2

SPECIFYING THE PATH MODEL AND EXAMINING DATA

LEARNING OUTCOMES

1. Understand the basic concepts of structural model specification, including mediation, moderation, and the use of control variables.
2. Explain the differences between reflective and formative measurement models and specify the appropriate measurement model.
3. Comprehend that the selection of the mode of measurement model and the indicators must be based on theoretical reasoning before data collection.
4. Explain the difference between multi-item and single-item measures and assess when to use each measurement type.
5. Understand the nature of higher-order constructs.
6. Describe the data collection and examination considerations necessary to apply PLS-SEM.
7. Learn how to develop a PLS path model using the SmartPLS software.

CHAPTER PREVIEW

This chapter introduces the basic concepts of structural and measurement model specification when PLS-SEM is used. The concepts are associated with completing the first three stages in the application of PLS-SEM, as described in Chapter 1. To begin with, Stage 1 is specifying the structural model. Next, Stage 2 is selecting and specifying the measurement models. Stage 3 summarizes the major guidelines for data collection when the application of PLS-SEM is anticipated, as well as the need to examine your data after they have been collected to ensure the results from applying PLS-SEM are valid and reliable. An understanding of these three topics will prepare you for Stage 4, estimating the model, which is the focus of Chapter 3.

STAGE 1: SPECIFYING THE STRUCTURAL MODEL

In the initial stages of a research project that involves the application of SEM, an important first step is to prepare a diagram that illustrates the research hypotheses and visually displays the variable relationships that will be examined. This diagram is often referred to as a **path model**. Recall that a path model is a diagram that connects indicators and constructs based on theory and logic to visually display the hypotheses that will be tested (Chapter 1). Preparing a path model early in the research process enables researchers to organize their thoughts and visually consider the relationships between the variables of interest. Path models also are an efficient means of sharing ideas between researchers working on or reviewing a research project.

Path models are made up of two elements: (1) the **structural model** (also called the **inner model** in PLS-SEM), which describes the relationships between the latent variables, and (2) the **measurement model** (also called **outer model** in PLS-SEM), which describes the relationships between the latent variable and its measures (i.e., its indicators). We discuss structural models first, which are developed in Stage 1. In the next section, we explain Stage 2, measurement models.

When a structural model is being developed, two primary issues need to be considered: the sequence of the constructs and the relationships between them. Both issues are critical to the concept of modeling because they represent the hypotheses and their relationship to the theory being tested.

The sequence of the constructs in a structural model is based on theory, logic, or practical experiences observed by the researcher. The sequence is displayed from left to right, with independent (predictor) constructs on the left and dependent (outcome) variables on the right-hand side. That is, constructs on the left are assumed to precede and predict constructs on the right. Constructs that act only as independent variables are generally referred to as **exogenous latent variables** and are on the very left side of the structural model. Exogenous latent variables only have arrows that point out of them and never have arrows from other latent variables pointing into them. Constructs considered dependent in a structural model (i.e., those that have an arrow pointing into them from other latent variables) are called **endogenous latent variables** and are on the right side of the structural model. Constructs that operate as both independent and dependent variables in a structural model also are considered endogenous and appear in the middle of the diagram.

The structural model in Exhibit 2.1 illustrates the three types of constructs and the relationships among them. The reputation construct on the far left is an exogenous (i.e., independent) latent variable. It is modeled as predicting the satisfaction construct. The satisfaction construct is an endogenous latent variable that has a dual relationship as both independent and dependent. It is a dependent construct because it is predicted by reputation. But it is also an independent construct because it predicts loyalty. The loyalty construct on the right end is an endogenous (i.e., dependent) latent variable predicted by satisfaction.

EXHIBIT 2.1 ■ Example of Path Model and Types of Constructs

Determining the sequence of the constructs is seldom an easy task because contradictory theoretical perspectives can lead to different sequencing of latent variables. For example, some researchers assume that customer satisfaction precedes and predicts corporate reputation (e.g., Walsh, Mitchell, Jackson, & Beatty, 2009), while others argue that corporate reputation predicts customer satisfaction (Eberl, 2010; Sarstedt, Wilczynski, & Melewar, 2013). Theory and logic should always determine the sequence of constructs in a structural model, but when the literature is inconsistent or unclear, researchers must use their best judgment to determine the sequence.

Acknowledging that there is not one unique model that characterizes a phenomenon well, researchers can also establish and empirically compare theoretically justified alternative models (Burnham & Anderson, 2002). The models selected for comparison should be motivated by theory from relevant fields, in line with PLS-SEM's "causal predictive" nature (Jöreskog & Wold, 1982, p. 270). Because PLS path models focus on providing theoretical explanations, considering purely empirically motivated models would be akin to "snooping" and is not recommended for theoretical research that focuses on both explanation and prediction (Gregor, 2006). Establishing alternative models requires leveraging the existing literature to provide valid theoretical rationale for all the models being considered. In particular, you should be able to (1) describe the theoretical commonalities among the proposed alternative models (i.e., whether certain proposed effects are common across models), (2) contrast the models to highlight the differences in theoretical mechanisms being captured (such differences may manifest as additional/different paths or antecedents), and (3) explain why the commonalities and differences are important to consider in terms of the effect on the target variable for the population under study. We discuss **model comparisons** in the context of the structural model evaluation in Chapter 6. Sharma, Sarstedt, Shmueli, Kim, and Thiele (2019) introduce a five-step procedure for model comparison and inference in PLS-SEM. These authors also discuss possible misconceptions related to model comparisons.

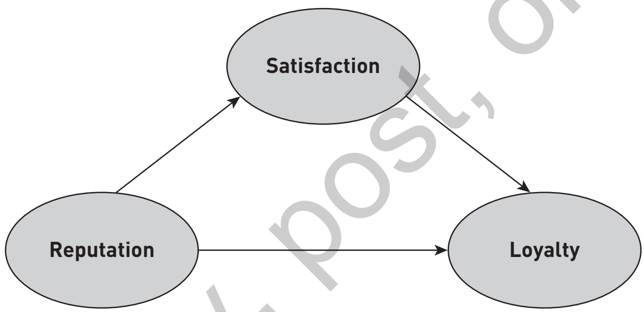
Once the sequence of the proposed constructs has been decided, the relationships between them must be established by drawing arrows. The arrows are inserted with the arrowhead pointing to the right. This approach indicates the sequence and that the constructs on the left predict the constructs on the right side. The predictive relationships are sometimes referred to as **causal links**, if the structural theory supports a causal relationship. But researchers should be cautious in concluding causal links. In drawing arrows between the constructs, researchers face a trade-off between theoretical soundness (i.e., including those relationships that are strongly supported by theory) and model parsimony (i.e., using fewer relationships). The latter should be of crucial concern as the most nonrestrictive statement, "everything is predictive of everything else," is also the most uninformative. As pointed out by Falk and Miller (1992, p. 24), "a parsimonious approach to theoretical specification is far more powerful than the broad application of a shotgun."

In most instances, researchers examine linear independent–dependent relationships between two or more constructs in the path model. Theory often suggests, however, that model relationships are more complex and involve mediation or moderation relationships. In addition, researchers commonly specify control variables that account for some of the variation in the endogenous constructs. In the following section, we briefly introduce these different relationship types. In Chapter 7, we explain how they can be estimated and interpreted using PLS-SEM.

Mediation

A **mediating effect** is created when a third variable or construct intervenes between two other related constructs (Memon, Cheah, Ramayah, Ting, & Chuah, 2018; Nitzl, Roldán, & Cepeda Carrión, 2016), as shown in Exhibit 2.2. To understand how mediating effects work, let's consider a path model in terms of direct and indirect effects. A **direct effect** is a relationship that links two constructs with a single arrow. An **indirect effect** is a relationship that involves a sequence of relationships with at least one intervening construct involved. Thus, an indirect effect is a sequence of two or more direct effects (compound path) that are represented visually by multiple arrows. This indirect effect is characterized as the mediating effect. In Exhibit 2.2, satisfaction is modeled as a possible mediator between reputation and loyalty.

EXHIBIT 2.2 ■ Example of a Mediating Effect



From a theoretical perspective, the most common application of mediation is to "explain" why a relationship between an exogenous and endogenous construct exists. For example, a researcher may observe a relationship between two constructs but not be sure *why* the relationship exists or if the observed relationship is the only relationship between the two constructs. In such a situation, a researcher might posit an explanation of the relationship in terms of an intervening variable that operates by receiving the "inputs" from an exogenous construct and translating them into an "output," in the form of an endogenous construct. The role of the mediator variable then is to reveal the mechanism through which the independent constructs impact the dependent construct.

Consider the example in Exhibit 2.2, in which we want to examine the effect of corporate reputation on customer loyalty. On the basis of theory and logic, we know that a relationship exists between reputation and loyalty, but we are unsure how the relationship actually works (Eberl & Schwaiger, 2005; Schwaiger, 2004). As researchers, we might want to explain how companies translate their reputation into higher loyalty among their customers. We may observe that sometimes a customer perceives a company as being highly reputable, but this perception does not translate into high levels of loyalty. In other situations, we observe that some customers with lower corporate reputation assessments are highly loyal. These observations are confusing and lead to the question as to whether there is some other process going on that translates corporate reputation into customer loyalty.

In the diagram, the intervening process (mediating effect) is modeled via the construct satisfaction. If a respondent perceives a company to be highly reputable, this assessment may lead to higher satisfaction levels and ultimately to increased loyalty. In such a case, the relationship between reputation and loyalty may be explained by the reputation → loyalty sequence, or the reputation → satisfaction → loyalty sequence, or perhaps even by both sets of relationships (Exhibit 2.2). The reputation → loyalty sequence is an example of a direct relationship. In contrast, the reputation → satisfaction → loyalty sequence is an example of an indirect relationship. After empirically testing these relationships, the researcher would be able to explain how reputation is related to loyalty, as well as the role that satisfaction might play in mediating that relationship. Chapter 7 offers additional details on mediation and explains how to test mediating effects in PLS-SEM.

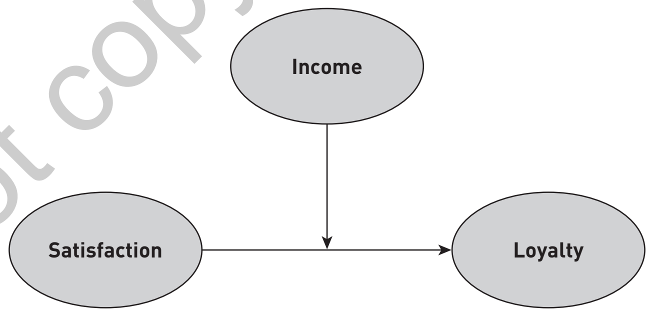
Moderation

Moderation is another important statistical analysis concept. In statistical **moderation**, a third variable directly affects the relationship between the exogenous and endogenous latent variables but in a different way from mediation. Referred to as a **moderator effect**, this situation occurs when the moderator (a variable or construct) changes the strength or even the direction of a relationship between two constructs in the model (Becker, Sarstedt, & Ringle, 2018; Memon et al., 2019). The crucial distinction between moderation and mediation is that the moderator variable does not depend on the exogenous latent variable.

For example, income has been shown to significantly affect the strength of the relationship between customer satisfaction and customer loyalty (Homburg & Giering, 2001). In that context, income serves as a moderator variable on the satisfaction → loyalty relationship, as shown in Exhibit 2.3. Specifically, the strength of the relationship (as measured by the path coefficient) between satisfaction and loyalty has been shown to be weaker for people with high income than for people with low income. For higher-income individuals, there may be little or no relationship between satisfaction and loyalty. But for lower-income individuals, there often is a strong relationship between the two variables. As such, moderation may be understood as a way to account for **heterogeneity** in the theoretical model. Heterogeneity means that different types of effects can be expected for different groups of respondents. That is, instead of assuming that the relationship between customer satisfaction and customer loyalty is the same for all respondents, we acknowledge that this effect is different for low- and high-income individuals.

