Testing measurement invariance of composites using partial least squares

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Abstract

Purpose – Research on international marketing usually involves comparing different groups of respondents. When using structural equation modeling (SEM), group comparisons can be misleading unless researchers establish the invariance of their measures. While methods have been proposed to analyze measurement invariance in common factor models, research lacks an approach in respect of composite models. The purpose of this paper is to present a novel three-step procedure to analyze the measurement invariance of composite models (MICOM) when using variance-based SEM, such as partial least squares (PLS) path modeling.
Design/methodology/approach – A simulation study allows us to assess the suitability of the MICOM procedure to analyze the measurement invariance in PLS applications.
Findings – The MICOM procedure appropriately identifies no, partial, and full measurement invariance.
Research limitations/implications – The statistical power of the proposed tests requires further research, and researchers using the MICOM procedure should take potential type-II errors into account.
Originality/value – The research presents a novel procedure to assess the measurement invariance in the context of composite models. Researchers in international marketing and other disciplines need to conduct this kind of assessment before undertaking multigroup analyses. They can use MICOM procedure as a standard means to assess the measurement invariance.

Keywords Methodology, Structural equation modelling, Measurement, Measurement invariance, Partial least squares, MICOM, Multigroup, Variance-based SEM, Composite models, Permutation test, Path modelling

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Introduction

Variance-based structural equation modeling (SEM) using the partial least squares (PLS) method is a key multivariate statistical technique to estimate cause-effect relationships between constructs in international marketing research (Hair *et al.*, 2012b;

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Henseler *et al.*, 2009). Many studies using PLS engage in comparisons of model estimation results across different groups of respondents (Okazaki *et al.*, 2007). For example, Brettel *et al.* (2008) compare antecedents of market orientation across three countries. Similarly, Singh *et al.* (2006) analyze international consumers' acceptance and use of websites designed specifically for different countries. Such multigroup comparisons require establishing measurement invariance to ensure the validity of outcomes and conclusions (Millsap, 2011).

Over the last decades, research suggested a wide array of methods to assess various aspects of measurement invariance (e.g. Jong *et al.*, 2007; Meade and Lautenschlager, 2004; Morris and Pavett, 1992; Raju *et al.*, 2002; Raykov and Calantone, 2014; Salzberger and Sinkovics, 2006). While these methods have undisputed value for assessing measurement invariance in international marketing research and related fields, their applicability is limited to common factor models as implied by reflective measurement. However, researchers frequently follow a different philosophy of measurement referred to as composite models. Composite models are the dominant measurement model of variance-based SEM (Henseler *et al.*, 2014; Sarstedt *et al.*, 2014). Unfortunately, the well-established measurement invariance techniques for common factor models cannot be readily transferred to composite models. This issue leaves researchers in international marketing without a procedure to assess the measurement invariance of composite models (MICOM). Since variance-based SEM, especially using PLS (Hair *et al.*, 2017; Lohmöller, 1989; Wold, 1982), recently experienced widespread dissemination in international marketing (Henseler *et al.*, 2009), marketing in general (Hair *et al.*, 2017), and different management disciplines (e.g. Hair *et al.*, 2012a; Ringle *et al.*, 2012; Sarstedt *et al.*, 2014), this gap in prior research needs urgent attention.

Building on recent literature on the nature of composite models generally (Henseler, 2012; Hwang and Takane, 2004) and PLS specifically (Henseler *et al.*, 2014; Rigdon, 2014), this paper introduces a novel procedure to measurement invariance assessment in composite modeling, which contrasts group-specific measurement model estimates with those obtained from a model estimation using pooled data. We introduce a three-step procedure that consists of the following elements: configural invariance; compositional invariance; and the equality of composite mean values and variances. Using simulated and empirical data, we illustrate the procedure's efficacy for invariance assessment in the context of PLS.

The remainder of the paper is organized as follows: we first characterize the distinction between common factors and composites before addressing the need to assess the composite model's measurement invariance when conducting a multigroup analysis. In light of the shortcomings of existing approaches, we develop a novel procedure for assessing measurement invariance in the context of composite models. Next, we reveal the capabilities of the MICOM procedure by running a simulation study. After this validation of MICOM's performance, we apply the procedure in an empirical example. The paper closes with our conclusions and an overview of possible future research opportunities.

Three types of measurement models: common factors, composites, and causal indicators

When researchers aim to measure latent variables using multiple indicators, they have several options. In the context of SEM, particularly three types of measurement models are discussed (Bollen, 2011): common factor models (reflective measurement), causal indicator models (formative measurement), and composite models. Figure 1 is a schematic representation of the three models.

Reflective measurement models are based on the assumption that a latent variable equals the common factor underlying a set of observed variables (indicators). Common factors in SEM entail a causality direction from construct to its measure (Bollen, 1989). The indicators of a reflective measurement model are considered to be error-prone manifestations of a latent (unobserved) variable. The relationship between an observed and an unobserved variable is usually modeled as expressed in the following equation:

$$x = \lambda \cdot \xi + \varepsilon, \tag{1}$$

where x is the observed indicator variable; ξ is the latent variable, the loading λ is a regression coefficient quantifying the strength of the relationship between x and ξ; and ε represents the random measurement error. One expects correlated indicators, and the common factor represents the shared variance of the indicators. Dropping one of multiple indicators in a reflective measurement model would not alter the meaning of the common factor (Jarvis *et al.*, 2003). Consistent versions of variance-based SEM are required to obtain consistent estimates for reflective measurement models (Dijkstra, 2014; Dijkstra and Henseler, 2015a, b).

Not all concepts are operationalized using reflective indicators. Specifically, a latent variable can also be operationalized using relationships from the indicators to the latent variable (Figure 1). Blalock (1964) was the first to introduce the distinction between what he called the effect (i.e. reflective) and the causal indicators to social science research. This distinction was later adopted in the marketing discipline under the similar, yet different, formative indicators concept. Fornell and Bookstein (1982, p. 442) characterize the formative indicator concept as follows: "In contrast, when constructs are conceived as explanatory combinations of indicators (such as 'population change' or 'marketing mix') which are determined by a combination of variables, their indicators should be formative." Diamantopoulos and Winklhofer

