# 2 HIGHER-ORDER CONSTRUCTS

## LEARNING OUTCOMES

1. Understand the logic and usefulness of higher-order constructs.
2. Appreciate the different types of higher-order constructs and understand how to specify them in PLS-SEM.
3. Comprehend how to estimate higher-order constructs using the SmartPLS software as well as how to interpret the results.

## CHAPTER PREVIEW

With the rising complexity of theories and cause-effect models in the social sciences, researchers have increasingly used higher-order constructs in their PLS-SEM studies (e.g., Sarstedt, Hair, Pick, Liengaard et al., 2022). Higher-order constructs differ from regular constructs in that they include a more general component that measures a conceptual variable at a higher level of abstraction, while simultaneously including several subcomponents, each of which measure more concrete traits of the concepts. Higher-order constructs permit reducing the number of structural model relationships, making the PLS path model more parsimonious, while increasing the bandwidth of content covered by certain constructs (e.g., Johnson, Rosen, & Chang, 2011), and facilitating minimization of multicollinearity. In this chapter, we describe the nature of higher-order constructs and discuss how to develop and validate them in a PLS-SEM context.

## HIGHER-ORDER CONSTRUCTS

### Terminology and Motivation

Most PLS path models like those covered in the *Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (Hair, Hult, Ringle, & Sarstedt, 2022) deal with first-order constructs. These constructs represent conceptual variables, such as customer engagement, satisfaction, or loyalty using a set of items that capture a single



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layer of abstraction. In some instances, however, the constructs researchers wish to examine are quite complex and can also be operationalized at higher levels of abstraction. Establishing a **higher-order model** or a **hierarchical component model**, as they are sometimes referred to in the context of PLS-SEM (Lohmöller, 1989, Chapter 3; Wold, 1982), most often involves testing a **second-order construct** that contains two layered structures of constructs. For example, satisfaction can be measured at two levels of abstraction. An ensuing **higher-order construct** would include a general satisfaction construct along with several subconstructs that capture different more concrete attributes of satisfaction, such as satisfaction with the price, satisfaction with the service quality, satisfaction with the personnel, or satisfaction with the servicescape. These more concrete lower-order attributes then form the more abstract, higher-order satisfaction construct, as shown in Exhibit 2.1.

Instead of modeling the attributes of satisfaction as drivers of the respondent's overall satisfaction—or other target constructs (e.g., customer loyalty)—higher-order modeling involves simultaneously mapping the **lower-order components (LOCs)** and a single **higher-order component (HOC)**. Theoretically, this process can be extended to any number of layers yielding third-, fourth-, or fifth-order models, but researchers usually restrict their modeling to two layers (i.e., second-order models).

There are several reasons for including higher-order constructs in a PLS path model (e.g., Edwards, 2001; Johnson, Rosen, & Chang, 2011; Polites, Roberts, & Thatcher, 2012). One reason pertains to the **bandwidth-fidelity tradeoff**, or the idea that broader constructs are better predictors of criteria that span over multiple domains and/or periods of time. That is, if the goal is to predict broadly defined behaviors, then higher-order constructs might prove valuable. Another reason is to overcome the

**EXHIBIT 2.1 ■ Higher-Order Construct of Satisfaction**


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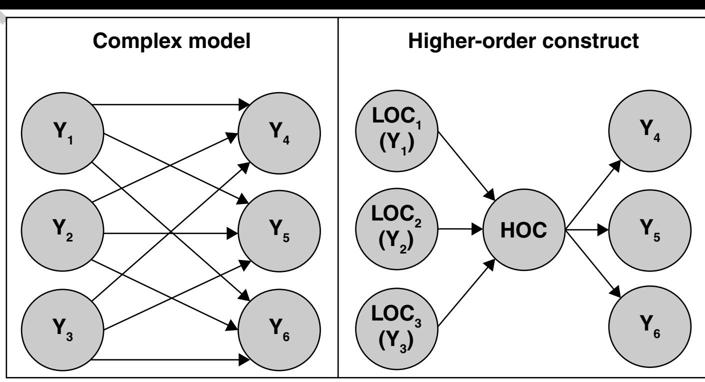
**jangle fallacy**, which occurs when a single phenomenon is examined separately under the guise of two or more variables with different labels.

From a practical perspective, higher-order constructs enable researchers to reduce the number of relationships in the structural model, making the PLS path model more parsimonious, easier to comprehend, and reducing multicollinearity among antecedent constructs. Exhibit 2.2 illustrates this aspect. As can be seen in the complex model, there are nine structural model relationships linking the exogenous constructs ($Y_1$, $Y_2$, and $Y_3$) with the endogenous constructs ($Y_4$, $Y_5$, and $Y_6$). By including a higher-order construct, the number of path coefficients can be reduced to six, yielding a more parsimonious model in terms of structural model relationships. In this case, the HOC is assumed to fully mediate the LOCs' effects on the endogenous constructs (for more detail on mediation, see Hair, Hult, Ringle, & Sarstedt, 2022; Sarstedt, Hair, Nitzl, Ringle, & Howard, 2020). This reduction in model complexity may come at the expense of explanatory power with respect to the endogenous constructs that the HOC explains (i.e., $Y_4$, $Y_5$, and $Y_6$ in Exhibit 2.2). The reason is, different from a direct effects model where all exogenous constructs explain one endogenous construct (Exhibit 2.2, left panel), in the higher-order construct set-up, only the HOC explains the endogenous constructs (Exhibit 2.2, right panel).

Finally, higher-order constructs also prove valuable if formative indicators in a construct's measurement model exhibit high levels of collinearity. High collinearity among the indicators of a formative measurement model can result in biased weights and their signs being reversed. Furthermore, collinearity increases standard errors and, thus, trigger Type II errors (i.e., false negatives; Hair, Hult, Ringle, & Sarstedt, 2022, Chapter 5). Higher-order models facilitate handling of collinearity problems by offering a means to rearrange measurement models. Provided that measurement theory supports this step, researchers can split up the set of indicators and establish separate constructs in a higher-order structure. Consider, for example, a formatively measured

**EXHIBIT 2.2 ■ Higher-Order Constructs and Model Complexity**

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construct with four indicators ($x_1 - x_4$), of which $x_1$ and $x_2$ as well as $x_3$ and $x_4$ are highly correlated. If conceptually meaningful, researchers could split up the formative construct into two LOCs, each one being measured with noncollinear indicators (e.g., $x_1$ and $x_3$ on the one hand and $x_2$ and $x_4$ on the other).

## Types of Higher-Order Constructs

Establishing a higher-order structure requires researchers to develop and use an appropriate operational definition of the conceptual variable under consideration. The operational definition facilitates conceptualizing an abstract idea so that it represents the scope of measurable, observable qualities that can be studied (see Chapter 1). The operational definition guides the identification of relevant LOCs, each of which refers to a distinctive element (or component) associated with the HOC, and each of which has a set of indicators that can be specified by the distinctiveness of the element that characterizes the LOC. At the same time, this characterizing distinctiveness should also be sufficiently relevant so only those LOCs that are important for the specific study are captured in a higher-order construct. The operational definition, with its characterizing elements, can vary from study to study since a theoretical concept is not per se determined as multidimensional or unidimensional. Rather, a concept can be specified either way, representing different levels of theoretical abstraction (Bollen, 2011).

