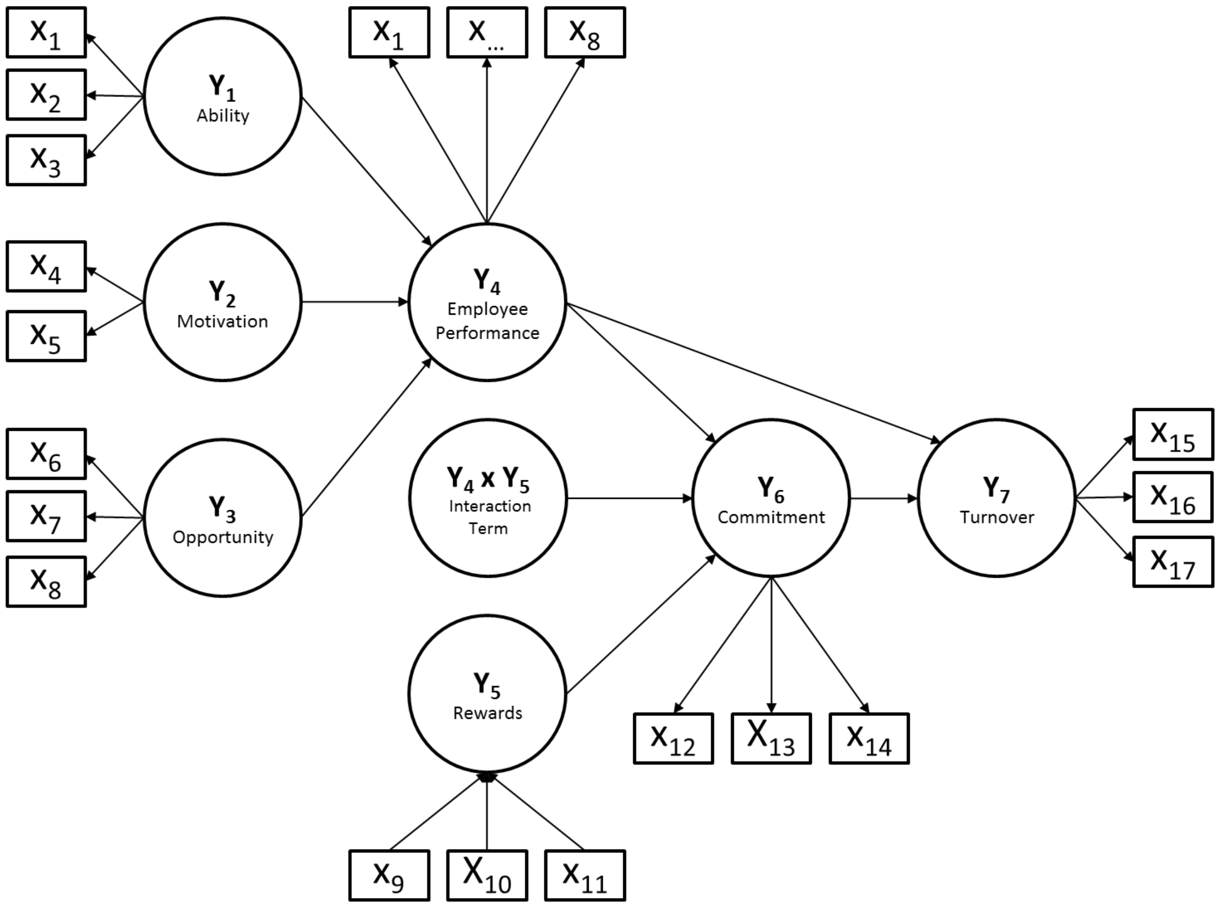


Figure 1: PLS-SEM analysis process.



Note: The measurement model of the interaction term Y_4 x Y_5 has been excluded for clarity purposes.

Figure 2: PLS path model example.

