5

ASSESSING PLS-SEM RESULTS PART II

Evaluation of the Formative Measurement Models

CASE STUDY ILLUSTRATION—EVALUATION OF FORMATIVE MEASUREMENT MODELS

Extending the Simple Path Model

The simple path model introduced in Chapter 2 describes the relationships between the two dimensions of corporate reputation (i.e., competence and likeability) as well as the two outcome variables (i.e., customer satisfaction and loyalty). While the simple model is useful to explain how corporate reputation affects customer satisfaction and customer loyalty, it does not indicate how companies can manage (i.e., improve) their corporate reputation effectively.

Schwaiger (2004) identified four driver constructs of corporate reputation that companies can steer by means of corporate-level marketing activities. Specifically, the driver constructs of corporate reputation are (1) the quality of a company's products and services as well as its quality of customer orientation (*QUAL*), (2) its economic and managerial performance (*PERF*), (3) the company's corporate social responsibility (*CSOR*), and (4) its attractiveness (*ATTR*). All four driver constructs are related to the competence and likeability dimensions of corporate reputation. Exhibit A5.1 shows the constructs and their relationships, which represent the extended structural model for our PLS-SEM example in the remaining chapters of the text. To summarize, the

extended corporate reputation model has three main theoretical components: (1) the target constructs of interest (namely, *CUSA* and *CUSL*); (2) the two corporate reputation dimensions, *COMP* and *LIKE,* that represent key determinants of the target constructs; and (3) the four exogenous driver constructs (i.e., *ATTR, CSOR, PERF,* and *QUAL*) of the two corporate reputation dimensions.

The endogenous latent variables on the right-hand side in Exhibit A5.1 include a single-item construct (i.e., *CUSA*) and three reflective constructs (i.e., *COMP, CUSL,* and *LIKE*). In contrast, the four new driver constructs (i.e., exogenous latent variables) on the left-hand side of the exhibit (i.e., *ATTR, CSOR, PERF,* and *QUAL)* have formative measurement models in accordance with their role in the reputation model (Schwaiger, 2004). Specifically, the four new constructs are measured by a total of 21 formative indicators that have been derived from literature, qualitative studies, and quantitative pretests (for more details, see Schwaiger, 2004). Exhibit A5.2 shows a complete list of the formative indicators and the corresponding survey questions.

Again, we use a data set with 344 observations for our empirical PLS-SEM analyses. Unlike in the simple model we used in prior chapters, we now also have to consider the formative measurement models when deciding on the minimum sample size required to estimate the model. The maximum number of arrowheads pointing at a particular construct occurs in the measurement model of *QUAL.* All other formatively measured constructs have fewer indicators. Similarly, there are fewer arrows pointing at each of the endogenous constructs in the structural model. Therefore, when building on the 10 times rule of thumb, we would need 8·10 = 80 observations. Alternatively, following Cohen's (1992) recommendations for multiple ordinary least

Exhibit A5.1 ■ The Theoretical Model of Corporate Reputation
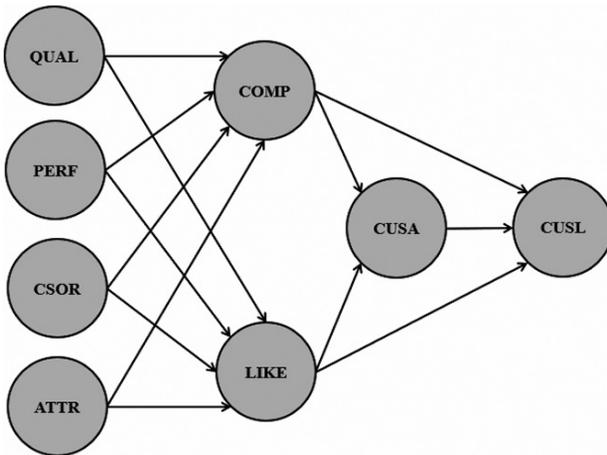
Exhibit A5.2 ■ Indicators of the Formative Measurement Models	
Quality (*QUAL*)	
qual_1	The products/services offered by [the company] are of high quality.
qual_2	[The company] is an innovator, rather than an imitator with respect to [industry].
qual_3	[The company]'s products/services offer good value for money.
qual_4	The services [the company] offered are good.
qual_5	Customer concerns are held in high regard at [the company].
qual_6	[The company] is a reliable partner for customers.
qual_7	[The company] is a trustworthy company.
qual_8	I have a lot of respect for [the company].
Performance (*PERF*)	
perf_1	[The company] is a very well-managed company.
perf_2	[The company] is an economically stable company.
perf_3	The business risk for [the company] is modest compared to its competitors.
perf_4	[The company] has growth potential.
perf_5	[The company] has a clear vision about the future of the company.
Corporate Social Responsibility (*CSOR*)	
csor_1	[The company] behaves in a socially conscious way.
csor_2	[The company] is forthright in giving information to the public.
csor_3	[The company] has a fair attitude toward competitors.
csor_4	[The company] is concerned about the preservation of the environment.
csor_5	[The company] is not only concerned about profits.
Attractiveness (*ATTR*)	
attr_1	[The company] is successful in attracting high-quality employees.
attr_2	I could see myself working at [the company].
attr_3	I like the physical appearance of [the company] (company, buildings, shops, etc.).

