

Estimating hierarchical constructs using consistent partial least squares

Estimating hierarchical constructs

The case of second-order composites of common factors

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Abstract

Purpose – Many important constructs of business and social sciences are conceptualized as composites of common factors, i.e. as second-order constructs composed of reflectively measured first-order constructs. Current approaches to model this type of second-order construct provide inconsistent estimates and lack a model test that helps assess the existence and/or usefulness of a second-order construct. The purpose of this paper is to present a novel three-stage approach to model, estimate, and test second-order constructs composed of reflectively measured first-order constructs.

Design/methodology/approach – The authors compare the efficacy of the proposed three-stage approach with that of the dominant extant approaches, i.e. the repeated indicator approach, the two-stage approach, and the hybrid approach by means of simulated data whose underlying population model is known. Moreover, the authors apply the three-stage approach to a real research setting in business research.

Findings – The study based on simulated data illustrates that the three-stage approach is Fisher-consistent, whereas the dominant extant approaches are not. The study based on real data shows that the three-stage approach is meaningfully applicable in typical research settings of business research. Its results can differ substantially from those of the extant approaches.

Research limitations/implications – Analysts aiming at modeling composites of common factors should apply the proposed procedure in order to test the existence and/or usefulness of a second-order construct and to obtain consistent estimates.

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Originality/value – The three-stage approach is the only consistent approach for modeling, estimating, and testing composite second-order constructs made up of reflectively measured first-order constructs.

Keywords PLS, Consistency, Second-order construct, Composite of common factors, Goodness-of-fit, Variance-based structural equation modelling

Paper type Technical paper

Introduction

Structural equation modeling (SEM) is an analytical technique that is increasingly used in many scientific disciplines. Two different approaches exist: covariance-based SEM, for example, implemented in LISREL (Jöreskog and Sörbom, 1989) or AMOS (Arbuckle, 2003), and variance-based SEM (Reinartz *et al.*, 2009), implemented in software such as SmartPLS (Ringle *et al.*, 2005), PLSGraph (Chin and Frye, 2003), or ADANCO (Henseler and Dijkstra, 2015). SEM allows researchers to represent complex relationships between theoretical – often latent – constructs in a so-called structural or theoretical model, while also making it possible, at least in principle, to estimate the fit of that structural model with empirical data through a measurement model. Various types of constructs have been distinguished. For the present discussion it is crucial to understand the differences between these types.

Early SEM researchers often implicitly assumed that all constructs must be measured through common factors, i.e., using a reflective measurement model. The common factor model assumes that each indicator is a measurement-error-prone consequence of an underlying latent variable. While variance in common factors is modelled to cause variance in the items, it was recognized early on that for some constructs it made more sense conceptually to view causality flowing from the measures to the construct (Bagozzi, 1981, 1984; Blalock, 1964; Fornell and Bookstein, 1982). These constructs were measured by using the latent variable's antecedents as indicators. In this case, the indicators are called causal indicators. These causal indicators are obtained from several different, unique sources, and using them led to formative rather than reflective measurement (Bagozzi, 1994). Only recently, the awareness has grown among researchers that there are actually two subtypes of formative measurement: causal-formative and composite-formative (or simply composite) measurement (Bollen and Diamantopoulos, 2015; Henseler, 2017). Whereas a reflectively measured construct is assumed to cause its indicators (satisfaction causes the customer to smile), and a causal-formatively measured construct is assumed to be caused by its indicators (depression may be caused by a recent job loss), a composite construct is assumed to be composed by its indicators. Examples for composite constructs would be brand image, which is composed by brand associations (Keller, 1993); IT infrastructure capability, which is composed by technological IT infrastructure, managerial IT infrastructure, and technical IT infrastructure capabilities (Ajamieh *et al.*, 2016); or relationship value, which is made up of the difference of benefits and costs (Ulaga and Eggert, 2006). Indicators of a composite construct essentially make up the construct. Indicators of a causal-formative construct cause the construct.

The adequate and valid construction and estimation of the measurement model and of the paths in the structural model are conditions for the studies using them to deliver accurate, meaningful, and useful results. Results from incorrectly specified models may lead to flawed theoretical conclusions, and equally flawed practical implications. Law and Wong (1999), for example, provide an empirical example showing that the misspecification of the direction of causality between a construct and its indicators can lead to incorrect conclusions about the structural relationships between theoretical constructs[1].

Partial least squares (PLS) path modeling is a widespread estimator of SEM. The PLS algorithm, independent of the epistemic relationships between constructs and their observed indicators, estimates all constructs as composite constructs (Henseler, 2017), aggregating the observed variables (Chin and Newsted, 1999), rather than estimating them as reflective common factors, or as causal-formative constructs. It can be understood as a prescription for

dimension reduction (Dijkstra and Henseler, 2011). If constructs are meant to be reflective, PLS will generate inconsistent estimates, which may lead to flawed theoretical conclusions (Henseler *et al.*, 2014). As a remedy, Dijkstra and Henseler (2015a, b) introduced consistent PLS (PLSc). PLSc corrects inter-construct correlations for attenuation so that the estimates of path coefficients and loadings become consistent.

While PLSc enables researchers to obtain consistent estimates for composite and common factor models, the situation is less clear for so-called hierarchical constructs. Hierarchical constructs are constructs that are not measured by means of manifest indicators, but by means of other constructs. According to Polites *et al.* (2012), it is important to carefully conceptualize the relationship not only between the first-order constructs and their indicators, but also between lower-order constructs and the higher-order construct. Extant approaches to estimate hierarchical constructs using PLS, such as the repeated indicators approach (Wold, 1982), or the two-stage approach (Ringle *et al.*, 2012), were proposed before the advent of PLSc, and have two major drawbacks: First, they yield inconsistent estimates. Second, they do not include model fit tests and, hence, cannot provide empirical evidence for or against the existence of a hierarchical construct.

