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How to specify, estimate, and validate higher-order constructs in PLS-SEM

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ABSTRACT

Higher-order constructs, which facilitate modeling a construct on a more abstract higher-level dimension and its more concrete lower-order subdimensions, have become an increasingly visible trend in applications of partial least squares structural equation modeling (PLS-SEM). Unfortunately, researchers frequently confuse the specification, estimation, and validation of higher-order constructs, for example, when it comes to assessing their reliability and validity. Addressing this concern, this paper explains how to evaluate the results of higher-order constructs in PLS-SEM using the repeated indicators and the two-stage approaches, which feature prominently in applied social sciences research. Focusing on the reflective-reflective and reflective-formative types of higher-order constructs, we use the well-known corporate reputation model example to illustrate their specification, estimation, and validation. Thereby, we provide the guidance that scholars, marketing researchers, and practitioners need when using higher-order constructs in their studies.

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1. Introduction

Composite-based methods for modeling complex interrelationships between observed and latent variables have recently gained substantial traction in the social sciences and beyond (Hwang & Takane, 2014). Partial least squares structural equation modeling (PLS-SEM) in particular has attracted much attention in marketing and related fields of business research (Hair et al., 2017b; Hair et al., 2019). As PLS-SEM becomes more widespread, researchers are gradually moving from relatively small and focused models to more advanced model designs (Sharma et al., 2019), such as higher-order constructs (Ringle et al., 2019).

Higher-order constructs (also known as hierarchical component models in the context of PLS-SEM; Lohmöller, 1989) provide a framework for researchers to model a construct on a more abstract dimension (referred to as higher-order component) and its more concrete subdimensions (referred to as lower-order components).

As such, they extend standard construct conceptualizations, which typically rely on a single layer of abstraction.

Higher-order constructs have several advantageous features. For example, higher-order constructs help to reduce the number of path model relationships, thereby achieving model parsimony (Edwards, 2001; Johnson et al., 2011; Polites et al., 2012). Instead of specifying relationships between multiple independent and dependent constructs in a path model, researchers can summarize the independent constructs in a higher-order construct, making the relationships from the (then) lower-order components to the dependent constructs in the model obsolete. As another advantage, higher-order constructs also help to overcome the bandwidth-fidelity dilemma (Cronbach & Gleser, 1965, p. 100), according to which there is a tradeoff “between variety of information (bandwidth) and thoroughness of testing to obtain more certain information (fidelity).” Finally, higher-order constructs provide a means for reducing collinearity among formative indicators by offering a vehicle to re-arrange the indicators and/or constructs across different concrete subdimensions of the more abstract construct (Hair et al., 2018).

To reap the benefits of higher order constructs, researchers must address at least three concerns. First, the higher-order con-

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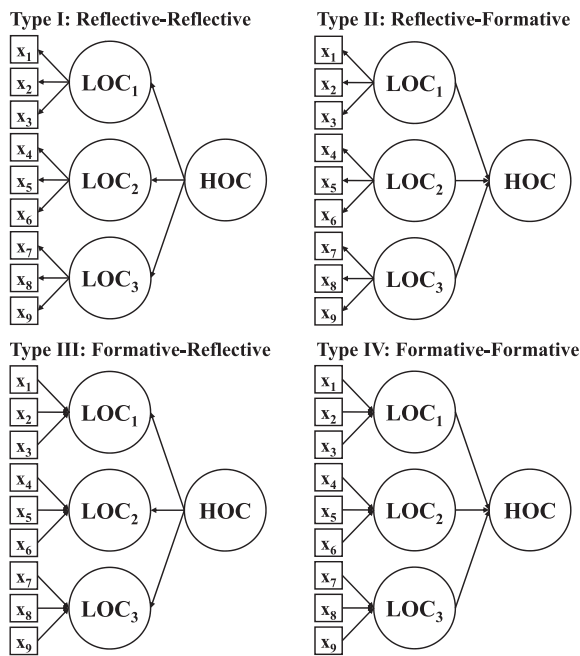


Fig. 1. Different types of higher-order constructs.

Note: LOC = lower-order component; HOC = higher-order component

struct's conceptualization and specification needs to be grounded in well-developed measurement theory. In fact, this step can be as challenging and tedious as developing a new measurement scale (DeVellis, 2016; Relling et al., 2016). Specifically, when implementing a higher-order construct, researchers have to decide on (1) the measurement model specification of the lower-order components, and (2) the relationship between the higher-order component and its lower-order components (Jarvis et al., 2003; Wetzels et al., 2009), both of which can be reflective or formative in nature. As a result, research has proposed four types of higher-order constructs (Figure 1): reflective-reflective, reflective-formative, formative-reflective, and formative-formative (see Becker et al., 2012; Cheah et al., 2019; Ringle et al., 2012).

Prior studies on higher-order constructs in PLS-SEM have shown that reflective-reflective and reflective-formative higher-order types feature prominently in different fields (Becker et al., 2012; Cheah et al., 2019; Ringle et al., 2012). Our own review of all PLS-SEM studies published in the *Journal of Marketing Research*, *Journal of Marketing*, and *Journal of the Academy of Marketing Science* in the past thirty years (1989–2018) supports these findings. Of the fifty-seven studies that used PLS-SEM, sixteen (28.07%) specified higher-order constructs. Seven of these studies used reflective-reflective type, whereas eight studies applied reflective-formative type higher-order constructs. One study used both types in the path model.¹

Second, researchers can choose among different approaches to identify the higher-order construct. Prominent approaches are the repeated indicators approach or the two-stage approach (Hair et al., 2018), as evidenced in our literature review. Thirteen of the sixteen studies identified in our literature review (81.25%) used the

two-stage approach, whereas three studies (18.75%) applied the repeated indicators approach.²

Third, evaluating the measurement quality of higher-order constructs is highly challenging—as evidenced in our literature review of their use in the context of PLS-SEM. For example, some authors do not assess the reliability and validity of the lower-order components and higher-order components, while others erroneously interpret the relationships between higher- and lower-order components as structural model relationships—instead of assessing the lower-order components as elements of the higher-order construct's measurement model. We also find that while researchers frequently analyze the discriminant validity of the lower-order components, they neglect the discriminant validity assessment of the higher-order construct as a whole.

With these issues in mind, this paper aims to illustrate how to specify, estimate, and validate higher-order constructs in PLS-SEM. After a general introduction to higher-order constructs and the key technical aspects researchers must consider, we discuss how to evaluate the results by applying standard model assessment criteria. Focusing on the most prominent reflective-reflective and reflective-formative types of higher-order constructs, we use the corporate reputation model example, well-known from prior PLS-SEM applications (Hult et al., 2018a; Matthews et al., 2016; Sharma et al., 2019), to illustrate their specification and estimation using the repeated indicators and two-stage approaches. As part of our descriptions, we discuss how to apply standard model assessment criteria to validate higher-order constructs. In doing so, we pay particular attention to the assessment of discriminant validity, which prior research on higher-order constructs has not (or only incompletely) covered (Becker et al., 2012; Van Riel et al., 2017; Wetzels et al., 2009).

2. Specifying higher-order constructs

Researchers have proposed several approaches for specifying and estimating higher-order constructs in PLS-SEM. The most prominent ones are the (extended) repeated indicators approach and the two-stage approach (Ringle et al., 2012). Becker et al. (2012) have evaluated both approaches for reflective-formative type higher-order constructs in a large-scale simulation study.³ Their results show that the (extended) repeated indicators approach produces smaller biases in the estimation of the higher-order construct's measurement model (i.e., the relations between lower- and higher-order components). In contrast, the two-stage approach shows a better parameter recovery of paths pointing (1) from exogenous constructs to the higher-order construct, and (2) from the higher-order construct to an endogenous construct in the path model. While we recommend choosing the approach that best aligns with the research objective, the repeated indicators and two-stage approaches typically produce highly similar results when sample sizes are sufficiently large.

2.1. The (extended) repeated indicators approach

In the repeated indicators approach, all indicators of the lower-order components are assigned to the higher-order component (Lohmöller, 1989; Wold, 1982). For example, when a higher-order construct consists of three lower-order components, each measured with three indicators (x₁–x₃, x₄–x₆, and x₇–x₉), the higher-order component would be measured with the same nine indicators x₁–x₉ (Fig. 2) as the lower-order components.

¹ In addition, we also reviewed all PLS-SEM studies published in the *Australasian Marketing Journal* in the past twenty years (1999–2018) to support this finding. Of the fifteen studies that used PLS-SEM, three (20.00%) specified higher-order constructs. Two studies specified reflective-reflective higher-order constructs (Cass, 2001; Harrigan et al., 2015) and one study used a reflective-formative higher-order construct (Hourigan & Bougoure, 2012).

² All three (100%) *Australasian Marketing Journal* studies that specified higher-order constructs used the two-stage approach.

³ More precisely, these authors have considered the disjoint two-stage approach, which we discuss in detail in the remainder of this paper.