squares regression analysis or running a power analysis using the G*Power program (Faul, Erdfelder, Buchner, & Lang, 2009), one would need only 54 observations to detect R^2 values of around 0.25, assuming a significance level of 5% and a statistical power of 80% (Chapter 1). When considering the more conservative approach suggested by Kock and Hadaya (2018), we obtain a higher minimum sample size. For example, when assuming a minimum path coefficient of 0.15 at a 5% probability of error level, the required sample size is about 275 observations (see Exhibit 1.7 in Chapter 1).

The SmartPLS project and data files for the extended corporate reputation model can be downloaded at https://www.pls-sem.net (i.e., *Corporate Reputation.zip*). Save the *Corporate Reputation.zip* file on your hard drive, run the SmartPLS software and click on *Files → Import project from backup file* in the menu. In the box that appears on the screen, locate and open the *Corporate Reputation.zip* file that you just downloaded. A new project appears with the name Corporate Reputation in the SmartPLS *Workspace window* on the left-hand side. This project contains several models (.splsm files) labeled *Simple model*, *Extended model*, *Redundancy analysis ATTR*, *Redundancy analysis CSOR*, and so forth, plus the data set *Corporate reputation data.csv.* Note that you do not see the file extensions such as .splsm and.csv in the SmartPLS Project *Workspace window.* Alternately, you can simply run SmartPLS 4. In the main screen of the *Workspace* view, under *Sample projects*, you see the *Corporate reputation—PLS-SEM book (primer)* example. After clicking on the link with the label *Install* next to this sample project, the *Example—Corporate reputation (primer)* project will appear in the *Workspace*. Next, double-click on *Extended model* and the extended PLS path model for the corporate reputation example opens as displayed in Exhibit A5.3.

If you want to practice using the SmartPLS software, you can create the extended model by yourself. For this purpose, right-click on *Simple model* that you created in the previous steps and select the option *Copy resource* (Exhibit A5.4). Next, right-click on the Corporate Reputation project file and select *Paste resource* (Exhibit A5.5). A menu opens and gives you the option to select a name for the copy of the existing project; for example, type in the name *Extended model* or something similar. By clicking on *Create***,** SmartPLS will copy the simple model under a new name within the *Corporate Reputation* project. Alternatively, you can use the *Duplicate* option. While copy and paste uses the model when the SmartPLS session was started or from the last time it was saved, the duplicate option creates a copy of the model with all its changes as it is shown in the modeling window. In this case, since we did not change the simple model, both options will lead to the same results.