In this short paper, we discuss how a prevalent type of hierarchical construct – a second-order composite construct, with first-order reflective constructs as dimensions – should be specified and estimated using variance-based SEM to obtain consistent path coefficients and indicator weight estimates. We therefore introduce a three-stage approach, which makes use of the PLSc implementation in ADANCO (Henseler and Dijkstra, 2015).

The structure of the paper is as follows. The second section reviews the extant literature on how to model second-order constructs using PLS, and identifies their major shortcomings. The third section presents the three-stage approach as a novel approach for estimating and testing second-order constructs specified as composites of common factors. The fourth section demonstrates the superiority of the three-stage approach by means of a simulation study, and it illustrates the relevance of choosing an adequate approach by means of an application to an empirical example. The last section discusses the consequences of our findings for past and future research that modeled or will model second-order constructs as composites of common factors.

Literature review

The use of more abstract levels of constructs, i.e. constructs consisting of several dimensions and levels, is increasingly common for a range of theoretical and empirical reasons (see Jarvis *et al.*, 2003; Wetzels *et al.*, 2009 for an overview), most importantly, because such models reduce model complexity and increase parsimony, as fewer paths need to be estimated (see e.g. Becker *et al.*, 2012).

Often, multidimensional constructs include combinations of composite and reflective measurement (Jarvis *et al.*, 2003). This means that both for the first-order constructs and the second-order construct the type of measurement model can and should be determined separately.

A particularly important configuration of second-order constructs is a composite of common factors. In a composite of common factors configuration, the first-order constructs employ a reflective measurement model, whereas the second-order construct is a composite formed by the first-order constructs. This is the most frequently used approach in research in the social sciences (Ringle *et al.*, 2012), implying a need to deeper examine this type of hierarchical component model. Many of the seminal constructs in business research are typically modeled in this way, such as quality (e.g. service quality as measured by Parasuraman *et al.*, 1988), value (e.g. relationship value as measured by Ulaga and Eggert, 2006), perceived risk (Srinivasan and Ratchford, 1991), or organizational orientation (e.g. market orientation and learning orientation as measured by Baker and Sinkula, 1999). In most instances, these second-order constructs can be regarded as artifacts made up of elements, each of which is captured without measurement error by means of reflective

measurement. While this type of second-order construct has received particular attention in past research, the extant approaches to estimate such models have been shown to provide inconsistent estimates (Becker *et al.*, 2012).

To estimate models consisting of higher-order constructs, three approaches have been proposed in the context of PLS path modeling (Wilson and Henseler, 2007): the repeated indicators approach, the two-stage approach, and the hybrid approach. They are depicted in Figure 1.

In the repeated indicators approach, the manifest indicators of the first-order constructs are reused for the second-order construct. This procedure to model second order constructs with PLS is based on the hierarchical components approach suggested by Wold (1982). In essence, in this approach a second-order construct is directly measured by using all of the first-order common factors' manifest variables. For example, when a second-order construct is made up of three first-order constructs with four manifest variables each, all these 12 variables would be reused as indicators for the second-order construct. This is the most frequently used method for estimating higher-order constructs in PLS (Wilson and Henseler, 2007).

The disadvantage of this approach is that the repeated indicators can evoke artificially correlated residuals (Becker *et al.*, 2012). A serious pitfall of the repeated indicator approach is sometimes neglected (Ringle *et al.*, 2012): if the second order variable is used as an

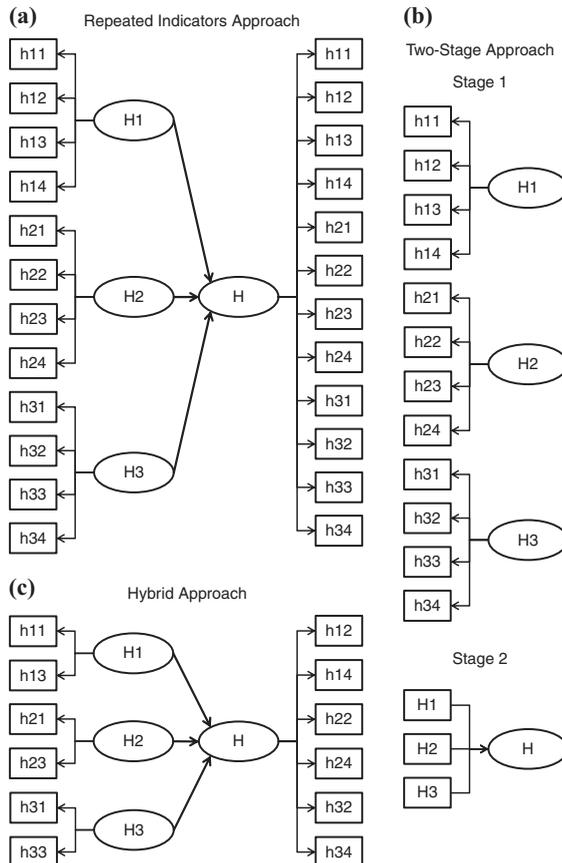


Figure 1.
Extant approaches to estimate hierarchical constructs specified as composites of common factors

endogenous construct, almost all of its variance is explained by its indicators. Consequently, there is no variance left to be explained by other potential predictors. Analysts may come to the wrong conclusion that a predictor is irrelevant although, in fact, it is not. As a solution, Ringle *et al.* (2012) introduced an alternative version of the repeated indicators approach, in which the second-order construct is not directly affected by other constructs in the model, but only indirectly through the first-order constructs. The effect of a construct on a second-order composite is thus viewed as being fully mediated by the first-order constructs (see Nitzl *et al.*, 2016 for the analysis of mediating effects using PLS).