Conceptually, higher-order constructs can be established following a bottom-up (i.e., inductive) or top-down (i.e., deductive) approach (e.g., Johnson, Rosen, & Chang, 2011). In the **bottom-up approach**, several constructs are combined into a single, more abstract construct. On the contrary, in the **top-down approach**, a more abstract construct is defined to consist of several components, as is the case in the satisfaction example described above (Exhibit 2.1). Even though frequently used in empirical research to reduce model complexity, we do not recommend simply summarizing information in a more abstract construct.

Establishing a higher-order construct in PLS-SEM always involves a loss of information—at least in principle. The reason is that the direct effects between the LOCs (e.g., $Y_1 - Y_3$ in Exhibit 2.2, left panel) and the criterion constructs (e.g., $Y_4 - Y_6$ in Exhibit 2.2, left panel) are being replaced by three indirect effects via the newly established HOC (Exhibit 2.2, right panel). The PLS-SEM method, however, allows estimating all relationships in a wider nomological net of constructs (i.e., without the HOC) without loss of information. Therefore, when structural theory supports the inclusion of a larger number of constructs, which could be summarized in a HOC, justifying their joint consideration in form of a higher-order construct on the grounds of model parsimony only is not sufficient. Instead, higher-order constructs derived in a top-down manner offer researchers additional insights regarding the effects of different components embedded in a specific construct. Here, the researcher's intention is to determine the effect of such components on other constructs in the model via the HOC.

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In addition to using theory to identify inclusion criteria for selecting suitable LOCs, the nature of relations among the LOCs and the HOC must be clarified. A HOC is a general concept that is either represented (in the reflective mode) or constituted (in the formative mode) by its specific components (i.e., the LOCs). If the higher-order construct is reflective, the more general HOC manifests itself in several more specific LOCs. That is, the relationships go from the HOC to its LOCs. This type of model is also referred to as a **spread model** (Lohmöller, 1989, Chapter 3). If the higher-order construct is formative, several specific LOCs represent more concrete components that jointly form the more general HOC (Becker, Klein, & Wetzels, 2012; Edwards, 2001; Wetzels, Odekerken-Schroder, & van Oppen, 2009). That is, the relationships go from the LOCs to the HOC. This model type is also referred to as a **collect model** (Lohmöller, 1989, Chapter 3). The higher-order construct in Exhibit 2.1 has formative relationships going from the LOCs to the HOC, representing each LOC's relative contribution to forming the HOC. However, if operationalized differently, these relationships could also have been modeled in the opposite direction with the LOCs reflecting the HOC.

A formative specification is appropriate when the operational definition of the conceptual variable suggests that a change in a LOC's value due to, for example, a change in a respondent's assessment of the trait being captured by the LOC changes the value of the HOC. Analogous to indicators in formative measurement models, the LOCs do not need to, but can, be correlated as they do not represent concrete manifestations of the HOC. In contrast, a reflective specification is appropriate when there is a more general, abstract construct that explains the correlations between the LOCs as shown in Exhibit 2.2. Hence, there should be substantial correlations between the LOCs that—analogous to reflective measurement models in first-order constructs—are assumed to be "caused" by the HOC.

In addition to the measurement specification of the higher-order construct as a whole, as represented by the relationships between the HOC and the LOCs, higher-order constructs need to be characterized on the grounds of the specification of the LOCs' measurement models. The LOCs' measurement models can also be reflective or formative. As a result, four main types of higher-order constructs are possible (Exhibit 2.3), as discussed in the extant literature (Jarvis, MacKenzie, & Podsakoff, 2003; Wetzels, Odekerken-Schroder, & van Oppen, 2009). The **reflective-reflective higher-order construct** (**Type I higher-order construct**) shown in Exhibit 2.3 has reflective relationships between the HOC and the LOCs, and also between the LOCs and the indicators. In this type of higher-order construct, the LOCs are highly correlated and the HOC represents the cause explaining these correlations. Lohmöller (1989, Chapter 3) calls this type of higher-order construct **hierarchical common factor model**, in which the general HOC represents the common factor of several specific factors (i.e., LOCs). The use of reflective-reflective higher-order constructs has been subject to considerable debate, with critics arguing that such models do not exist (or are meaningless)

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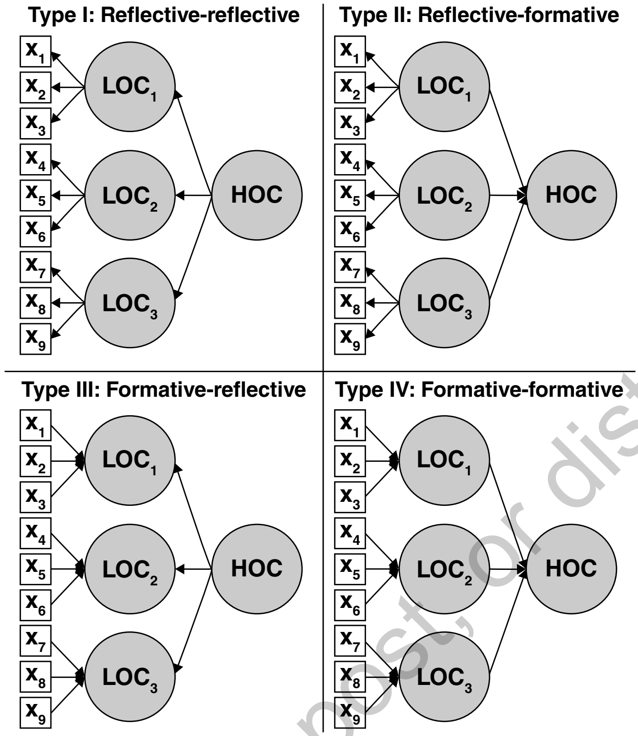
**EXHIBIT 2.3 ■ Types of Higher-Order Constructs**




*Source:* Adapted from Figure B1 in Ringle, Sarstedt, & Straub (2012).

since reflective measures should be unidimensional and conceptually interchangeable, which conflicts with the view of multiple underlying dimensions being distinct in nature (Lee & Cadogan, 2013). That is, if the indicators of each LOC would correlate highly, any indicator should also relate to any other LOC. This would make the LOC-level redundant, implying that the indicators should be directly linked to the primary source of reflection—that is, the HOC (Mikulic, 2022). Temme and Diamantopoulos (2016) bemoan that this line of reasoning rests on the flawed assumption that unidimensionality of the higher-order models' elements (i.e., the LOCs and the HOC) is a necessary condition for reflective measurement (Bollen & Lennox, 1991). However, psychometric theory has long established that indicators can serve as measurements of more than one construct (e.g., Bollen 1989)—as is the case in, for example, bifactor models (e.g., Zhang, Sun, Cao, & Drasgow, 2021). Hence, the assumption that highly correlated indicators in the LOCs' measurement models imply high indicator correlations with all other LOCs stands on quicksand.

Reflective-reflective higher-order constructs might also be used in other settings, for example, in a situation where the LOCs represent different measurements of a

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concept at different points in time (i.e., different batteries of a test sequence), which the HOC explains simultaneously. Lohmöller (1989, Chapter 3) characterizes this constellation as a **multiple battery model** and presents the example of the general ability of schoolchildren. In this example, each LOC represents a test battery of verbal, numerical, and spatial indicators measured at different points in time (e.g., tests at the beginning, middle, and end of the school year) for the same class (i.e., the same individuals). However, extant reviews of PLS-SEM's use in different fields have not disclosed any applications of the multiple battery model thus far.