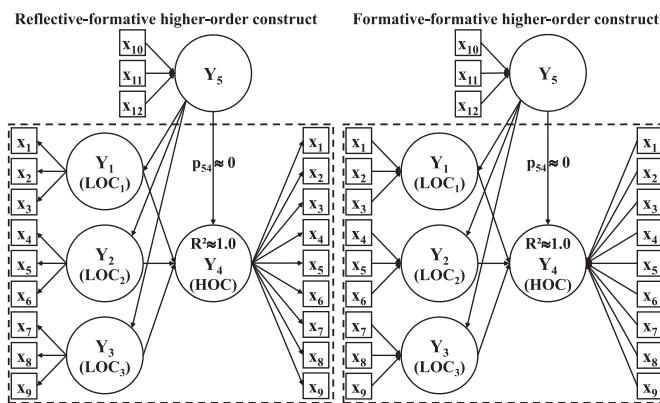


Fig. 2. Extended repeated indicators approach.

Note: LOC = lower-order component; HOC = higher-order component. In the left panel of the Figure, for the reflective-formative higher-order construct, software applications usually execute Mode A as default setting for the reflective items (i.e., the repeated indicators $x_1, \dots, x_9$) of the higher-order component Y_4 ; here it is important that the researchers pay particular attention to the Mode B being selected for the higher-level component Y_4 .

Even though the repeated indicators approach is easy to apply in PLS-SEM, its use becomes problematic when a reflective-formative and formative-formative higher-order construct also serves as a dependent construct in a path model—as is the case in Fig. 2. When using a reflective-formative or a formative-formative higher-order construct, PLS-SEM regresses the higher-order component on its lower-order components. Since all indicators of the lower-order components (x_1 – x_3 , x_4 – x_6 , and x_7 – x_9 in Fig. 2) are repeated to identify the higher-order component (x_1 – x_9 in Fig. 2), the higher-order component's variance will be fully explained by the lower-order components (i.e., the R^2 value will be unity by default). As a result, it is not possible for any antecedent construct (in this example Y_5 in Fig. 2) in the path model that is not part of the higher-order construct, to explain any variance of the higher-order component—its path coefficient estimate (p_{54} in Fig. 2) will be close to zero and nonsignificant (Ringle et al., 2012).

To deal with this problem, Becker et al. (2012) proposed the *extended repeated indicators approach* (also referred to as the *total effects analysis of collect-type hierarchical component models*; Fig. 2). Based on the extended repeated indicators approach, researchers need to additionally specify the relationships between the antecedent construct (Y_5) and the lower-order components (Y_1 – Y_3). Instead of analyzing the direct relationship between the antecedent construct and the higher-order component (p_{54}), which is zero by design, researchers need to analyze the antecedent construct's total effect on the higher-order component. This total effect also includes all indirect effects of Y_5 on Y_4 via the lower-order components, thereby portraying an accurate picture of the antecedent construct's actual effect on the higher-order component (Becker et al., 2012). Fig. 2 illustrates the extended repeated indicators approach for reflective-formative (left panel) and formative-formative (right panel) type higher-order constructs and one antecedent construct (Y_5).

2.2. The two-stage approach

Researchers have proposed the two-stage approach as an alternative to the repeated indicators approach (Wetzels et al., 2009). In fact, research has proposed two versions of the two-stage approach, (1) the *embedded two-stage approach* (Ringle et al., 2012) and (2) the *disjoint two-stage approach* (Agarwal & Karahanna, 2000; Becker et al., 2012), which slightly differ in their model specification in both stages. For example, while the embedded

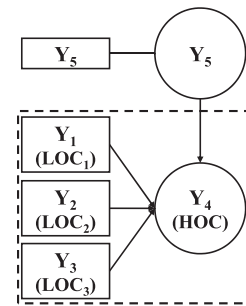


Fig. 3. Stage two of the embedded two-stage approach.

Note: LOC = lower-order component; HOC = higher-order component

approach models the entire higher-order construct in its first stage, the disjoint approach initially only draws on the lower-order components (hence the denominations “embedded” and “disjoint”). As both versions of the two-stage approach lead to similar results (see Cheah et al., 2019), there is no compelling reason for preferring one over the other. In the following, we introduce both versions for the case of reflective-formative type higher-order constructs, which represent a standard case for their use.

2.2.1. The embedded two-stage approach

The first stage of the embedded two-stage approach corresponds to the standard repeated indicators approach, which has an antecedent construct in the structural model (i.e., Y_5 in Fig. 2) and produces a nonsignificant path coefficient estimate from the antecedent construct to the higher-order component (p_{54} in Fig. 2)⁴. Instead of interpreting the model estimates, however, researchers need to save the scores of all constructs in the model and add these as new variables to the dataset. In stage two, the construct scores are used as indicators in the higher-order construct's measurement model as shown in Fig. 3. For example, in case of the higher-order constructs displayed in Fig. 2, the higher-order component Y_4 would be measured with three formative indicators capturing the latent variable scores of Y_1 , Y_2 , and Y_3 from stage one. All other constructs in the model (e.g., Y_5 in Fig. 3) are measured with single items that capture each construct's latent variable scores from the previous stage.

2.2.2. The disjoint two-stage approach

The disjoint two-stage approach differs from the embedded two-stage approach in the specification of both stages. Rather than using the repeated indicators approach in stage one, the disjoint two-stage approach considers only the lower-order components of the higher-order construct (i.e., without the higher-order component) in the path model. These are directly linked to all other constructs that the higher-order construct is theoretically related to.

To execute the disjoint two-stage approach, researchers then need to save the construct scores, but only those of the lower-order components (e.g., the scores of constructs Y_1 , Y_2 , and Y_3 in our example). In stage two, these scores are then used to measure the higher-order construct. However, different from the embedded two-stage approach, all other constructs in the path model are estimated using their standard multi-item measures as in stage one (e.g., Y_5 in Fig. 4).

⁴ Note: To determine the results, the higher-order construct must be embedded in the nomological network of the underlying path model with its predecessor or successor constructs; it is not permissible to estimate the higher-order construct as a stand-alone construct in the first stage of the embedded two-stage approach.

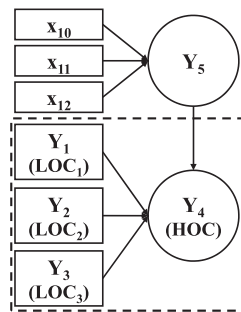


Fig. 4. Stage two of the disjoint two-stage approach.

Note: LOC = lower-order component; HOC = higher-order component

3. Estimating higher-order constructs

When estimating higher-order constructs in PLS-SEM, researchers need to pay special attention to the algorithm settings. The PLS-SEM algorithm uses two different modes to estimate the measurement models – Mode A and Mode B. When using Mode A (i.e., correlation weights), the bivariate correlations between each indicator and the construct determine the indicator weights used to compute the latent variable scores. In contrast, Mode B (i.e., regression weights) computes indicator weights by regressing each construct on its associated indicators. While researchers typically use Mode A to estimate reflectively specified measurement models and Mode B to estimate formatively specified measurement models, Becker et al. (2012) show that this choice of measurement mode for repeated indicators does not apply to the orientation of the lower-order components, but the higher-order component. Specifically, their simulation study shows that Mode B estimation of the higher-order component in a reflective-formative type higher-order construct produces the smallest parameter estimation bias. Hence, even though the (repeated) indicators identifying the higher-order constructs are specified reflectively on the lower-order components, researchers should use Mode B for these repeated indicators on the higher-order component. In light of these findings, researchers should use Mode A for a reflectively specified higher-order constructs (i.e., reflective-reflective and formative-reflective types) and Mode B for formatively specified higher-order constructs (i.e., reflective-formative and formative-formative types). This recommendation also holds for the first stage of the embedded two-stage approach. In contrast, the disjoint two-stage approach should be estimated using the standard settings on both stages; that is, Mode A for reflectively specified measurement models and Mode B for formatively specified measurement models.

Finally, Becker et al. (2012) also show that the path weighting scheme (Lohmöller, 1989) to estimate the PLS path model produces the overall best parameter recovery in formatively specified higher-order constructs (i.e., reflective-formative and formative-formative types). Even though prior research has not extended Becker et al.'s (2012) study in this regard, we expect that their findings generalize to reflectively specified higher-order constructs (i.e., reflective-reflective and formative-reflective types). Hence, we recommend using the path weighting scheme as default setting when estimating higher-order constructs in PLS-SEM.

4. Validating higher-order constructs

When evaluating higher-order models, the same model evaluation criteria generally apply as for any PLS-SEM analysis (Chin, 2010b). However, higher-order constructs need to consider two additional measurement models for which the evaluation criteria apply: (1) The measurement models of the lower-order components, and (2) the measurement model of the higher-order construct as a

whole, represented by the relationships between the higher-order component and its lower-order components.

4.1. The (extended) repeated indicators approach

To begin with, we focus on the (extended) repeated indicators approach. Table 1 provides an overview of the metrics relevant to validate a higher-order construct's measurement model when using the (extended) repeated indicators approach.