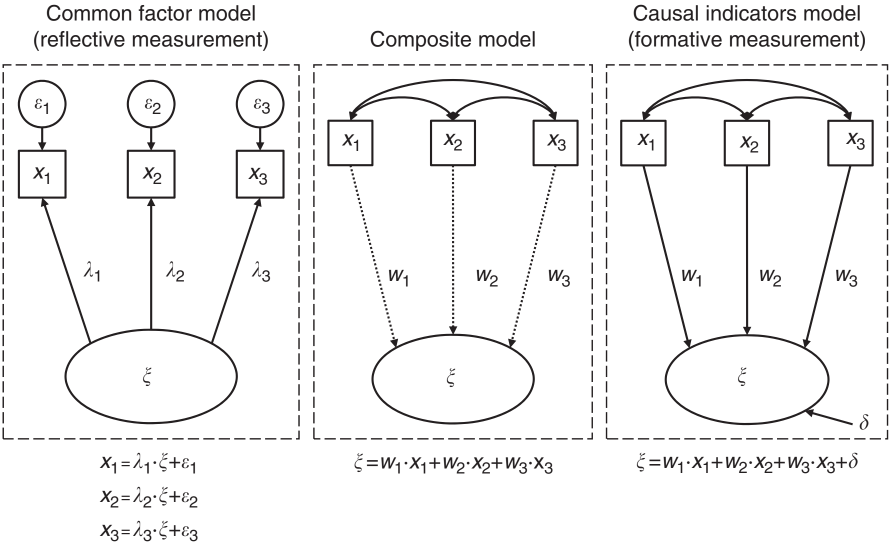

Figure 1.
Types of measurement

(2001) and Diamantopoulos *et al.* (2008) introduce formative measurement models in detail to SEM (also see Jarvis *et al.*, 2003). Besides the causality direction from the indicator to the construct, they do not require correlated indicators. If researchers dropped an indicator from a formative measurement model, they would remove content, which would change the meaning of the construct. Causal indicators in formative measurement models do not form the latent variable, as the name might imply, but "cause" it. Consequently, causal indicators must correspond to a theoretical definition of the concept under investigation. Therefore, latent variables measured with causal indicators have an error term (Figure 1) that captures all the other causes of the latent variable not included in the model (Diamantopoulos, 2006). Equation 2 represents a measurement model comprising causal indicators, where w_i indicates the contribution of x_i $(i = 1, \ldots, I)$ to ξ, and δ is an error term:

$$\xi = \sum_{i=1}^{I} w_i \cdot x_i + \delta. \tag{2}$$

Composite models strongly resemble formative measurement models, except for a small detail. In contrast to formative measurement models, composite models do not contain an error term on the level of the latent variable (Figure 1). This subtle distinction has important implications for the characterization of composite models (Henseler *et al.*, 2014). First, formative indicators operate as contributors to a composite variable. They form the composite fully by means of linear combinations, thereby ensuring that the composite has no error term. Psychometric literature thus refers to composite rather than formative indicators (Bollen, 2011; Bollen and Bauldry, 2011). The resulting composite variable may be a proxy for a latent concept (Rigdon, 2012), but the indicators do not necessarily need to be conceptually united. There are several ways to interpret composite models (i.e. models with composite variables). Some authors regard composite models as a useful tool to create new entities, which allow for capturing systems, compounds, and other constructs comprising various components (Rigdon, 2014). Others understand these models as a prescription for dimension reduction, where the aim is to condense the data so that it reflects a concept's salient features adequately (Dijkstra and Henseler, 2011). Equation 3 illustrates a measurement model with composite indicators, where C is a linear combination of indicators x_i $(i = 1,\ldots,I)$, each weighted by an indicator weight w_i $(i = 1,\ldots,I)$ (Rigdon, 2012):

$$C = \sum_{i=1}^{I} w_i \cdot x_i. \tag{3}$$

All variance-based SEM techniques model latent variables as composites; that is, they create proxies as linear combinations of indicator variables. In particular, no matter which outer weighting scheme is used in PLS (Mode A or Mode B), the resulting latent variable is always modeled as a composite (Henseler, 2010).

Scholars have started questioning the default application of reflective common factor models in SEM (e.g. Jarvis *et al.*, 2003). They emphasize that the composite model perspective offers a more general and potentially more realistic measurement approach, especially when considering formative measurement (Rigdon, 2012, 2014). The composite model relaxes the strong assumption that a common factor explains all the covariation between a block of indicators (i.e. there is no reason that researchers need to expect correlated indicators). Hence, the composite model does not impose any restrictions on the covariances between the same construct indicators. Linear combinations with predefined or estimated weights determine the composite that results from its underlying indicators. These linear combinations serve as proxies for the scientific concept under investigation (Henseler *et al.*, 2014). Consequently, dropping an indicator from the measurement model usually alters the meaning of the composite. Moreover, measures of internal consistency reliability only make sense if the composite approximates a reflective construct. Table I summarizes the conceptual differences between reflective, composite, and causal indicators.

On the need of a procedure for measurement invariance assessment of composite models

Measurement invariance is a crucial issue that researchers must address in multigroup SEM analyses. Measurement invariance refers to "whether or not, under different conditions of observing and studying phenomena, measurement operations yield measures of the same attribute" (Horn and McArdle, 1992, p. 117). By establishing measurement invariance, researchers ensure that dissimilar group-specific model estimations do not result from distinctive content and the meanings of the latent variables across groups. For example, variations in the structural relationships between latent variables could stem from different meanings that the alternative groups' respondents attribute to the phenomena, rather than the true differences in the structural relations. Similarly, cross-national differences might emerge from culture-specific response styles (e.g. Johnson *et al.*, 2005), such as acquiescence (i.e. different tendencies regarding agreeing with questions regardless of the question's content; Sarstedt and Mooi, 2014). Summarizing these and similar concerns, Hult *et al.* (2008, p. 1028) conclude that "failure to establish data equivalence is a potential source of measurement error (i.e. discrepancies of what is intended to be measured and what is actually measured), which accentuates the precision of estimators, reduces the power of statistical tests of hypotheses, and provides misleading results." A lack of evidence of measurement invariance casts doubt on any conclusions based on the corresponding measures. Measurement invariance is a necessary but not sufficient requirement for multigroup SEM analyses. Ensuring the validity of latent variables, for instance, by content, criterion, construct, convergent, and discriminant validity assessments in SEM (e.g. Bollen, 1989), remains a requirement for all group-specific model estimations.

Over the last decades, for common factor models in SEM, researchers suggested a wide array of methods to assess various aspects of measurement invariance (e.g. Jong *et al.*, 2007; Meade and Lautenschlager, 2004; Meredith, 1993; Millsap, 2011; Morris and Pavett, 1992; Raju *et al.*, 2002; Raykov and Calantone, 2014; Salzberger and Sinkovics, 2006). Multigroup confirmatory factor analysis (CFA) is by far the most common

Table I. Overview of conceptual differences between three types of measurement models

Characteristic	Common factor model	Composite model	Causal indicators model
Error term on the indicator level	Yes	No	No
Error term on the latent variable level	No	No	Yes
Indicators fully form the composite	No	Yes	No

approach to invariance assessment, as evidenced by the scientific impact of the guiding articles on invariance assessment by Steenkamp and Baumgartner (1998) and Vandenberg and Lance (2000). Hence, for many researchers, invariance assessment is equivalent to running a series of model comparisons with increasingly restrictive constraints within a CFA-based framework. Studies that conduct multigroup SEM analysis (e.g. in an international and cross-cultural context) usually distinguish between the following invariance levels (for more details about the levels, see, e.g. Steenkamp and Baumgartner, 1998; Steinmetz *et al.*, 2009; Vandenberg and Lance, 2000): first, configural invariance, which requires that the same basic factor structure exists in all the groups (in terms of number of constructs and items associated with each construct); second, metric invariance to ensure that item loadings are invariant across groups; third, scalar invariance to safeguard the equality of measurement intercepts (i.e. intercepts of like items' regressions on the construct); and fourth, error variance invariance, which tests the amount of the items' measurement error and the extent to which measurement errors are equivalent across groups.