As the name suggests, the two-stage approach consists of two steps. The aim of the first stage is to obtain latent variable scores for the first-order constructs. In this first stage of the analysis, the second-order construct is not yet included. It is only in the second stage that the model containing the second-order construct is estimated. In the second stage, the scores of the first-order constructs serve as manifest variables of the second-order construct. In essence, the measurement of the first-order constructs is reduced to single items. This reduction is not only useful for statistical reasons (e.g. to avoid multicollinearity among the indicators), but also for practical reasons (e.g. to prevent “double-counting”, see Arnett *et al.*, 2003). Most importantly, the two-stage approach allows to place the second-order construct in an endogenous position within the structural model (Ringle *et al.*, 2012).

The hybrid approach, proposed by Wilson and Henseler (2007), splits the manifest variables of the first-order constructs, such that half of them are used to measure the first-order constructs and the other half are used to measure the second-order construct. It aims at eliminating the issue of artificially correlated residuals. The approach remains vague about how to proceed in case of an odd number of indicators and does not say anything about which specific indicators should be assigned to the first- and second-order constructs. This approach is seldom used in actual practice.

Empirical assessments of the relative efficacy of the various approaches are scarce. Based on a Monte Carlo simulation, Becker *et al.* (2012) conclude that both the repeated indicator approach using the “Mode B” outer weighting scheme (see Henseler, 2010, for an explanation of model weighting options in PLS) and the two-stage approach can be used. If researchers are interested in the paths to and from the second-order construct, the two-stage approach is more useful. Although Becker *et al.* (2012) do not emphasize it, it also becomes clear from their simulation that none of the explored approaches actually provides consistent estimates. Another major shortcoming of the extant approaches is their lack of formal model fit tests. Without testing the fit of the model that includes the hierarchical construct, researchers do not obtain any empirical support for or against the hierarchical construct. At the time the three approaches were introduced, no goodness-of-fit tests were available for PLS (Henseler and Sarstedt, 2013). Despite the recent introduction of goodness-of-fit tests for PLS (Dijkstra and Henseler, 2015a; Henseler *et al.*, 2014; Henseler *et al.*, 2016), none of the extant approaches has incorporated them so far. In order to overcome the identified shortcomings, we introduce a new PLS-based three-stage approach to consistently estimate and test hierarchical constructs specified as composites of common factors.

A PLS-based three-stage approach to consistently estimate and test hierarchical constructs specified as composites of common factors

We propose a new PLS-based approach to consistently estimate and test hierarchical constructs that are composed of reflective first-order constructs. We call it a “three-stage approach,” because it requires three rounds of estimation. The three-stage approach is meant to excel over the extant approach in two pivotal ways. First, the approach provides the means to calculate consistent estimates. Loadings, weights, and path coefficients can be estimated consistently. Second, the three-stage approach includes two assessments of the goodness of model fit. It thereby facilitates answering the research question about the existence or

usefulness of a second-order construct – a question of confirmatory research. Figure 2 depicts the three-stage approach and its steps.

In the following paragraphs we describe the steps required for the consistent estimation of a hierarchical model. For illustration purposes, we employ a model consisting of an exogenous construct (X), an endogenous, hierarchical construct (H) specified as a composite of three reflective first-order constructs (H1-H3), as well as a further endogenous construct (Y) partially explained by H (see Figure 3). Solid arrows represent linear causal relationships, dotted arrows signify a composing relationship, while bowed, double-headed arrows characterize correlations.

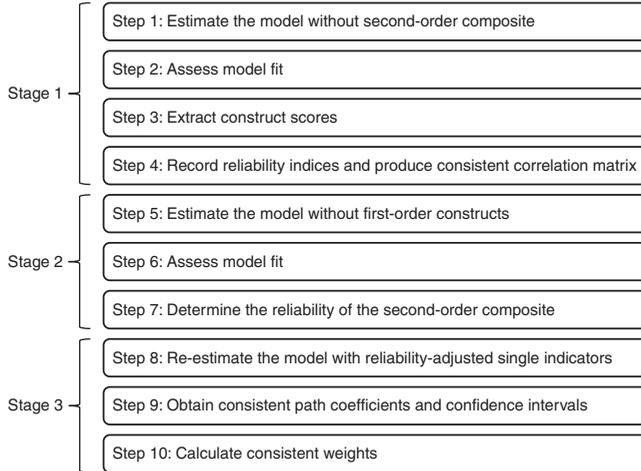


Figure 2. The steps of the three-stage approach to consistently estimate and test hierarchical constructs specified as composites of common factors