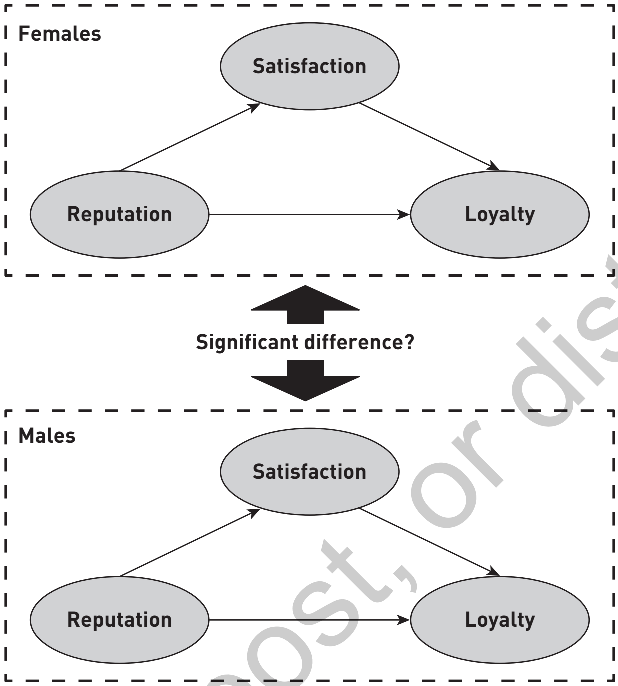
In the example outlined in Exhibit 2.3, income may be measured on a continuous scale, for example, the annual income measured based on Euros or the U.S. dollar. But a moderator variable can also be measured categorically, for example, high income is > 50 thousand Euros a year, and low income is ≤ 50 thousand Euros a year. If this is the case, the variable frequently serves as a grouping variable that divides the data into subsamples. The same theoretical model is then estimated for each of the distinct subsamples. Since researchers are usually interested in comparing the models and learning about significant differences between the subsamples, the model estimates for the subsamples are usually compared by means of **multigroup analysis** (Matthews, 2017). Specifically, multigroup analysis enables the researcher to test for differences between identical models estimated for different groups of respondents. The general objective is to see if there are statistically significant differences between the group-specific path coefficients. For example, we might be interested in evaluating whether the effects between reputation, satisfaction, and loyalty shown in Exhibit 2.2 are significantly different for males compared with females (Exhibit 2.4).

EXHIBIT 2.3 ■ Theoretical Model of a Continuous Moderating Effect



In Chapter 7, we discuss in greater detail how to use categorical and continuous variables for the moderator analysis. Chapter 8 offers a brief overview of multigroup analysis.

EXHIBIT 2.4 ■ Example of a Multigroup Analysis



Control Variables

When specifying theoretical models to be tested, researchers sometimes include control variables. The business disciplines of accounting, finance, international business, and management often include control variables in their research. **Control variables** are designed to measure the influence of independent variables that are not part of the primary theoretical model being examined. The control variables are used as a constant and unchanging standard of comparison, but they are not the primary interest of the researcher. Including control variables in a statistical model is most important when the control variable is significantly correlated with both the dependent variable and one or more of the other independent variables in the model. Control variables have been included in multiple regression models for many years, but with the increasing popularity of PLS-SEM and the underlying characteristics it has in common with regression, researchers are beginning to explore the usefulness of control variables in PLS-SEM.

By adding control variables to the hypothesized structural model, researchers hope to account for other explanatory factors (independent variables) that potentially influence the dependent variables (or constructs). For example, when estimating the impact of customer satisfaction on stock returns, researchers also need to account for the influence of several firm characteristics such as R&D intensity, marketing investments, and firm size (Raithel, Sarstedt, Scharf, & Schwaiger, 2012). Failure to account for these characteristics could lead to an overestimation of the effect of customer satisfaction on stock returns, potentially triggering a type I error (i.e., false positive).

From a statistical perspective, adding control variables to the model entails that the hypothesized effects are estimated at constant levels of the control variables. If the hypothesized relationships remain largely constant, researchers can rule out alternative explanations related to the control variables. As such, control variables help strengthening the causal inference of the effects. In addition, adding control variables improves the precision of the model estimates as they explain the statistical noise in the endogenous construct. This particularly holds when the control variables are lowly correlated with the predictor constructs of the endogenous construct (Klarmann & Feurer, 2018).

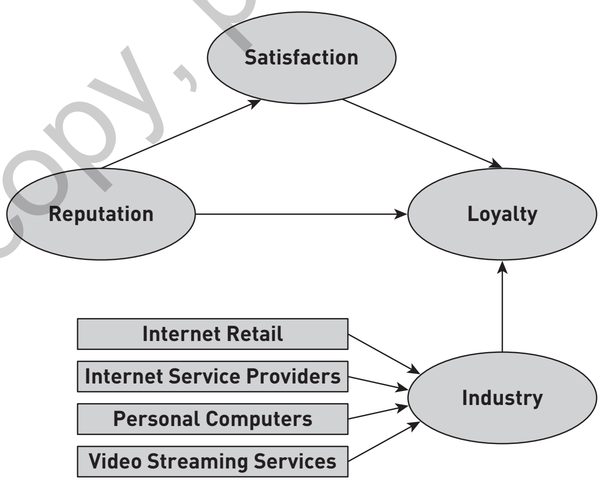
To add control variables into a PLS path model, researchers need to establish a separate exogenous construct for each control variable to be considered and link each new construct to the endogenous latent variable under consideration. For example, suppose that a researcher wants to control for the impact of the respondent's age on loyalty when estimating the mediation model shown in Exhibit 2.2. To do so, the researcher needs to add a new construct into the model, measured with the single age item, and link this construct to the loyalty construct. By adding the age measure as a control, the effects of reputation on loyalty and customer satisfaction on loyalty will decrease, provided that age has an impact on the endogenous construct.

In some situations, researchers wish to control for the impact of categorical variables such as industry type. If the categorial variable has only two categories such as gender, one uses a binary (dummy) variable and includes it as a single-item construct in the PLS path model. In this case, zero becomes the reference category (e.g., female customers) and the relationship between control variable and endogenous construct shows the effect of switching from the reference category to the other category (e.g., male customers).

When the variable has more than two categories, the categorical variable needs to be recoded into a series of binary (dummy) variables. Specifically, when the control variable has k categories, researchers need to create k-1 binary variables. The category that is left out is referred to as the reference category. To identify the reference category, all binary variables take the value zero. The values of the dummy variables other than zero (typically one) then denote the deviation from this reference category. When an observation falls into the reference category, which is typically the first category, all binary (dummy) variables are zero. When an observation falls into the second category, the first binary (dummy) variable is one, all others are zero, and so on. The *k*-1 binary variables need to be included as measures of a single construct (Henseler, Hubona, & Ray, 2016) using a formative measurement model specification (see the next section for more details on formative measurement models). Exhibit 2.5 shows an example of a categorical control variable for five industries, whereby the first industry serves as the reference category, which is not included as a binary (dummy) variable. As a result, the control variable become a composite that is formed by all binary (dummy) coded category variables except the reference category. In the model shown in Exhibit 2.5, we control for the impact of *Industry* on the relationships of *Reputation* and *Satisfaction* on *Loyalty*. *Industry* has the following five categories: 1 = *Computer software*, 2 = *Internet retail*, 3 = *Internet service providers*, 4 = *Personal computers*, and 5 = *Video streaming services*. We use the first industry (i.e., *Computer software*) as the reference category. Hence it is not included as a binary (dummy) indicator variable for the *Industry* control construct.

Researchers are typically only interested in controlling for the impact of the control variables, rather than explicitly hypothesizing and testing their impact. As a consequence, the path coefficients quantifying the effect of the control variables on the endogenous construct and their significances are not interpreted. However, when including control variables, researchers need to offer compelling

EXHIBIT 2.5 ■ Categorical Control Variable With Multiple Categories in PLS-SEM



Note: This exhibit does not show the measurement models and indicators of the constructs *Reputation*, *Satisfaction*, and *Loyalty*. The control variable *Industry* includes dummy-coded indicator variables of industries 2 to 5, where the first industry (i.e., Computer Software) represents the reference category.

theoretical arguments as to why these variables are important rather than following a kitchen sink approach, which considers all potential control variables available (Spector & Brannick, 2011). Berneth and Aguinis (2016) offer best-practice recommendations that can be followed to make decisions on the appropriateness of including a specific control variable within a particular theoretical framework, research domain, and empirical study.

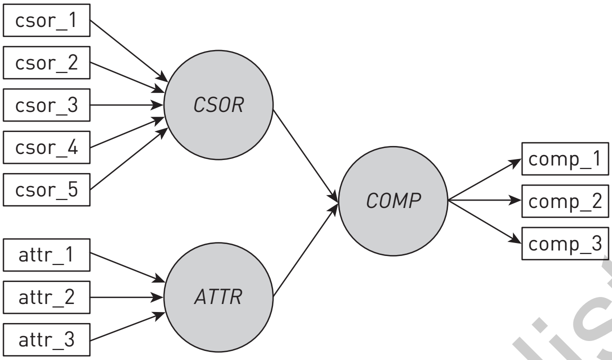
STAGE 2: SPECIFYING THE MEASUREMENT MODELS

The structural model describes the relationships between latent variables (constructs). In contrast, the measurement models represent the relationships between constructs and their corresponding indicator variables (Sarstedt, Ringle, & Hair, 2017a). The basis for determining these relationships is measurement theory. A sound measurement theory is a necessary condition to obtain useful results from PLS-SEM. Hypothesis tests involving the structural relationships among constructs will be only as reliable or valid as the measurement models are explaining how these constructs are measured.

Researchers typically have several established measurement approaches to choose from, each a slight variant from the others. In fact, almost all social science researchers today use established measurement approaches published in prior research studies or scale handbooks (e.g., Bearden, Netemeyer, & Haws, 2011; Bruner, 2019; Zarantonella & Pauwels-Delassus, 2015) that performed well (Ramirez, David, & Brusco, 2013). In some situations, however, the researcher is faced with the lack of an established measurement approach and must develop a new set of measures (or substantially modify an existing approach). A description of the general process for developing indicators to measure a construct can be long and detailed. Hair, Black, Babin, and Anderson (2019) describe the essentials of this process. Likewise, Diamantopoulos and Winklhofer (2001), DeVellis (2017), and MacKenzie, Podsakoff, and Podsakoff (2011) offer thorough explications of different approaches to measurement development. In each case, decisions regarding how the researcher selects the indicators to measure a particular construct provide a foundation for the remaining analysis.

The path model shown in Exhibit 2.6 shows an excerpt of the path model we use as an example throughout the book. The model has two exogenous constructs—*corporate social responsibility* (*CSOR*) and *attractiveness* (*ATTR*)—and one endogenous construct, which is *competence* (*COMP*). Each of these constructs is measured by means of multiple indicators. For instance, the endogenous construct *COMP* has three measured indicator variables, *comp_1*, *comp_2*, and *comp_3*. Using a scale from 1 to 7 (*fully disagree* to *fully agree*), respondents had to evaluate the following statements: "[The company] is a top competitor in its market," "As far as I know, [the company] is recognized worldwide," and

EXHIBIT 2.6 ■ Example of a Path Model With Three Constructs



"I believe that [the company] performs at a premium level." The answers to these three inquiries represent the measures for this construct. The construct itself is measured indirectly by these three indicator variables and, for that reason, is referred to as a latent variable.

The other two constructs in the model, *CSOR* and *ATTR*, can be described in a similar manner. That is, the two exogenous constructs are measured by indicators that are each directly measured by responses to specific questions. Note that the relationship between the indicators and the corresponding construct is different for *COMP* compared with *CSOR* and *ATTR*. When you examine the *COMP* construct, the direction of the arrows goes from the construct to the indicators. This type of measurement model is referred to as *reflective*. When you examine the *CSOR* and *ATTR* constructs, the direction of the arrows is from the measured indicator variables to the constructs. This type of measurement model is called *formative*. As discussed in Chapter 1, an important characteristic of PLS-SEM is that the technique readily incorporates both reflective and formative measures. Likewise, PLS-SEM can easily be used when constructs are measured with only a single item (rather than multiple items). Both of these measurement issues are discussed in the following sections.