Once configural invariance has been established, further measurement invariance assessments focus primarily on the systematic error of the measures. Such systematic errors might result from group-specific response styles (e.g. extreme response styles, acquiescence) and come in two forms. First, indicator loadings might differ across the groups, which implies that the constructs have different meanings in each group. Only if loadings of like items are invariant across the groups (i.e. metric invariance is being established), can differences in the item scores be meaningfully compared in that they are indicative of similar group differences in the underlying construct (Steenkamp and Baumgartner, 1998). Second, measurement intercepts may differ across the groups, which contradicts mean comparisons across them. Such comparisons are only meaningful if the scalar invariance of the items holds. Scalar invariance implies that group differences in the mean values of the observed items are due to differences in those of the underlying construct (Steenkamp and Baumgartner, 1998). Finally, the invariance assessment may also focus on the random error. Most types of measurement and structural model comparisons do not require establishing the error variance invariance, which is therefore generally neglected in SEM (Hair *et al.*, 2010).

If the analyses and tests on different required levels do not support full measurement invariance, applied research typically focusses on the at least partial fulfillment of measurement invariance (Hair *et al.*, 2010). In case of partial metric and/or scalar measurement invariance, at least two indicators of a construct must have equal loadings and/or intercepts across groups (e.g. Steenkamp and Baumgartner, 1998). Partial metric and/or scalar measurement invariance allows researchers to at least compare the group-specific (standardized) coefficients of the relationships in the structural model. Otherwise, when less than two items per latent variable have equal loadings and/or intercepts, multigroup comparisons in SEM may be problematic.

When conducting multigroup comparisons in international marketing research and related fields, assessing measurement invariance usually builds on the step-wise analyses previously described. These analyses have been solely proposed for common factor models in SEM. Since composite models are conceptually different, existing measurement invariance assessment procedures do not apply to composite models (similarly, reflective measurement model assessment criteria do not apply to formative measurement models; Diamantopoulos and Winklhofer, 2001). Researchers have overlooked this important aspect for a long time, despite the increasing popularity of variance-based SEM using composite models.

Although there is a requirement to develop approaches to assess the measurement invariance of composites, extant advances in this direction must be regarded as limited or incomplete at best. In an initial approach, Hsieh *et al.* (2008) aimed at ensuring that the way a composite was formed in two groups does not influence the multigroup comparison of variance-based SEM results. For this purpose, the authors used the first group's weight estimates to compute the composite scores of the second, and vice versa. They demonstrated that the choice of weights hardly affected the structural results in their application, which is a typical phenomenon for composites (Dijkstra and Henseler, 2011). Hsieh *et al.*'s (2008) approach assists researchers in gaining additional confidence that a lack of measurement invariance does not confound their multigroup comparisons in variance-based SEM. However, they only address the issue of compositional invariance, while other sources of measurement invariance may also be relevant for composite models (e.g. configural invariance). Moreover, they do not present a statistical test, which researchers require to draw their conclusions. In contrast, Ringle *et al.* (2011) used PLS in combination with the bootstrap method (Davison and Hinkley, 1997; Hair *et al.*, 2017) to obtain inference statistics for the correlations between constructs and indicators. Relying on the bootstrap confidence intervals, Ringle *et al.* (2011) conducted a series of tests, which provided an assessment of the measurement invariance. An obvious caveat against this approach is the potential multiple testing error. The more indicators a composite has, the larger this risk becomes. Moreover, this approach ignores the role of different inter-item correlations, and it is only indirectly linked to the composite's formation. Money *et al.* (2012) implemented a combination of both approaches, using PLS and the bootstrap method to infer whether two composites using the same indicators, but different weights, have a correlation of less than one. Their approach's disadvantage is that it is limited to equal-sized groups. Apart from these conceptual concerns, none of these approaches have yet formally demonstrated (e.g. by means of simulated data) that they hold. Moreover, none of these approaches can be regarded as a complete framework comparable in rigor to those developed for common factor models.

In a wider context, Diamantopoulos and Papadopoulos (2010) introduced guidelines for assessing the measurement invariance in causal indicator models. The authors propose assessing three types of invariance for SEM with causal indicators[1]. First, structure invariance refers to the extent to which the same pattern of salient (non-zero) indicator weights defines the structure of the formative measure in different groups. In respect of this type – the weakest form of invariance – Diamantopoulos and Papadopoulos (2010, p. 362) note, "the absence of structure invariance essentially means that the very nature of the construct is different across countries." Second, slope invariance refers to the extent to which each indicator's contribution is equal across the groups. This kind of invariance implies that a certain indicator influences the composite variable equally in each group. Third, residual invariance refers to the extent to which the variance of the error term is similar across the groups.

Diamantopoulos and Papadopoulos's (2010) procedure requires estimating a baseline multiple-indicators-multiple-causes model (Jöreskog and Goldberger, 1975) to ensure that the formative measurement model is identified, after which a set of equality constraints is introduced. As such, their approach – analogous to classic CFA-based approaches – follows the common factor model logic. As composite models are subject to different conceptual characteristics, Diamantopoulos and Papadopoulos's (2010) approach to invariance assessment cannot be universally transferred to composite models. For example, the concept of residual invariance is not applicable to composite models, as the composite variable has, by definition, no error term. In addition, since composite indicators do not correspond to a predefined concept, but define it, the comparison of the indicator weights must go beyond the assessment of the slope invariance. More specifically, the invariance assessment should ensure that the way the composite is formed does not differ across the groups. In this regard, two issues may negatively affect composite models' measurement invariance (see Equation (3)). First, the composite constituents can differ. Composite indicators can have different meanings and/or different magnitudes, as expressed, for instance, by the location and the dispersion parameters. Second, analogous to the slope invariance of causal indicators, the set of weights can differ across the groups. If the composites are formed differently across the groups, the interpretation of multigroup comparisons becomes blurred.

For these reasons, the measurement invariance assessment of composite models requires its own procedure. In line with prior research (e.g. Steenkamp and Baumgartner, 1998; Steinmetz *et al.*, 2009; Vandenberg and Lance, 2000), this procedure needs to address elements (or levels) that are relevant for establishing measurement invariance. At the same time, the procedure must fit the conceptual characteristics of the composite model. Hence, we develop the three-step MICOM procedure that involves the assessment of configural invariance (i.e. equal parameterization and way of estimation), compositional invariance (i.e. equal indicator weights), and the equality of a composite's mean value and variance across groups. In the next section, we introduce the MICOM procedure in detail assure measurement invariance of composites.

A three-step procedure to assess measurement invariance of composites

Overview

We designed the MICOM procedure to comply fully with the nature of composite models, as well as resemble extant procedures as far as possible. Since variance-based SEM techniques typically do not make distributional assumptions (Hair *et al.*, 2017; Lohmöller, 1989; Wold, 1982), our procedure builds on non-parametric tests. The MICOM procedure comprises three steps: (1) configural invariance, (2) compositional invariance, and (3) the equality of composite mean values and variances. The three steps are hierarchically interrelated, as displayed in Figure 2. Research should only continue with the next step, if the previous step's analyses support measurement invariance.

Configural invariance is a precondition for compositional invariance, which is again a precondition for meaningfully assessing the equality of composite mean values and variances. Researchers must establish the configural (Step 1) and compositional (Step 2)

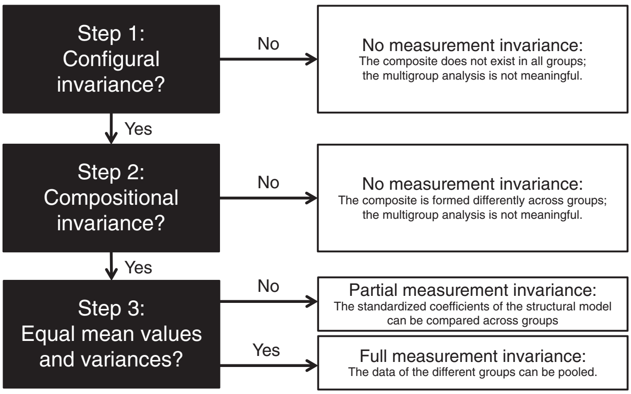

Figure 2.
The MICOM procedure

invariance in order to appropriately compare the standardized path coefficient estimates of the structural relationships between the composites across the groups. If configural and compositional invariance are established, we can speak of partial measurement invariance; otherwise, no measurement invariance is established.