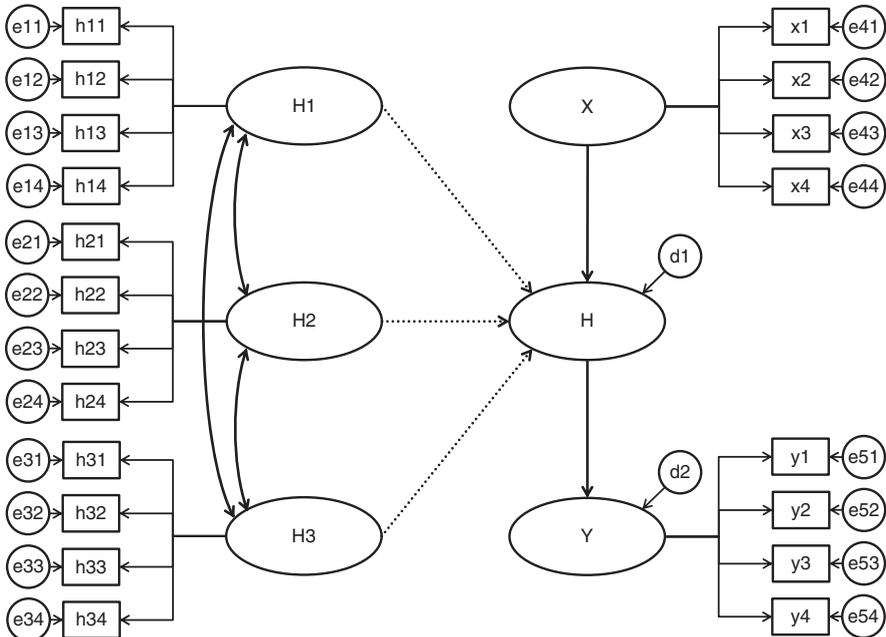


Figure 3. An example of a model containing a hierarchical construct H

Stage 1

In Stage 1, we estimate our model with the second-order construct not included. The purpose of the first stage is to obtain the scores and the consistent correlations of the first order constructs.

Step 1: estimating the model without second-order composite

In a first step, a PLS path model containing all first-order constructs – but without the second-order composite(s) – must be specified and estimated. The specification of the structural model is up to the researcher as long as every construct is sufficiently embedded in a nomological net. Typical choices are a full graph, in which all possible connections are included, and graphs respecting adjacency, which try to reflect a priori-specified structural models. Figure 4 depicts a viable model specification for the example model. Since the model contains common factors (with reflective indicators), it is imperative that consistent PLS be used to estimate this model, in order to obtain consistent inter-construct correlations (Dijkstra and Henseler, 2015b). To estimate the reflective first-order constructs correctly, the “Mode A consistent” weighting scheme should be used in ADANCO.

Step 2: assessing model fit

To allow the researcher to decide whether it makes sense to continue building and estimating the hierarchical model, the model constructed in Step 1 needs to be assessed. Building a composite of common factors only makes sense if the validity and reliability of the first-order construct can be ensured. Various assessment procedures of model fit need to be considered, i.e. both bootstrap-based exact fit measures, such as the 95 percent quantile of the geodesic discrepancy between the empirical and the model-implied correlation matrix, as well as approximate fit measures, such as the SRMR. The majority of the available fit measures for variance-based SEM analyze the discrepancy between the empirical and the model-implied correlation matrix. For an interpretation and guidelines about how to report PLS results, the researcher should refer to Henseler *et al.* (2016).

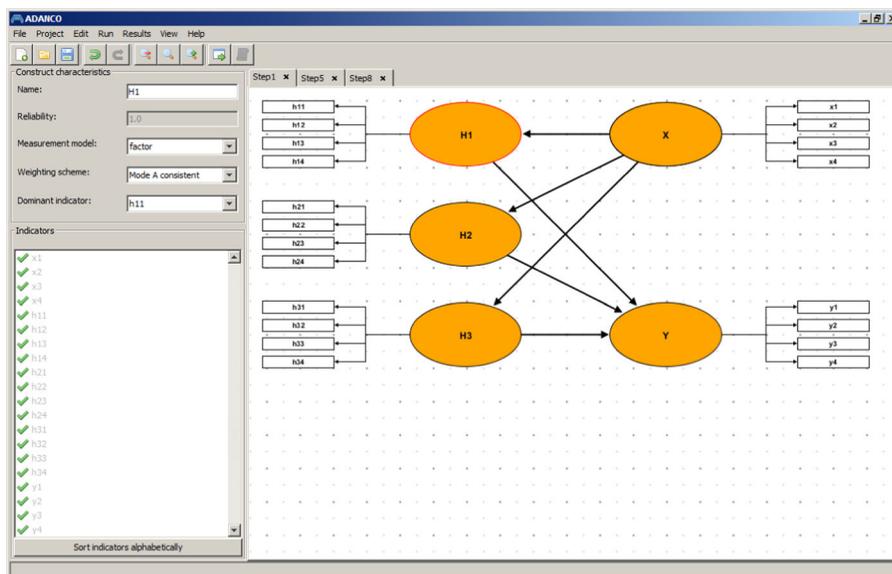


Figure 4.
Stage I, model without second-order construct

Step 3: extracting composite scores

Once the model fit has been found to be acceptable in Step 2, the scores of the first-order constructs need to be extracted. These scores are to be appended to the data file as additional variables. These variables will be used in Stage 2. Usually, the standardized scores are sufficient for the next steps. Only if the scores are of a particular interest, such as in national customer satisfaction indices (Fornell, 1992) or importance-performance matrix analyses (Ringle and Sarstedt, 2016), do unstandardized construct scores have merits.

Step 4: recording reliability indices and producing the consistent inter-construct correlation matrix

To manually determine the reliability of the second-order construct in Step 7, we need to note the reliability scores (Dijkstra-Henseler's ρ_A) of the first-order constructs at this stage. To determine the consistent weights in Step 10, we must note down the consistent correlation matrix R of the first-order constructs. By completing Steps 1-4, the first stage will be concluded.

Stage 2

In the second stage, the second-order construct is included in the model. The purpose of the second stage is to obtain consistent estimates for the structural model. Several steps need to be taken to obtain consistent estimates.