Reflective and Formative Measurement Models

When developing constructs, researchers must consider two broad types of measurement specification: reflective and formative measurement models. The **reflective measurement** model has a long tradition in the social sciences and is directly based on classical test theory. According to this theory, measures represent the effects (or manifestations) of an underlying construct. Therefore, causality is from the construct to its measures (*COMP* in Exhibit 2.6). Reflective indicators (sometimes referred to as **effect indicators** in the psychometric literature) can be viewed as a representative sample of all the possible items available within the conceptual domain of the construct (Nunnally & Bernstein, 1994). Therefore, since a reflective measure dictates that all indicator items are "caused" by the same construct (i.e., they stem from the same domain), indicators associated with a particular construct should be highly correlated with each other. In addition, individual items should be interchangeable, and any single item can generally be left out without changing the meaning of the construct, as long as the construct has sufficient reliability. The fact that the relationship goes from the construct to its measures implies that if the evaluation of the latent trait changes (e.g., because of a change in the standard of comparison), all indicators will change simultaneously. A set of reflective measures is commonly called a **scale.**

In contrast, **formative measurement** models are based on the assumption that the indicators form the construct by means of linear combinations. Therefore, researchers typically refer to this type of measurement model as being a formative **index**. An important characteristic of formative indicators is that they are not interchangeable, as is true with reflective indicators. Thus, each indicator for a formative construct captures a specific aspect of the construct's domain. Taken jointly, the items ultimately determine the meaning of the construct, which implies that omitting an indicator potentially alters the nature of the construct. As a consequence, breadth of coverage of the construct domain is extremely important to ensure that the content of the focal construct is adequately captured (Diamantopoulos & Winklhofer, 2001).

Researchers distinguish between two types of indicators in the context of formative measurement: composite and causal indicators. **Composite indicators** largely correspond to the above definition of formative measurement models in that they are combined in a linear way to form a variate (Chapter 1), which is also referred to as composite variable in the context of SEM (Bollen, 2011; Bollen & Bauldry, 2011). More precisely, the indicators fully form the composite variable (i.e., the composite variable's R^2 value is 1.0). Composite indicators have often been used to measure **artifacts**, which can be understood as human-made concepts (Henseler, 2017b). Examples of such artifacts in marketing include the retail price index or the marketing mix (Hair, Sarstedt, & Ringle, 2019). However, composite indicators can also be used to measure attitudes, perceptions, and behavioral intentions (Sarstedt, Hair, Ringle, Thiele, & Gudergan, 2016; Rossiter, 2011; Rossiter, 2016), provided that the indicators have conceptual unity in accordance with a clear theoretical definition. The PLS-SEM algorithm relies solely on the concept of composite indicators because of the way the algorithm estimates formative measurement models (e.g., Diamantopoulos & Riefler, 2011).

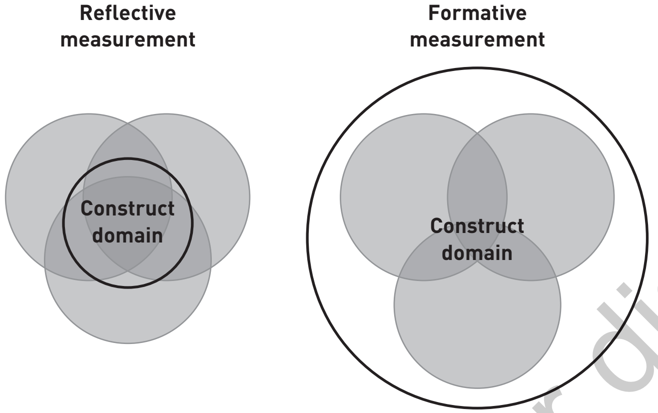
Causal indicators also form the latent variable but this type of measurement acknowledges that it is highly unlikely that any set of causal indicators can fully capture every aspect of a latent phenomenon (Diamantopoulos & Winklhofer, 2001). Therefore, latent variables measured with causal indicators have an error term, which is assumed to capture all the other causes of the latent variable not included in the model (Diamantopoulos, 2006). The use of causal indicators is prevalent in CB-SEM, which—at least in principle—allows for explicitly defining the error term of a formatively measured latent variable. However, the nature and magnitude of this error term is questionable as its magnitude partly depends on other constructs embedded in the model and their measurement quality (Aguirre-Urreta, Rönkkö, & Marakas, 2016).

In a nutshell, the distinction between composite and causal indicators relates to a difference in measurement philosophy. Causal indicators assume that a certain concept can—at least in principle—be fully measured using a set of indicators and an error term. Composite indicators make no such assumption but view measurement explicitly as an approximation of a certain theoretical concept. The inclusion of an error term in causal indicator models appears appealing on first sight but as its magnitude depends on the measurement quality of downstream constructs, the error term's value for judging the quality of the formative measurement model is ambiguous (Rigdon et al., 2014). In addition, by including an error term in a formative measurement model, CB-SEM treats the formative measurement as if it was a common factor model. PLS-SEM, on the other hand, estimates formative measurement models with composite indicators, which is fully en par with the composite-based approach underlying the PLS-SEM algorithm. That is, regardless of whether estimating reflective or formative measurement models, PLS-SEM uses linear combinations to form composites to measure the constructs in a path model (Chapter 3).

In light of the above, the distinction between causal and composite indicators in measurement appears rather artificial with little consequence for method choice. For the sake of simplicity and in line with seminal research in the field (e.g., Fornell & Bookstein, 1982), we therefore refer to formative indicators when assuming composite indicators (as used in PLS-SEM) in the remainder of this book. Similarly, we refer to formative measurement models to describe measurement models comprising composite indicators. Henseler et al. (2014), Rigdon, Sarstedt, and Ringle (2017), and Sarstedt, Hair, Ringle, Thiele, and Gudergan (2016) provide further information on composite models as well as common factor models and their distinction.

Exhibit 2.7 illustrates the key difference between the reflective and formative measurement perspectives. The black circle illustrates the construct domain, which is the domain of content the construct is intended to measure. The gray circles represent the content domain that each indicator captures. Whereas the reflective measurement approach aims at maximizing the overlap between interchangeable indicators, the formative measurement approach tries to fully cover the domain of the latent concept under investigation (black circle) by the different formative indicators (gray circles), which should have small overlap.

EXHIBIT 2.7 ■ Conceptual Difference Between Reflective and Formative Measures



Note: The black circle represents the construct domain of interest and the gray-shaded circles the content domain captured by each indicator.

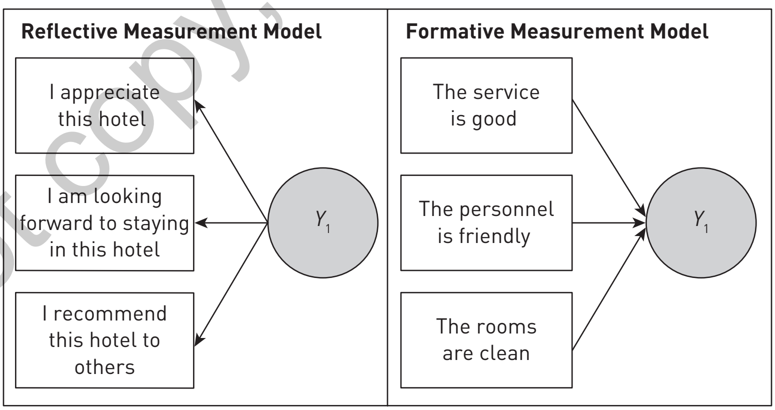
Unlike the reflective measurement approach whose objective is to maximize the overlap between interchangeable indicators, there are no specific expectations about patterns or the magnitude of intercorrelations between formative indicators (Diamantopoulos, Riefler, & Roth, 2008). Since there is no "common cause" for the items in the construct, there is not any requirement for the items to be correlated, and they may be completely independent. In fact, collinearity among formative indicators can present significant problems because the weights linking the formative indicators with the construct can become unstable and nonsignificant. Furthermore, formative indicators have no individual measurement error terms. That is, they are assumed to be error-free in a conventional sense. These characteristics have broad implications for the evaluation of formatively measured constructs, which rely on a totally different set of criteria compared with the evaluation of reflective indicators (Chapter 5). For example, analyzing the internal consistency reliability of a formatively measured construct could suggest that individual indicators need to be removed because of low inter-item correlations. However, such a step would decrease the content validity of the measurement approach (Diamantopoulos & Siguaw, 2006). Broadly speaking, researchers need to pay closer attention to the content validity of the measures by determining how well the indicators represent the domain (or at least its major aspects) of the latent concept under research (e.g., Bollen & Lennox, 1991).

But when do we measure a construct reflectively or formatively? There is not a definite answer to this question since constructs are not inherently reflective or formative. Instead, the specification depends on the construct conceptualization and the objective of the study. Consider Exhibit 2.8 which shows how the construct "satisfaction with hotels" (Y_1) can be operationalized in both ways (Albers, 2010).

The left side of Exhibit 2.8 shows a reflective measurement model setup. This type of model setup is likely to be more appropriate when a researcher wants to test theories with respect to satisfaction. In many managerially oriented business studies, however, the aim is to identify the most important drivers of satisfaction that ultimately lead to customer loyalty. In this case, researchers should consider the different facets of satisfaction, such as satisfaction with the service or the personnel, as shown on the right side of Exhibit 2.8. In the latter case, a formative measurement model specification is more promising as it allows identifying distinct drivers of satisfaction and thus deriving more nuanced recommendations. This especially applies to situations where the corresponding constructs are exogenous. However, formative measurement models may also be used on endogenous constructs when measurement theory supports such a specification.

Apart from the role a construct plays in the model and the recommendations the researcher wants to give based on the results, the specification of the

EXHIBIT 2.8 ■ Satisfaction as a Formatively and Reflectively Measured Construct



Adapted from source: Albers, S. (2010). PLS and success factor studies in marketing. In V. Esposito Vinzi, W. W. Chin, J. Henseler, & H. Wang (Eds.), *Handbook of partial least squares: Concepts, methods and applications in marketing and related fields* (pp. 409–425). Berlin: Springer.

content of the construct (i.e., the domain content the construct is intended to capture) primarily guides the measurement perspective. Still, the decision as to which measurement model is appropriate has been the subject of considerable debate in a variety of disciplines and is not fully resolved. In Exhibit 2.9, we present a set of guidelines that researchers can use in their decision of whether to measure a construct reflectively or formatively. Note that there are also empirical means to determine the measurement perspective. Gudergan, Ringle, Wende, and Will (2008) propose the **confirmatory tetrad analysis in PLS-SEM** (**CTA-PLS**), which allows testing the null hypothesis that the construct measures are reflective in nature. We discuss the CTA-PLS technique

EXHIBIT 2.9 ■ Guidelines for Choosing the Measurement Model Mode

Criterion	Decision	Reference
What is the causal priority between the indicator and the construct?	• From the construct to the indicators: reflective • From the indicators to the construct: formative	Diamantopoulos & Winklhofer (2001)
Is the construct a trait explaining the indicators or rather a combination of the indicators?	• If trait: reflective • If combination: formative	Fornell & Bookstein (1982)
Do the indicators represent consequences or causes of the construct?	• If consequences: reflective • If causes: formative	Rossiter (2002)
Is it necessarily true that if the assessment of the trait changes, all items will change in a similar manner (assuming they are equally coded)?	• If yes: reflective • If no: formative	Chin (1998)
Are the items mutually interchangeable?	• If yes: reflective • If no: formative	Jarvis, MacKenzie, & Podsakoff (2003)

in greater detail in Chapter 8 (also see Hair, Sarstedt, Ringle, & Gudergan, 2018, Chapter 3). Clearly, a purely data-driven perspective needs to be supplemented with theoretical considerations based on the guidelines summarized in Exhibit 2.9.