If partial measurement invariance is established and the composites have equal mean values and variances (Step 3) across the groups, we can speak of full measurement invariance. In that case, researchers can pool the data of different groups, but they must still take into account possible structural model differences. Pooling the data into one larger dataset is an attractive option, because it can increase the statistical power and generalizability of the model in question. For instance, it can very well be that a structural relationship between two composites does not turn out to be significant if analyzed separately per group, but it does become significant when the pooled dataset is analyzed. Even though pooling the data is advantageous from a statistical power perspective, researchers who analyze the data on the aggregate level must not disregard potential (observed or unobserved) heterogeneity in the structural model (see Becker *et al.*, 2013; Jedidi *et al.*, 1997). When using pooled data, researchers can account for potential structural heterogeneity by including interaction effects that serve as moderators (Henseler and Fassott, 2010). In the following subsections, we present each of the three steps in detail.

Step 1: configural invariance

Configural invariance entails that a composite, which has been specified equally for all the groups, emerges as a unidimensional entity in the same nomological net across all the groups. The assessment of configural invariance must therefore consist of a qualitative assessment of the composites' specification across all the groups. Specifically, the following criteria must be fulfilled:

- Identical indicators per measurement model: each measurement model must employ the same indicators across the groups. Checking if exactly the same indicators apply to all the groups seems rather simple. However, in cross-cultural research, the application of good empirical research practices (e.g. translation and back-translation) is of the utmost importance to establish the indicators' equivalence. In this context, an assessment of the face and/or expert validity (see Hair *et al.*, 2017) can help verify whether the researcher used the same set of indicators across the groups. At this stage, the significance of the indicator weights is irrelevant, because differences in their significance (an indicator may be significant in one group, but not in another) do not imply that the coefficients differ significantly (Gelman and Stern, 2006).
- Identical data treatment: the indicators' data treatment must be identical across all the groups, which includes the coding (e.g. dummy coding), reverse coding, and other forms of re-coding, as well as the data handling (e.g. standardization or missing value treatment). Outliers should be detected and treated similarly.
- Identical algorithm settings or optimization criteria: variance-based model estimation methods, such as PLS consist of many variants with different target functions and algorithm settings (e.g. choice of initial outer weights and the inner model weighting scheme; Hair *et al.*, 2012b; Henseler *et al.*, 2009). Researchers must ensure that differences in the group-specific model estimations do not result from dissimilar algorithm settings.

Configural invariance is a necessary but not sufficient condition for drawing valid conclusions from multigroup analyses. Researchers also must ensure that differences in structural coefficients do not result from differences in the way the composite is formed. The next step, compositional invariance, therefore focusses on analyzing whether a composite is formed equally across the groups.

Step 2: compositional invariance

Compositional invariance means that the prescription for condensing the indicator variables into composites is the same for all groups (for dimension reduction, see Dijkstra and Henseler, 2011). This invariance type is established when a composite's scores are created equally across groups. A simple way to achieve compositional invariance is to use fixed indicator weights, for instance unit weights resulting in sum scores. In this case, compositional invariance is ensured by design. In other cases, when the indicator weights are estimated per group, it is indispensable to ensure that – despite possible differences in the weights – the scores of a composite remain the same.

Let c be the correlation between the composite scores using the weights as obtained from the first group ($\xi^{(1)}$) and the composite scores using the weights as obtained from the second group ($\xi^{(2)}$):

$$c = \operatorname{cor}\left(\xi^{(1)}, \xi^{(2)}\right) = \operatorname{cor}\left(\mathbf{X}w^{(1)}, \mathbf{X}w^{(2)}\right). \quad (4)$$

In this equation, $\xi^{(k)}$ are the composite scores using the indicator weight vectors $w^{(k)}$ as obtained from group k, and $\mathbf{X}$ is the matrix of pooled indicator data. Compositional invariance requires that c equals one. Accordingly, we postulate the following hypothesis:

H1. $c = 1$.

If c is significantly different from one, we must reject the hypothesis and conclude that there is no compositional invariance. In the opposite case, which supports compositional invariance, we can assume that the composite has been established similarly across the groups.

In order to statistically test for compositional invariance, we propose a permutation test over the correlation c. Just like the bootstrap, permutation tests are non-parametric. Permutation tests have already been proposed and applied for PLS multigroup comparisons (Chin and Dibbern, 2010), but their potential for assessing measurement invariance has been unrecognized. Based on the principles Edgington and Onghena (2007) described, the permutation test of compositional invariance builds on the random assignment of the observations to groups. For two groups with $n^{(1)}$ and $n^{(2)}$ observations, respectively, the procedure is as follows:

(1) The indicator weights are estimated for each group, using the PLS algorithm. We obtain the indicator weight vectors $w^{(1)}$ and $w^{(2)}$.

(2) We compute c, the correlation between the composite scores using $w^{(1)}$ and $w^{(2)}$ according to Equation (4).

(3) The data are randomly permuted a number of times, meaning that the observations are randomly assigned to the groups. In formal terms, $n^{(1)}$ observations are drawn without replacement from the pooled dataset and assigned to Group 1. The remaining observations are assigned to Group 2.

Thus, in each permutation run u ($u \in \{1, \ldots, U\}$), the group-specific sample size remains constant. In accordance with rules of thumb for non-parametric tests (e.g. Hair *et al.*, 2012b), we recommend a minimum of 5,000 permutation runs.

(4) For each permutation run u, the indicator weights are estimated for each group using the PLS path modeling algorithm, resulting in the indicator weight vectors $w_u^{(1)}$ and $w_u^{(2)}$.

(5) For each permutation run u, we compute c_u, the correlation between the composite scores using the weights as obtained from the first group and the composite scores using the weights as obtained from the second group of run u: $c_u = \text{cor}\left(\mathbf{X}w_u^{(1)}, \mathbf{X}w_u^{(2)}\right)$.

(6) We test the null hypothesis that c equals one. If c is smaller than the five percent-quantile of the empirical distribution of c_u, we must reject the hypothesis of compositional invariance, because the deviation from one is unlikely to stem from sampling variation.

Figure 3 depicts an example of the empirical distribution of c_u. If the value of c exceeds the five percent-quantile (dark filled area to the right), we assume compositional invariance. Notably, the position of the quantile depends – among other things – on the sample size of both groups. For very small sample sizes, a low value of c would still imply compositional invariance. If the study involves small sample sizes, then researchers should consider using fixed weights or apply Hsieh *et al.*'s (2008) procedure.

Step 3: equality of composite mean values and variances

While using a multigroup analysis requires establishing configural and compositional invariance, running analyses on the pooled data-level necessitates establishing the equality of the composites' mean values and variances (Step 3).