You can now start extending the simple PLS path model on corporate reputation. Double-click on *Extended model* in the *Corporate Reputation* project and the existing PLS path model elements will open it in the *Modeling window.* Select all existing PLS path model elements and move them further to the right-hand side. Note that if your simple model filled the screen, you may

Exhibit A5.3 ■ Extended Model in SmartPLS

Exhibit A5.4 ■ Options in the SmartPLS Workspace window
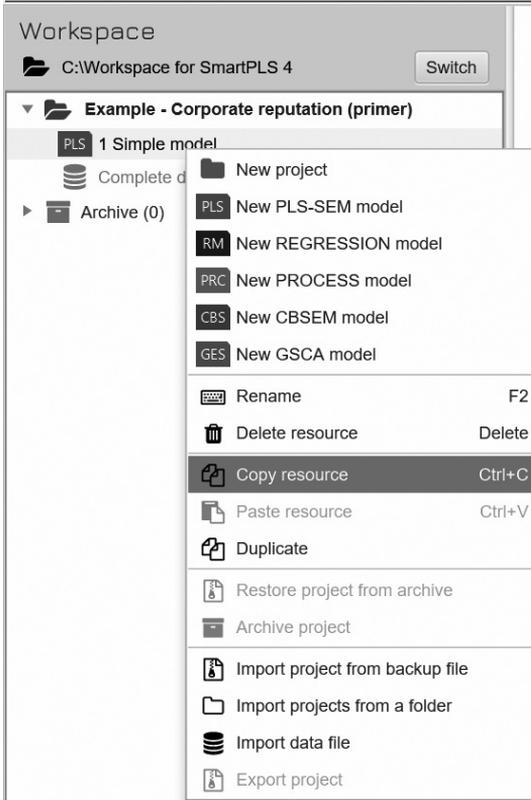
wish to reduce the model size by clicking on the *Zoom* button at the bottom of the *Tools* window. Next, go to the toolbar and click on *Latent variable,* and place four additional constructs into the *Modeling* window (*ATTR, CSOR, PERF,* and *QUAL*). Refer to Exhibit A5.3 to see where to place the new constructs.

Next draw the path relationships between the constructs. Go to the toolbar, click on the *Connect* button, and connect the new constructs with the existing ones as shown in Exhibit A5.3. To draw path relationships, you need to first click on the starting constructs and then click on the target construct.

Finally, drag and drop the corresponding indicators from the *Indicators window* to each of the constructs. Initially, the indicators will be associated with the constructs as reflective indicators. To change the measurement model setup to formative, right-click on the construct, and a dialog box opens with several options (Exhibit A5.6). The *Invert measurement model* option al-

Exhibit A5.5 ■ Paste resource option in the SmartPLS Workspace window
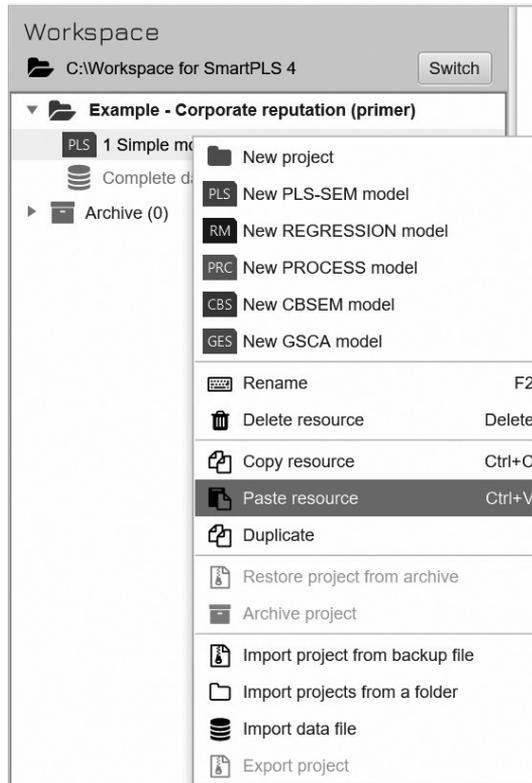
lows you to switch the indicators from reflective to formative. The final model in your case should look similar to the one shown in Exhibit A5.3. At this point, be sure to save your newly drawn extended model.