Three aspects require particular attention when validating higher-order constructs. First, the higher-order construct must *not* be evaluated in terms of its (repeated) indicators used to identify the higher-order component (x_1 – x_9 in Fig. 1). These indicators only ensure that the higher-order construct is identified—they do not represent its actual measurement model. The higher-order construct's measurement model is, instead, defined by the relationships between the higher-order component and its lower-order components. When the lower-order components are reflections of the higher-order component (reflective-reflective and formative-reflective types), the direction of relationships is from the higher-order component to the lower-order component (Fig. 1) and, therefore, represent loadings. Conversely, when the lower-order components form the higher-order component (reflective-formative and formative-formative types), the direction of relationships is from the lower-order constructs to higher-order construct (Fig. 1) and, therefore, represent weights. Hence, researchers need to apply the standard measurement model assessment criteria to the path relationships between the higher- and lower-order components (Table 1).

Second, assessing the higher-order construct's discriminant validity requires additional scrutiny. The lower-order components must exhibit discriminant validity among each other and to all other constructs in the model—except for their own higher-order component of which they are a part of. This is also the reason why higher-order constructs cannot be used to solve discriminant validity issues in a model—despite contrary claims in the literature (Kocuyigit & Ringle, 2011). In addition, the higher-order construct as a whole must exhibit discriminant validity to all other constructs in the model. Researchers have to assess the discriminant validity of the higher-order component by considering its lower-order components as the measurement model of the higher-order component (and not in terms of its repeated indicators such as x_1 – x_9 in Fig. 2).

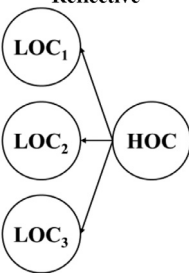
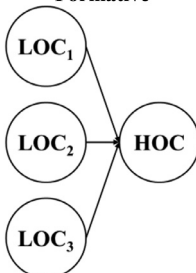
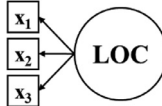
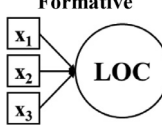
Third, for the relationships of the higher-order component to constructs in the model *other than* its lower-order components, the standard structural model evaluation criteria apply. In other words, the lower-order components are not considered as being part of the structural model. Researchers only need to assess the higher-order component as part of the structural model. Table 2 (left panel) illustrates a sample model in which Y_4 represents a higher-order construct and Y_5 , Y_6 , and Y_7 are additional constructs in the path model. In such a model set-up, researchers need to apply the standard structural model assessment criteria (Table 2, right panel) to the relationships between Y_4 , Y_5 , Y_6 , and Y_7 . The analysis should be complemented by structural model robustness checks (Sarstedt et al., 2019).

4.2. The two-stage approach

The PLS-SEM results assessment of the two-stage approach also applies the procedures and criteria that have been recommended for the measurement models and the structural model (e.g., Chin, 2010b; Hair et al., 2017a; Ramayah et al., 2016). That is, the results evaluation in stage one considers all measurement models, including those of the lower-order components. But the repeated indicators used to identify the higher-order construct are

Table 1

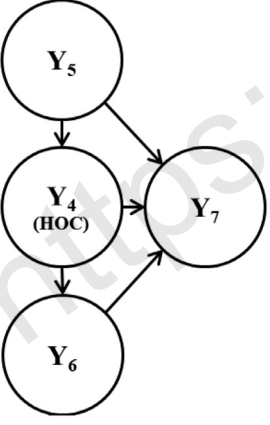
Measurement model results assessment of higher-order constructs when using the (extended) repeated indicators approach.

Measurement specification of the higher-order construct			
		Reflective	Formative
			
Measurement specification of the lower-order components		LOCs and HOC (LOCs represent the indicators of the HOC)	LOCs
		• Internal consistency (Cronbach's alpha, composite reliability, ρ_A) • Convergent validity (indicator reliability, average variance extracted) • Discriminant validity	• Internal consistency (Cronbach's alpha, composite reliability, ρ_A) • Convergent validity (indicator reliability, average variance extracted) • Discriminant validity
		LOCs • Convergent validity • Collinearity between indicators • Significance and relevance of outer weights HOC (LOCs represent the indicators of the HOC) • Internal consistency (Cronbach's alpha, composite reliability, ρ_A) • Convergent validity (indicator reliability, average variance extracted) • Discriminant validity	HOC (LOCs represent the indicators of the HOC) • Convergent validity • Collinearity between indicators • Significance and relevance of outer weights LOCs and HOC (LOCs represent the indicators of the HOC) • Convergent validity • Collinearity between indicators • Significance and relevance of outer weights

Note: The criteria also apply to stage one of the embedded two-stage approach.

Table 2

Results assessment of higher-order constructs.

Structural model	
	• Collinearity between constructs • Significance and relevance of the path coefficients • Explanatory (R^2) and predictive power (most notably PLSpredict)

not being evaluated. The stage two results need to be assessed in terms of the higher-order construct's measurement model—as expressed by the relationships between higher- and lower-order components—and the structural model. However, researchers need to pay particular attention to any structural model assessment that involves interpreting the indicators, such as in blindfolding (Chin, 2010a), PLSpredict (Shmueli et al., 2016; Shmueli et al.,

2019), and IPMA (Ringle & Sarstedt, 2016). Specifically, in the case of the embedded two-stage approach, corresponding structural model assessments should be carried out in the first stage. The reason is that stage two uses the latent variable scores of stage one as single items, which renders the validation on the grounds of the items meaningless. In contrast, the disjoint two-stage approach uses multi items in the second stage, which permits the application of all structural model assessment criteria. Hence, when using the disjoint two-stage approach, researchers should assess the structural model on the grounds of stage two results.

5. Empirical illustration

5.1. Model and data

In order to illustrate the validation of higher-order constructs in PLS-SEM, we replicate the corporate reputation model used by Hair et al. (2017a; 2018).⁵ The model will be used to demonstrate how competence (COMP) and likeability (LIKE), which represent the two dimensions of corporate reputation, affect customer satisfaction (CUSA) and customer loyalty (CUSL). Furthermore, the model includes four antecedent constructs that potentially explain COMP and LIKE: (1) the quality of a company's products and services, as well as its quality of customer orientation (QUAL), (2) its economic and managerial performance (PERF), (3) a company's corporate social responsibility (CSOR), and (4) its attractiveness (ATTR). The

⁵ The dataset and the SmartPLS project file with all model set-ups can be downloaded at www.pls-sem.com → Downloads → Other Files and Sample Projects.

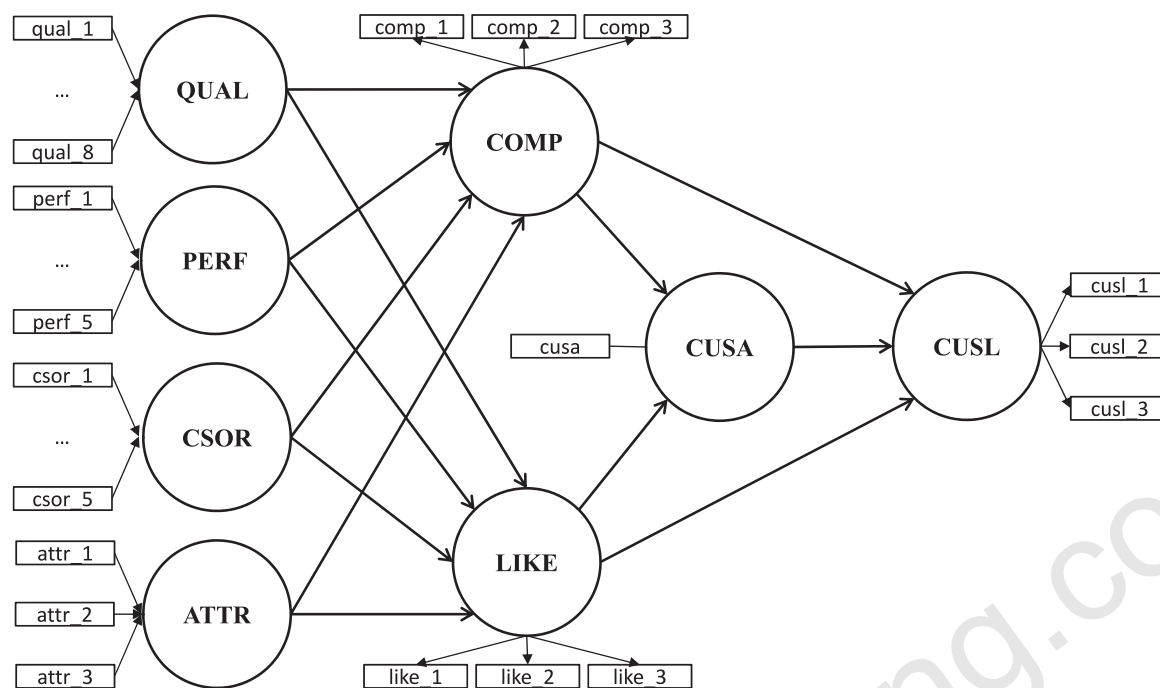


Fig. 5. Original corporate reputation model.

measurement models of *COMP*, *LIKE*, and *CUSL* draw on three reflective items each, whereas *CUSA* is measured with a single item. In contrast, the four antecedent constructs (i.e., *ATTR*, *CSOR*, *PERF*, and *QUAL*) have formative measurement models with a total of twenty-one indicators (Eberl, 2010; Schwaiger, 2004). All measures were rated for each item on a seven-point Likert scale.⁶ Figure 5 shows the original path model, including the measurement models.