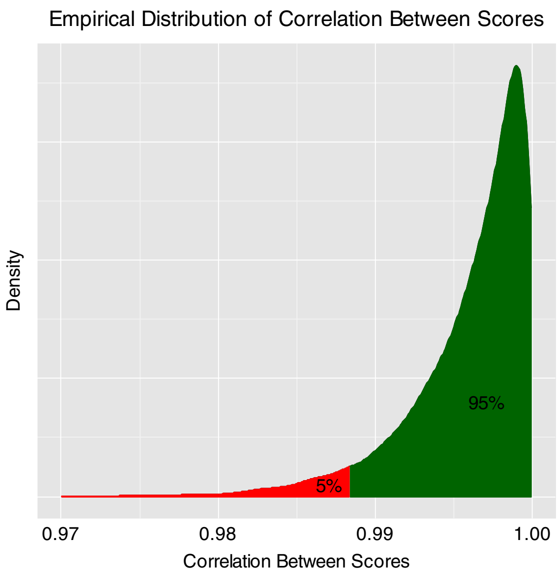

Figure 3.
Example of an empirical distribution of a correlation between scores resulting from permutation

Again, we rely on permutation as the statistical workhorse. First, we apply PLS to obtain construct scores, using the pooled data. We then examine whether the mean values and variances between the construct scores of the observations of the first group and the construct scores of the observations of the second group differ from each other. Full measurement invariance would imply that both differences equal zero (or are at least non-significant). Hence, we simply calculate the difference between the average construct scores of the observations of the first group ($\bar{\xi}^{(1)}_{\text{pooled}}$) and the average construct scores of the observations of the second group ($\bar{\xi}^{(2)}_{\text{pooled}}$). In accordance, for the mean values, we postulate the following hypothesis:

H2. $\bar{\xi}^{(1)}_{\text{pooled}} - \bar{\xi}^{(2)}_{\text{pooled}} = 0.$

Analyzing the equivalence of variances requires determining the logarithm of the variance ratio of the construct scores of the first group's observations and the variance of the construct scores of the second group's observations. If the logarithm of this ratio is zero (or at least non-significant), we conclude that a composite's variances across groups are equal. In line with these considerations, we formulate the following hypothesis:

H3. $\log\left(\text{var}\,\xi^{(1)}_{\text{pooled}} / \text{var}\,\xi^{(2)}_{\text{pooled}}\right) = \log\left(\text{var}\,\xi^{(1)}_{\text{pooled}}\right) - \log\left(\text{var}\,\xi^{(2)}_{\text{pooled}}\right) = 0.$

To test *H2* and *H3*, we then permute the observations' group membership many times, and generate the empirical distributions of the differences in mean values and logarithms of variances. If the confidence intervals of differences in mean values and logarithms of variances between the construct scores of the first and second group include zero, the researcher can assume that the composite mean values and variances are equal. In this case, full measurement invariance has been established, which facilitates the analysis on the pooled data level. In contrast, if the differences in mean values or logarithms of variances between the construct scores of the first and second are significantly different from zero, researchers must acknowledge that full measurement invariance cannot be established, and they should not pool the data.

If full measurement invariance has been established, it is in principle admissible to pool the data and benefit from the increase in statistical power. At this stage, researchers should pay attention to the structural invariance of their model. If multigroup analysis did not reveal any structural differences between the groups, researchers can pool the data right away. In contrast, if multigroup analysis provided evidence of structural differences between the groups, the model must be extended by including additional interaction terms that account for structural differences in the corresponding model relationships (e.g. Henseler and Fassott, 2010). That is, researchers must run a moderation analysis. Neglecting observed (or unobserved) heterogeneity in the structural model will negatively affect the validity of the path coefficients estimated by using the pooled data (Becker *et al.*, 2013).

MICOM illustration with simulated data

Motivation and setup

In variance-based SEM, simulation studies are well established to study the performance of algorithms (e.g. Reinartz *et al.*, 2009), segmentation techniques (e.g. Ringle *et al.*, 2014), segment retention criteria (e.g. Sarstedt *et al.*, 2011b), moderator analysis methods (e.g. Henseler and Chin, 2010), discriminant validity assessment procedures (e.g. Henseler *et al.*, 2015), and other purposes (e.g. Chin *et al.*, 2012; Goodhue *et al.*, 2012; Lu *et al.*, 2011). These simulation studies build on artificially generated data for a priori determined levels of relevant parameters. When using this data, the researcher can compare the model estimation results with the expected outcomes to assess the efficacy of a certain method.

In this initial assessment of the MICOM procedure, we use a simple population model and keep the number of factors (and their levels) as small as possible, but large enough to facilitate an illustration of how the procedure performs in different situations. The model, as shown in Figure 4, consists of an exogenous composite variable ξ_1 with two indicators, x_1 and x_2, and an endogenous construct ξ_2 with a single indicator y. For this model, we generate normally distributed data for two groups, with 100 (Group 1) and 300 (Group 2) observations, respectively[2].

The structural model coefficient β (for the relationship from ξ_1 to ξ_2) always has a pre-specified value of 0.6 in both groups. The correlation φ of the indicators x_1 and x_2 is fixed at 0.3125. In total, we generate data for seven multigroup analysis situations (Table II). While we identically create the data of Group 1 across the analyzed situations, we alter the outer weights, the mean value, and the standard deviation of the indicators x_1 and x_2 when generating the data for Group 2.

We used the PLS method (Hair *et al.*, 2017; Lohmöller, 1989; Wold, 1982) as implemented in the semPLS package (Monecke and Leisch, 2012) of the statistical software R (R Core Team, 2014) for the model estimations. PLS is regarded as the "most fully developed and general system" (McDonald, 1996, p. 240) of all variance-based SEM techniques and, as such, recently experienced widespread

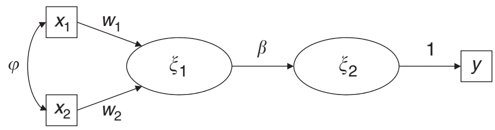

Figure 4.
Population model of the simulation

Situation 1	All indicators have a mean value of 0, a standard deviation of 1, and indicator weights w_1 and w_2 of 0.4 and 0.8, respectively. Thereby, the creation of composite ξ is equal in both groups
Situation 2	As in situation 1, but the mean value of indicator x_2 is increased by one unit in Group 2. This implies an inequality of composite means
Situation 3	As in situation 1, but the mean value of indicator x_2 is increased by one unit and the mean value of indicator x_1 is increased to 0.7027 in Group 2. The choice of these values is motivated by the fact that they imply an inequality of composite means without harming the compositional invariance
Situation 4	As in situation 1, but the standard deviation of indicator x_2 is doubled in Group 2. This implies an inequality of composite variances
Situation 5	As in situation 1, but the standard deviations of indicators x_1 and x_2 are doubled in Group 2. This implies an inequality of composite variances without harming the compositional invariance
Situation 6	As in situation 1, but the indicator weights are flipped; that is, the indicator weights become 0.8 and 0.4, respectively in Group 2. Essentially, the composite is created differently across groups, which implies a lack of compositional invariance
Situation 7	As in situation 6, but the standard deviation of indicator x_1 is decreased to a value of 0.9022. Despite the different indicator variances, we anticipate equal composite variances and means in combination with a lack of compositional invariance

Table II.
Different situations considered by the MICOM simulation study

dissemination in (international) marketing (Hair *et al.*, 2012b; Henseler *et al.*, 2009, 2012) and other. It fully supports the estimation of composite models (Henseler *et al.*, 2014).