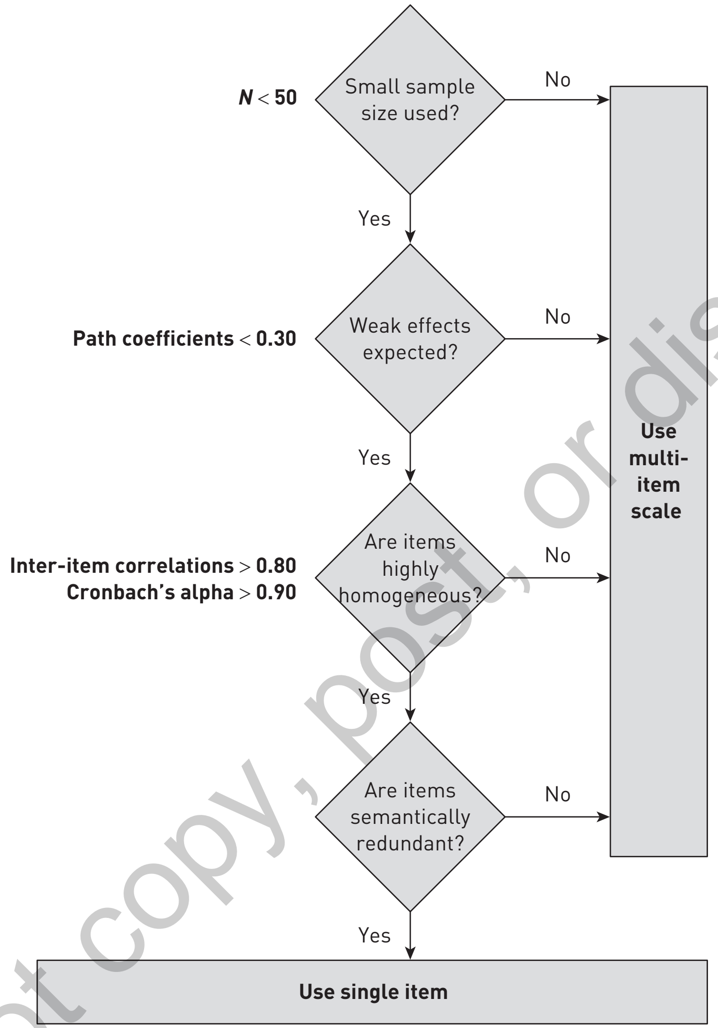
Single-Item Measures and Sum Scores

Rather than using multiple items to measure a construct, researchers sometimes choose to use a single item. PLS-SEM proves valuable in this respect as the method does not suffer from identification problems when using fewer than three items in a measurement model as is the case with CB-SEM. Single items have practical advantages such as ease of application, brevity, and lower costs associated with their use. Unlike long and complicated scales, which often result in a lack of understanding and mental fatigue for respondents, single items promote higher response rates as the questions can be easily and quickly answered (Fuchs & Diamantopoulos, 2009; Sarstedt & Wilczynski, 2009). However, single-item measures do not offer more for less. For instance, when partitioning the data into groups, researchers have fewer options since scores from only a single variable are available to partition the data. Similarly, information is available from only a single measure instead of several measures when using imputation methods to deal with missing values.

More importantly, from a psychometric perspective, single-item measures do not allow for the removal of measurement error (as is the case with multiple items), which generally decreases their reliability. Note that, contrary to commonly held beliefs, single-item reliability can be estimated (e.g., Cheah, Sarstedt, Ringle, Ramayah, & Ting, 2018; Loo, 2002; Wanous, Reichers, & Hudy, 1997)—see Exhibit 5.3 in Chapter 5 for details. In addition, opting for single-item measures in most empirical settings is a risky decision when it comes to predictive validity considerations. Specifically, the set of circumstances that would favor the use of single-item over multi-item measures is very unlikely to be encountered in practice. According to the guidelines by Diamantopoulos, Sarstedt, Fuchs, Kaiser, and Wilczynski (2012), single-item measures should be considered only in situations when (1) small sample sizes are present (i.e., $N < 50$), (2) path coefficients (i.e., the coefficients linking constructs in the structural model) of 0.30 and lower are expected, (3) items of the originating multi-item scale are highly homogeneous (i.e., inter-item correlations > 0.80, Cronbach's alpha > 0.90), and (4) the items are semantically redundant (Exhibit 2.10). For further discussions on the efficacy of single-item measures, see Kamakura (2015).

Nevertheless, when setting up measurement models, this purely empirical perspective should be complemented with practical considerations. Some research situations call for or even necessitate the use of single items. Respondents frequently feel they are oversurveyed, which contributes to lower response rates. The difficulty of obtaining large sample sizes in surveys, often due to a lack of

EXHIBIT 2.10 ■ Guidelines for Single-Item Use



Source: Diamantopoulos, A., Sarstedt, M., Fuchs, C., Kaiser, S., & Wilczynski, P. (2012). Guidelines for choosing between multi-item and single-item scales for construct measurement: A predictive validity perspective. *Journal of the Academy of Marketing Science*, *40*(3), 434–449.

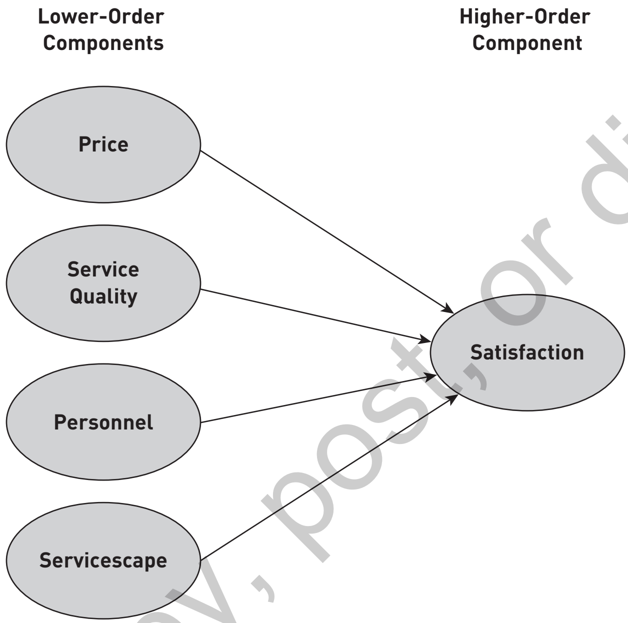
willingness to take the time to complete questionnaires, leads to the necessity of considering reducing the length of construct measures where possible. Therefore, if the population being surveyed is small or only a limited sample size is available (e.g., due to budget constraints, difficulties in recruiting respondents, or dyadic data), the use of single-item measures may be a pragmatic solution. Even if researchers accept the consequences of lower predictive validity and use single-item measures anyway, one fundamental question remains: What should this item be? Unfortunately, research clearly points to severe difficulties when choosing a single item from a set of candidate items, regardless of whether this selection is based on statistical measures or expert judgment (Sarstedt, Diamantopoulos, Salzberger, & Baumgartner, 2016). Against this background, we clearly advise against the use of single items for construct measurement, unless indicated otherwise by Diamantopoulos et al.'s (2012) guidelines. Finally, it is important to note that the above issues must be considered for the measurement of unobservable phenomena, such as perceptions or attitudes. But single-item measures are clearly appropriate when used to measure observable characteristics such as sales, quotas, profits, and so on.

In a similar manner, and as indicated in Chapter 1, we recommend avoiding using regressions based on **sum scores**, which some scholars have recently propagated. Similar to reflective and formative measurement models, sum scores use several indicators to measure a construct. However, instead of explicitly estimating their varying relationships with the construct, the sum scores approach uses the average value of the indicators to compute latent variable scores. Sum scores therefore represents a simplification of PLS-SEM, where all indicator weights in the measurement model are equal. This practice is problematic as it ignores the effect of measurement error inherent in each indicator. In contrast, the individual weighting of the indicators in a PLS-SEM analysis accounts for measurement error, thereby increasing the reliability and validity of the model estimates (Yuan, Wen, & Tang, 2020). For example, Hair, Hult, Ringle, Sarstedt, and Thiele (2017) have shown that sum scores can produce substantial parameter biases and often lag behind PLS-SEM in terms of statistical power. Apart from these reliability- and validity-related concerns of the sum scores approach, the researcher does not learn which indicator has a higher or lower relative importance. Since PLS-SEM provides this additional information, its use is clearly superior compared with sum scores.

Higher-Order Constructs

Thus far, we have considered constructs, which are measured on a single layer of abstraction. That is, we measured each construct with a set of indicators that are similar in terms of their concreteness. However, PLS-SEM also allows researchers to model a construct on multiple layers of abstraction simultaneously. **Higher-order constructs**, also referred to as **higher-order models** or **hierarchical component models** in the context of PLS-SEM (Lohmöller, 1989; Sarstedt, Hair, Cheah, Becker, & Ringle, 2019), allow specifying a single construct on a more abstract dimension and more concrete subdimensions at the same time (Cheah et al., 2019; Hair, Sarstedt, Ringle, & Gudergan, 2018, Chapter 2; Wetzels, Odekerken-Schröder, & van Oppen, 2009). For example, the construct satisfaction can be represented by a number of more concrete aspects, measured by **lower-order components** that capture separate attributes of satisfaction. In the context of services, these might include satisfaction with the quality of the service, the service personnel, the price, or the servicescape. These lower-order components might form the more abstract **higher-order component** satisfaction, as shown in Exhibit 2.11.

EXHIBIT 2.11 ■ Example of a Higher-Order Construct



Instead of modeling the attributes of satisfaction as drivers of the respondent's overall satisfaction on a single construct layer, the higher-order construct summarizes the lower-order component into a single multidimensional construct. This modeling approach leads to more parsimony and reduces model complexity. Theoretically, this process can be extended to any number of multiple layers, but researchers usually restrict their modeling approach to two layers of abstraction (i.e., one higher-order component and several lower-order components). Constructs with two layers of abstraction are also referred to as **second-order constructs**. Chapter 8 offers more details on higher-order constructs.

At this point, you should be able to create a path model. Exhibit 2.12 summarizes some key guidelines you should consider when preparing your path model. The next section continues with collecting the data needed to empirically test your PLS path model.

EXHIBIT 2.12 ■ Guidelines for Preparing Your PLS Path Model

Structural model

- The constructs considered relevant to the study must be clearly identified and defined.
- The structural model discussion states how the constructs are related to each other, that is, which constructs are dependent (endogenous) or independent (exogenous). If applicable, this also includes more complex relationships such as mediators or moderators and the inclusion of control variables.
- If possible, the nature (positive or negative) of the relationships as well as the direction is hypothesized on the basis of theory, logic, previous research, or researcher judgment.
- There is a clear explanation of why you expect these relationships to exist. The explanation cites theory, qualitative research, business practice, or some other credible source.
- A theoretical model or framework is prepared to clearly illustrate the hypothesized relationships.

Measurement model

- The measurement model discussion states whether constructs are conceptualized as regular or higher-order constructs.
- The measurement specification (i.e., reflective vs. formative) has to be clearly stated and motivated. A construct's conceptualization and the aim of the study guide this decision.
- Single-item measures should be used only if indicated by Diamantopoulos et al.'s (2012) guidelines.
- Do not use regressions based on sum scores.

STAGE 3: DATA COLLECTION AND EXAMINATION

Application of PLS-SEM requires that quantitative data are available. Social science researchers typically use primary data, which have been collected for a specific research project, commonly using questionnaires (Sarstedt & Mooi, 2019; Chapter 3.2). However, researchers are increasingly turning their attention to secondary data, which are available from databases or come in the form of website tracking information; social media, geospatial, and sensor data; as well as other information obtained through scraping and similar data collection methods (Hulland, Baumgartner, & Smith, 2018).

When empirical data are collected using questionnaires, typically data collection issues must be addressed after the data are collected. The primary issues that need to be examined include missing data, suspicious response patterns (straight lining or inconsistent answers), outliers, and data distribution. We briefly address each of these on the following pages. The reader is referred to more comprehensive discussions of these issues in Hair, Black, Babin, and Anderson (2018).