Prior applications of Schwaiger's (2004) measurement approach considered *COMP* and *LIKE* as two distinct constructs (e.g., Radomir & Wilson, 2018; Raithel & Schwaiger, 2015; Sarstedt et al., 2013), as shown in Fig. 5. In his original conceptualization of corporate reputation, Schwaiger (2004, p. 63) notes that the construct "can be split into affective and cognitive components." Based on this notion, corporate reputation can be conceptualized as a higher-order construct comprising the two lower-order components *COMP* and *LIKE*.

From a measurement theory perspective, *COMP* and *LIKE* can be considered as reflections of corporate reputation (e.g., Schwaiger, 2004), thereby implying the use of a reflective-reflective higher-order construct, since each of the lower-order components is measured reflectively. However, Eberl (2010) argues that *COMP* and *LIKE* determine corporate reputation, which suggests a reflective-formative specification. In the following, we illustrate the estimation of the higher-order constructs using the (extended) repeated indicators approach and the two-stage approach. More precisely, we focus on the disjoint two-stage approach, because it is less well documented in the literature.

The model estimation uses the software SmartPLS 3 (Ringle et al., 2015) and draws on data from four major Malaysian mobile communications network providers; namely, Digi, Maxis, Celcom, and U Mobile. The survey design followed a sequence of steps, including a pre-test (three postgraduate students and five adult volunteers who regularly purchase online travel products) and a

pilot test with 30 respondents to identify problematic items and further improve the survey (Fink, 2017). Using a mall intercept approach in one of Kuala Lumpur's largest malls, respondents were asked to rate corporate reputation, their satisfaction, and loyalty toward their primary mobile network provider. A total of 361 responses were collected for the study. Observations with missing values and straight lining were deleted (Sarstedt & Mooi, 2019, Chapter 5), leaving a total sample size of 347. Table A1 in the Appendix shows a description of the sample characteristics.

5.2. Reflective-reflective specification

5.2.1. The repeated indicators approach

To establish the reflective-reflective higher-order construct of corporate reputation, we first draw on the repeated indicators approach. The constructs *COMP* and *LIKE* represent the lower-order constructs of the more general higher-order construct corporate reputation (*REPU*), which is measured with the six indicators *comp_1*, *comp_2*, *comp_3*, *like_1*, *like_2*, and *like_3*. That is, all indicators of the reflectively measured lower-order components are simultaneously assigned to the reflective measurement model of the higher-order construct. In terms of structural model specification, the four antecedent constructs *ATTR*, *CSOR*, *QUAL*, and *PERF* directly relate to the higher-order component *REPU* (instead of having a relationship to *COMP* and *LIKE*). Similarly, *REPU* is now directly related to the two criterion variables *CUSA* and *CUSL* (Fig. 6), and *CUSA* is directly related to *CUSL*. Note that we follow the assumption of the original corporate reputation model, that all relationships from the independent latent variables *ATTR*, *CSOR*, *QUAL*, and *PERF* to the dependent constructs *CUSA* and *CUSL* are fully mediated by the higher-order reputation construct *REPU*. In line with Becker et al. (2012), we use Mode A to estimate *REPU*.

Next, we focus on the measurement model assessment of the higher-order construct *REPU* and its lower-order components *COMP* and *LIKE*. The assessment of the lower-order components draws

⁶ See Hair et al. (2017a) for a complete list of item wordings.

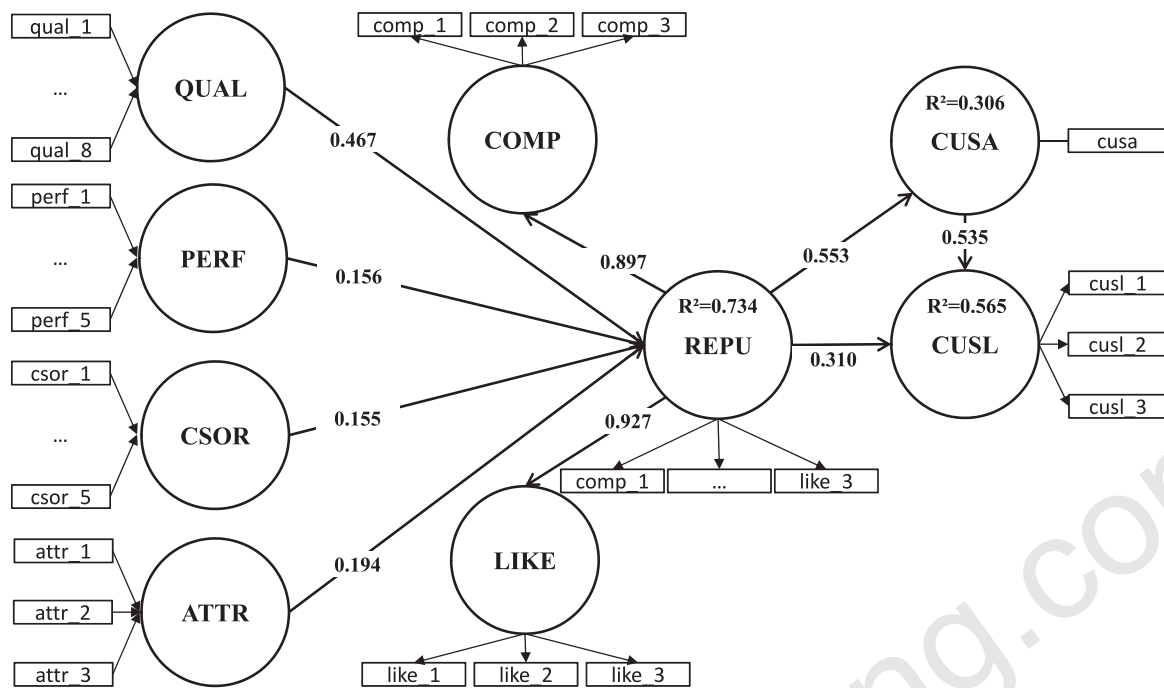


Fig. 6. Reflective-reflective specification of corporate reputation and PLS-SEM results (repeated indicators approach).

Table 3
Reliability and validity statistics.

	Cronbach's α	ρ_A	Composite reliability ρ_C	Average variance extracted (AVE)
COMP	0.773	0.774	0.869	0.688
CUSL	0.849	0.856	0.909	0.769
LIKE	0.841	0.842	0.904	0.759
REPU*	0.799	0.814	0.908	0.832

Note: Italics used for higher-order construct values.

Table 4
Discriminant validity assessment using the HTMT criterion.

	COMP	CUSA	CUSL	REPU*	LIKE
COMP					
CUSA	0.507				
CUSL	0.551	0.765			
REPU*	–	0.613	0.722		
LIKE	0.817	0.598	0.752	–	

Note: Italics used for higher-order construct values.

on the standard reliability and validity criteria for reflective measurement models as documented in the extant literature (e.g., Hair et al., 2017a; Latan & Noonan, 2017; Sarstedt et al., 2017). The results in Table 3 show that the measures of COMP yield satisfactory levels of convergent validity in terms of average variance extracted (AVE=0.688) and internal consistency reliability (composite reliability ρ_C =0.869; Cronbach's alpha=0.773; ρ_A =0.774). Similarly, the measures of LIKE exhibit convergent validity (AVE=0.759) and internal consistency reliability (composite reliability ρ_C =0.904; Cronbach's alpha=0.841; ρ_A =0.842).

Finally, we find support for the lower-order components' discriminant validity, because all HTMT values (Franke & Sarstedt, 2019; Henseler et al., 2015; Voorhees et al., 2016) are below the conservative threshold of 0.85 (Table 4). However, we do not consider the discriminant validity between both COMP and LIKE and their higher-order component REPU. A violation of discrim-

inant validity between these constructs is expected, because the measurement model of the higher-order component repeats the indicators of its two lower-order components. In addition, the repeated indicators of the REPU construct are only included for identification and—by design—do not stem from a unidimensional domain. This not only means discriminant validity assessment for these relationships is not relevant, but all other types of reliability and validity assessment of the REPU construct on the grounds of the six items comp_1, comp_2, comp_3, like_1, like_2, and like_3 are not meaningful.

The reliability and validity assessment of the higher-order construct REPU draws on its relationship with its lower-order components. The constructs COMP and LIKE are specifically interpreted as if they were indicators of the REPU construct. As a consequence, the (reflective) relationships between the REPU construct and its lower-order components COMP and LIKE, are interpreted as loadings although they appear as path coefficients in the path model.

The analysis produces loadings of 0.897 for COMP and 0.927 for LIKE, thereby providing support for indicator reliability. By using these indicator loadings and the correlation between the constructs (0.665) as input, we can manually calculate the relevant statistics for assessing the higher-order construct's reliability and validity.

The AVE is the mean of the higher-order construct's squared loadings for the relationships between the lower-order components and the higher-order component:

$$AVE = \frac{(\sum_{i=1}^M l_i^2)}{M}, \quad (1)$$

where l_i represents the loading of the lower-order component i of a specific higher-order construct measured with M lower-order components ($i=1, \dots, M$). For this example, the AVE is $(0.897^2 + 0.927^2)/2 = 0.832$, which is clearly above the 0.5 threshold, therefore indicating convergent validity for REPU (Sarstedt et al., 2017).