Assessment of results

We created the model in such a way that it warrants configural invariance if researchers apply Step 1 of the three-step MICOM procedure. The assessment therefore focusses on answering the question whether the estimates satisfy the requirements of compositional invariance (Step 2) and equal composite mean values and variances (Step 3). Table III shows the results of our analyses. The first five columns summarize the data specifications of the seven situations considered. Thereafter, the table displays the results of the composite variable's ξ_1 measurement invariance assessment. The rightmost column contains the estimated value of the path coefficient β if pooled data were used.

A closer look at the results of each situation allows us to expose a more detailed picture. In Situation 1, besides the given establishment of the configural invariance (Step 1), the compositional invariance (Step 2), and the equality of the composite mean values and variances have been established (Step 3). We can therefore assume full measurement invariance of the composite across groups. Not surprisingly, pooling the data before conducting the analysis yields the pre-specified β value of 0.60; this value does not differ from the group-wise model estimations. Pooling the data in this situation allows establishing more general findings and conclusions.

In contrast, in Situation 2, the change of x_2's location parameter results in inequality of the composite's mean values across groups. Since the analysis meets MICOM's requirements of Step 2, researchers face a situation of at least partial measurement invariance, which permits multigroup comparison. However, the analysis of Step 3a reveals correctly that there are differences in mean values, which implies that full measurement invariance cannot be stablished. Estimating model parameters based on pooled data confirms this notion. The rightmost column demonstrates that if the data were pooled, one would obtain a slightly downward biased estimate of 0.5925 that deviates from the group-specific estimates of 0.60.

If, in Group 2, the location parameters of both indicators are changed to one (Situation 3), Step 3 in MICOM reveals that the composite's mean values are unequal across groups. In this situation, compositional invariance has been confirmed again, which means that we can assume partial measurement invariance. Therefore, researchers can carry out meaningful multigroup analyses by comparing the standardized coefficients in the structural model. The biased estimate in the rightmost column (0.5330 instead of 0.60) reinforces the notion that partial measurement invariance is not a sufficient criterion for pooling the data.

In Situation 4, the change in one indicator's dispersion parameter implies that the equality of the composite variances (Step 3) no longer hold. Here, the consequence equals that of Situation 3: partial measurement invariance can be established, which means that one can carry out multigroup analyses, whereas the data should not be pooled for analysis.

Also if the dispersion parameters of both indicators change equally in Group 2 (Situation 5), we substantiate the inequality of a composite's variances across the groups (Step 3). As in the partial measurement invariance of Situation 3, researchers can conduct meaningful multigroup analyses by comparing the standardized coefficients in the structural model, but they cannot pool the data.

Table III. Simulation results

		Weight		Mean value		SD		Step 1	Step 2			Step 3a			Step 3b				
Group	Situation	w_1	w_2	x_1	x_2	x_1	x_2	Configural invariance	c	5%-quantile of c_u	Compositional invariance	$\bar{\xi}^{(1)}_{\text{pooled}} - \bar{\xi}^{(2)}_{\text{pooled}}$	$CI_{95\%}$	Equal mean values	$\log\left(\frac{\text{var}\,\xi^{(1)}_{\text{pooled}}}{\text{var}\,\xi^{(2)}_{\text{pooled}}}\right)$	$CI_{95\%}$	Equal variances	Measurement invariance	Path coefficient estimate using pooled data
1	1-7	0.4	0.8	0	0	1	1												
2	1	0.4	0.8	0	0	1	1	Yes	1.00	0.95	Yes	0.00	[−0.23; 0.23]	Yes	0.00	[−0.33; 0.34]	Yes	Full	0.6000
	2	0.4	0.8	0	1	1	1	Yes	1.00	0.95	Yes	−0.34	[−0.23; 0.23]	No	0.00	[−0.34; 0.34]	Yes	Partial	0.5925
	3	0.4	0.8	1	1	1	1	Yes	1.00	0.93	Yes	−1.05	[−0.24; 0.23]	No	0.00	[−0.31; 0.31]	Yes	Partial	0.5330
	4	0.4	0.8	0	0	1	3	Yes	1.00	0.95	Yes	0.00	[−0.22; 0.23]	Yes	−0.34	[−0.33; 0.34]	No	Partial	0.5949
	5	0.4	0.8	0	0	3	3	Yes	1.00	0.94	Yes	0.00	[−0.21; 0.23]	Yes	−2.20	[−0.43; 0.39]	No	Partial	0.5671
	6	0.8	0.4	0	0	1	1	Yes	0.89	0.94	No			(not evaluated)				No	0.5875
	7	0.8	0.4	0	0	1	3	Yes	0.89	0.94	No			(not evaluated)				No	0.5878

The analysis of Situation 6 shows that the lack of compositional invariance implies that the scores obtained through group-specific model estimations differ from the scores resulting from the pooled data (no measurement invariance established). Researchers should only analyze and interpret the group-specific model estimations separately.

Finally, applying the MICOM procedure to Situation 7 allows researchers to come to an identical conclusion as in the previous situation (no measurement invariance established). The procedure correctly detects the lack of compositional invariance (Step 2).

In summary, our PLS multigroup analyses using artificially generated data for different measurement invariance situations empirically substantiates the efficacy of our three-step MICOM procedure. The configural and compositional invariance are prerequisites for assessing the equality of the composite mean values and the variances. The assessment of the equality of the composite mean values and the variances is irrelevant if compositional invariance has not been established. Finally, we can see that pooling the data is only admissible if all the MICOM criteria have been fulfilled (Situation 1) and structural heterogeneity – if present – has been dealt with.

Empirical example

We use the corporate reputation model (Schwaiger, 2004), as shown with its latent variables in Figure 5, to provide a MICOM example with empirical data. In the corporate reputation model, the quality (QUAL), performance (PERF), corporate social responsibility (CSOR) and attractiveness (ATTR) explain the corporate reputation dimensions likability (LIKE) and competence (COMP), which themselves explain customer satisfaction (CUSA) and customer loyalty (CUSL). While the exogenous latent variables (i.e. QUAL, PERF, CSOR, ATTR) represent composites that build on a formative measurement model (Mode B), the endogenous latent variables (i.e. LIKE, COMP, CUSL) are composites with a reflective measurement model (Mode A); CUSA is a single-item composite. The book on PLS-SEM by Hair *et al.* (2017) explains in detail the cooperate reputation model with its latent variables and indicators as well as the data of a mobile phone provider used for model estimation[3]. These authors use the PLS method (Lohmöller, 1989; Wold, 1982) for the model estimation.