In a **reflective-formative higher-order construct** (**Type II higher-order construct**; Exhibit 2.3), the HOC is a combination of several reflectively measured LOCs. That is, the specific LOCs do not necessarily share a common cause but rather form the general HOC—the relationships go from the LOCs to the HOC. Barroso and Picón (2012) offer an example of a reflective-formative higher-order construct in their analysis of perceived switching costs. They identify a set of six dimensions (benefit loss costs, personal relationship loss costs, economic risks costs, evaluation costs, set-up costs, and monetary loss costs) that represent LOCs of the more general HOC, perceived switching costs. Commenting on their measurement specification, Barroso and Picón (2012, p. 532) note: "A modification in one dimension does not necessarily imply a modification in another. In other words, they do not necessarily covary; rather, each dimension can vary independently of the others." For this reason, unlike some prior research, Barroso and Picón (2012) propose that perceived switching costs is an aggregate construct that is expressed as a composition of its different LOCs—see Becker, Klein, and Wetzels (2012) for further examples of reflective-formative higher-order constructs. When the higher-order construct is specified formatively (i.e., the relationships go from the LOCs to the HOC), the HOC fully mediates the relationships between the LOCs and any other construct the higher-order construct explains. For example, in the formative higher-order construct in Exhibit 2.2, all relations from $Y_1$, $Y_2$, and $Y_3$ to the criterion constructs $Y_4$, $Y_5$, and $Y_6$ go through the HOC.

Another higher-order construct is the formative-reflective type (**Type III higher-order construct**; Exhibit 2.3). The **formative-reflective higher-order construct** includes a more general HOC that explains the formatively measured LOCs. The objective of this type is extracting the common part of several formatively measured LOCs that have been established to represent the same theoretical content. However, every LOC builds on a set of different indicators. By using several formatively measured LOCs, researchers can overcome the problem that a stand-alone construct measured with formative indicators can hardly cover the construct's domain in full. Using similar yet distinct formatively measured LOCs as representations of the HOC offers a broader coverage of the construct domain (Becker, Klein, & Wetzels, 2012). A typical example of this higher-order construct type is overall firm performance in which several formatively measured LOCs represent performance-relevant characteristics (e.g., market share, number of employees, or turnover). The HOC represents the common

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part of the LOCs (i.e., overall firm performance; Jarvis, MacKenzie, & Podsakoff, 2003; Petter, Straub, & Rai, 2007). Alternatively, the formative-reflective higher-order construct can serve as a multiple battery model as explained in the context of the reflective-reflective higher-order construct. In that case, the LOCs represent the same construct that has been formatively measured with the same indicators and for the same observations at different points in time. In this type of multiple battery model, the relationships from the HOC to the LOCs will be of similar magnitude since they represent one concept measured at different points in time.

Finally, the **formative-formative higher-order construct** (**Type IV higher-order construct**; Exhibit 2.3) determines the relative contribution of the formatively measured LOCs to the more abstract HOC. This type is useful to structure a complex formative construct with many indicators into several subconstructs, as is the case when researchers subsume several concrete aspects under a more general concept. Again, firm performance would represent a concept of this nature that could be measured using this higher-order construct type. While the formative-reflective higher-order construct type would comprise different indices of overall firm performance by the LOCs, the formative-formative type includes LOCs representing different aspects of performance, such as the performance of different organizational activities or subdivisions (e.g., R&D performance, HR performance, sales performance) that together determine overall firm performance (i.e., the HOC; Jarvis, MacKenzie, & Podsakoff, 2003; Petter, Straub, & Rai, 2007), but do not necessarily have to correlate with each other.

Theoretical models with higher-order constructs feature prominently in applications of PLS-SEM as evidenced in various review articles. Sarstedt, Hair, Pick, Liengaard et al.'s (2022) analysis of higher-order construct applications in the top 30 marketing journals between 2011 and 2020 showed that 71 of the 239 analyzed studies (29.71%) included at least one such construct. The majority of these studies proposed second-order constructs (65 studies), while the remaining studies included third-order constructs (5 studies) or both (1 study). Analyzing the construct types used, the authors found that most of the studies employ Type I (reflective-reflective; 30 studies), Type II (reflective-formative; 26 studies), or both (4 studies). Only five studies employ Type IV (formative-formative), while no study draws on a Type III (formative-reflective) measurement specification. In an earlier review, Ringle, Sarstedt, and Straub (2012) found a similar share of higher-order construct types published in the management information systems flagship journal *MIS Quarterly*. Higher-order constructs are typically embedded in a larger nomological network of constructs, in which they serve as an antecedent, consequence, or both. For example, revisiting Sarstedt, Hair, Pick, Liengaard et al.'s (2022) analysis shows that in 67 of the 71 studies (94.37%), the higher-order construct is part of a larger network of constructs. In Ringle, Sarstedt, and Straub (2012), this share was only marginally smaller (86.67%). Therefore, the discussion should not be limited to higher-order constructs as separate constructs, also referred to as a **stand-alone higher-order construct**, but should also consider their

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potential application in a nomological network of constructs embedded in a structural model (Becker, Klein, & Wetzels, 2012).

## Specifying Higher-Order Constructs

### Overview

PLS-SEM allows the specification and estimation of all higher-order construct types, as shown in Exhibit 2.3. However, the specific type of HOC demands careful consideration when specifying and estimating the model, since PLS-SEM requires each construct in the PLS path model to have at least one indicator in its measurement model. This necessity holds not only for LOCs but also for the HOC, which is an abstract representation of the conceptual variable under consideration. As such, the nature of a higher-order construct in PLS-SEM is different from that in covariance-based SEM (CB-SEM), where the HOC has no indicators in its measurement model. For this reason, higher-order constructs are sometimes called phantom variables in CB-SEM.

To handle the measurement issue of higher-order constructs in PLS-SEM, researchers can draw on four approaches. In the **repeated indicators approach**, all indicators of the LOCs are assigned to the measurement model of the HOC (Lohmöller, 1989, Chapter 3; Wold, 1982). In the second-order model examples in Exhibit 2.3, the repeated indicators approach would use the indicators $x_1$ to $x_9$ of the LOCs to establish the measurement model of the HOC. Consequently, the indicators are used twice: once for the LOCs and again for the HOC. Becker, Klein, and Wetzels (2012) introduced the **extended repeated indicators approach** to handle problems that emerge when the HOC in a reflective-formative or formative-formative higher-order construct has one or more antecedent construct(s). In this case, the LOCs fully explain the variance of the HOC, producing an $R^2 \approx 1.0$. However, with all the HOC's variance being explained by its LOCs, there is no variance left to be explained by an antecedent construct. As a consequence, any path relationship from an antecedent construct to the higher-order construct (i.e., to the HOC) will be close to zero and nonsignificant by design.

Finally, researchers have proposed the embedded (Agarwal & Karahanna, 2000) and disjoint (Wilson, 2010) two-stage approaches, which use construct scores generated in the first stage as input for the model computation in the second stage. Since all approaches generally yield similar results (Cheah, Ting, Ramayah, Memon et al., 2019), there is often no compelling reason to prefer one over the other. However, as the two-stage approach resolves problems that occur in specific model constellations when using the (extended) repeated indicators approach and because of their simple implementation in the SmartPLS 4 software, Becker, Cheah, Gholamzade, Ringle et al. (2023) recommend routinely drawing on the two-stage approaches. We, therefore, focus our discussions on the two-stage approaches (i.e., embedded and disjoint) while mentioning the (extended) repeated indicators' approach where needed.