Once the model is set up, we click on *Calculate → PLS-SEM algorithm* and run PLS-SEM using the default options presented in Chapter 3 (e.g., use the path weighting scheme). Just like the indicator data that we used in the previous chapters, the *Corporate reputation data.csv* data set has almost no missing values. Only the indicators *cusl_1* (three missing values; 0.87% of all responses on this indicator), *cusl_2* (four missing values; 1.16% of all responses on this indicator), *cusl_3* (three missing values; 0.87% of all responses on this indicator), and *cusa* (one missing value; 0.29% of all responses on this indicator) have missing values. Since the number of missing values is relatively small (i.e., less than 5% missing values per indicator; Chapter 2), we use mean value replacement instead of casewise or pairwise

Exhibit A5.6 ■   Options in the SmartPLS Modeling Window
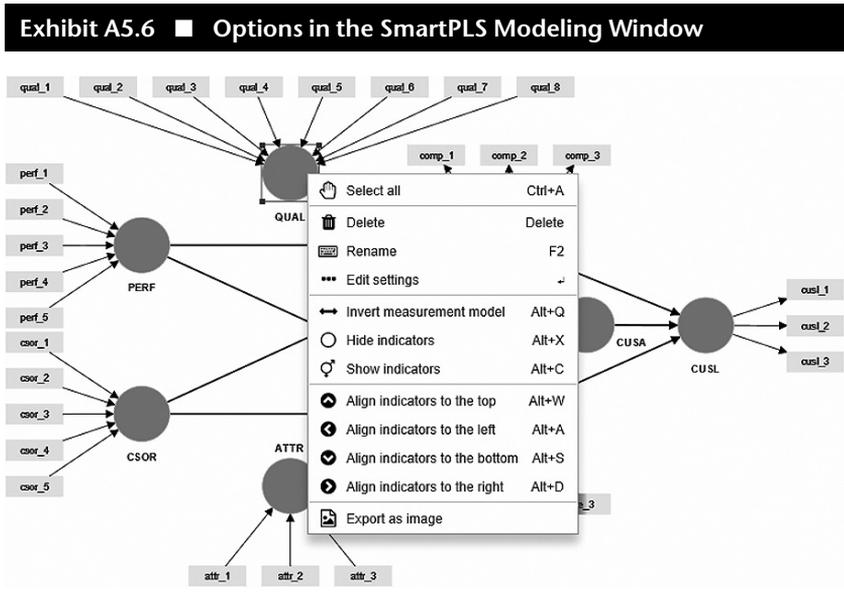
deletion to treat the missing values when running the PLS-SEM algorithm. Then, tick the box next to *Open report* and click on *Start calculation*.

When the PLS-SEM algorithm stops running, check whether the algorithm converged (Chapter 3). The PLS-SEM algorithm will stop when the stop criterion of 1.0E-7 (i.e., 0.0000001) has been reached (or the maximum number of 3,000 iterations). Go to *Algorithm → Stop criterion changes* in the results report to determine how the algorithm stopped. If the algorithm stopped based on the stop criterion, continue with the measurement model evaluation. If the algorithm stopped based on the number of iterations (which is, however, practically never the case; see Henseler, 2010), the calculation results cannot be reliably interpreted and the model setup or data need to be reconsidered. In the present example, the algorithm converged after eight iterations, so we can proceed with the analysis.

The results presentation in the *Modeling* window gives you a first overview of the outcomes. As shown in Exhibit A5.7, you see the standardized outer weights for the formative measurement models (e.g., *QUAL*), standardized outer loadings for the reflective measurement models (e.g., *CUSL*), and a 1.000 for the relationship between the *CUSA* construct and its single-item measure. In the latter case, the outer relationship is always 1 as construct and indicator values are equivalent—as indicated by the undirected relation between them. The standardized path relationships between the constructs in the structural model are also shown, as well as the R^2 values for the endogenous latent variables (i.e., the values in the circles). Note that the exogenous