Table 5
Loadings and cross loadings.

Indicator	Construct				
	COMP	CUSA	CUSL	LIKE	REPU
comp_1	0.802	0.464	0.456	0.637	0.786
comp_2	0.817	0.321	0.317	0.476	0.691
comp_3	0.867	0.325	0.34	0.529	0.747
cusa	0.450	1.000	0.706	0.549	0.553
cusl_1	0.452	0.574	0.853	0.603	0.585
cusl_2	0.408	0.673	0.924	0.603	0.563
cusl_3	0.322	0.608	0.852	0.467	0.439
like_1	0.632	0.542	0.579	0.879	0.841
like_2	0.527	0.463	0.568	0.881	0.787
like_3	0.575	0.426	0.52	0.852	0.791

Note: The (cross) loadings of the formative items have been omitted.

The composite reliability is defined as

$$\rho_c = \frac{(\sum_{i=1}^M l_i)^2}{(\sum_{i=1}^M l_i)^2 + \sum_{i=1}^M \text{var}(e_i)}, \quad (2)$$

where e_i is the measurement error of the lower-order component i , and $\text{var}(e_i)$ denotes the variance of the measurement error, which is defined as $1 - l_i^2$. Entering the two loading values yields the following:

$$\begin{aligned} \rho_c &= \frac{(0.897 + 0.927)^2}{(0.897 + 0.927)^2 + (1 - 0.897^2) + (1 - 0.927^2)} \\ &= \frac{3.327}{3.327 + 0.195 + 0.141} = 0.908 \end{aligned} \quad (3)$$

Similarly, Cronbach's α is given by

$$\text{Cronbach's } \alpha = \frac{M \cdot \bar{r}}{(1 + (M - 1) \cdot \bar{r})}, \quad (4)$$

where $\bar{r}$ represents the average correlation between the lower-order components. Since the higher-order construct *REPU* has only two lower-order components (i.e., $M = 2$), the average correlation is equal to the correlation between the *COMP* and *LIKE* construct scores (i.e., 0.665). Hence, Cronbach's alpha is given by:

$$\text{Cronbach's } \alpha = \frac{2 \cdot 0.665}{(1 + (2 - 1) \cdot 0.665)} = \frac{1.33}{1.665} = 0.799. \quad (5)$$

Finally, to compute the reliability metric ρ_A , we follow [Dijkstra and Henseler \(2015\)](#);

$$\rho_A := (\hat{w}'\hat{w})^2 \cdot \frac{\hat{w}'(S - \text{diag}(S))\hat{w}}{\hat{w}'(\hat{w}\hat{w}' - \text{diag}(\hat{w}\hat{w}'))\hat{w}}, \quad (6)$$

whereby $\hat{w}$ represents the estimated weight vector of the latent variable (the dimension of $\hat{w}$ is the number of indicators directly associated with the latent variable) and S is the empirical covariance matrix of the latent variable's indicators. In order to adapt the ρ_A computation to reflective-reflective type (and formative-reflective type) higher-order constructs in PLS-SEM, the weight estimates $\hat{w}$ are determined for the relationships between the lower- and higher-order components. In addition, the latent variable scores of the lower-order components are used for establishing the empirical covariance matrix S .

To calculate ρ_A according to [Eq. \(6\)](#) in our example, we estimate the model displayed in [Fig. 6](#) and save the latent variable scores

to compute the weight relationships ([Eq. \(7\)](#)) and construct correlations, which represent S in [Eq. \(6\)](#). On these grounds, we can compute the weight relationships between the lower-order components and the higher-order component by running the following ordinary least squares (OLS) regression analysis:

$$\hat{W} = (X^T X)^{-1} X^T Y, \quad (7)$$

where $\hat{W}$ is the estimated weights vector, X is the matrix of the lower-order components' latent variable scores and Y is the vector of the higher-order component's latent variable scores. The regression produces weights of 0.503 for *COMP* and 0.592 for *LIKE* and a construct correlation of 0.665. Entering these values into [Eq. \(6\)](#), together with the construct correlations S , produces a ρ_A value of the higher-order construct *REPU* of 0.814.⁷ Overall, these results provide clear support for the higher-order construct's internal consistency reliability as all criteria (i.e., ρ_c , Cronbach's α , and ρ_A) are well above the commonly recommended threshold of 0.708 ([Hair et al., 2017a](#)).

In the next step, we need to assess the higher-order construct's discriminant validity by using [Henseler et al.'s \(2015\)](#) HTMT criterion, which is defined as the mean value of the item correlations across constructs (i.e., the heterotrait-heteromethod correlations) relative to the geometric mean of the average correlations for the items measuring the same construct (i.e., the monotrait-heteromethod correlations). The heterotrait-heteromethod correlations of a higher-order construct are represented by the cross loadings of the other (reflective or single-item) constructs in the model with the lower-order components. The higher-order construct's monotrait-heteromethod correlations are equal to the (construct) correlations between the lower-order components. [Tables 5 and 6](#) document the statistics relevant for manually computing the higher-order construct's HTMT values.

The higher-order construct's average heterotrait-heteromethod correlation with *CUSA* is the average cross loading of the *cusa* indicator with the *COMP* (0.450) and *LIKE* (0.549) constructs ([Table 5](#)), which is 0.500. When it comes to *CUSL*, the same statistic is given by the average cross loadings of *cusl_1*,

⁷ An Excel spreadsheet that illustrates how to compute the ρ_A metric manually can be downloaded at www.pls-sem.com → Downloads → Other Files and Sample Projects.

Table 6
Indicator correlations.

	<i>comp_1</i>	<i>comp_2</i>	<i>comp_3</i>	<i>cusa</i>	<i>cusl_1</i>	<i>cusl_2</i>	<i>cusl_3</i>	<i>like_1</i>	<i>like_2</i>	<i>like_3</i>
<i>comp_1</i>	1	0.435	0.525	0.464	0.459	0.424	0.311	0.627	0.515	0.518
<i>comp_2</i>	0.435	1	0.634	0.321	0.329	0.276	0.227	0.455	0.358	0.428
<i>comp_3</i>	0.525	0.634	1	0.325	0.329	0.306	0.258	0.478	0.426	0.477
<i>cusa</i>	0.464	0.321	0.325	1	0.574	0.673	0.608	0.542	0.463	0.426
<i>cusl_1</i>	0.459	0.329	0.329	0.574	1	0.696	0.545	0.564	0.537	0.473
<i>cusl_2</i>	0.424	0.276	0.306	0.673	0.696	1	0.716	0.539	0.538	0.497
<i>cusl_3</i>	0.311	0.227	0.258	0.608	0.545	0.716	1	0.415	0.413	0.392
<i>like_1</i>	0.627	0.455	0.478	0.542	0.564	0.539	0.415	1	0.678	0.603
<i>like_2</i>	0.515	0.358	0.426	0.463	0.537	0.538	0.413	0.678	1	0.632
<i>like_3</i>	0.518	0.428	0.477	0.426	0.473	0.497	0.392	0.603	0.632	1

Note: The correlations of the formative items have been omitted.

cusl_2, and *cusl_3* with *COMP* and *LIKE* (Table 5), which is: $(0.452+0.408+0.322+0.603+0.603+0.467)/6 = 0.476$.

In the next step, we compute all monotrait-heteromethod correlations that are relevant for assessing the higher-order construct. Since *CUSA* is a single-item construct, its average monotrait-heteromethod correlation is by definition one. The three items of *CUSL* have item correlations of 0.696, 0.545, and 0.716 (Table 6), thereby yielding an average monotrait-heteromethod correlation of 0.652. Finally, the average monotrait-heteromethod correlation of the *REPU* construct is equal to the construct correlation between *COMP* and *LIKE*, which is 0.665.

Finally, we need to compute the quotient of the heterotrait-heteromethod correlations and the geometric mean of the average monotrait-heteromethod correlations:⁸

$$HTMT(REPU, CUSA) = \frac{0.500}{\sqrt[3]{0.665 \cdot 1}} = 0.613, \text{ and} \quad (8)$$

$$HTMT(REPU, CUSL) = \frac{0.476}{\sqrt[3]{0.665 \cdot 0.652}} = 0.722 \quad (9)$$

Both values are clearly lower than the conservative threshold of 0.85 (see also Table 4), thereby providing clear evidence for the higher-order construct's reliability and validity.