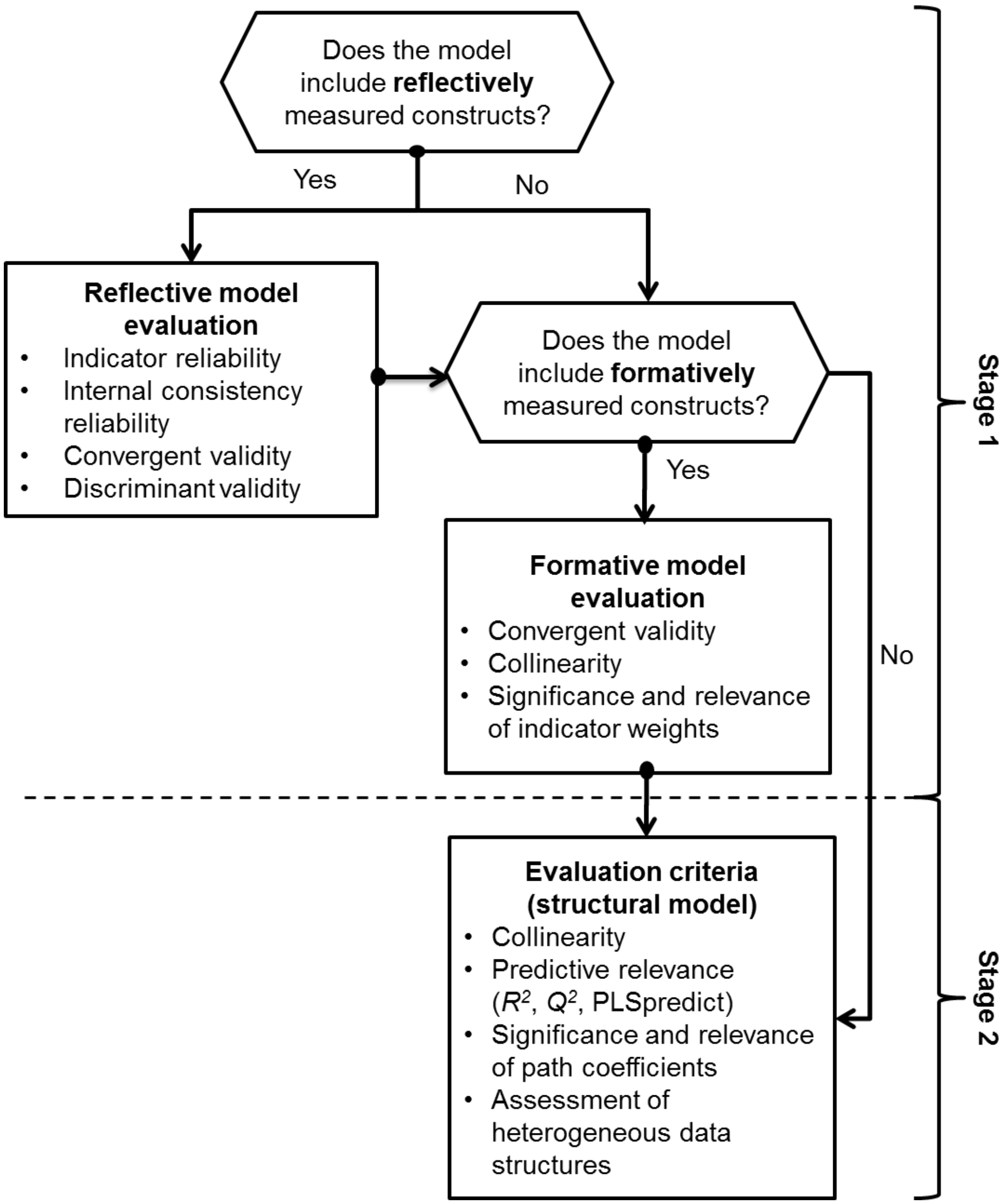


Figure 3: PLS-SEM evaluation guideline (adapted from Sarstedt et al., 2014).

TABLES

Table 1: Model characteristics.

Criterion	Results (n=114)	Proportion (%)
Number of latent variables		
Mean	7.80	-
Median	7.00	
Range	(3; 32)	
Number of structural model path relations		
Mean	8.76	-
Median	7.00	
Range	(2; 30)	
Mode of measurement models		
Only reflective	47	41.23
Only formative	0	0.00
Reflective and formative	49	42.98
Not specified	18	15.79
Number of indicators per reflective construct[1, 2]		
Mean	4.52	-
Median	4.00	
Range	(1; 36)	
Number of indicators per formative construct[2, 3]		
Mean	4.30	-
Median	4.00	
Range	(1; 13)	
Total number of indicators in models[2]		
Mean	34.97	-
Median	26.00	
Range	(7; 161)	
Number of models with single-item constructs	87	76.32
Mediating effects	9	7.89
Interaction effects	26	22.81
Higher-order models	6	5.26

[1] Includes only models with reflective indicators.[2] Constructs with product indicator measurement models from computing interaction effects with more than 100 indicators have been excluded from the analysis.[3] Includes only models with formative indicators.

Table 2: Evaluation of measurement models.