Exhibit A5.7 ■ PLS-SEM Results
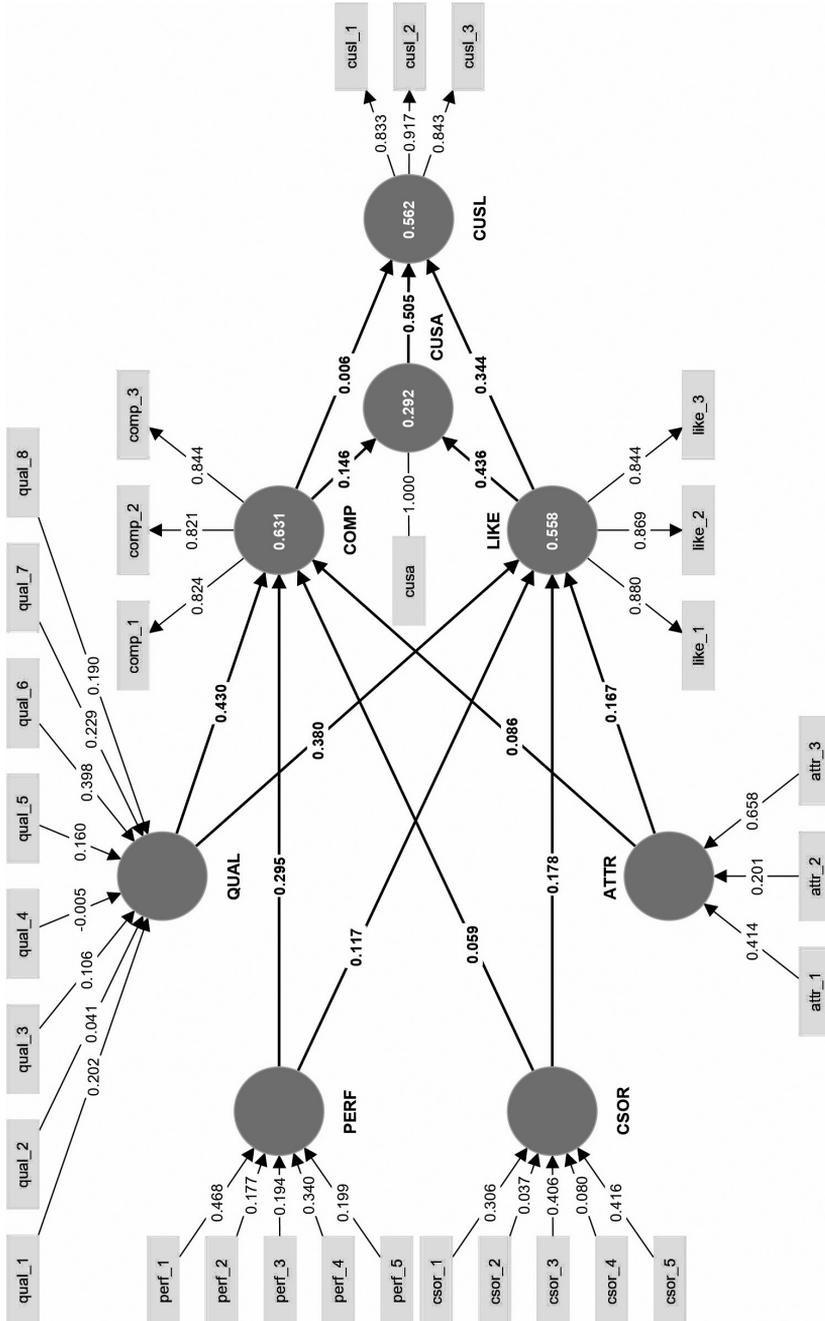
constructs *ATTR, CSOR, PERF,* and *QUAL,* by definition, have no R^2 value. The boxes above the *Graphical output* enables you to browse different parameter estimates for the constructs, as well as the outer and the inner models (see Chapter 3).

Reflective Measurement Model Evaluation

An important characteristic of PLS-SEM is that the model estimates always depend on the model under consideration. For instance, eliminating or adding certain indicators or constructs will also have an effect on the model estimates in different parts of the model. Since we extended the initial model by adding four constructs, we need to reassess the reflective measurement models according to the criteria presented in Chapter 4. However, we present the assessment in a much more concise way, which gives the reader some guidance on how to write up his or her own report in a straight-to-the-point manner—see, for example, the assessment of PLS-SEM results in applications such as Ahrholdt et al. (2019), and Svensson et al. (2018).

To examine the results, go to the SmartPLS 4 results report. If this report did not open automatically after running the *PLS-SEM algorithm*, go to the *Modeling window* and click on *Open report* next to the combo box under *Report*. First check for the measures' convergent validity and internal consistency reliability (i.e., Cronbach's alpha, reliability ρ_A, and composite reliability ρ_C) under *Quality criteria → Construct reliability and validity.* The results reveal that all reflectively measured constructs have AVE values of 0.688 (*COMP*) or higher, which is considerably above the critical value of 0.5 (Chapter 4). In addition, all Cronbach's alpha and composite reliability (ρ_A and ρ_C) values are well above the critical threshold of 0.70.