Step 5: estimating the model without first-order constructs

In line with McDonald and Ho (2002), a structural equation model can be viewed as a composite of a measurement model and a structural model, and it has merits to analyze them separately. While the four steps of the first stage have focused on the measurement model, the subsequent steps are devoted to the structural model. Hence in Step 5, only the structural model is estimated and tested. We use the composite scores that were approximated in Step 1 and extracted and appended to the data set in Step 3 as indicators for the second-order construct. Now, the measurement model of the second-order construct is "composite." "Mode B" should be the first choice if a researcher would like to extract as much information as possible out of the data. In case of high levels of multicollinearity, it may be recommendable to use "Mode A" instead. Weights predefined by the researcher or obtained through external routines, such as the analytic hierarchy process or similar approaches (Dijkstra, 2013), are also possible[2]. Figure 5 depicts the model specification for Step 5. An important result obtained in Step 5 is the weight vector \mathbf{w} , which contains the weights of the second-order composite.

Step 6: assessing model fit

Again, we need to assess the fit of the new model: this time to determine if it makes sense to estimate a model containing hierarchical constructs. Various assessment procedures of model fit should be considered again, both bootstrap-based exact fit measures, as well as approximate fit measures, such as SRMR (see Step 2).

Step 7: determining the reliability of the second-order composite

The scores of the second-order composite are a linear combination of the scores of the first-order constructs. Since the latter contain measurement error, their linear combination will contain error, too (Rigdon, 2012). Unfortunately, extant reliability coefficients, such as Dijkstra-Henseler's ρ_A , Jöreskog's ρ_C , or Cronbach's α , are not applicable to composite constructs, because these coefficients rely on inter-item correlations or loadings to quantify the amount of random measurement error in the scores. In case of composites, neither the inter-item correlations nor the loadings are informative about the amount of measurement error.

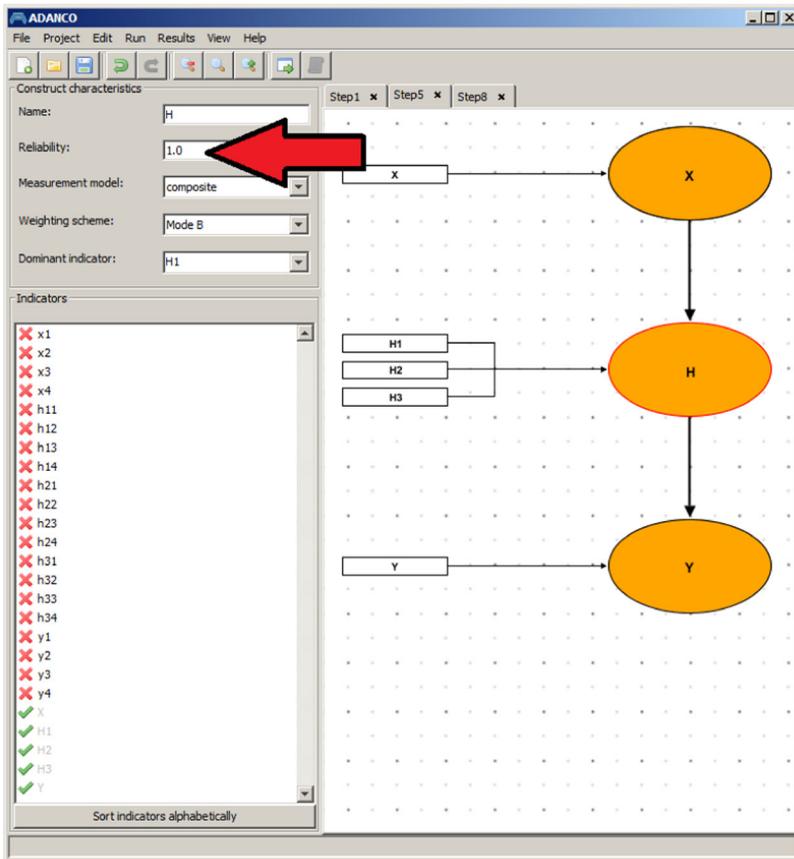


Figure 5. Stages 2 and 3, model with second-order construct

Instead, we can exploit the fact that we do have reliability estimates for each indicator of the composite (obtained in Step 1) as well as weight estimates (obtained in Step 5). Since the scores of the first-order constructs are typically standardized, we can apply a simplified version of Mosier's (1943) equation for determining the reliability of a weighted composite (ρ_S):

$$\rho_S = \mathbf{w}' \mathbf{S}^* \mathbf{w},$$

where \mathbf{w} is a column vector containing the indicator weights of the second-order composite (obtained in Step 5), and \mathbf{S}^* is the consistent correlation matrix of the second-order composite's indicators (obtained in Step 1), with the respective reliabilities (ρ_A) on the diagonal. Figure 6 illustrates how to determine the reliability of the second-order composite using Microsoft Excel. Since the formula in cell A7 is an array formula, researchers should not forget to press CTRL+SHIFT+ENTER after editing the formula.

Stage 3

The third stage strongly resembles the second stage, but differs in purpose. The purpose of the third stage is to obtain consistent estimates for the structural model including the relationships between the first-order common factors and the second-order composite. In the

third stage, again the second-order construct is included in the model, but this time its correlations are corrected for attenuation. Several steps need to be taken to obtain consistent estimates.

Step 8: re-estimating the model with reliability-adjusted single indicators

Now that we have obtained a value for ρ_S , we can reestimate the model, including the second-order construct, but correcting the composite for disattenuation. Again, we use the scores obtained in Step 1 for the first-order constructs as indicators. In this step, it is important to use the same weighting scheme as in Step 5, because otherwise the weights might differ from those used in Step 7 to determine the reliability of the composite. The reliability of the composite construct is manually set to ρ_S as obtained in Step 7 in order to correct the composite's correlations for attenuation[3].