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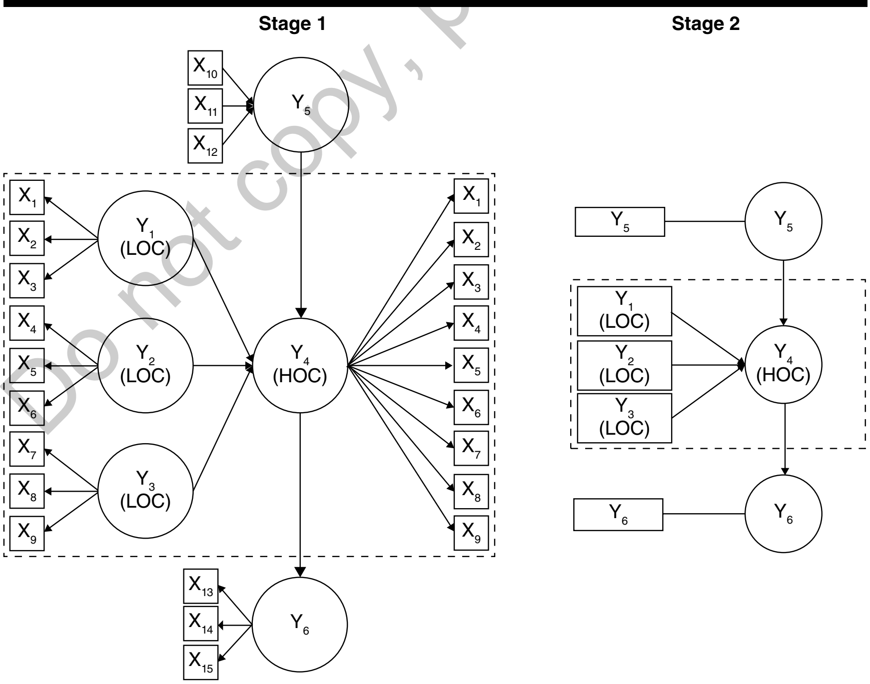
## The Embedded Two-Stage Approach

The first stage of the **embedded two-stage approach** (Agarwal & Karahanna, 2000) corresponds to the standard repeated indicators approach in that all indicators of the LOCs are assigned to the HOC's measurement model. Exhibit 2.4 shows such a set-up in a model where a Type II higher-order construct with three LOCs ($Y_1 - Y_3$) is embedded in a path model with one antecedent construct ($Y_5$) and one criterion construct ($Y_6$). As can be seen, all indicators of the LOCs ($x_1 - x_9$) are repeated in the measurement model of the HOC ($Y_4$). Stage 1 of the embedded two-stage approach entails estimating the model in Exhibit 2.4 (left panel), but instead of interpreting the estimates, researchers need to save the construct scores that result from this analysis.

In Stage 2, these construct scores are used as single-item indicators in the HOC's measurement model as shown in the right panel of Exhibit 2.4. That is, the HOC $Y_4$ is measured with three formative indicators capturing the construct scores of $Y_1$, $Y_2$, and $Y_3$ from Stage 1. Except for the HOC, all other constructs in the model (e.g., $Y_5$ in Exhibit 2.4) are measured with single items that capture each construct's scores from the previous stage. Importantly, when using the embedded two-stage approach, the entire path model must already be considered in Stage 1. 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 and successively integrate it into the full path model.

**EXHIBIT 2.4 ■ The Embedded Two-Stage Approach**

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### The Disjoint Two-Stage Approach

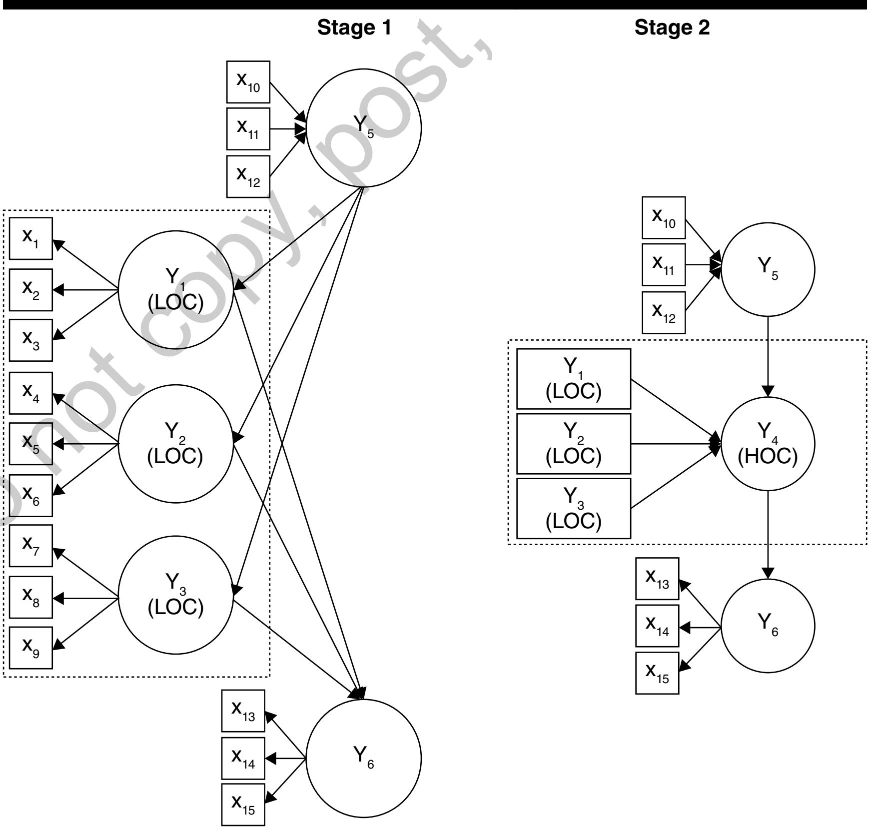
The **disjoint two-stage approach** (Wilson, 2010) differs from the embedded two-stage approach in the specification of both stages. Rather than using the repeated indicators approach in Stage 1, the disjoint two-stage approach considers only the LOCs of the higher-order construct (i.e., without the HOC) in the path model. These are directly linked to all other constructs that the higher-order construct is theoretically related to (Exhibit 2.5, left panel). We then need to only save the construct scores of the LOCs (e.g., the scores of the constructs $Y_1$, $Y_2$, and $Y_3$ similar to the previous example).

In Stage 2, these scores are then used to establish the HOC's measurement model. 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 1 (Exhibit 2.5, right panel).

### Recommendations

The two-stage approaches offer researchers more modeling flexibility than the (extended) repeated indicators approach. For example, they allow assessing the

**EXHIBIT 2.5 ■ The Disjoint Two-Stage Approach**

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higher-order construct's measurement specification on the grounds of a confirmatory tetrad analysis (CTA-PLS; see Chapter 3). Using the construct scores of the LOCs from Stage 1 as input for the measurement model specification in Stage 2, the CTA-PLS assesses the covariance structure of the HOC's measurement model to test whether the HOC should be specified reflectively or formatively. Such an assessment is not feasible with the repeated indicators approach because the CTA-PLS—as implemented in software programs, such as SmartPLS 4—considers the covariances only in the measurement models and not among the constructs. Based on the CTA-PLS results, researchers gain additional insights regarding the higher-order construct's measurement specification.