Missing Data

Researchers often have to deal with missing data. There are two levels at which missing data occur:

- Entire surveys are missing (survey non-response), and
- Respondents have not answered all the items (item non-response)

Survey non-response (also referred to as unit non-response) occurs when entire surveys are missing. Survey non-response is very common as only 5–25% of surveys are typically filled out. Item non-response occurs when respondents do not provide answers to certain questions. There are different forms of missingness, including people not filling out or refusing to answer questions. Item non-response is common and 2–10% of questions usually remain unanswered. However, this number greatly depends on various factors, such as the subject matter, the length of the questionnaire, and the method of administration. Non-response can be much higher in respect to questions that people consider sensitive and varies from country to country. In some countries, for instance, reporting income is a sensitive issue (Sarstedt & Mooi, 2019; Chapter 3.9). As a rule of thumb, when the amount of missing data for a specific respondent exceeds 15%, the observation should be removed from the data set. Similarly, we recommend excluding an indicator from the analysis if it has more than 15% missing values.

Once observations with too many missing responses have been removed, the next step is to decide how to deal with the remaining missing values in the data set. The software used in the book, SmartPLS 3 (Ringle, Wende, & Becker, 2015), offers three types of **missing value treatment**. In **mean value replacement**, the missing values of an indicator variable are replaced with the mean of valid values of that indicator. While easy to implement, mean value replacement decreases the variability in the data and likely reduces the possibility of finding meaningful relationships. It should therefore be used only when the data exhibit extremely low levels of missing data. As a rule of thumb, we recommend using mean value replacement when there are less than 5% values missing per indicator.

Alternatively, SmartPLS offers an option to remove all cases from the analysis that include missing values in any of the indicators used in the model (referred to as **casewise deletion** or **listwise deletion)**. Grimm and Wagner (2020) show that PLS-SEM estimates are very stable when using casewise deletion on data sets with up to 9% missing values. However, when using casewise deletion, researchers need to ensure that they do not systematically delete a certain group of respondents. For example, market researchers frequently observe that wealthy respondents are more likely to refuse answering questions related to their income. Running casewise deletion would systematically omit this group of respondents and therefore yield erroneous conclusions. Second, using casewise deletion can dramatically diminish the number of observations in the data set. It is therefore crucial to carefully check the number of observations used in the final model estimation when this type of missing value treatment is used.

Instead of discarding all observations with missing values, **pairwise deletion** uses all observations with complete responses in the calculation of the model parameters. For example, assume we have a measurement model with three indicators (x_1, x_2, and x_3). To estimate the model parameters, all valid values in x_1, x_2, and x_3 are used in the computation. That is, if a respondent has a missing value in x_3, the valid values in x_1 and x_2 are still used to calculate the model. Consequently, different calculations in the analysis may be based on different sample sizes, which can bias the results. Some researchers, therefore, call this approach "unwise deletion," and we also generally advise against its use. Exceptions are situations in which many observations have missing values—thus hindering the use of mean replacement and especially casewise deletion—and the aim of the analysis is to gain first insights into the model structure. In addition, more complex procedures for handling missing values can be conducted before analyzing the data with SmartPLS.

Among the best approaches to overcome missing data is to first determine the demographic profile of the respondent with missing data and then calculate the mean for the sample subgroup representing the identified demographic profile. For example, if the respondent with missing data is male, aged 25 to 34, with 14 years of education, then calculate the mean for that group on the questions with missing data. Next, determine if the question with missing data is associated with a construct with multiple items. If yes, then calculate an average of the responses to all the items associated with the construct. The final step is to use the subgroup mean and the average of the construct indicator responses to decide what value to insert for the missing response. This approach minimizes the decrease in variability of responses and also enables the researcher to know specifically what is being done to overcome missing data problems. Finally, research has brought forward a variety of methods that impute missing observations using information from the available data (Little & Rubin, 2002; Schafer & Graham, 2002). The choice of the best imputation method depends on several factors, including the number of missing values and the missing value pattern—see Sarstedt and Mooi (2019; Chapter 5.4) for an overview. However, since knowledge on their suitability specifically in a PLS-SEM context is scarce, we recommend drawing on the methods described above when treating missing values in PLS-SEM analyses.

Suspicious Response Patterns

Before analyzing their data, researchers should also examine response patterns. In doing so, they are looking for a pattern often described as straight lining. **Straight lining** occurs when a respondent marks the same response for a high proportion of the questions. For example, if a 7-point scale is used to obtain answers and the response pattern is all 4s (the middle response), then that respondent in most cases should be deleted from the data set. Similarly, if a respondent selects only 1s or only 7s, then that respondent should in most cases be removed. Other suspicious response patterns are **diagonal lining** and **alternating extreme pole responses**. A visual inspection of the responses or the analysis of descriptive statistics (e.g., mean, variance, and distribution of the answers per respondent) allows identifying suspicious response patterns.

Inconsistency in answers may also need to be addressed before analyzing the data. Many surveys start with one or more screening questions. The purpose of a screening question is to ensure that only individuals who meet the prescribed criteria complete the survey. For example, a survey of mobile phone users may screen for individuals who own an Apple iPhone. But a question later in the survey is posed and the individual indicates he or she uses an Android device. This respondent would therefore need to be removed from the data set. Surveys often ask the same question with slight variations, especially when reflective indicators are used. If a respondent gives a very different answer to the same question asked in a slightly different way, this too raises a red flag and suggests the respondent was not reading the questions closely or simply was marking answers to complete and exit the survey as quickly as possible. Finally, researchers sometimes include specific questions to assess the attention of respondents. For example, in the middle of a series of questions, the researcher may instruct the respondent to check only a 1 on a 7-point scale for the next question. If any answer other than a 1 is given for the question, it is an indication the respondent is not closely reading the question.

Outliers

An **outlier** is an extreme response to a particular question, or extreme responses to all questions. Outliers must be interpreted in the context of the study, and this interpretation should be based on the type of information they provide. Outliers can result from data collection of entry errors (e.g., the researcher coded "77" instead of "7" on a 1 to 9 Likert scale). However, exceptionally high or low values can also be part of reality (e.g., an exceptionally high income). Finally, outliers can occur when combinations of variable values are particularly rare (e.g., spending 80% of annual income on holiday trips). The first step in dealing with outliers is to identify them. Standard statistical software packages offer a multitude of univariate, bivariate, or multivariate graphs and statistics, which allow identifying outliers. For example, when analyzing box plots, one may characterize responses as extreme outliers, which are three times the interquartile range below the first quartile or above the third quartile. Moreover, IBM SPSS Statistics has an option called Explore that develops box plots and stem-and-leaf plots to facilitate the identification of outliers by respondent number (Sarstedt & Mooi, 2019; Chapter 5.4).

Once the outliers are identified, the researcher must decide what to do. If there is an explanation for exceptionally high or low values, outliers are typically retained, because they represent an element of the population. However, their impact on the analysis results should be carefully evaluated. That is, one should run the analyses with and without the outliers to ensure that a very few (extreme) observations do not influence the results substantially. If the outliers are a result of data collection or entry errors, they are always deleted or corrected (e.g., the value of 55 on a 7-point scale). If there is no clear explanation for the exceptional values, outliers should be retained—see Sarstedt and Mooi (2019; Chapter 5.4) for more details about outliers.

Outliers can also represent a unique subgroup of the sample. There are two approaches to use in deciding if a unique subgroup exists. First, a subgroup can be identified based on prior knowledge, for example, based on observable characteristics such as gender, age, or income. Using this information, the researcher partitions the data set into two or more groups and runs a multigroup analysis to disclose significant differences in the model parameters. The second approach to identifying unique subgroups is the application of latent class techniques. Latent class techniques allow researchers to identify and treat unobserved heterogeneity, which cannot be attributed to a specific observable characteristic or a combination of characteristics. Several latent class techniques have recently been proposed that generalize finite mixture modeling, iteratively reweighted least squares, hill-climbing approaches, and genetic algorithms to PLS-SEM (Sarstedt, Ringle, & Hair, 2017b). In Chapter 8, we discuss several of these techniques in greater detail.

Data Distribution

PLS-SEM is a nonparametric statistical method. Different from CB-SEM, which draws on a maximum likelihood estimator that requires normally distributed data, PLS-SEM does not make any distributional assumptions (Hair, Ringle, & Sarstedt, 2011). Nevertheless, it is important to verify that the data are not too far from normal as extremely nonnormal data prove problematic in the assessment of the parameters' significances. Specifically, extremely nonnormal data inflate standard errors obtained from bootstrapping (see Chapter 5 for more details) and thus trigger type II errors (i.e., false negatives).

For instance, the Shapiro–Wilks test is designed to test normality by comparing the data to a normal distribution with the same mean and standard deviation as in the sample (Sarstedt & Mooi, 2019; Chapter 5). However, this test only indicates whether the null hypothesis of normally distributed data should be rejected or not. As the bootstrapping procedure performs fairly robustly when data are nonnormal, these tests provide only limited guidance when deciding whether the data are too far from being normally distributed. Instead, researchers should examine two measures of distributions—skewness and kurtosis.

Skewness assesses the extent to which a variable's distribution is symmetrical. If the distribution of responses for a variable stretches toward the right or left tail of the distribution, then the distribution is characterized as skewed. A negative skewness indicates a greater number of larger values, whereas a positive skewness indicates a greater number of smaller values. As a general guideline, a skewness value between –1 and +1 is considered excellent, but a value between –2 and +2 is generally considered acceptable. Values beyond –2 and +2 are considered indicative of substantial nonnormality. **Kurtosis** is a measure of whether the distribution is too peaked (a very narrow distribution with most of the responses in the center). A positive value for the kurtosis indicates a distribution more peaked than normal. In contrast, a negative kurtosis indicates a shape flatter than normal. Analogous to the skewness, the general guideline is that if the kurtosis is greater than +2, the distribution is too peaked. Likewise, a kurtosis of less than –2 indicates a distribution that is too flat. When both skewness and kurtosis are close to zero, the pattern of responses is considered a normal distribution (George & Mallery, 2019).

Serious effort, considerable amounts of time, and a high level of caution are required when collecting and analyzing the data that you need for carrying out multivariate techniques. Always remember the garbage in, garbage out rule. All your analyses are meaningless if your data are inappropriate. Exhibit 2.13 summarizes some key guidelines you should consider when examining your data and preparing them for PLS-SEM. For more detail on examining your data, see Chapter 2 of Hair, Black, Babin, and Anderson (2019).

EXHIBIT 2.13 ■ Guidelines for Examining Data Used With PLS-SEM

- Missing data must be identified. When missing data *per observation* (i.e., item non-response) and *per indicator* exceed 15%, they should be removed from the data set. Other missing data should be dealt with before running a PLS-SEM analysis. When less than 5% of values *per indicator* are missing, use mean replacement. Otherwise, use casewise deletion, but make sure that the deletion of observations does not occur systematically and that enough observations remain for the analysis. Generally, avoid using pairwise deletion. Also consider using more complex imputation procedures before importing the data into the PLS-SEM software.
- Suspicious and inconsistent response patterns typically justify removing a response from the data set.

(Continued)

EXHIBIT 2.13 ■ (Continued)

- Outliers should be identified before running PLS-SEM. Subgroups that are substantial in size should be identified based on prior knowledge or by statistical means (e.g., using a latent class analysis).
- Lack of normality in variable distributions can distort the results of multivariate analysis. This problem is much less severe with PLS-SEM, but researchers should still examine PLS-SEM results carefully when distributions deviate substantially from normal. Absolute skewness and kurtosis values of greater than 2 are indicative of nonnormal data.

CASE STUDY ILLUSTRATION—SPECIFYING THE PLS-SEM MODEL

The most effective way to learn how to use a statistical method is to apply it to a set of data. Throughout this book, we use a single example that enables you to do that. We start the example with a simple model, and in Chapter 5, we expand that same model to a much broader, more complex model. For our initial model, we hypothesize a path model to estimate the relationships between corporate reputation, customer satisfaction, and customer loyalty. The example will provide insights on (1) how to develop the structural model representing the underlying concepts/theory, (2) the setup of measurement models for the latent variables, and (3) the structure of the empirical data used. Then, our focus shifts to setting up the SmartPLS 3 software (Ringle, Wende, & Becker, 2015) for PLS-SEM.