Step 9: obtaining consistent path coefficients and confidence intervals

The path coefficients obtained from this model are consistent. The respective confidence intervals can be obtained by bootstrapping (see e.g. Streukens and Leroi-Werelds, 2016). This step also provides estimates for indirect and total effects.

Step 10: calculating consistent weights

If the relationships between the second-order construct and its first-order constructs are of interest, analysts may examine the weights with which the first-order construct make up the second-order construct. Consistent weights can be calculated using the following set of equations, a three-step approach:

- (1) For each indicator of the second-order construct, determine consistent covariances between the second-order composite and its first-order common factors as $q_i = \lambda_i \rho_{A_i}^{-0.5}$, where λ_i is the correlation between the second-order construct scores and the i th first-order construct's scores as obtained in Step 5, and ρ_{A_i} is the reliability of the i th first-order construct as obtained in Step 4.
- (2) Use these consistent covariances between the second-order composite and its first-order common factors and the first-order common factors' consistent correlations to determine the vector of the unstandardized weights by means of an ordinary least squares regression: $v = R^{-1}q$.
- (3) Standardize the weights by dividing the unstandardized weights by the standard deviation that the linear combination of first-order constructs would yield: $w = (1/\sqrt{v'Rv})v$.

Figure 7 illustrates how to perform these three sub steps for the example model using Microsoft Excel.

	A	B	C	D	E
1	Weights		Consistent Correlations, Reliabilities in the Diagonal		
2	w1		$\rho_A(H1)$	cor(H1, H2)	cor(H1, H3)
3	w2		cor(H1, H2)	$\rho_A(H2)$	cor(H2, H3)
4	w3		cor(H1, H3)	cor(H2, H3)	$\rho_A(H3)$
5					
6	Reliability				
7	=MMULT(TRANPOSE(A2:A4), MMULT(C2:E4, A2:A4))				

Figure 6.
How to determine the reliability of a composite by means of Microsoft Excel

	A	B	C	D	E	F	G
1	ρ_A		Consistent Correlations				λ
2	$\rho_A(H1)$		1	cor(H1, H2)	cor(H1, H3)		cor(H, H1)
3	$\rho_A(H2)$		cor(H1, H2)	1	cor(H2, H3)		cor(H, H2)
4	$\rho_A(H3)$		cor(H1, H3)	cor(H2, H3)	1		cor(H, H3)
5							
6	q		v				
7	=G2/SQRT(A2)		=MMULT(MINVERSE(C2:E4), A7:A9)				
8	=G3/SQRT(A3)						
9	=G4/SQRT(A4)						
10							
11	w						
12	=C7:C9/SQRT(MMULT(TRANPOSE(C7:C9), MMULT(C2:E4, C7:C9)))						
13							
14							

Figure 7. How to determine the consistent weights of a second-order composite by means of Microsoft Excel

Study 1: simulated data

In order to demonstrate the efficacy of the new three-stage approach for modeling and estimating second-order composites of common factors, we expose the three-stage approach to simulated data, and compare it to the repeated-indicator approach, the two-stage approach, and the hybrid approach. Simulated data offers the advantage that the true population model is known.

We define a population model as depicted in Figure 8. All coefficients are standardized. We generate 100 observations of normal-distributed random data, on which we impose the

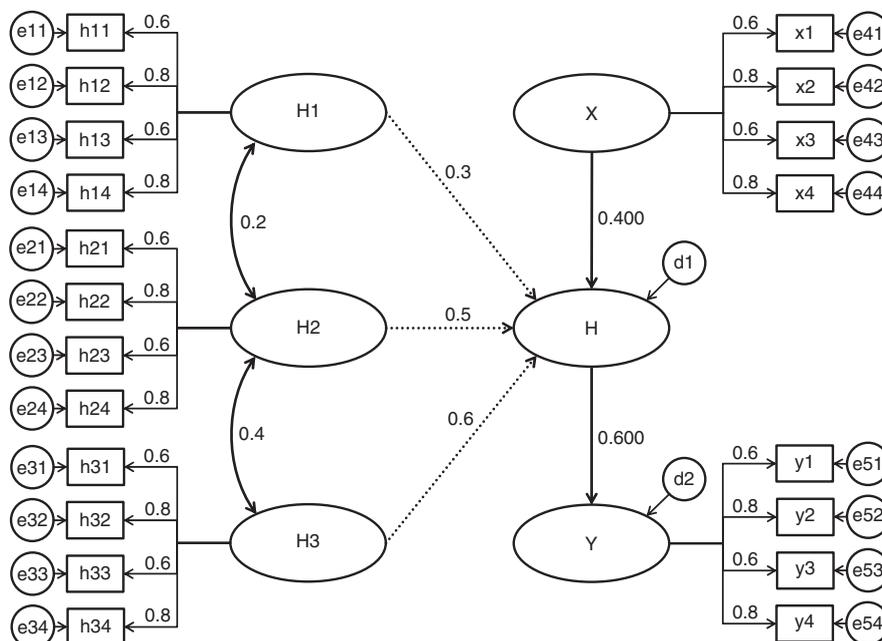


Figure 8. Population model

structure of the population model. Thus, the empirical correlation matrix of the indicators equals the population correlation matrix.

To this generated data set we apply the new three-stage approach as well as the repeated-indicator approach (both in its original form and the alternative form suggested by Ringle *et al.*, 2012), the two-stage approach, and the hybrid approach. For both model assessments of the three-stage approach, the model fit turns out to be excellent. We obtain an SRMR for the saturated model of 0.000 in the first stage as well as in the second stage (both below a bootstrap-based 95 percent quantile)[4].