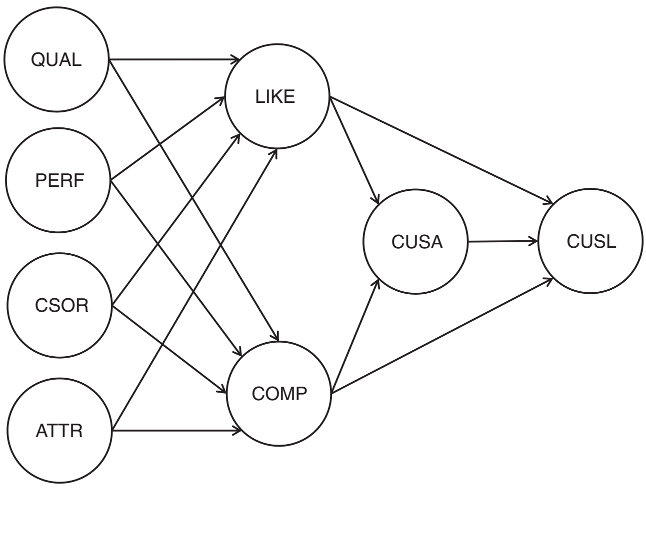

Figure 5.
Corporate reputation model

Hair *et al.* (2017) also present a PLS multigroup analysis for this corporate reputation model example from the mobile phone industry (see also Sarstedt and Ringle, 2010). They compare PLS-SEM results of customers with a contract plan (Group 1) to those with a prepaid plan (Group 2), without, however, establishing measurement invariance first. This analysis reveals significantly different group-specific PLS-SEM results for the relationship from the reputation dimension LIKE to CUSA and the relationship from CUSA to CUSL in the structural model (Hair *et al.*, 2017). Extending Hair *et al.* (2017), we apply the MICOM procedure to the corporate reputation model example and its multigroup analysis for two groups of customers.

In Step 1, the configural invariance assessment, we ensure that the following three aspects are identical for both groups: first, setup of the measurement models and the structural model; second, data treatment for the model estimation using the full set of data and each group of data; and third, algorithm settings for all model estimations. As a result of MICOM's Step 1, we conclude that configural invariance has been established.

The assessment of compositional invariance is the purpose of Step 2. Compositional invariance requires that c equals one. A permutation test reveals if the correlation c is significantly different from one or not. The statistical software R (R Core Team, 2014), the semPLS package (Monecke and Leisch, 2012), and our MICOM code in R allow us to conduct the computations of Step 2 and the subsequent Step 3. Note that the MICOM procedure has been implemented in the SmartPLS 3 software (Ringle *et al.*, 2015). Table IV shows the results of 5,000 permutations. With a value of 0.9608, which is very close to one, quality has the lowest c value of all composites in the corporate reputation model. The permutation test substantiates that none of the c values are significantly different from one. We therefore conclude that compositional invariance has been established for all composites in the corporate reputation model.

Having established configural and compositional invariance in Steps 1 and 2, we could compare the path coefficients of contract plan and prepaid plan customers using a multigroup analysis. However, if compositional invariance represented a problem for one or more composites in the analyses – which is not the case in this example – we could exclude those composites from the group-specific comparisons, provided theory supports such a step.

Finally, in Step 3, we assess the composites' equality of mean values and variances across groups. We find that full measurement invariance is established. The permutation test results (5,000 permutations) show that the mean value and the variance of a composite in Group 1 do not significantly differ from the results in Group 2. This finding holds for all composites in the corporate reputation model. Therefore, the outcomes of MICOM's Step 3 also support measurement invariance.

All three steps of the MICOM procedure for the corporate reputation model example and two customer groups (i.e. customers with a contract plan and customers with a prepaid plan) support measurement invariance. We therefore conclude that full measurement invariance has been established for the two groups of data. Consequently, researchers could analyze the example model using the pooled data. However, any analysis using the pooled data could be misleading if possible differences in the structural model are not accounted for (i.e. there is a lack of structural invariance). Group differences in the structural model should be accounted for, using the grouping variable as a moderator. In this example, the binary variable "servicetype" may serve as moderator for the relationships from LIKE to CUSA as well as from CUSA to CUSL in the corporate reputation model.

Composite	c value (= 1)	95% confidence interval	Compositional invariance?
ATTR	0.9930	[0.9440; 1.0000]	Yes
COMP	0.9982	[0.9975; 1.0000]	Yes
CSOR	0.9851	[0.9109; 1.0000]	Yes
CUSA	1.0000	[1.0000; 1.0000]	Yes
CUSL	0.9999	[0.9981; 1.0000]	Yes
LIKE	0.9998	[0.9988; 1.0000]	Yes
PERF	0.9795	[0.9334; 1.0000]	Yes
QUAL	0.9608	[0.9386; 1.0000]	Yes
Composite	*Difference of the composite's mean value (= 0)*	*95% confidence interval*	*Equal mean values?*
ATTR	−0.0641	[−0.2196; 0.2224]	Yes
COMP	0.0595	[−0.2231; 0.2266]	Yes
CSOR	0.0720	[−0.2175; 0.2229]	Yes
CUSA	−0.0967	[−0.2146; 0.2245]	Yes
CUSL	−0.0597	[−0.2253; 0.2191]	Yes
LIKE	−0.0542	[−0.2173; 0.2147]	Yes
PERF	−0.0227	[−0.2240; 0.2251]	Yes
QUAL	−0.0098	[−0.2194; 0.2250]	Yes
Composite	*Logarithm of the composite's variances ratio (= 0)*	*95% confidence interval*	*Equal variances?*
ATTR	0.1938	[−0.2807; 0.2687]	Yes
COMP	0.1386	[−0.3012; 0.2830]	Yes
CSOR	−0.1025	[−0.2768; 0.2725]	Yes
CUSA	0.2331	[−0.3676; 0.3638]	Yes
CUSL	−0.0662	[−0.3698; 0.3405]	Yes
LIKE	0.0155	[−0.2645; 0.2552]	Yes
PERF	0.0418	[−0.3107; 0.3069]	Yes
QUAL	0.1580	[−0.2905; 0.2744]	Yes

Table IV. MICOM results of the corporate reputation model example

Conclusion and future research

The use of composites in variance-based SEM, such as PLS, is a particularly important approach in international business research to model complete theories and simultaneously estimate their cause-effect relationships (e.g. Henseler *et al.*, 2009, 2012). These studies often require exploring structural variance by multigroup comparisons across countries and cultures (e.g. Steenkamp and Hofstede, 2002; Wedel and Kamakura, 2000). In order to ensure that these multigroup analyses are meaningful and lead to proper conclusions, researchers must establish the invariance of the composites used in their model. A lack of measurement invariance suggests that the composites carry different meanings across the groups, which may be a misleading source of structural coefficients' group-specific differences. Alternatively, if the composites in both groups are (almost) identical and entail the same coefficients for each group in the structural model, researchers may want to pool the data. Thereby, the findings and conclusions account for a more comprehensive sample, which increases the generalizability of the tested theory or concepts. The increased statistical power due to a larger sample size is another argument for pooling the data. However, researchers must avoid validity threats to their results imposed by heterogeneity in the structural model relationships. In case of using pooled data, they should account for heterogeneity in the structural model by including suitable moderator variables where appropriate.

The three-step MICOM procedure is the first approach to assess the measurement invariance in the context of composite models that systematically relies on inference statistics computed by using a permutation procedure. The procedure allows for a systematic measurement invariance assessment in a hierarchical framework and is applicable to all forms of variance-based SEM (e.g. PLS). Researchers must follow the hierarchy that requires safeguarding certain invariance aspects in the previous step before continuing with the next step.

In Steps 1 and 2, researchers need to assess configural and compositional invariance. If measurement invariance problems occur in these two steps, researchers cannot conduct a multigroup analysis, since one or more composites differ regarding their configuration and/or composition across the groups, which can go along with differences in meaning (i.e. there is no measurement invariance). Thus, researchers must estimate and interpret the models group wise by considering a composite's different meanings across the groups.