Looking at the indicator loadings (*Final results → Outer loadings* in the results report) reveals that all indicators of the reflective constructs *COMP, LIKE* and *CUSL* have loadings of 0.821 and higher, as shown in Exhibit A5.8. It is important to note that PLS software applications such as SmartPLS always provide outer loadings and outer weights for all constructs in the PLS path model, regardless of whether they are measured reflectively or formatively. Thus, the report shown in Exhibit A5.8 displays the outer loadings for both the reflective and formative constructs. For the reflective measurement model evaluation, however, the assessment focuses only on the outer loadings of the reflective constructs (i.e., *COMP, LIKE,* and *CUSL*).

In the next step, we examine the measures' discriminant validity using the HTMT criterion. To do so, go to *Quality criteria → Discriminant validity → Heterotrait-monotrait ratio (HTMT)*. Note, however, that the HTMT results of the extended model do not change compared with those produced in the simple model. The reason is that the HTMT statistic is purely based on correlations among items of the reflectively measured constructs. Adding formative constructs has no bearing on the computation of heterotrait-heterometh-

Exhibit A5.8 ■ PLS-SEM Results for Outer Loadings

	ATTR	COMP	CSOR	CUSA	CUSL	LIKE	PERF	QUAL
attr_1	0.754							
attr_2	0.506							
attr_3	0.891							
comp_1		0.824						
comp_2		0.821						
comp_3		0.844						
csor_1			0.771					
csor_2			0.571					
csor_3			0.838					
csor_4			0.617					
csor_5			0.848					
cusa				1.000				
cusl_1					0.833			
cusl_2					0.917			
cusl_3					0.843			
like_1						0.880		
like_2						0.869		
like_3						0.844		
perf_1							0.846	
perf_2							0.690	
perf_3							0.573	
perf_4							0.717	
perf_5							0.638	
qual_1								0.741
qual_2								0.570
qual_3								0.749
qual_4								0.664
qual_5								0.787
qual_6								0.856
qual_7								0.722
qual_8								0.627

od and monotrait-heteromethod correlations. The results therefore parallel those presented in Chapter 4, which clearly showed that all reflectively measured constructs exhibit discriminant validity. Recall that an HTMT value significantly lower than 0.85—or lower than 0.90 when the constructs in the path model are conceptually not too different (e.g., the two reputation dimensions *COMP* and *LIKE* as well as *CUSA* and *CUSL* in our example)—supports discriminant validity. Thus, all constructs in the extended model exhibit discriminant validity based on the HTMT method.
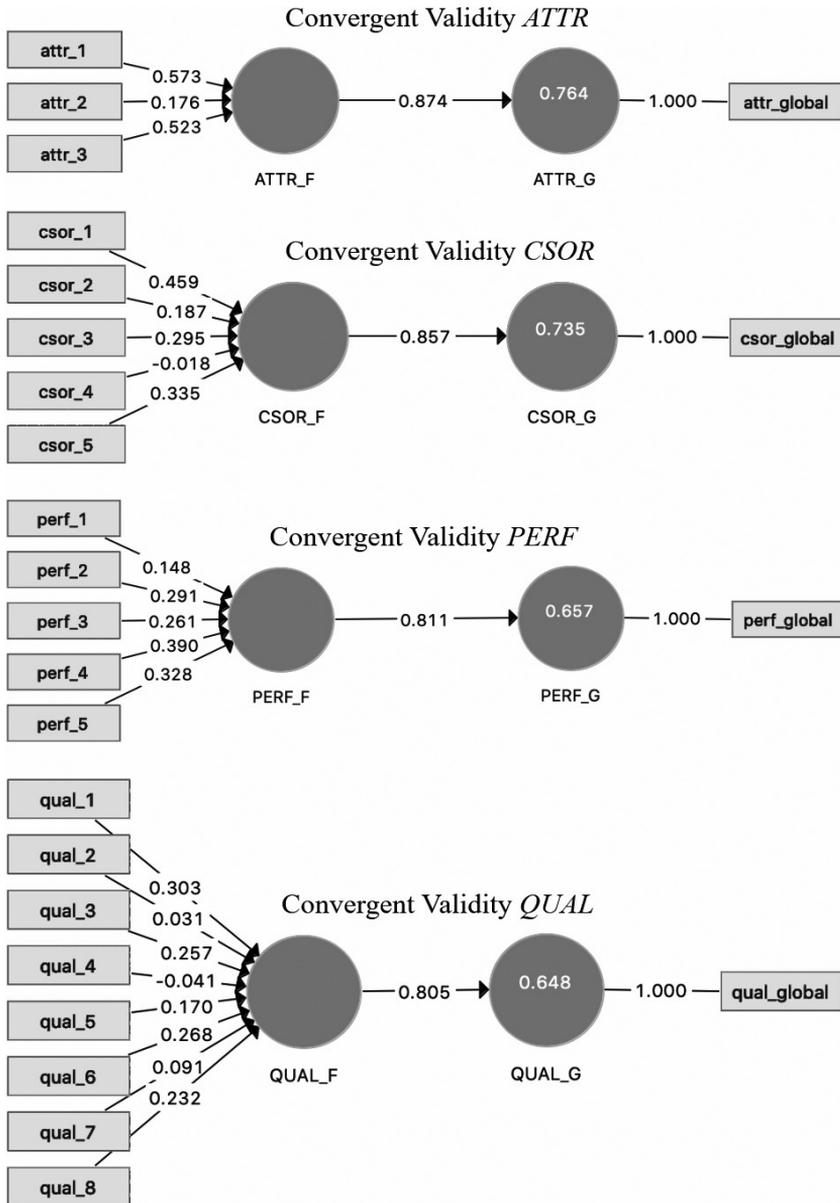
Formative Measurement Model Evaluation