Application of Stage 1: Structural Model Specification

To specify the structural model, we must begin with some fundamental explications about theoretical models. The corporate reputation model by Eberl (2010) is the basis of our theory. The goal of the model is to explain the effects of corporate reputation on customer satisfaction (*CUSA*) and, ultimately, customer loyalty (*CUSL*). Corporate reputation represents a company's overall evaluation by its stakeholders (Helm, Eggert, & Garnefeld, 2010). It is measured using two dimensions. One dimension, the company's competence (*COMP*), represents cognitive evaluations of the company. The second dimension captures affective judgments, which determine the company's likeability (*LIKE*). This two-dimensional approach to measure reputation was developed by Schwaiger (2004). It has been validated in different countries (e.g., Eberl, 2010; Zhang & Schwaiger, 2012) and applied in various research studies (e.g., Eberl & Schwaiger, 2005; Radomir & Moisescu, 2019; Radomir & Wilson, 2018;

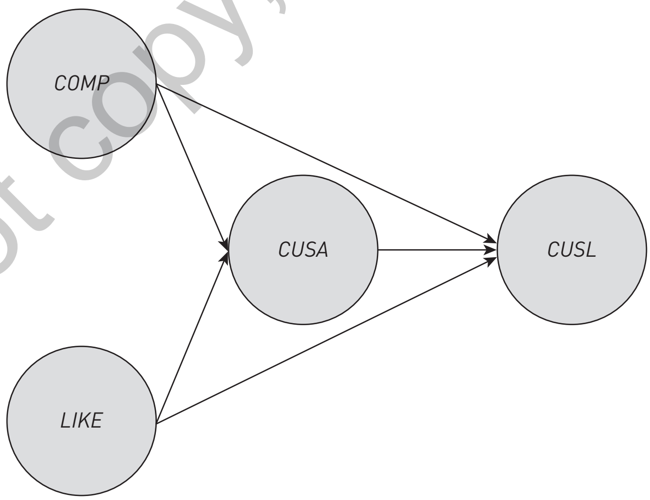
Raithel & Schwaiger, 2015; Raithel, Wilczynski, Schloderer, & Schwaiger, 2010; Sarstedt & Schloderer, 2010; Schloderer, Sarstedt, & Ringle, 2014; Schwaiger, Raithel, & Schloderer, 2009; Yun, Kim, & Cheong, 2020). Research also shows that the approach performs favorably (in terms of convergent validity and predictive validity) compared with alternative reputation measures (Sarstedt, Wilczynski, & Melewar, 2013).

Building on a definition of corporate reputation as an attitude-related construct, Schwaiger (2004) further identified four antecedent dimensions of reputation—quality, performance, attractiveness, and corporate social responsibility—measured by a total of 21 formative indicators. These driver constructs of corporate reputation are components of the more complex example we will use in the book and will be added in Chapter 5. Likewise, we do not consider more complex model setups such as mediation or moderation effects yet. These aspects will be covered in the case studies in Chapter 7.

In summary, the simple corporate reputation model has two main theoretical components: (1) the target constructs of interest—namely *CUSA* and *CUSL* (endogenous constructs)—and (2) the two corporate reputation dimensions *COMP* and *LIKE* (exogenous constructs), which represent key determinants of the target constructs. Exhibit 2.14 shows the constructs and their relationships, which represent the structural model for the PLS-SEM case study.

To propose a theory, researchers usually build on existing research knowledge. When PLS-SEM is applied, the structural model displays the theory with its key elements (i.e., constructs) and cause-effect relationships (i.e., paths). Researchers

EXHIBIT 2.14 ■ Example of a Theoretical Model (Simple Model)



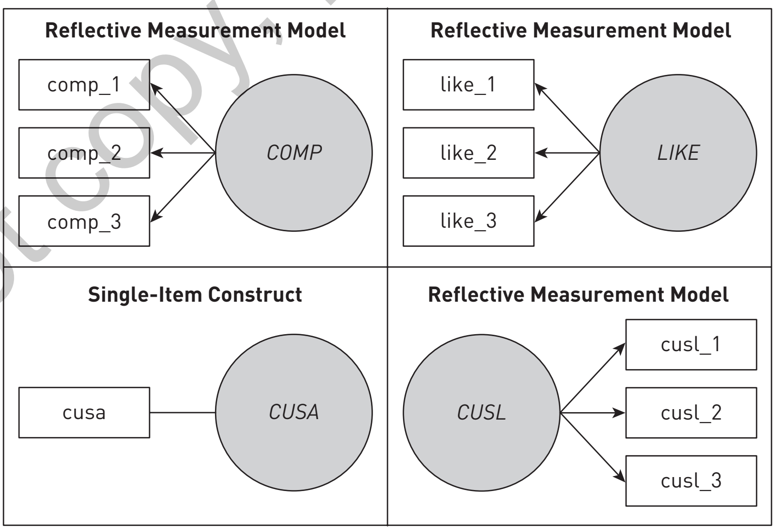
typically develop hypotheses for the constructs and their path relationships in the structural model. For example, consider Hypothesis 1 (H_1): Customer satisfaction has a positive effect on customer loyalty. PLS-SEM enables statistically testing the significance of the hypothesized relationship (Chapter 6). When conceptualizing the theoretical constructs and their hypothesized structural relationships for PLS-SEM, it is important to make sure the model has no circular relationships (i.e., causal loops). A circular relationship would occur if, for example, we reversed the relationship between *COMP* and *CUSL* as this would yield the causal loop *COMP* → *CUSA* → *CUSL* → *COMP*.

Application of Stage 2: Measurement Model Specification

Since the constructs are not directly observed, we need to specify a measurement model for each construct. The specification of the measurement models (i.e., multi-item vs. single-item measures and reflective vs. formative measures) draws on prior research studies by Schwaiger (2004) and Eberl (2010).

In our simple example of a PLS-SEM application, we have three constructs (*COMP*, *CUSL*, and *LIKE*) measured by multiple items (Exhibit 2.15). All three constructs have reflective measurement models as indicated by the arrows pointing from the construct to the indicators. For example, *COMP* is measured by means of the three reflective items *comp_1*, *comp_2*, and *comp_3*, which relate to

EXHIBIT 2.15 ■ Types of Measurement Models in the Simple Model



the following survey questions (Exhibit 2.16): "[The company] is a top competitor in its market," "As far as I know, [the company] is recognized worldwide," and "I believe that [the company] performs at a premium level." Respondents had to indicate the degree to which they (dis)agree with each of the statements on a 7-point scale from 1 = *fully disagree* to 7 = *fully agree*.

Different from *COMP*, *CUSL*, and *LIKE*, the customer satisfaction construct (*CUSA*) is operationalized by a single item (*cusa*) that is related to the following question in the survey: "If you consider your experiences with [company], how satisfied are you with [company]?" The single indicator is measured with a 7-point scale indicating the respondent's degree of satisfaction (1 = *very dissatisfied*; 7 = *very satisfied*). The single item has been used due to practical considerations in an effort to decrease the overall number of items in the questionnaire. As customer satisfaction items are usually highly homogeneous, the loss in predictive validity compared with a multi-item measure is not considered severe. As *cusa* is

EXHIBIT 2.16 ■ Indicators for Reflective Measurement Model Constructs

Competence (COMP)	
comp_1	[The company] is a top competitor in its market.
comp_2	As far as I know, [the company] is recognized worldwide.
comp_3	I believe that [the company] performs at a premium level.
Likeability (LIKE)	
like_1	[The company] is a company that I can better identify with than other companies.
like_2	[The company] is a company that I would regret more not having if it no longer existed than I would other companies.
like_3	I regard [the company] as a likeable company.
Customer Loyalty (CUSL)	
cusl_1	I would recommend [the company] to friends and relatives.
cusl_2	If I had to choose again, I would choose [the company] as my mobile phone services provider.
cusl_3	I will remain a customer of [the company] in the future.

Note: For data collection, the actual name of the company was inserted in the bracketed space that indicates company.

the only item measuring customer satisfaction, construct and item are equivalent (as indicated by the fact that the relationship between construct and single-item measure is always one in PLS-SEM). Therefore, the choice of the measurement perspective (i.e., reflective vs. formative) is of no concern and the relationship between construct and indicator is undirected.

Application of Stage 3: Data Collection and Examination

To estimate the PLS-SEM, data were collected using computer-assisted telephone interviews (Sarstedt & Mooi, 2019; Chapter 4) that asked about the respondents' perception of and their satisfaction with four major mobile network providers in Germany's mobile communications market. Respondents rated the questions on 7-point Likert scales, with higher scores denoting higher levels of agreement with a particular statement. In the case of *cusa*, higher scores denote higher levels of satisfaction. Satisfaction and loyalty were measured with respect to the respondents' own service providers. The data set used in this book is a subset of the original set and has a sample size of 344 observations. The data have been collected using a quota sampling approach (Sarstedt, Bengart, Shaltoni, & Lehmann, 2018) by a professional market research company in the German market. The resulting sample is representative of the German population.

Exhibit 2.17 shows the data matrix for the model. The 10 columns represent a subset of all variables (i.e., specific questions in the survey as described in the previous section) that have been surveyed, and the 344 rows (i.e., cases) contain the answers of every respondent to these questions. For example, the first row contains the answers of Respondent 1 while the last row contains the answers of Respondent 344. The columns show the answers to the survey questions. Data in the first nine columns are for the indicators associated with the three constructs, and the tenth column includes the data for the single indicator of *CUSA*. The data set contains further variables that relate to, for example, the driver constructs of *LIKE* and *COMP*. We will cover these aspects in Chapter 5.

EXHIBIT 2.17 ■ Data Matrix for the Indicator Variables

Case Number	Variable Name									
	comp_1	comp_2	comp_3	like_1	like_2	like_3	cusl_1	cusl_2	cusl_3	cusa	...
1	6	7	6	6	6	6	7	7	7	7	...
2	4	5	6	5	5	5	7	7	5	6	...
...	...	...	...	...	...	...	...	...	...	...	...
344	6	5	6	6	7	5	7	7	7	7	...

If you are using a data set in which a respondent did not answer a specific question, you need to insert a number that does not appear otherwise in the responses to indicate the missing values. Researchers commonly use –99 to indicate missing values, but you can use any other value that does not normally occur in the data set. In the following, we will also use –99 to indicate missing values. If, for example, the first data point of *comp_1* were a missing value, the –99 value would be inserted into the space as a missing value space holder instead of the value of 6 that you see in Exhibit 2.17. Missing value treatment procedures (e.g., mean replacement) could then be applied to these data (e.g., Hair, Black, Babin, & Anderson, 2019). Again, if the number of missing values in your data set per indicator is relatively small (i.e., less than 5% missing per indicator), we recommend mean value replacement instead of casewise deletion to treat the missing values when running PLS-SEM. Furthermore, we need to ascertain that the number of missing values per observation and per indicator does not exceed 15%. If this was the case, the corresponding observation should be eliminated from the data set.

The data example shown in Exhibit 2.17 (and in the book's example) has only very few missing values. More precisely, *cusa* has one missing value (0.29%), *cusl_1* and *cusl_3* have three missing values (0.87%), and *cusl_2* has four missing values (1.16%). Since the missing values per indicator are less than 5%, mean value replacement can be used. Furthermore, none of the observations and indicators has more than 15% missing values, so we can proceed analyzing all 344 respondents.

To run outlier diagnostics, we compute a series of box plots using IBM SPSS Statistics—see Chapter 5 in Sarstedt and Mooi (2019) for details on how to run these analyses in IBM SPSS Statistics. The results indicate some influential observations but no outliers. Moreover, nonnormality of data regarding skewness and kurtosis is not an issue. The kurtosis and skewness values of all the indicators are within the –2 and +2 range.