While the results of these two approaches do not differ significantly (Cheah, Ting, Ramayah, Memon, Cham, & Ciavolino, 2019), we recommend using the disjoint two-stage approach, as it allows for validating the entire path model on the grounds of the original construct measures in Stage 2 (Becker, Cheah, Gholamzade, Ringle et al., 2023). For example, researchers can use the $\text{PLS}_{\text{predict}}$ procedure (Shmueli, Ray, Velasquez Estrada, & Chatla, 2016; Shmueli, Sarstedt, Hair, Cheah, Ting, & Ringle, 2019) or the cross-validated predictive ability test (Liengaard, Sharma, Hult, Jensen, Sarstedt, Hair, & Ringle, 2021; Sharma, Liengaard, Hair, Sarstedt, & Ringle, 2023) to estimate the model's predictive power on an indicator level. This sets the disjoint approach apart from the embedded two-stage approach, which is restricted to validating the measurement models in a model that includes the HOC with its repeated indicators (Exhibit 2.4, left panel; i.e., this model set-up, however, only serves identification purposes and does not fully correspond to the path model as hypothesized by the researcher). In addition, the estimates of the relationships between the HOC and the LOCs in Stage 1 of the embedded two-stage approach can be adversely impacted by unevenly distributed numbers of indicators in the LOCs. If, for example, in a reflective formative higher-order construct, one LOC is measured with more indicators than the other LOCs, its weight for forming the HOC will be higher due to the repetition of indicators in the HOC's measurement model. The weight estimate can therefore paint a misleading picture of the LOC's relative relevance for forming the HOC. In light of the above, researchers should draw on the disjoint two-stage approach when specifying higher-order constructs.

## Estimating Higher-Order Constructs

The PLS-SEM algorithm draws on two modes to estimate the indicator weights that represent each indicator's relative contribution to forming a construct (Chapter 1). In Mode A indicator weight estimates correspond to the bivariate correlations between each indicator and the construct (i.e., correlation weights). In contrast, Mode B computes indicators by regressing each construct on its associated indicators (i.e., regression weights). While researchers typically use Mode A to estimate reflectively specified measurement models and Mode B to estimate formatively specified measurement

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models (Hair, Hult, Ringle, & Sarstedt, 2022), Becker, Klein, and Wetzels (2012) show that the choice of measurement mode should consider the relationship between the HOC and the LOCs rather than the operationalization of the HOC when applying the repeated indicators approach. Specifically, their simulation study shows that Mode B estimation of the HOC in a reflective-formative type higher-order construct produces the smallest parameter estimation bias. Hence, even though the (repeated) indicators identifying the HOC are specified reflectively, researchers should use Mode B for estimating these repeated indicators on the HOC. In light of these findings, researchers should use Mode A for 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) when estimating the model in Stage 1 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, Klein, and Wetzels (2012) show that the path weighting scheme (Lohmöller, 1989, Chapters 2) 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 more recent research has not extended Becker, Klein, and Wetzels's (2012) study in this regard, we expect 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 the default setting when estimating higher-order constructs in PLS-SEM.

## Validating Higher-Order Constructs

When validating higher-order constructs, the same model evaluation criteria generally apply as for any PLS-SEM analysis (Hair, Howard, & Nitzl, 2020; Hair, Hult, Ringle, & Sarstedt, 2022; Ramayah, Cheah, Chuah, Ting, & Memon, 2016). However, researchers need to consider two additional measurement models in higher-order constructs for which the evaluation criteria apply: (1) the measurement models of the LOCs, and (2) the measurement model of the higher-order construct as a whole, represented by the relationships between the HOC and its LOCs. In light of our previous recommendations, we focus our discussion of model validation on the embedded and disjoint two-stage approaches. See Sarstedt, Hair, Cheah, Becker, and Ringle (2019) and Hair, Moisescu, Radomir, Ringle et al. (2020) for a discussion of model validation under the (extended) repeated indicators approach.

The procedures and criteria that have been recommended for the measurement models and the structural model also apply to the PLS-SEM results assessment of the two-stage approach (Hair, Howard, & Nitzl, 2020; Hair, Hult, Ringle, & Sarstedt, 2022; Ramayah, Cheah, Chuah, Ting, & Memon, 2016). That is, the results evaluation

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in Stage 1 considers all measurement models, including those of the LOCs, but with a single exception. Specifically, when applying the embedded two-stage approach the higher-order construct must *not* be evaluated in terms of its (repeated) indicators directly associated with the HOC ($x_1$-$x_9$ in Exhibit 2.4). These indicators only ensure that the higher-order construct is identified—they do not represent its actual measurement model. In fact, the repetition of the LOCs' indicators in the measurement model of the HOC automatically violates discriminant validity as evidenced in high HTMT values. Similarly, the set of indicators assigned to the HOC is not unidimensional by design as they stem from LOCs that represent different concepts.

After model estimation in Stage 2, all measurement models need to be assessed again in terms of reliability and validity, even if their reliability and validity have already been established in the Stage 1 analysis. The reason is that the inclusion of the higher-order construct in Stage 2 changes the model set-up, which entails changes in the model estimates. Generally, however, these changes will not result in reliability or validity issues if these have been confirmed in the Stage 1 analysis. More importantly, this assessment also needs to take the newly established higher-order construct into account whose measurement model is defined by the relationships between its indicators, which come in the form of construct scores derived from Stage 1. That is, in cases of Type I and Type III models, the standard evaluation criteria for reflective measurement models need to be applied, while for Type II and Type IV models, the evaluation criteria for formative measurement models need to be applied.

Once the measures' reliability and validity have been established, the structural model results need to be analyzed, drawing on the standard criteria as documented in, for example, Hair, Hult, Ringle, and Sarstedt (2022). Researchers need to pay particular attention to any structural model assessment that involves interpreting the indicators, such as when using $\text{PLS}_{\text{predict}}$ (Shmueli, Ray, Velasquez-Estrada, & Chatla, 2016; Shmueli, Sarstedt, Hair, Cheah, Ting, & Ringle, 2019), or running an 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 2 uses the construct scores of Stage 1 as single items, which renders validation on the grounds of the items meaningless. In contrast, the disjoint two-stage approach uses multiple 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 the Stage 2 results. As with the measurement model assessment, this evaluation must disregard the HOC.

Finally, situations occur in which researchers are uncertain whether or not to measure a theoretical concept by means of a higher-order construct. To make a decision, Becker, Cheah, Gholamzade, Ringle et al. (2023) suggest comparing models with and without the higher-order construct. For this purpose, they can use model selection criteria that are well known from the regression literature. Sharma, Sarstedt, Shmueli, Kim, and Thiele (2019) and Sharma, Shmueli, Sarstedt, Danks, and Ray (2018) compared the efficacy of various metrics for model comparison tasks and found that the

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Bayesian information criterion (BIC) and the criterion suggested by Geweke and Meese (GM) perform well in selecting a parsimonious model that fits the data well and has a good predictive power. As the BIC is easier to compute, extant literature recommends focusing on this criterion (Hair, Hult, Ringle, & Sarstedt, 2022, Chapter 6). If this analysis suggests the model with the higher-order construct produces lower BIC values compared to the model without the higher-order specification, researchers should consider the higher-order construct in their model specification and estimation. In addition, researchers can compute BIC-based Akaike weights, which offer relative weights of evidence in favor of the models under consideration (Danks, Sharma, & Sarstedt, 2020). Alternatively, researchers can compare the model specifications with regard to their predictive power using Liengaard, Sharma, Hult, Jensen, Sarstedt, Hair, & Ringle's (2021) cross-validated predictive ability test (see also Sharma, Liengaard, Hair, Sarstedt, & Ringle, 2023) to empirically justify its consideration.