To evaluate the corporate reputation model's formative measures, we follow the formative measurement models assessment procedure (Exhibit 5.1). First, we need to examine whether the formative constructs exhibit convergent validity. To do so, we carry out separate redundancy analyses for each construct. The original questionnaire contained global single-item measures with generic assessments of the four concepts—*attractiveness, corporate social responsibility, performance,* and *quality*—that we can use as measures of the dependent construct in the redundancy analyses. Note that when you are designing your own research study that includes formatively measured constructs, you need to include this type of global measure in the survey to be able to conduct this type of test for your formative constructs. If you plan to include a formatively measured constructs in repeated studies, you should follow the guidelines for generating and validating a global single item outlined in Exhibit 5.3.

To assess convergent validity, we need to create the new models, as shown in Exhibit A5.9. Each model is included in the SmartPLS project file *Corporate Reputation* that you can download and import into the SmartPLS software. Alternatively, you can create these four models for the convergent validity assessment in the *Corporate Reputation* project. To do so, select *Corporate Reputation* in the *Workspace* window (click with the left mouse button) and then click the right mouse button. A box with several options appears (Exhibit A5.4). Select the option *New PLS-SEM model*. Next, you can select a name for the new model (e.g., *Redundancy analysis ATTR*). After pressing on the *Save* button, the new model (e.g., *Redundancy analysis ATTR*) appears in the *Corporate Reputation* project, and an empty modeling window shows up. Now, we follow the steps explained in the earlier chapters to create one of the models displayed in Exhibit A5.9 (e.g., the first one, *Redundancy analysis ATTR*).

The first box in Exhibit A5.9 shows the results for the redundancy analysis for the *ATTR* construct. The original formative construct is labeled with *ATTR_F,* whereas the global assessment of the company's attractiveness using a single-item construct is labeled with *ATTR_G.* As can be seen, this analysis

Exhibit A5.9 ■ Redundancy Analysis Assessment of Formative Measurement Models

Convergent Validity *ATTR*

Convergent Validity *CSOR*

Convergent Validity *PERF*

Convergent Validity *QUAL*

yields a path coefficient of 0.874, which is above the recommended threshold of 0.70, thus providing support for the formative construct's convergent validity. The redundancy analyses of *CSOR, PERF,* and *QUAL* yield estimates of 0.857, 0.811, and 0.805, respectively. Thus, all formatively measured constructs exhibit convergent validity.