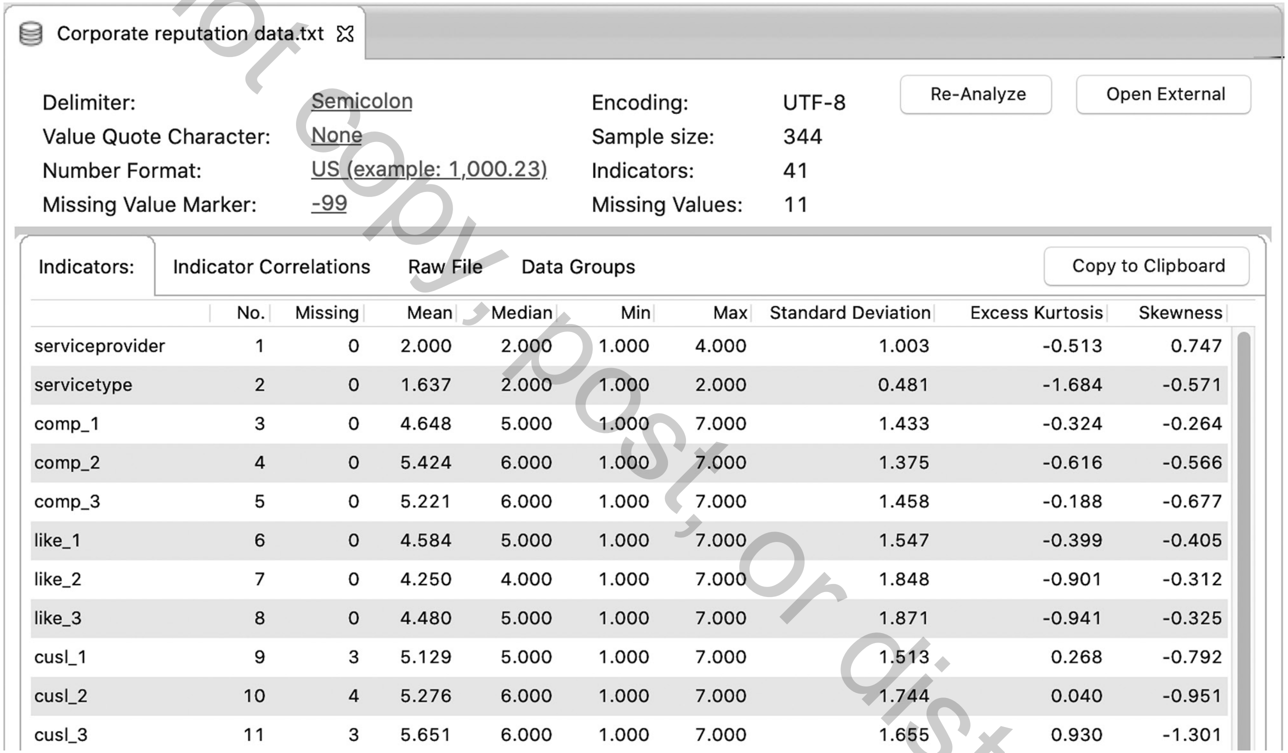
Path Model Creation Using The SmartPLS Software

The SmartPLS 3 software (Ringle, Wende, & Becker, 2015) is used to execute all the PLS-SEM analyses in this book. The discussion includes an overview of the software's functionalities. The student version of the software is available free of charge at https://www.smartpls.com. The student version offers practically all functionalities of the full version but is restricted to data sets with a maximum of 100 observations. However, as the data set used in this book has more than 100 observations (344 to be precise), you should use the professional version of SmartPLS, which is available as a 30-day trial version at https://www.smartpls.com. After the trial period, a license fee applies. Licenses are available for different periods of time (e.g., 1 month, 1 year, or 2 years) and can be purchased through the SmartPLS website. The SmartPLS website includes a download area for the software, including the old SmartPLS 2 (Ringle, Wende, & Will, 2005) software, and many additional resources such as short explanations of PLS-SEM and software-related topics, a list of recommended literature, answers to frequently asked questions, tutorial videos for getting started using the software, and the SmartPLS forum, which allows you to discuss PLS-SEM topics with other users. Sarstedt and Cheah (2019) provide a comprehensive software review.

SmartPLS has a graphical user interface that enables the user to estimate the PLS path model. Exhibit 2.20 at the end of this section shows the graphical interface for the SmartPLS software, with the simple model already drawn. In the following paragraphs, we describe how to set up this model using the SmartPLS software. Before you draw your model, you need to have data that serve as the basis for running the model. The data we will use with the reputation model can be downloaded either as comma-separated value (.csv) or text (.txt) data sets in the download section of this book's webpage at the following URL: https://www.pls-sem.net/. SmartPLS can use both data file formats (i.e., .csv or .txt). Follow the onscreen instructions to save one of these two files on your hard drive. Click on *Save Target As . . .* to save the data to a folder on your hard drive and then *Close*. Now run the SmartPLS software by clicking on the desktop icon that is available after the software installation on your computer device. Alternatively, go to the folder where you installed the SmartPLS software on your computer. Click on the file that runs SmartPLS and then on the *Run* tab to start the software.

To create a new project after running SmartPLS, click on *File* → *Create New Project*. First type a name for the project into the Name box (e.g., *PLS-SEM BOOK - Corporate Reputation Extended*). After clicking *OK*, the new project is created and appears in the *Project Explorer* window that is in the upper left below the menu bar. All previously created SmartPLS projects also appear in this window. Next, you need to assign a data set to the project, in our case, *Corporate reputation data.csv* (or whatever name you gave to the data you downloaded). To do so, click on the information button labeled *Double-click to import data!* below the project you just created, find and highlight your data folder, and click *Open*. It is important to note that if you use your own data set for a project using the SmartPLS software, the data must not include any string elements (e.g., respondents' comments to open-ended questions). For example, SmartPLS interprets single dots (such as those produced by IBM SPSS Statistics in case an observation has a system-missing value) as string elements. In our example, the data set does not include any string elements, so this is not an issue. In the screen that follows, you can adjust the name of the data set. In this example, we use the original name (i.e., *Corporate reputation data*) and proceed by clicking *OK*. SmartPLS will open a new tab (Exhibit 2.18), which provides information on the data set and its format (data view).

EXHIBIT 2.18 ■ Data View in SmartPLS



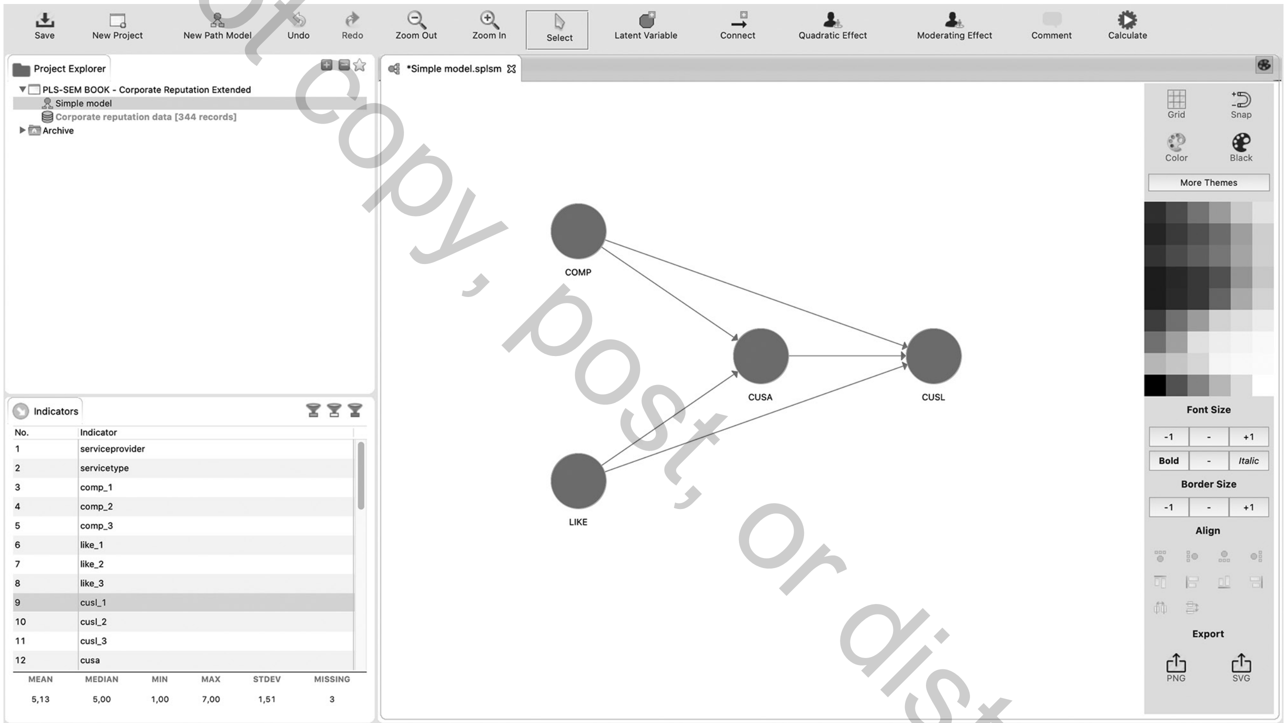
	No.	Missing	Mean	Median	Min	Max	Standard Deviation	Excess Kurtosis	Skewness
serviceprovider	1	0	2.000	2.000	1.000	4.000	1.003	-0.513	0.747
servicetype	2	0	1.637	2.000	1.000	2.000	0.481	-1.684	-0.571
comp_1	3	0	4.648	5.000	1.000	7.000	1.433	-0.324	-0.264
comp_2	4	0	5.424	6.000	1.000	7.000	1.375	-0.616	-0.566
comp_3	5	0	5.221	6.000	1.000	7.000	1.458	-0.188	-0.677
like_1	6	0	4.584	5.000	1.000	7.000	1.547	-0.399	-0.405
like_2	7	0	4.250	4.000	1.000	7.000	1.848	-0.901	-0.312
like_3	8	0	4.480	5.000	1.000	7.000	1.871	-0.941	-0.325
cusl_1	9	3	5.129	5.000	1.000	7.000	1.513	0.268	-0.792
cusl_2	10	4	5.276	6.000	1.000	7.000	1.744	0.040	-0.951
cusl_3	11	3	5.651	6.000	1.000	7.000	1.655	0.930	-1.301

At the bottom of the screen appears a list with all variables, their number of missing values and basic descriptive statistics (e.g., mean, median, minimum, and maximum values, standard deviation, excess kurtosis, and skewness). At the top right of the screen you can see the *Sample Size* as well as the number of indicators and missing values. At the top left of the screen, you can specify the *Delimiter* to determine the separation of the data values in your data set (i.e., comma, semicolon, tabulator, or space), the *Value Quote Character* (i.e., none, single quote, or double quote) in case the values use quotations (e.g., "7"), and the *Number Format* (i.e., United States with a dot as decimal separator or Europe with a comma as decimal separator). Furthermore, you can specify the coding of missing values. Click on *None* next to *Missing Value Marker*. In the screen that follows, you need to specify missing values. Enter *–99* in the field and click on *OK*. SmartPLS dynamically updates the descriptive statistics of the indicators that contain missing values and indicates the number of missing values next to *Missing Values* (Exhibit 2.18). You can specify only one specific value for all missing data in SmartPLS. Thus, you have to make sure that all missing values have the same coding (e.g., –99) in your original data set. That is, you need to code all missing values uniformly, regardless of their type (user-defined missing or system-missing) and the reason for being missing (e.g., respondent refused to answer, respondent did not know the answer, not applicable). The additional tabs in the data view show the *Indicator Correlations* and the *Raw File* with the imported data. At this point, you can close the data view. Note that you can always reopen the data view by double-clicking on the data set (i.e., *Corporate reputation data*) in the *Project Explorer*.

Each project can have one or more path models and one or more data sets (i.e., .csv or .txt files). When setting up a new project, SmartPLS will automatically add a model with the same name as the project. You can also rename the model by right-clicking on it. In the menu that opens, click on *Rename* and type in the new name for the model. To distinguish our introductory model from the later ones, rename it to *Simple Model* and click on *OK* (Exhibit 2.19).

Next, double-click on *Simple Model* in the *Project Explorer* window and SmartPLS will open the graphical *Modeling Window* on the right, where you can create a path model. We start with a new project (as opposed to working with a saved project), so the *Modeling Window* is empty and you can start creating the path model shown in Exhibit 2.19. By clicking on *Latent Variable* in the menu bar (Latent Variable), you can place one new construct into the *Modeling Window*. Each time you left-click in the *Modeling Window*, a new construct represented by a red circle will appear. Alternatively, go to the *Edit* menu and click Add *Latent Variable(s)*. Now a new construct will appear each time you left-click in the *Modeling Window*. To leave this mode, click on **Select** in the menu bar (Select).