### Rules of Thumb

The previous descriptions have shown that higher-order constructs are a useful means to retain information while making the structural model more parsimonious. At the same time, their specification and particularly their validation requires special care. In Exhibit 2.6, we summarize the rules of thumb to consider when using higher-order constructs.

## CASE STUDY ILLUSTRATION

Drawing on the case study model and data presented in Chapter 1, we outline how to create a higher-order construct for the construct corporate reputation. The corporate reputation model focuses on the *COMP* and *LIKE* constructs representing two separate dimensions of corporate reputation (*REPU*). Instead of modeling the distinct

**EXHIBIT 2.6 ■ Rules of Thumb for Using Higher-order Constructs**

| Aspect | Rules of Thumb |
|---|---|
| Conceptualization | ● Closely examine and describe the theoretical and conceptual foundations of the higher-order construct type. |
| Specification | ● 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.<br>● Use the two-stage approaches to specify the higher-order construct. The disjoint two-stage approach should be preferred due to its greater flexibility in model validation. |

*(Continued)*

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**EXHIBIT 2.6 ■ Rules of Thumb for Using Higher-order Constructs (Continued)**

| Aspect | Rules of Thumb |
|---|---|
| Estimation | • Use Mode A to estimate the HOC of a reflective-reflective and formative-reflective type higher-order construct in Stage 1 of the embedded two-stage approach.<br>• Use Mode B to estimate the HOC of a reflective-formative and formative-formative type higher-order construct in Stage 1 of the embedded two-stage approach.<br>• Use the path weighting scheme. |
| Validation | • Preferably, use the disjoint two-stage approach and validate the measurement models' reliability and validity in both stages, including those of the LOCs.<br>• In case of using the embedded two-stage approach, do not consider the HOC's measurement model, operationalized by repeated indicators, in Stage 1. Also, when using the embedded two-stage approach, apply criteria for assessing the model's explanatory and predictive power in Stage 1.<br>• Apply the standard structural model assessment criteria and procedures for assessing the relationships between the higher-order construct and any predecessor and successor constructs.<br>• Compare the model with the higher-order construct to the model without the higher-order construct (e.g., by selecting the model specification that produces lower BIC values). |

impact of the antecedent constructs (i.e., *ATTR, CSOR, PERF*, and *QUAL*) on *COMP* and *LIKE* as well as their effect on the criterion variables (i.e., *CUSA* and *CUSL*) separately, these two constructs could be handled as subdimensions of a more general *REPU* construct. By establishing a second-order construct with *COMP* and *LIKE* as LOCs, the PLS path model becomes more parsimonious. From a measurement theory perspective, *COMP* and *LIKE* determine *REPU* (e.g., Eberl, 2010), therefore inferring a reflective-formative higher-order construct type specification. Since we deal with only two LOCs, the CTA-PLS procedure, which would require at least four LOCs (see Chapter 3 for more detail), cannot provide additional empirical substantiation concerning the direction of the relationship between the LOCs and the HOC. For the empirical illustration, however, we consider *REPU*'s reflective-formative higher-order construct type specification.

To establish the reflective-formative higher-order construct *REPU*, we draw on the disjoint two-stage approach. Stage 1 requires estimating the model with the LOCs (*COMP* and *LIKE*), but without the HOC *REPU*, which will be included in Stage 2—just like in the original corporate reputation model. Navigate to the SmartPLS

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**Workspace**, and double-click on **Corporate reputation model** in the **Example – Corporate reputation (advanced)** project. To estimate this model, click on **Calculate → PLS-SEM algorithm** in the SmartPLS menu. Alternatively, we can left-click on the wheel symbol with the label **Calculate** in the tool bar. Run the PLS-SEM algorithm using the default settings (i.e., path weighting scheme, standardized results, and default initial weights) and make sure to check the box **Open report** in the lower right corner. After clicking the **Start calculation** button, SmartPLS opens the **Results report**. We find that all construct measures meet the required standards in terms of reliability and validity. For example, measures of *LIKE* yield satisfactory levels of convergent validity (AVE = 0.747) and internal consistency reliability (Cronbach's alpha = 0.831; $\rho_A$ = 0.836; $\rho_C$ = 0.899). Similarly, the measures of *COMP* exhibit convergent validity (AVE = 0.688) and internal consistency reliability (Cronbach's alpha = 0.776; $\rho_A$ = 0.786; $\rho_C$ = 0.869). For a detailed overview of the model evaluations of all reflective and formative measurement models, see Chapters 4 and 5 in Hair, Hult, Ringle, and Sarstedt (2022).

On these grounds, we can proceed to Stage 2 of the disjoint two-stage approach, which requires replacing the LOCs with the HOC, the latter of which is measured using the construct scores of *COMP* and *LIKE* from Stage 1. SmartPLS allows to conveniently process the construct scores from a previous algorithm run and include them in a separate dataset that is being added to an existing project. To do so, select the **Create data file** option in the tool bar of the **Results report**. In the menu that opens, select the **Example – Corporate reputation (advanced)** project, the file name (e.g., **HCM disjoint 2nd stage**), and check the boxes next to **Manifest variable scores** (i.e., to include the indicators used in the model in the new dataset), **Latent variable scores** (i.e., to include new variables for the construct scores in the new dataset), and **Other** (i.e., to include all other variables available in the new dataset). Then, left-click on the **Create** button. Click on the orange arrow button labeled **Edit** in the tool bar to return to the **Modeling window**. Next, click on the orange arrow button labeled **Back** to enter the **Workspace** view where the new dataset appears under the selected project. In the **Example – Corporate reputation (advanced)** project, we now see the newly created **HCM disjoint 2nd stage** dataset. Next, right-click on **Corporate reputation model**. In the menu that opens, select the **Duplicate** option. A dialog opens that allows us to enter a name for the copy of the newly added model. Use a self-explaining name such as **HCM reflective-formative 2nd stage**. After pressing the **Create** button, the new model, which is a duplicate of the corporate reputation model shown in **Corporate reputation model**, appears in the project displayed in the **Workspace**. Double-click on the **HCM reflective-formative 2nd stage** model to open it in the modeling window. On the left-hand side, above the list of indicators, left-click on the **Select dataset** button and choose the newly created dataset (i.e., **HCM disjoint 2nd stage**). The **HCM reflective-formative 2nd stage** model already includes the final model with the HOC. In case we want to set up the Stage 2 model ourselves, we need to delete the *COMP* and *LIKE* constructs, and establish a new construct *REPU*, measured formatively by means of the indicators labeled *LV scores – COMP* and *LV*

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*scores – LIKE*. Note that by default, newly added constructs have a reflective measurement model in SmartPLS. In order to switch to a formative specification, right-click on *REPU* and select the **Invert measurement model** option. Finally, we need to add paths from *ATTR, CSOR, PERF*, and *QUAL* to *REPU* as well as from *REPU* to *CUSA* and *CUSL*. The final model should look like the **HCM reflective-formative 2nd stage** model in Exhibit 2.7. Estimate the model by going to **Calculate → PLS-SEM algorithm** in the SmartPLS tool bar. Using the **Results report** that opens, we can now assess the reflective and formative measurement models. The results of the regular constructs are very similar to those reported in Chapters 4 and 5 in Hair, Hult, Ringle, and Sarstedt (2022). Therefore, in the following, our assessment will focus on the higher-order construct.