Panel A: Reflective measurement models

	Empirical test criterion in PLS-SEM	Number of models reporting (n=96)	Proportion reporting (%)
Indicator reliability	Indicator loadings	73	76.04
Internal consistency reliability	Only composite reliability	36	37.50
	Only Cronbach's alpha	13	13.54
	Both	31	32.29
Convergent validity	AVE	75	78.13
	Other	2	0.02
Discriminant validity	Only Fornell-Larcker criterion	42	43.75
	Only cross-loadings	3	0.03
	Cross-loadings and Fornell-Larcker criterion	15	15.62
	Other	1	0.01

Panel B: Formative measurement models

	Empirical test criterion in PLS-SEM	Number of models reporting (n=49)	Proportion reporting (%)
-	Reflective criteria used to evaluate formative constructs	32	65.31
Indicator's absolute contribution to the construct	Indicator weights	9	18.37
Significance of weights	Standard errors, significance levels, t values/p values for indicator weights	10	20.41
Collinearity	Only VIF/tolerance	8	16.33
	Only condition index	0	0.00
	Both	1	2.04
Convergent validity	Redundancy analysis	0	0.00

Table 3: Evaluation of structural models.

Criterion	Empirical test criterion in PLS-SEM	Number of models reporting (n=114)	Proportion reporting (%)
Endogenous constructs' explained variance	R^2	94	82.46
Effect size	f^2	6	5.26
Predictive relevance	Cross-validated redundancy Q^2	8	7.02
Relative predicted relevance	q^2	0	0.00
Overall goodness-of-fit	GoF	8	7.02
Path coefficients	Absolute values	114	100.00
Significance of path coefficients	Standard errors, significance levels, *t* values, *p* values	113	99.12
Confidence intervals	-	5	4.39
Total effects	-	6	5.26
Criterion	**Empirical test criterion in PLS-SEM**	**Number of studies reporting (n=62)**	**Proportion reporting (%)**
Heterogeneity	Multigroup analysis	19	24.68
	Response-based segmentation techniques (e.g., FIMIX-PLS)	0	0.00

ONLINE APPENDIX

Table OA1: List of analyzed journals.

Asia Pacific Journal of Human Resources	Journal of Industrial Relations
Asia Pacific Journal of Management	Journal of Institutional and Theoretical Economics
British Journal of Industrial Relations	Journal of Labor Economics
Economic and Industrial Democracy	Journal of Labor Research
Employee Relations	Journal of Law, Economics and Organization
European Journal of Industrial Relations	Journal of Management Studies
European Journal of Work and Organizational Psychology	Journal of Organizational Behavior
Gender, Work and Organization	Journal of Vocational Behavior
Group and Organization Management	Labor Studies Journal
Human Performance	Leadership Quarterly
Human Relations	Monthly Labor Review
Human Resource Management (US)	New Technology, Work and Employment
Human Resource Management Journal (UK)	Organization
Human Resource Management Review	Organization Science
Industrial and Labor Relations Review	Organization Studies
Industrial Relations Journal	Organizational Behavior and Human Decision Processes
Industrial Relations: A Journal of Economy and Society	Organizational Behavior and Human Performance
International Journal of Human Resource Management	Organizational Dynamics
International Journal of Manpower	Personnel Psychology
International Journal of Selection and Assessment	Personnel Review
International Labour Review	Public Personnel Management
Journal of Applied Behavioral Science	Research in Organizational Behavior
Journal of Applied Psychology	Research in the Sociology of Organizations
Journal of Economic Behavior and Organization	Sociologie du Travail
Journal of Human Resources	Work and Occupations
	Work, Employment and Society

Table OA2: Analyzed PLS-SEM applications in HRM studies.

Asia Pacific Journal of Management
Li and Chen 2012

Employee Relations
Eskildsen, Kristensen and Westlund 2004

European Journal of Work and Organizational Psychology
Van der Heijden, Schepers and Nijssen 2011

Group & Organization Management
Chi and Huang 2014
Howell and Shea 2006
Jae, Litzky et al 2012
Jung and Sosik 2003
Kahai, Sosik and Avolio 2004
Sosik, Jung & Dinger 2009
Yagil and Luria 2010
Kahai, Huang and Jestice 2012

Human Performance
Potosky and Ramakrishna 2002

Human Relations
Kang, Yang and Rowley 2006
Mitchell, Parker and Giles 2011
Mitchell et al. 2014