EXHIBIT 2.19 ■ Initial Model



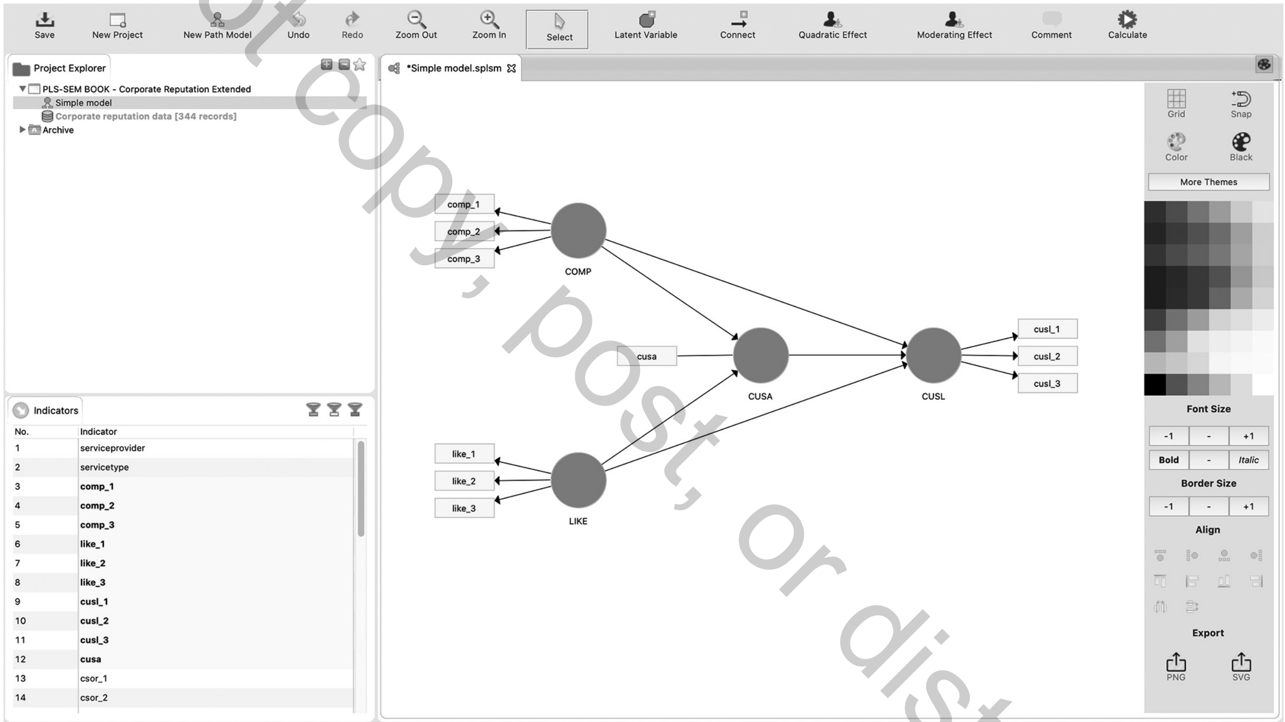
Once you have created all your constructs, you can left-click on any of the constructs to select, resize, or move it in the *Modeling Window*. To connect the latent variables with each other (i.e., to draw path arrows), left-click on *Connect* in the menu bar ( ). Next, left-click on an exogenous (independent) construct and move the cursor over the target endogenous (dependent) construct. Now left-click on the endogenous construct, and a path relationship (directional arrow) will be inserted between the two constructs. Repeat the same process and connect all the constructs based on your theory. Alternatively, go to the Edit menu and click *Add Connection(s)*.

The next step is to name the constructs. To do so, right-click on the construct to open a menu with different options and left-click on *Rename*. Type the name of your construct in the window of the *Rename* box (i.e., *COMP*) and then click *OK*. The name *COMP* will appear under the construct. Follow these steps to name all constructs. When you finish, it will look like Exhibit 2.19.

Next, you need to assign indicators to each of the constructs. On the left side of the screen, there is an *Indicators* window that shows all the indicators that are in your data set along with some basic descriptive statistics when you left-click on an indicator. Start with the *COMP* construct by dragging the first competence indicator *comp_1* from the *Indicators* window and dropping it on the construct (i.e., left-click the mouse and hold the button down, then move it until over a construct, then release). After assigning an indicator to a construct, it appears in the graphical *Modeling Window* as a yellow rectangle attached to the construct (as reflective). Assigning an indicator to a construct will also turn the color of the construct from red to blue. You can move the indicator around, but it will remain attached to the construct (unless you delete it). By right-clicking on the construct and choosing one of the options under *Align* (e.g., *Indicators Top*), you can align the indicator(s). You can also hide the indicators of a construct by selecting the corresponding option in the menu that appears when right-clicking on it. Moreover, you can access the align indicators option via the *Modeling Toolbox* on the right-hand side of the *Modeling Window*. Continue until you have assigned all the indicators to the constructs as shown in Exhibit 2.20. Make sure to save the model by going to *File* → *Save*.

Right-clicking on selected construct(s) in the graphical *Modeling Window* opens a menu with several options. Apart from renaming the constructs, you can for example invert the measurement model from reflective to formative measurement, and vice versa (*Switch between Formative/Reflective*), hide and show the indicators of the construct, and access more advanced options such as adding interaction and quadratic effects. Additionally, when double-clicking on construct, a different menu opens that allows you to select an indicator weighting scheme per construct (i.e., *Automatic*, *Mode A*, *Mode B*, *Sumscores*, and *Predefined*) and a value for the construct reliability between 0 and 1 for formatively measured constructs. To add a note to your *Modeling Window*, left-click on the *Comment* button in the menu bar.

EXHIBIT 2.20 ■ Simple Model With Names and Data Assigned



Clicking on the right mouse button while the cursor is placed over other elements also opens a menu with additional functions. As a further example, if you place the cursor in the *Project Explorer* window and right-click on the project name, you can create a new model (*Create New Path Model*), create a new project (*Create New Project*), or import a new data set (*Import Data File*). Moreover, you can select the *Copy*, *Paste*, and *Delete* options for projects and models that appear in the *Project Explorer* window. For example, the *Duplicate* option is useful when you would like to modify a PLS path model but want to keep your initial model setup. Using the *Copy* option, you can copy and paste a PLS path model from one project to the other. The *Import Data File* option allows you to add more data sets to an existing project (e.g., data from different years if available). You can also export a project by selecting the *Export Project* option. Using this option, SmartPLS will export the entire project, including all models and data sets you may have included in it, in a .zip folder. You can also directly import this "ready-to-use" project by going to *File → Import Project from Backup File*. You can use this option to import the project that includes the PLS-SEM example on corporate reputation. The file name is Corporate Reputation.zip. This project is ready to download on your computer system in the download section at https://www.pls-sem.net/. Download this file and save it on your computer system. Then, go to *File → Import Project from Backup File*. SmartPLS allows you to browse your computer and select the downloaded project *Corporate Reputation.zip* for import. After successful import, double-click on the model in this project, and the path model as shown in Exhibit 2.20 will appear in a new *Modeling Window*.

Summary

- **Understand the basic concepts of structural model specification, including mediation, moderation, and the use of control variables.** This chapter includes the first three stages in the application of PLS-SEM. Building on an established theory, prior research, and logic the model specification starts with the structural model (Stage 1). Each element of the theory represents a construct in the structural model. Moreover, assumptions for the causal relationships between the elements must be considered. The relationships between the constructs are directed (i.e., the arrows linking the constructs go from one construct to the next), but they can also be more complex and contain mediating or moderating relationships. In addition, researchers frequently specify control variables in order to control for the impact of other characteristics or phenomena that are not part of the primary theoretical model being tested. The goal of the PLS-SEM analysis is to empirically test the theory or a certain element thereof in the form of the structural model.

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- **Explain the differences between reflective and formative measurement models and specify the appropriate measurement model.** Stage 2 focuses on selecting a measurement model for each construct in the structural model to obtain reliable and valid measurements. Generally, there are two types of measurement models: reflective and formative. The reflective mode has arrows (relationships) pointing from the construct to the indicators in the measurement model. If the construct changes, it leads to a simultaneous change of all items in the measurement model. Thus, all indicators are highly correlated. In contrast, in formative measurement models, arrows point from the indicators in the measurement model to the constructs. Hence, all indicators together form the construct, and all major elements of the domain must be represented by the selected formative indicators. Since formative indicators represent independent sources of the construct's content, they do not necessarily need to be correlated (in fact, they shouldn't be highly correlated).

- **Comprehend that the selection of the mode of measurement model and the indicators must be based on theoretical reasoning before data collection.** A reflective specification would use different indicators than a formative specification of the same construct. Researchers typically use reflective constructs as target constructs of the PLS path model, while formative constructs may be particularly valuable as explanatory sources (independent variables) or drivers of these target constructs. During the data analysis phase, the measurement mode of the constructs can be empirically tested by using confirmatory tetrad analysis.

- **Explain the difference between multi-item and single-item measures and assess when to use each measurement type.** Rather than using multiple items to measure a construct, researchers sometimes choose to use a single item. Single items have practical advantages such as ease of application, brevity, and lower costs associated with their use. However, single-item measures do not offer more for less. From a psychometric perspective, single-item measures are less reliable and lag behind in terms of predictive validity. The latter aspect is particularly problematic in the context of PLS-SEM in light of the method's causal-predictive character. Furthermore, identifying an appropriate single item from a set of candidate items, regardless of whether this selection is based on statistical measures or expert judgment, proves very difficult. For these reasons, the use of single items should generally be avoided. The above issues are important considerations when measuring unobservable phenomena, such as perceptions or attitudes. But single-item measures are clearly appropriate when used to measure observable characteristics such as gender, sales, profits, and so on.

- **Understand the nature of higher-order constructs.** Higher-order constructs, also referred to as hierarchical component models, are used to specify a single construct on a more abstract dimension and more concrete subdimensions at the same time. Higher-order constructs have become increasingly popular in research since they offer a means of establishing more parsimonious path models. Researchers often specify and estimate higher-order constructs with two layers of abstraction, also referred to as second-order constructs.
- **Describe the data collection and examination considerations necessary to apply PLS-SEM.** Stage 3 underlines the need to examine your data after they have been collected to ensure that the results from the methods application are valid and reliable. The primary issues that need to be examined include missing data, suspicious response patterns (straight lining or inconsistent answers), and outliers. Distributional assumptions are of less concern because of PLS-SEM's nonparametric nature. However, as highly skewed data can cause issues in the estimation of significance levels, researchers should ensure that the data are not too far from normal. As a general rule of thumb, always remember the garbage in, garbage out rule. All your analyses are meaningless if your data are inappropriate.
- **Learn how to develop a PLS path model using the SmartPLS software.** The first three stages of conducting a PLS-SEM analysis are explained by conducting a practical exercise. We discuss how to draw a PLS path model focusing on corporate reputation and its relationship with customer satisfaction and loyalty. We also explain several options that are available in the SmartPLS software. The outcome of the exercise is a PLS path model drawn using the SmartPLS software that is ready to be estimated.

Review Questions

1. What is a structural model?
2. What is a reflective measurement model?
3. What is a formative measurement model?
4. What is a single-item measure?
5. When do you consider data to be "too nonnormal" for a PLS-SEM analysis?

Critical Thinking Questions

1. How can you decide whether to specify a construct reflectively or formatively?
2. Which research situations favor the use of reflective and formative measures?
3. Discuss the pros and cons of single-item measures.
4. Create your own example of a PLS path model (including the structural model with latent variables and the measurement models).
5. Why is it important to carefully analyze your data prior to analysis? What particular problems do you encounter when the data set has relatively large amounts of missing data per indicator (e.g., more than 5% of the data are missing per indicator)?

Key Terms

Alternating extreme pole responses 64
Artifacts 52
Casewise deletion 62
Causal indicators 52
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Composite indicators 52
Confirmatory tetrad analysis in PLS-SEM (CTA-PLS) 56
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Suggested Readings

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