Alternatively, if the results of MICOM's Steps 1 and 2 (but not Step 3) indicate that there is no lack of measurement invariance, partial measurement invariance has been established. This result allows comparing the standardized path coefficients across the groups by conducting a multigroup analysis. Hence, researchers are recommended to interrupt the MICOM procedure and conduct a multigroup analysis to examine whether the structural model is equal across groups (structural invariance) or whether some effects differ in magnitude or even in signs across groups. Depending on the degree of structural invariance (i.e. whether none, some, most, or all of the structural effects are invariant across groups), pooling the data may be advantageous. Table V shows the consequences of the assessment of structural invariance for the overall analysis and for MICOM's further steps. Pooling the data is only recommended if most of the structural effects are invariant across groups. Since the equality of composite mean values and variances is a prerequisite for pooling the data, the MICOM procedure should then be resumed in order to assess whether full measurement invariance can be established.

Our study reinforces the need to carefully consider data heterogeneity. If there is heterogeneity within the sample (i.e. with regard to the location or dispersion parameters), the overall estimates are most likely invalid (Becker *et al.*, 2013).

Result of multigroup analysis	Consequence for … … the overall analysis	… MICOM
(1) No effect is invariant across groups in the structural model	Pooling the data leads to invalid and meaningless results	Stop
(2) Hardly any effect is invariant across groups in the structural model	The added value of pooling the data is limited	Stop
(3) Most effects are invariant across groups (in the structural model)	Pooling the data is an option as long as the structural differences are modeled as moderating effects	Resume
(4) All effects are invariant across groups in the structural model	It would be advantageous to pool the data	Resume

Table V. Proceeding after multigroup analysis

The reason becomes obvious if one looks at it from the measurement invariance perspective: Only if researchers can ensure a composite's full measurement invariance as a result of MICOM's Steps 1-3, they should start analyzing the pooled data. If no such assurance is possible, they must conclude that the composite is (partially) different and the data should be divided into groups for multigroup analyses. Researchers should therefore not only rely on observed variables to form groups, but also to actively uncover potential unobserved heterogeneity (Becker *et al.*, 2013; Jedidi *et al.*, 1997).

Various techniques allow researchers to uncover unobserved heterogeneity (Sarstedt, 2008). In PLS, for example, the most prominent segmentation methods are PLS-TPM (Squillacciotti, 2010), REBUS-PLS (Esposito Vinzi *et al.*, 2007, 2008), and FIMIX-PLS (Hahn *et al.*, 2002; Sarstedt *et al.*, 2011b; Sarstedt and Ringle, 2010). Two newer approaches, PLS-GAS (Ringle *et al.*, 2013, 2014) and PLS-POS (Becker *et al.*, 2013), offer superior characteristics compared to previously developed methods. After uncovering unobserved heterogeneity by using these techniques, researchers could try in an *ex post* analysis to explain groups of data by mean values of an explanatory variable (e.g. Ringle *et al.*, 2010). Before comparing the different group-specific path coefficients, researchers must ensure measurement invariance in accordance with Steps 1 and 2 of the MICOM procedure. Finally, it is important to note that unobserved heterogeneity may also affect a priori determined groups of data (e.g. different nations or cultures). Researchers must therefore also consider assessing and uncovering within-group heterogeneity (Rigdon *et al.*, 2011).

As the first paper on this topic, there is scope for future research. First and foremost, the analysis of configural invariance in Step 1 of the MICOM procedure may be extended beyond the naïve comparison of model settings and initial estimates by means of a more detailed testing of nomological validity, using confirmatory composite analysis (Henseler *et al.*, 2014). Such an analysis allows testing whether the discrepancy between the empirical variance-covariance matrix and the variance-covariance matrix that the composite model implies is too large to merely exist due to sampling error. Confirmatory composite analysis has recently been proposed for PLS (Dijkstra and Henseler, 2015a), but can, in principle, also be applied in conjunction with other variance-based SEM techniques. Currently, confirmatory composite analysis is far less understood than its factor-based sibling, CFA. For instance, while CFA has a whole range of fit measures, confirmatory composite analysis is currently limited to the test of exact model fit (Dijkstra and Henseler, 2015a) and the standardized root mean square residual (see Henseler *et al.*, 2014). Additional goodness-of-fit measures are desirable.

Another important question with regard to confirmatory composite analysis is its power and type-II error: How many observations are required to render a composite model wrong that is partially misspecified? The question of statistical power and type-II error is not only relevant for confirmatory composite analysis, but for the whole MICOM procedure. All hypotheses are formulated in the same way as the classical exact test (p-value) of SEM. As long as the tests are not significant, the researcher can assume that a certain step of the MICOM procedure has been fulfilled. This way of formulating hypotheses is disadvantageous, since there is hardly any control for error probability. Specifically, if researchers conclude that measurement invariance has been established, they cannot immediately indicate an error probability. There is no definite answer to the question: What is the probability that there is a lack of measurement invariance, although I believe the opposite? If researchers cannot reject the null hypotheses and conclude that measurement invariance is not a problem, they expose themselves to the danger that their empirical evidence may be the result of too little statistical power (e.g. due to a small sample size). Consequently, the statistical power of the proposed tests requires further research, and researchers using the procedure should take potential type-II errors into account; that is, the possibility of erroneously assuming measurement invariance. The examination of MICOM's type-II errors (e.g. by simulation studies) is a promising avenue for future research.

While our illustration and assessment focussed on the two-group case, researchers frequently need to compare composites across more than two groups of data. Comparing multiple groups of data, however, leads to an exponential increase in potential comparisons, inflating the familywise error rates of the corresponding tests (e.g. Sarstedt and Mooi, 2014). To maintain the familywise error rates, researchers can, for example, employ a Bonferroni correction on each test of PLS results (Gudergan *et al.*, 2008). Researchers may use the opportunity to examine the performance of the MICOM procedure under such conditions.

Future research should also explore possibilities to simultaneously assess the measurement invariance of both composite and common factor models in an unified framework. In this regard, a promising point of departure are the PLSe2 (Bentler and Huang, 2014) and consistent PLS path modeling (PLSc, see Dijkstra, 2014; Dijkstra and Henseler, 2015b) approaches. For instance, PLSc can estimate both composites and common factors, and its newly developed goodness-of-fit tests (Dijkstra and Henseler, 2015a) pave the way for refined and novel tools for measurement invariance testing.

Finally, this paper focusses on measurement invariance as a precondition for multigroup analyses among composites. Consequently, the use of an adequate method of multigroup analysis to assess the structural invariance of composites did not fit the scope of this paper. Although there is a variety of approaches to multigroup analysis using variance-based SEM (for an overview, see Sarstedt *et al.*, 2011a), none of them uses overall goodness-of-fit measures. Doing so may help controlling the overall error rate when testing for structural invariance. Since overall goodness-of-fit measures provide a promising point of departure for multigroup analysis (Henseler and Sarstedt, 2013), researchers may follow this avenue of future research to extend the set of available evaluation criteria for composite modeling. Our judgment is that permutation may not only be useful for assessing measurement invariance, but also structural invariance.

Notes

1. Note that the authors only refer to formative indicators and do not distinguish between formative, composite, and causal indicators as Bollen (2011) and Bollen and Bauldry (2011) require.
2. For more information about the data generation for pre-specified PLS path models, see, for example, Ringle *et al.* (2014).
3. The SmartPLS (Ringle *et al.*, 2015) project files and data of this example are available at: www.pls-sem.com

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