The first step in formative measurement model assessment is to establish the higher-order construct's convergent validity by means of a redundancy analysis (Cheah, Sarstedt, Ringle, Ramayah, & Ting, 2018; Hair, Hult, Ringle, & Sarstedt, 2022, Chapter 5). For this purpose, select the project in the **Workspace** and left-click on the **PLS-SEM** button in the tool bar to create a new model. Choose an intuitive name, such as **HCM redundancy analysis REPU**, and left-click on **Save**. An empty modeling window will appear next. On the left-hand side, above the indicators, make sure the **HCM disjoint 2nd stage** dataset has been selected. Next, drag and drop the two *REPU* indicators (*LV scores–COMP* and *LV scores-LIKE*) to the modeling window and assign a meaningful name (e.g., *REPU_F* in which *F* stands for "formative"). Make sure to change the construct's measurement model to formative. Next, establish a construct labeled *REPU_G* in which *G* stands for "global," indicating the construct is measured by means of the global single item *repu_global* ("[company] has a high reputation"). Then, draw a path from *REPU_F* to *REPU_G*. Estimating the model by going to **Calculate → PLS-SEM algorithm** will produce the results shown in Exhibit 2.8. Since the relationship between *REPU_F* and *REPU_G* is above the threshold of 0.7, we find support for the higher-order construct's convergent validity.

To continue the results assessment, we return to the **HCM reflective-formative 2nd stage** model, estimate it again, and check for potential collinearity among the LOCs. To do so, go to **Quality Criteria → Collinearity Statistics (VIF)**. We find that the VIF value of *LV scores–COMP* and *LV scores–LIKE* (1.686) is considerably below the threshold of 3, providing support that collinearity is not a critical issue. The final step requires assessing the higher-order construct's indicator weights in terms of their significance and relevance. Run the bootstrapping procedure with **10,000** subsamples, the **Most important (faster)** results computation option, the **Percentile bootstrap** confidence interval, **Two tailed** testing, and a significance level of **0.05**. In the **Results report** that opens, navigate to **Final results → Outer weights coefficients → Confidence intervals bias corrected**. The results show that both weights are significant as both confidence intervals' lower bounds are clearly larger than zero. We also find that the impact of *LIKE* (0.682) is stronger than the one of *COMP* (0.416), further emphasizing the relevance of reputation's affective dimension.

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**EXHIBIT 2.7 ■ Reflective-Formative Higher-Order Construct Example (Stage 2 Model)**

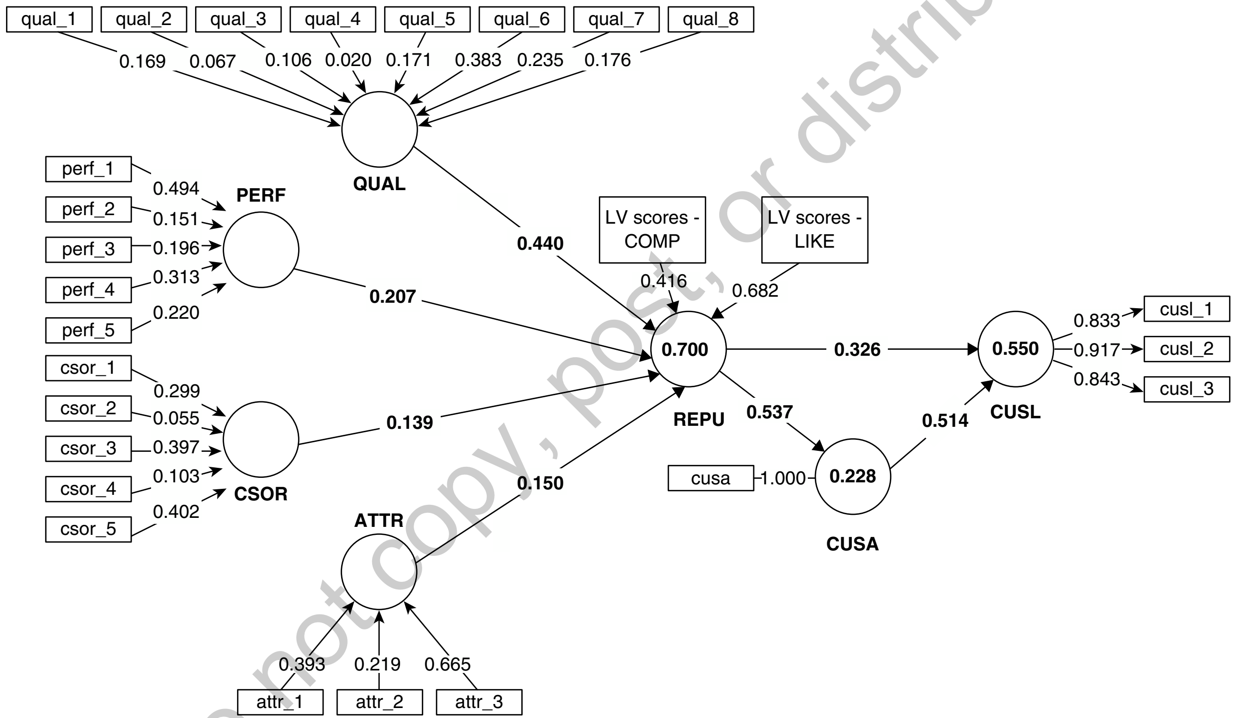


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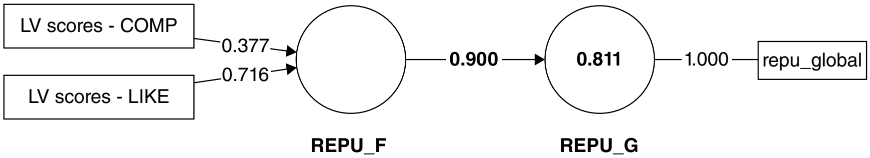
**EXHIBIT 2.8 ■ *REPU*'s Redundancy Analysis Results**




In terms of the structural model relationships, we find that the results of the reflective-formative higher-order construct also meet all structural model evaluation criteria (Hair, Hult. Ringle, & Sarstedt, 2022). All structural model relationships are significant ($p \leq 0.01$). The antecedent constructs *QUAL* (0.440) and *PERF* (0.207) have the strongest effects on *REPU*, while *CSOR* (0.139) and *ATTR* (0.150) are less relevant (Exhibit 2.7). *REPU* itself has a strong effect on *CUSA* (0.537), which, in turn, is strongly related to *CUSL* (0.514). The direct relationship between *REPU* and *CUSL* is somewhat weaker (0.326). The $R^2$ values of all the endogenous constructs (i.e., 0.700 for *REPU*, 0.288 for *CUSA*, and 0.550 for *CUSL*) are relatively high when taking the number of antecedent constructs into account. The results from $PLS_{predict}$ (Shmueli, Ray, Velasquez Estrada et al. 2016; Shmueli, Sarstedt, Hair, Cheah et al. 2019) support the model's predictive power with regard to its final target construct *CUSL* as all its indicators achieve lower RMSE values than the linear benchmark model.