The focal question of this simulation study is whether the path coefficients quantifying the strength of the linear relationships from X to H and from H to Y are estimated correctly. In Table I, we present the path coefficients obtained via the different approaches together with corresponding 95 percentile bootstrap confidence intervals based on 999 bootstrap samples. The results differ substantially. The path coefficient estimates obtained from the three-stage approach are equal to the population values. This provides evidence for the three-stage approach's Fisher-consistency. In contrast, in case of all other approaches, the path coefficients are substantially underestimated. In the case of the repeated indicator approach, the path coefficients from H to Y are similar to the path coefficients in the two-stage approach, but the path from the exogenous variable, X, to the second-order construct, H, is essentially zero. This peculiarity has been documented and discussed by Ringle *et al.* (2012). The first-order constructs will explain all the variance of the second-order construct ($R^2 \cong 1$), so that the effect of the exogenous variable is not able to explain any variance in the endogenous second-order construct. Table II reports the explained variance per construct and approach.

A similar picture can be found for the weight relationships between the first-order common factors and the second-order composite (see Table III). Again, the three-stage approach is capable of retrieving the true values. In contrast, none of the other approaches provides the correct estimates. Interestingly, the weight estimates obtained from the two-stage approach are relatively close to the true values, whereas the values of the repeated indicators approach and particularly the hybrid approach are quite far off.

Table I.

Structural model results: path coefficients and percentile bootstrap confidence intervals (CI)

Origin of values	Estimate	X→H		H→Y	
		Estimate	95% CI	Estimate	95% CI
True value	0.400	–	–	0.600	–
Three-stage approach	0.400	(0.193; 0.597)		0.600	(0.429; 0.774)
Repeated indicators approach, original	0.000	(–0.000; 0.007)		0.500	(0.354; 0.643)
Repeated indicators approach, alternative	0.333	(0.180; 0.497)		0.500	(0.353; 0.643)
Two-stage approach	0.335	(0.167; 0.503)		0.502	(0.361; 0.646)
Hybrid approach	0.084	(–0.035; 0.208)		0.470	(0.322; 0.620)

Table II.

Structural model results: variance explained

Origin of values	R^2	
	H	Y
True value	0.240	0.360
Three-stage approach	0.240	0.360
Repeated indicators approach, original	1.000	0.250
Repeated indicators approach, alternative	1.000	0.250
Two-stage approach	0.112	0.252
Hybrid approach	0.582	0.221

Study 2: field study

In this section, we apply the different approaches to empirical data. Thereby, we illustrate that also in empirical research settings, the results are substantially affected by the choice of approach. We obtained empirical data from the authors of a recently published field study (Bouzaabia *et al.*, 2013). In this paper, we only replicate the analysis, rather than focusing on theory building. For the theory and operationalization of the constructs we refer to the original article. The model in this example links three constructs: a dependent variable, store satisfaction (Oliver, 1980), a mediating variable, store image (cf. Bloemer and De Ruyter, 1998; Semeijn *et al.*, 2004), and an independent variable, in-store logistics performance (cf. Garrouch *et al.*, 2011; Mentzer *et al.*, 1999). In the following paragraphs we concisely explain the three constructs and provide a rationale for the model.

Satisfaction

Individuals develop patronage behavior towards a particular store, based on their satisfaction with the store. Satisfaction, in this context, is a one-dimensional, encompassing, positive attitude towards the store.

Store image

In the domain of retail marketing, the “Store Image” concept represents the comprehensive, multifaceted collection of associations individuals have with a specific store (cf. Bloemer and De Ruyter, 1998). It is dynamically updated with every visit to a store, and stored in the customer’s long-term memory. It is known to influence individuals’ behavioral intentions to revisit the store, or store loyalty. Store image is multidimensional, composed of salient aspects – not necessarily correlated – of the customer experience with the store. It has been conceptualized as a three-dimensional second-order construct, composed of customer perceptions of “store personnel,” “store physical layout,” and “store merchandise.”

In-store logistics performance

The concept of in-store logistics performance is directly relevant for operational managers in supermarkets and other retail outlets. The concept captures (a customer’s perception of) operational performance in the store: are products in stock and easy to find, are chariots available, are opening hours convenient, etc. (cf. McKinnon *et al.*, 2007).

Rationale

In their study, Bouzaabia *et al.* (2013) proposed that a substantial part of variance in satisfaction with a store is influenced by customer perceived in-store logistics performance. In-store logistics has a persistent effect on consumers and its effect on satisfaction is fully mediated by store image.

Origin of values	w1	Weights w2	w3
True value	0.300	0.500	0.600
Three-stage approach	0.300	0.500	0.600
Repeated indicators approach, original	0.275	0.597	0.550
Repeated indicators approach, alternative	0.274	0.600	0.548
Two-stage approach	0.302	0.532	0.604
Hybrid approach	0.205	0.449	0.409

Table III.
Relationships between first-order common factors and second-order composite

Method

In all, 200 responses were collected through a questionnaire by intercepting customers at the main exit of a store. The items are provided in the article by Bouzaabia *et al.* (2013). To analyze our data, we used the three-stage approach, the alternative repeated indicators approach, the two-stage approach, and the hybrid approach.

We first report results of the three-stage approach, and then compare the results of our analysis with outcomes produced by the other approaches. Dijkstra-Henseler's ρ_A was used to assess the construct reliability of satisfaction. The reliability of the second-order construct was calculated manually. The convergent validity of the reflective latent variable was assessed as average variance extracted (AVE) and should exceed 0.5 (Fornell and Larcker, 1981). To assess discriminant validity we relied on the heterotrait-monotrait ratio of correlations (HTMT; Henseler *et al.*, 2015) between all reflective constructs.