Next, we analyze the structural model by using bootstrapping with 5,000 subsamples (no sign changes) and found that all structural model relationships are significant ($p < 0.05$); see Table A2 in the Appendix. The antecedent construct *QUAL* (0.467) has the strongest effect on *REPU*. The effects of *ATTR* (0.194), *PERF* (0.156), and *CSOR* (0.155) are, in comparison, notably smaller. *REPU* itself has a strong effect on *CSUA* (0.553), which in turn is strongly related to *CUSL* (0.535). The direct relationship between *REPU* and *CUSL* is somewhat weaker (0.310). The R^2 values of all the dependent latent variables (i.e., *REPU*: 0.734, *CUSA*: 0.306; *CUSL*: 0.565) are relatively high when taking the number of antecedent constructs into account. The same holds for the blindfolding-based Q^2 values, all of which are larger than zero (Table A2). Finally, we checked the model's out-of-sample predictive power regarding *CUSL* by running Shmueli et al.'s (2016) PLSpredict procedure (ten folds, ten repetitions). We find that the PLS-SEM analysis produces

smaller MAE and RMSE values for all three indicators of *CUSL* compared to the naïve linear model (LM) benchmark, which supports the model's predictive power (Danks & Ray, 2018; Shmueli et al., 2019).

5.2.2. The disjoint two-stage approach

Applying the disjoint two-stage approach, we first create and estimate the original reputation model as displayed in Fig. 5 connecting all the antecedent constructs (*ATTR*, *CSOR*, *PERF*, and *QUAL*) to the lower-order components *COMP* and *LIKE*, as well as connecting *COMP* and *LIKE* with the endogenous constructs *CUSA* and *CUSL*. The model assessment first focuses on the reflective measurement models of the lower-order components, which, as noted earlier, satisfy all relevant criteria (internal consistency, convergent validity, and discriminant validity; Tables 3 and 4).

In stage two, we use the latent variable scores of the lower-order components *COMP* and *LIKE* obtained from stage one to create and estimate the stage two model as shown in Fig. 7. For this purpose, we need to locate the scores of *COMP* and *LIKE* and add these as new variables to the dataset. The results are similar to the ones of the repeated indicators approach as evidenced in small differences of the path coefficient estimates (Fig. 6 vs. Fig. 7).

The evaluation of stage two starts with focusing on the reflective measurement model of the higher-order component *REPU*. For *REPU*, we find that the loadings of 0.904 for *COMP* and 0.923 for *LIKE* are particularly high, which enables us to establish indicator reliabilities higher than 0.81 and an AVE of 0.834. These results are above the critical value of 0.5. Cronbach's alpha (0.802), ρ_A (0.808), and ρ_C (0.910) of *REPU* are also at satisfactory levels. Based on the HTMT criterion, discriminant validity with *CUSA* and *CUSL* can be established.

Finally, the assessment of the stage two results addresses the structural model. The analysis shows that all other structural model evaluation results are also at a satisfactory level (e.g., significance and relevance for path coefficients, Q^2 , $PLS_{predict}$).

5.3. Reflective-formative higher-order construct

5.3.1. The extended repeated indicators approach

As an alternative to the reflective-reflective specification, we now consider the case in which the two subdimensions *COMP* and *LIKE* form the higher-order component *REPU*. If we used the standard repeated indicators approach to identify the higher-order construct, we would find that *COMP* and *LIKE* explain almost the

⁸ Note that the computation of the geometric mean in the denominator uses a square root, because the *REPU* construct has two lower-order components. In case of, for example, three lower-order components, the denominator would include a cubic root.

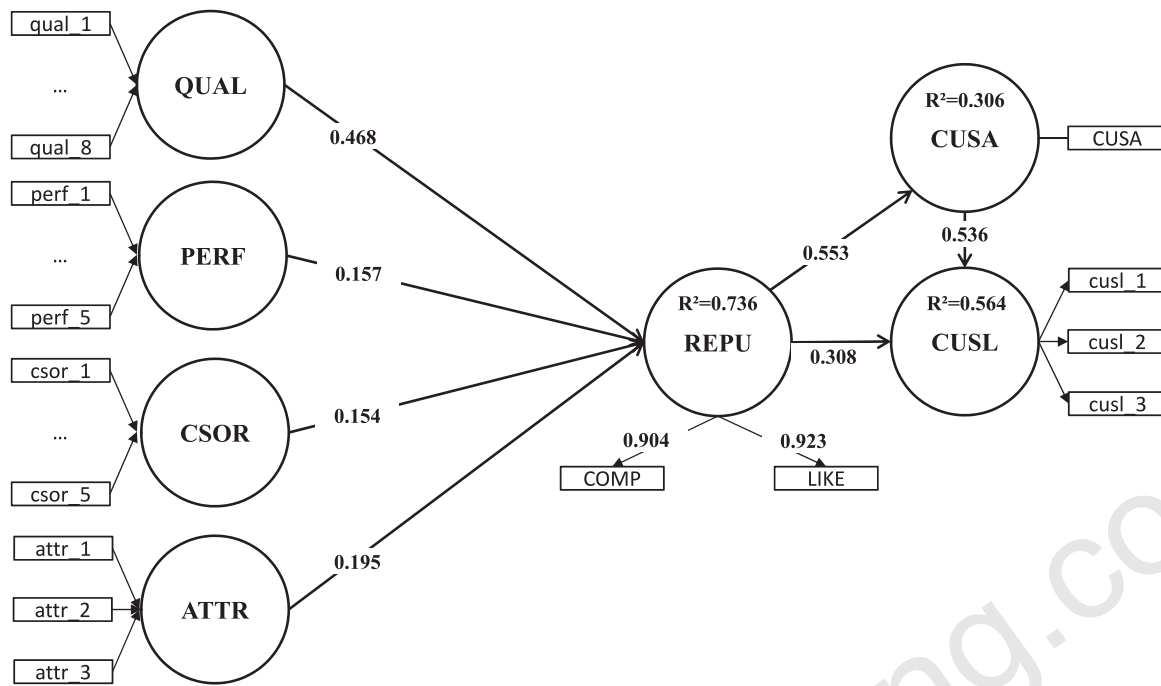


Fig. 7. Reflective-reflective stage two specification of corporate reputation and PLS-SEM results.

entire variance of the higher-order component *REPU* ($R^2 \approx 1.00$), because the partial regression of *REPU* on *COMP* and *LIKE* uses the same set of indicators (*comp_1* to *comp_3* and *like_1* to *like_3*) in the dependent and independent constructs. As a consequence, there is no variance left for the antecedent constructs (*ATTR*, *CSOR*, *PERF*, and *QUAL*) to explain—their estimated relationships with the *REPU* construct would be close to zero. However, concluding that these relationships are zero (and nonsignificant) would be incorrect, since these estimates result from using the repeated indicators approach to model a reflective-formative higher-order construct, which at the same time, is a dependent construct in the PLS path model (Hair et al., 2018).

In order to apply the extended repeated indicators approach, we need to extend the model by drawing direct relationships between the four antecedent constructs and the two lower-order components of reputation (Fig. 8). Following Becker et al. (2012), we use Mode B to estimate the measurement model of the higher-order component *REPU*.

As is the case in the reflective-reflective type higher-order construct, we first need to assess the measurement models of the two lower-order components *COMP* and *LIKE*. The model adjustment produces only minor changes in the indicator loadings so that the reliability and validity statistics are not negatively affected. Again, we do not need to assess any statistics emerging from the relationships between *REPU* and its six indicators *comp_1* to *comp_3* and *like_1* to *like_3*, because these indicators only serve for identification purposes of the higher-order construct.

In order to validate the formative higher-order reputation construct, we follow the three-step procedure outlined in Hair et al. (2017a). In the first step, we assess the higher-order construct's convergent validity by running a redundancy analysis (Chin, 1998) in which the higher-order construct is related to an alternative single-item measurement of corporate reputation. We use a global single item that captures the respondents' general assessment of the company's reputation as criterion construct (Cheah et al., 2018). The redundancy analysis yields a point estimate of 0.671 between the higher-order construct and the single-item measure of *REPU*. We ran bootstrapping on the model with 5000

subsamples (no sign changes), which produced a lower boundary of 0.601 and an upper boundary of 0.728 for the 95% percentile confidence interval (Aguirre-Urreta & Rönkkö, 2018). This result supports the convergent validity of the higher-order construct, because the path coefficient does not significantly differ from the 0.7 threshold (Hair et al., 2017a). In the second step, we checked for potential collinearity issues among the lower-order components of *REPU*. The analysis of the model shown in Fig. 8 produces VIF values of 2.957 for *COMP* and 2.568 for *LIKE*, which are lower than the (conservative) threshold of 3 (Hair et al., 2019).⁹ In the third step, we ran bootstrapping (5000 subsamples, no sign changes) to assess the significance and relevance of the relationships between the two lower-order components and their higher-order component. These relationships represent the higher-order construct's weights, but appear as path coefficients in the PLS path model. As shown in Fig. 9, we find that *LIKE*'s weight is pronounced (0.867) and significant ($p < 0.05$), while *COMP*'s weight is much smaller (0.157) and nonsignificant. However, as the bivariate correlation (i.e., the higher-order construct's loading) between *REPU* and *COMP* is larger than 0.5 (Hair et al., 2017a), we retain *COMP* in the higher-order construct's measurement model. These results offer clear support for the validity of the reflective-formative higher-order construct.

The structural model assessment starts with analyzing the relationships between the constructs. When using the extended repeated indicators approach, it is important that researchers do not analyze the direct but the total effects of the four antecedent constructs on *REPU*. Fig. 9 shows these total effects between the four antecedent constructs *ATTR*, *CSOR*, *PERF*, and *QUAL* and *REPU* in a simplified results representation of the extended indicators approach.¹⁰ We find that *ATTR*, *CSOR*, and *QUAL* have significant

⁹ When considering the higher-order construct in isolation (i.e., in a model, which only includes *COMP*, *LIKE*, and *REPU*), the analysis produces a VIF value of 1.788 for *COMP* and *LIKE*.