Human Resource Management Journal
Buonocore and Russo 2012
Brunetto et al. 2012

Human Resource Management (US)
Braunscheidel, Suresh and Boisner 2010
Minbaeva, Makela and Rabbiosi 2012
Mitchell, Obeidat and Bray 2013
Schmelter, Mauer et al 2012
Teo and Rodwell 2007

International Journal of Human Resource Management
Baluch, Salge and Piening 2013
Brunettoa, Shacklock, Teo and Farr-Wharton 2014
Buonocore and Russo 2013
Ceylan 2013
De Guinea and Webster 2012
Dögl and Holtbrügge 2014
Hartmann and Stapnicar 2012
Jayawardanaa, O'Donnell and Jayakody 2013
Lia, Alama and Meonskea 2013
Matzler, Renzi et al 2011
Rodwell and Teo 2008
Teo, LeClerc and Galang 2011

International Journal of Manpower
Gil-Marques and Moreno-Luzon 2013
Triguero-Sánchez, Peña-Vinces and Sánchez-Apellániz 2013
Wensley, Cegarra-Navarro et al 2011

International Journal of Selection and Assessment
Konradt, Warszta and Ellwart 2013

Journal of Applied Psychology
Duxbury and Higgins 1991

Journal of Management Studies
Bjorkman 2012
van Riel, Berens and Dijkstra 2009

Journal of Organizational Behavior
Berson and Oreg 2008
Choi and Sy 2010
Higgins and Duxbury 1992
Zhao 2011

Journal of Vocational Behavior
Waters 2004

Leadership Quarterly
Berson, Shamir, Avolio and Popper 2001
Cho and Dansereau 2010
Howell and Boies 2004
Howell, Neufeld and Avolio 2005
Jung, Wu and Chow 2008
Jung, Chow and Wu 2003
Nemanich and Vera 2009
Palanski and Yammarino 2011
Palrecha, Spangler and Yammarino 2012
Sosik and Dworakivsky 1998
Sosik 2005
Sosik, Avolio and Jung 2002
Sosik and Godshalk 2000
Sosik and Dinger 2007
Spangler, Gupta et al 2012
Wofford, Goodwin and Whittington 1998

New Technology, Work and Employment
Bayo-Moriones, and Bello-Pi 2010

Organizational Behavior and Human Decision Processes
Cron, Gilly, Graham and Slocum 2009
Higgins, Duxbury and Irving 1992

Organization Science
Jarvenpaa and Majchzak 2008
Milberg, Smith and Burke 2000
Nambisan and Baron 2010
Purvis, Sambamurthy and Zmud 2001
Staples, Hulland and Higgins 1999

Organization Studies
Lui 2009
Wiertz and de Ruyter 2007

Personnel Psychology
Kahai, Sosik and Avolio 1997
Plouffe and Gregoire 2011

Personnel Review
Lopez-Carbrales, Real and Valle 2011
Rabl 2010
Urtasun and Nunez 2012

Table OA3: Reasons for using PLS-SEM

	Number of studies reporting (n=77)	**Proportion (%)**
Total number of studies that give reasons for using PLS-SEM given	65	84.42
Specific reasons for using PLS-SEM given in studies		
Small sample size	51	66.23
Non-normal data	33	42.86
Theory development	20	25.97
Use of categorical variables	15	19.48
Formative measures	14	18.18
Focus on prediction	12	15.58
Theory testing	12	15.58
Exploratory research	9	11.69
Dependent observations	9	11.69
Model complexity	8	10.39
Latent variable scores	3	3.90
Convergence ensured	1	1.30

Note: The total of the percentages exceeds 100 percent because various studies mention multiple reasons for the use of PLS-SEM.

Table OA4: Descriptive statistics for data characteristics

	Number of models (n=114)	Proportion (%)
Sample size[1]		
Mean[2]	142.5	
Median	145.00	
Range	(6; 9,623)	
Less than 100 observations	38	33.33
Ten times rule of thumb not met	12	10.53
If not met, how many percentage points below?	52.76	
Holdout sample used	0	0.00
Skewness / kurtosis	0	0.00

[1] In four models, no sample size was given; [2] 5% trimmed mean

Table OA5: Reporting

	Number of studies reporting (n=77)	Proportion reporting (%)
Software specified	42	54.54
PLS Graph	20	26.00
SmartPLS	19	24.70
VisualPLS	1	1.30
..PLS-GUI	1	1.30
XLSTAT	1	1.30
Resampling method		
Use mentioned	69	89.61
Type mentioned	51	66.23
Parameter settings	15	19.48
Covariance/correlation matrix	68	88.31