Results

The geodesic discrepancy between the empirical correlation matrix and the implied correlation matrix of the saturated model (i.e. a model in which all constructs are allowed to covary) is 0.403 and lies below its corresponding HI99 value. Consequently, the implied correlation matrix does not differ significantly (1 percent level) from the empirical correlation matrix. Also, the SRMR of 0.065 provides evidence for an acceptable model fit (Hu and Bentler, 1999). We can thus conclude that the measurement model provides an adequate explanation of the covariation in the data. Dijkstra-Henseler's ρ_A for satisfaction is a healthy 0.865, and the reliability of the second-order composite is 0.842. The AVE of satisfaction is 0.608 and thus exceeds the threshold for acceptable convergent validity. The highest HTMT value in the whole model is 0.682, which means that there is sufficient discriminant validity throughout the model. The goodness-of-fit of the structural model including the second-order composite is good as well: The geodesic discrepancy of 0.107 lies even below its corresponding HI95 value of 0.126, and the SRMR is 0.059. This shows that the second-order composite does not create significant misfit.

The results of the field study are shown in Table IV. In-store logistics performance has a relatively large-sized effect on store image, and store image strongly influences satisfaction. The three-stage approach provides path coefficients that are clearly greater than those of the other approaches. The path coefficients obtained from the hybrid approach differ the most from the others. Moreover, the three-stage approach yields the highest R^2

Parameter	Approach			
	Three-stage approach	Repeated indicators approach (Alt.)	Two-stage approach	Hybrid approach
<i>Path coefficients</i>				
In-store logistics performance → Store image	0.656	0.598	0.602	0.249
Store image → Satisfaction	0.696	0.593	0.639	0.533
R^2				
Store image	0.430	1.000	0.362	0.646
Satisfaction	0.484	0.352	0.408	0.284
<i>Weights</i>				
Physical layout → Store image	0.292	0.309	0.274	0.180
Merchandise → Store image	0.509	0.579	0.557	0.439
Personnel → Store image	0.480	0.390	0.441	0.224

Table IV.
Estimates for the field study

values if one takes into account the peculiarity of the repeated indicator approach and the hybrid approach that the first-order common factors explain (part of) the variance of the second-order composite.

There are also some remarkable differences between the weight estimates. Whereas for instance the alternative repeated indicators approach and the hybrid approach suggest that merchandise has a much stronger role than personnel, the three-stage approach provides almost similar values for both first-order constructs' weights. Apparently, the choice of method can thus have consequences for the conclusions one would draw from estimates.

Discussion and conclusion

Research in the social sciences has increasingly made use of PLS path modeling techniques. A range of recent reports and critical studies on PLS path modeling has emphasized the importance of correct model specification and consistent estimates for theory building. Inappropriate modeling practices and inconsistent estimates may lead to wrong interpretations and conclusions.

In this paper, we provided a new three-stage approach to estimate and assess structural equation models containing hierarchical constructs. We focused on the most relevant hierarchical model with latent variables, the composite of common factors, which is a second-order construct composed of reflectively measured first-order constructs. In contrast to all extant approaches, the three-stage approach provides consistent estimates. Moreover, for the first time the goodness-of-fit of the model containing the hierarchical construct can be assessed. In this way, researchers receive an indication of the adequacy of the hierarchical construct. Our paper and the guidelines therein fully replace the findings and guidelines of Becker *et al.* (2012) and preceding papers on the topic of hierarchical constructs modeled as composite of common factors.

Research containing hierarchical constructs modeled as composites of common factors may be negatively affected by two shortcomings of the outdated approaches. First, the extant approaches did not provide any empirical evidence speaking against a hierarchical construct. Consequently, there might be second-order constructs in the scientific literature that are not tenable. Second, the extant approaches most likely underestimated the correlations between the second-order construct and other constructs in the nomological net. As a consequence, the Type-II error of some studies might be larger than anticipated by the researchers, and causal relationships may have been left unrevealed.

To our knowledge, the proposed three-stage approach is the only SEM approach so far that yields consistent estimates for the type of second-order construct covered in this paper. In the light of this, we recommend abandoning the use of inconsistent and thus outdated approaches, i.e., the repeated indicators approach, the hybrid approach, and the two-stage approach. While they might have merits for other types of second-order constructs, they should not be used anymore to estimate composites of common factors. Future research should examine how other types of hierarchical constructs, particularly composites of composites and common factors of composites, should be estimated and assessed.

A disadvantage of any multi-stage approach is that the second-order construct that is estimated in a later stage is not included in the estimation of the first-order constructs. Estimating all coefficients simultaneously may have advantages in terms of inference statistics. Therefore, future research should examine the confidence intervals obtained by our new procedure. Moreover, future research could strive for a simultaneous estimation of the coefficients instead of using a three-stage approach.

Notes

1. It can equally well be that the measurement model specification hardly affects the relationships between constructs (see e.g. Braojos-Gomez *et al.*, 2015).
2. Dijkstra has suggested repeatedly that researchers need not let statistical fit-criteria be the sole determinants of the contents of a concept, but that considerations of substance could, or even should play a role. For some very diverse suggestions how to do make that operational, see Dijkstra (2016)
3. ADANCO permits to manually define the reliability of constructs with a composite measurement model. An arrow in Figure 5 marks the pertaining field.
4. In the second stage, the SRMR of the estimated model is 0.007. This small amount of misfit is attributable to the just partial mediation evoked by the imperfect measurement of the mediator H (for an explanation of this mechanism, see Henseler, 2012).

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