¹⁰ Note: While Fig. 8 shows how to specify and estimate the model when using the extended repeated indicators approach, Fig. 9 is suitable for the final results presentation since it only includes the relationships between the high-order construct and its predecessors but displays the outcomes of their total effects.

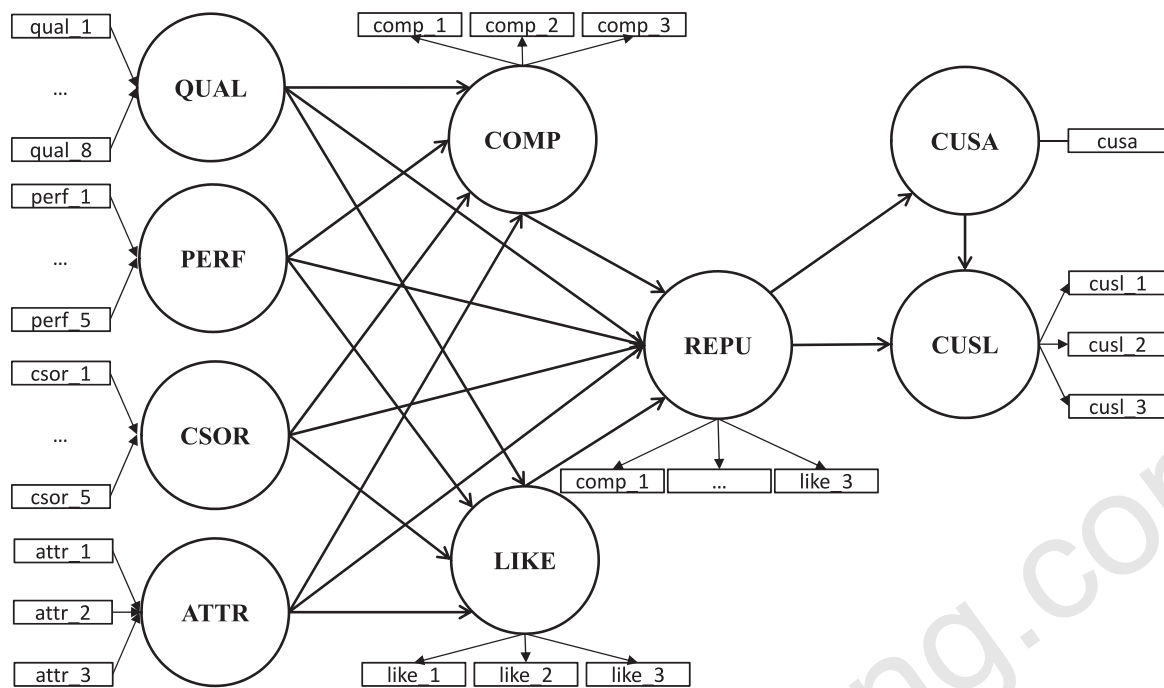


Fig. 8. Reflective-formative specification of corporate reputation (extended repeated indicators approach).

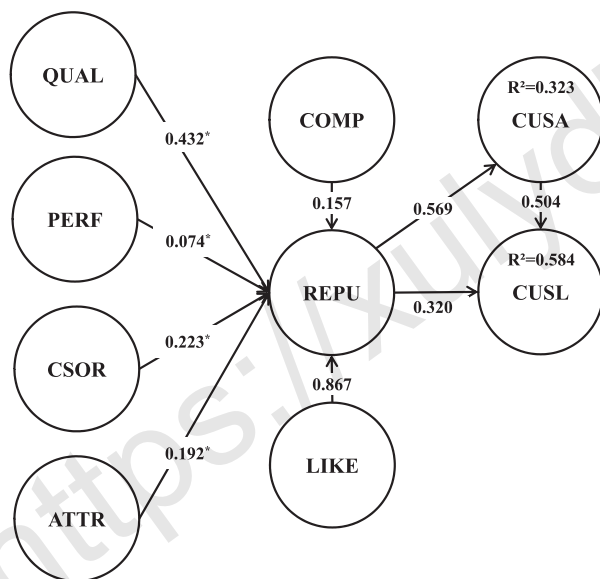


Fig. 9. Simplified higher-order model PLS-SEM results representation for the extended repeated indicator approach.

Note: * Total effect.

($p < 0.05$) total effects on REPU, while PERF is nonsignificant. Again, the path coefficients for the four exogenous constructs are similar to the reflective-reflective type (Fig. 9; also see Table A2). QUAL has the strongest total effect (0.432), followed by CSOR (0.223), ATTR (0.192), and PERF (0.074). REPU has a stronger effect on CUSA (0.569) than on CUSL (0.320) and the effect of CUSA on CUSL is pronounced (0.504). All R^2 and Q^2 values are similar to the reflective-reflective specification (Table A2). Note, however, that the formative specification of the higher-order construct renders an interpretation of R^2 and Q^2 for REPU meaningless. Finally,

the results gained from a PLSpredict analysis (Shmueli et al., 2016) support the model's predictive power with regard to CUSL, because the PLS-SEM analysis produces smaller prediction errors (in terms of MAE and RMSE) compared to the naïve linear benchmark model (Hair et al., 2019).

5.3.2. The disjoint two-stage approach

In stage one, the estimation and measurement model assessment for the lower-order components is based on the standard reputation model, which draws direct relationships between the four antecedent constructs (ATTR, CSOR, PERF, and QUAL), COMP and LIKE, and CUSA and CUSL (Fig. 5)—the higher-order component is not included in the PLS path model. Then, in stage two, the latent variable scores from the stage one results allow creating and estimating the model shown in Fig. 10. Contrary to the extended repeated indicators approach, REPU's measurement model now comprises two indicators representing the latent variable scores of COMP and LIKE from the first stage (Fig. 10). The assessment of the stage two results begins with REPU's formative measurement model. Running a redundancy analysis of the REPU construct, measured with the two formatively specified items COMP and LIKE, on the alternative single-item measure of corporate reputation yields a path coefficient of 0.666, which is not significantly different from 0.7 (95% percentile confidence interval: [0.603; 0.725]). We also find that the REPU's measurement model is not negatively affected by collinearity as the analysis produces a VIF value of 1.813 for the COMP and LIKE indicators. Our analysis also shows that both indicators have a pronounced (COMP: 0.386; LIKE: 0.700) and significant ($p < 0.05$) effect on REPU.

Finally, our analysis confirms that all structural model evaluation results are also at satisfactory level (e.g., significance and relevance for path coefficients, Q^2 , PLS_{predict}). While the structural model results are again very similar between the approaches, the difference in the formative weights is more pronounced compared to the extended repeated indicators approach.

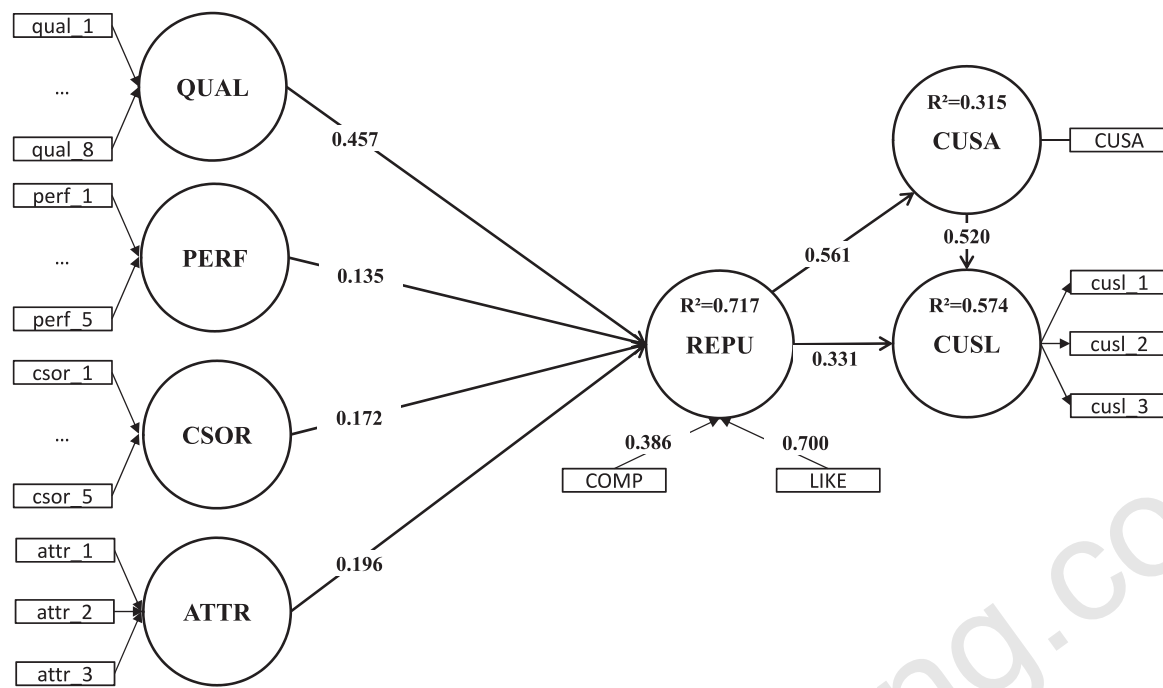


Fig. 10. Reflective-formative stage two specification of corporate reputation and PLS-SEM results.