Finally, we assess which model—with or without the higher-order construct *REPU*—has a better model fit. To do so, go to the **Results report** of the PLS-SEM algorithm and save the model estimates of the **HCM reflective-formative 2nd stage** model by clicking on the **Save** button in the toolbar and choosing a self-explanatory name (e.g., **HCM reflective-formative 2nd stage – PLS**). Next, return to the SmartPLS Workspace, open the **Corporate reputation model**, estimate it using the default settings and also save the results with a self-explanatory name (e.g., **Corporate reputation model – PLS**). Next, in the **Results Report** of the **Corporate reputation model**, click on the **Compare** button in the toolbar. Under **Saved reports → Example corporate reputation (advanced)**, select the saved report **HCM reflective-formative 2nd stage – PLS**. In the upper right area of the **Compare** view that opens, check the box next to **Synchronize navigation**. Then, on the left side, click on one of the **Select detail** button above the displayed model and navigate to **Quality Criteria → Model selection criteria** to obtain the results as displayed in Exhibit 2.9. The BIC value of the target construct **CUSL** is lower for the **Corporate reputation model** (–261.602) than for the **HCM reflective-formative 2nd stage** model (–258.515).

Analogously, we compare the models in terms of their predictive power. To do so, go to **Calculate → PLSpredict** and run the procedure using the default settings. In the **Results report**, go to **Final results → CVPAT → PLS-SEM vs. Indicator average (IA)**. We find that for the model's target construct *CUSL*, the corporate reputation model's PLS-SEM results have a smaller average loss (as an expression of the prediction

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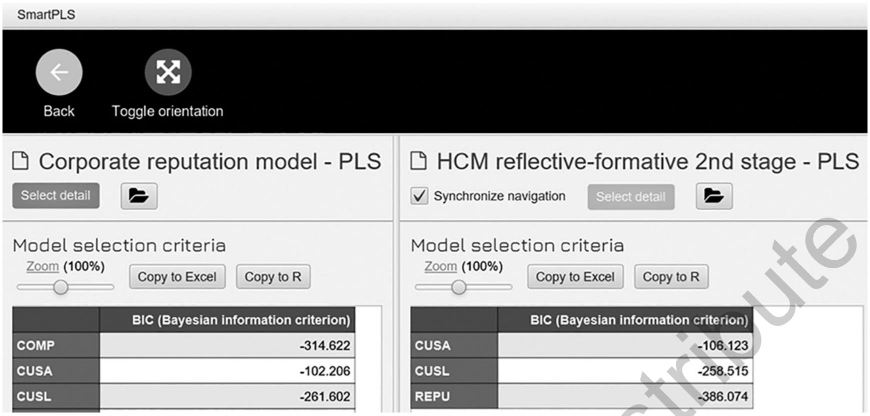
**EXHIBIT 2.9 ■ Comparison of Model Selection Criteria**




error) over the indicator average benchmark—as expressed by an average loss difference of PLS-SEM and the indicator average (IA) with a value of –0.561. The superior predictive capabilities of the PLS-SEM results compared to the IA benchmark also apply to the reflective-formative HCM model and are slightly more pronounced (i.e., with a value of –0.576 for the average loss difference of PLS-SEM and IA). The same finding holds for *CUSL* and the **PLS-SEM vs. Linear model (LM)** outcome with –0.082 for the **Corporate reputation model** and –0.083 for the **HCM reflective-formative** model. To summarize, the results suggest that both model specifications perform very similarly with regard to model fit and predictive power. Hence, researchers may choose either specification, for example, depending on whether they want to include reputation as a distinct concept in their model.

## SUMMARY

- **Understand the usefulness of higher-order constructs.** A higher-order construct embraces a more general component (i.e., HOC), measured at a higher level of abstraction, while simultaneously including several subcomponents (i.e., the LOCs), which cover more concrete traits of this conceptual variable under consideration. Higher-order constructs enable reducing the number of structural model relationships, making the PLS path model more parsimonious, while increasing the bandwidth of content covered by the respective constructs.
- **Appreciate the different types of higher-order constructs and understand how to specify them in PLS-SEM.** The use of higher-order constructs builds on carefully established theoretical and conceptual considerations. On these grounds, researchers choose from four major higher-order construct types. Each of these types depicts the specific relationship between the HOC and the LOCs

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as well as the measurement model used to operationalize the constructs on the lower-order level: reflective-reflective, reflective-formative, formative-reflective, and formative-formative. Generally, the HOC of a reflective-reflective and formative-reflective higher-order construct represents a more general construct that—similar to reflective measurement models—simultaneously explains all the underlying LOCs. Conversely, the HOC is formed by the LOCs in reflective-formative and formative-formative higher-order constructs, which are similar to formative measurement models. To specify a higher-order construct, researchers should draw on the disjoint two-stage approach. When estimating higher-order constricts in PLS-SEM, researchers need to consider further aspects, which relate to the PLS-SEM algorithm weighting scheme, and the use of Mode A and Mode B weighting.

- **Comprehend how to estimate higher-order constructs using the SmartPLS software and how to interpret the results.** Researchers can use SmartPLS to model any of the four higher-order construct types introduced in this chapter. When analyzing the results using the disjoint two-stage approach, researchers need to establish the constructs' reliability and validity in Stage 1. Stage 2 concerns the measurement model validation of the higher-order construct and the structural model assessment.

## REVIEW QUESTIONS

1. What is a higher-order construct? Describe each of the four different types of higher-order constructs introduced in this chapter.
2. Which criteria are relevant in the assessment of the different higher-order construct types?
3. What are the consequences of having substantially different numbers of indicators in the LOCs when specifying the higher-order construct using the embedded two-stage approach?
4. Should discriminant validity between lower- and higher-order components be evaluated when using the embedded two-stage approach?
5. Which criteria can researchers draw upon when comparing a model with a higher-order construct to a model without the higher-order construct?

## CRITICAL THINKING QUESTIONS

1. Discuss the advantages and disadvantages of higher-order constructs.
2. Can every concept be measured at different levels of abstraction?

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3. Screen the literature and identify concepts that are commonly measured using a higher-order construct.

4. When would we use the embedded vs. the disjoint two-stage approach?

5. Do higher-order constructs help resolve discriminant validity problems in PLS-SEM?

## KEY TERMS

Bandwidth-fidelity tradeoff
Bottom-up approach
Collect model
Disjoint two-stage approach
Embedded two-stage approach
Extended repeated indicators approach
Formative-formative higher-order construct
Formative-reflective higher-order construct
Hierarchical common factor model
Hierarchical component model
Higher-order component (HOC)
Higher-order construct
Higher-order model
Jangle fallacy
Lower-order components (LOCs)
Multiple battery model
Reflective-formative higher-order construct
Reflective-reflective higher-order construct
Repeated indicators approach
Second-order construct
Spread model
Stand-alone higher-order construct
Top-down approach
Type I higher-order construct
Type II higher-order construct
Type III higher-order construct
Type IV higher-order construct

## SUGGESTED READINGS

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