6. Summary and Conclusions

The use of higher-order constructs features prominently in applications of PLS-SEM. Researchers have, for example, used higher-order constructs to model customer engagement initiatives, relational information processes (Harrigan et al., 2015), materialism (Hourigan & Bougoure, 2012), stakeholder orientation (Patel et al., 2016), as well as consumer self-monitoring (Cass, 2001). Our review of prior higher-order construct applications in the top three marketing journals suggests there is much confusion when it comes to their validation. For example, in reflective-reflective

type higher-order constructs, researchers frequently neglect the assessment of the higher-order construct's discriminant validity. Similarly, in reflective-formative type constructs, researchers have overlooked the assessment of collinearity among the lower-order components. With these issues in mind, this paper clarifies the specification, estimation, and validation of higher-order constructs in applications of PLS-SEM. The checklist in Table 7 summarizes our recommendations with regard to model specification, algorithm settings, and validation.

Based on a corporate reputation model, which has frequently been used to illustrate the PLS-SEM method and its extensions

Table 7
Checklist for using higher-order constructs in PLS-SEM.

Specification	- The higher-order construct serves as an exogenous construct in the path model: - Use the repeated indicators approach when the focus is on minimizing the parameter bias in the higher-order construct's measurement model relationships - Use the two-stage approach when the focus is on minimizing the parameter bias in the structural model relationships - The higher-order construct serves as an endogenous construct in the path model: - While the above points hold, use the <i>extended</i> repeated indicators approach or two-stage approach for reflective-formative and formative-formative type higher-order constructs - The embedded and disjoint two-stage approaches produce very similar results and can both be used
Estimation	- Reflective-reflective and formative-reflective type higher-order constructs: Use Mode A for estimating the higher-order component - Reflective-formative and formative-formative type higher-order constructs: Use Mode B for estimating the higher-order component - Use the path weighting scheme
Measurement model evaluation	- Apply standard model evaluation criteria on the measurement models for the lower-order components - Interpret the relationships between the higher-order and lower-order components as the measurement model of the higher-order construct: - Reflective-reflective and formative-reflective type higher-order constructs: Interpret the relationships between higher-order and lower-order components as loadings and assess convergent validity, internal consistency reliability, and discriminant validity metrics - Reflective-formative and formative-formative higher-order constructs: Interpret the relationships between higher-order and lower-order components as weights and assess convergent validity, collinearity, and the significance and relevance of the weights
Structural model evaluation	- Apply standard model evaluation criteria on the structural model - Do not consider the lower-order components as elements of the structural model - Reflective-formative and formative-formative higher-order constructs estimated using the extended repeated indicators approach: Interpret the total effects of the antecedent constructs on the higher-order component

(Hult et al., 2018b; Matthews et al., 2016; Sharma et al., 2019), we demonstrate the specification and validation of the most prominent higher-order construct types (reflective-reflective and reflective-formative) using the (extended) repeated indicators approach and the disjoint two-stage approach. We specifically illustrate how standard measurement model assessment metrics, such as composite reliability and AVE, need to be adjusted to accommodate higher-order constructs. In doing so, we pay particular attention to the assessment of the HTMT criterion, which in the case of higher-order constructs, is grounded in cross-loadings of and correlations among the lower-order components.

Our article is intended as a comprehensive guideline for using higher-order constructs in PLS-SEM. Nevertheless, specifying and estimating higher-order constructs requires further technical considerations, such as handling highly unbalanced numbers of indicators in the lower-order components (Becker et al., 2012; Hair et al., 2018), and how to properly bootstrap the results of the two-stage approach in stage two, since the latent variable scores need to be generated in stage one for the different bootstrap samples.¹¹ Moreover, our descriptions cover the standard case of a second-order construct. Higher-order constructs can, however, be extended to more layers of subdimensions, which yield third- or fourth-order constructs (Patel et al., 2016). While the validation principles for such types of constructs are generally the same, the validation of relationships between second- and higher-order dimensions requires clarification. Similarly, the notion that the higher-order component fully mediates the relationships between the lower-order components and dependent constructs in the PLS path model in formatively specified higher-order constructs requires scrutiny. Should researchers test for full mediation in such higher-order construct types (Nitzl et al., 2016)? How to correctly test for full mediation with the different approaches? How to deal with higher-order components that only partially mediate the lower-order components' effects? Another area of future research must address how the analysis of higher-order constructs can be interrelated with other advanced PLS-SEM analysis techniques. More specifically, using the two-stage approach in combination with CTA-PLS (Gudergan et al., 2008), PLSpredict (Shmueli et al., 2016; Shmueli et al., 2019), the IPMA (Ringle & Sarstedt, 2016), or moderator analyses (Becker et al., 2018), may require the use of unstandardized latent variables scores from stage one. However, the use of unstandardized data in the two-stage approach has not been explored thus far. Future research should tackle these questions on both conceptual and empirical grounds.

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Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:[10.1016/j.ausmj.2019.05.003](https://doi.org/10.1016/j.ausmj.2019.05.003).

Appendix

Table A1
Sample demographic.

Demographic variable	Category	Frequency	Percentage
Gender	Male	127	36.6
	Female	220	63.4
Ethnicity	Malay	151	43.5
	Chinese	159	45.8
	Indian	19	5.5
	Others	18	5.2
Age	21-30 years old	218	62.9
	31-40 years old	89	25.6
	41-50 years old	34	9.8
	51 years old and above	6	1.7
Monthly Income	RM2,001- RM3,000	200	57.7
	RM3,001-RM4,000	38	11.0
	RM4,001-RM5,000	33	9.5
	RM5,001-RM6,000	22	6.3
	RM6,001-RM7,000	17	4.9
Occupation	RM7,001 and above	37	10.7
	Top management/ professionals	161	46.4
	Supervisory/ middle management	51	14.7
	Operational/ executive level	65	18.7
	Sales/ service line	11	3.2
	Self-employed/ freelancer	51	14.7
Service type	Others: lecturer/ tutor	8	2.3
	Postpaid	234	67.4
Service provider	Prepaid	113	32.6
	Celcom	121	34.9
Duration of using this mobile phone service provider	Maxis	76	21.9
	Digi	108	31.1
	U Mobile	42	12.1
	< 1 year	29	8.4
	1 to 3 years	106	30.5
	3 to 6 years	73	21.0
	7 to 9 years	33	9.5
	> 9 years	106	30.5

¹¹ Current practice only runs bootstrapping on the stage two model, which uses the latent variable scores of the lower-order components obtained from stage one as indicators. This may be problematic since one might also need to include stage one into the bootstrap resampling process to account for the variability in the model estimates and thus the latent variable scores in stage one. Not doing so might provide smaller standard errors, which inflates the type I error rates (more false positives than specified by the error level alpha).

Table A2
Structural model estimates.

Relationship	Higher-order construct specification			
	Reflective-reflective		Reflective-formative	
	Repeated indicators	Disjoint two-stage	Extended repeated indicators	Disjoint two-stage
QUAL → REPU	0.467 [0.359; 0.563]	0.468 [0.366; 0.564]	0.432* [0.312; 0.535]	0.457 [0.351; 0.555]
PERF → REPU	0.156 [0.075; 0.235]	0.157 [0.071; 0.235]	0.074* [-0.035; 0.167]	0.135 [0.043; 0.219]
CSOR → REPU	0.155 [0.071; 0.240]	0.154 [0.072; 0.238]	0.223* [0.132; 0.318]	0.172 [0.088; 0.261]
ATTR → REPU	0.194 [0.101; 0.294]	0.195 [0.106; 0.297]	0.192* [0.091; 0.310]	0.196 [0.102; 0.303]
REPU → CUSA	0.553 [0.470; 0.625]	0.553 [0.474; 0.629]	0.569 [0.486; 0.636]	0.561 [0.477; 0.629]
REPU → CUSL	0.310 [0.224; 0.394]	0.308 [0.229; 0.393]	0.355 [0.266; 0.435]	0.331 [0.245; 0.414]
CUSA → CUSL	0.535 [0.447; 0.614]	0.536 [0.443; 0.611]	0.504 [0.415; 0.590]	0.520 [0.430; 0.599]
R ² _{REPU}	0.734	0.736	1	0.717
R ² _{CUSA}	0.306	0.306	0.323	0.315
R ² _{CUSL}	0.565	0.564	0.584	0.574
Q ² _{REPU}	–	0.580	–	0.569
Q ² _{CUSA}	0.297	0.297	0.311	0.306
Q ² _{CUSL}	0.410	0.410	0.212	0.416

Notes: Numbers in brackets display the 95% bias-corrected percentile confidence intervals derived from bootstrapping with 5000 subsamples (no sign changes); * Total effect

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