In the next step, we check the formative measurement models for collinearity of indicators by looking at the formative indicators' VIF values. To do so, go to *Quality criteria → Collinearity statistics (VIF) → Outer model* in the results report. Note that SmartPLS also provides VIF values for reflective indicators. However, since we would expect high correlations among reflective indicators, we do not interpret these results but focus on the formative indicators' VIF values.

According to the results in Exhibit A5.10, *qual_3* has the highest VIF value (2.269). Hence, VIF values are uniformly below the threshold value of 5. We conclude, therefore, that collinearity does not reach critical levels in any of the formative constructs and is not an issue for the estimation of the PLS path model in the extended example on corporate reputation.

Next, we need to analyze the outer weights for their significance and relevance. We first consider the significance of the outer weights by means of bootstrapping. To run the bootstrapping procedure, go to *Calculate → Bootstrapping* in the SmartPLS menu or left-click on the wheel symbol in the tool bar labeled Calculate and select *Bootstrapping*. Then, the menu opens as displayed in Exhibit A5.11.

We retain all previous settings for the PLS-SEM algorithm (*PLS setup* tab) and the missing value treatment (*Data* tab) as in the initial model estimation. Instead, we focus on the *BT setup* tab where we can make the additional selections required to run the bootstrapping procedure (shown in Exhibit A5.11). In terms of bootstrap samples, we recommend using *10,000* bootstrap samples. Since using such a great number of samples requires much computational time, you may choose a smaller number of samples (e.g., 5,000) for the initial model estimation. For the final results preparation, however, you should use the suggested number of 10,000 bootstrap samples—as we do in this case study example. The selection *Do parallel processing* allows you to use all processors of your computer device. We recommend using this option since it makes bootstrapping much faster. The choice between *Most important (faster)* and *Complete (slower)* returns a reduced (basic) or a complete basic results report. The faster basic option returns a limited number of bootstrapping results, which include the measurement and structural model relationships. The complete option includes many additional results (e.g., Cronbach's alpha, HTMT, R^2) but needs considerably more time because of the many different outcomes. Hence, for the initial model estimation, you may use *Most important (faster)*, but we select *Complete (slower)* since we like to assess the HTMT outcomes.

Exhibit A5.10 ■ VIF Values

	VIF
attr_1	1.275
attr_2	1.129
attr_3	1.264
comp_1	1.397
comp_2	1.787
comp_3	1.888
csor_1	1.560
csor_2	1.487
csor_3	1.735
csor_4	1.556
csor_5	1.712
cusa	1.000
cusl_1	1.802
cusl_2	2.564
cusl_3	1.933
like_1	1.945
like_2	2.000
like_3	1.811
perf_1	1.560
perf_2	1.506
perf_3	1.229
perf_4	1.316
perf_5	1.331
qual_1	1.806
qual_2	1.632
qual_3	2.269
qual_4	1.957
qual_5	2.201
qual_6	2.008
qual_7	1.623
qual_8	1.362

Exhibit A5.11   ■   Bootstrapping Options in SmartPLS

Next you need to select an approach to compute the bootstrap confidence intervals. Following our previous recommendations, we use the *Percentile bootstrap* option, select the *0.05* significance level, and follow general convention by using *two-tailed* testing. Finally, make sure to select *Fixed seed* to allow for the reproducibility of your results. Before initiating the analysis by clicking on *Start calculation*, make sure to tick the box next to *Open report*.

SmartPLS opens the results report with the main results shown in the *Graphical output*. As we are primarily interested in the significance of the weights, we only consider the measurement models for now. Using the combo box under *Constructs* in the *Modeling* window, you can choose whether SmartPLS should display *t* values or *p* values in the, individually or jointly with the path coefficients.

Exhibit A5.12 shows *t* values for the measurement and structural model relationships that the bootstrapping procedure produces. Provided that you have selected the fixed seed option, you will have the same results as those

documented here. However, if you chose random seed, your results will differ and will change again when rerunning the bootstrapping routine. This is because bootstrapping builds on randomly drawn samples, and each time you run the bootstrapping routine, different samples will be drawn. The differences become very small, however, if the number of bootstrapping samples is sufficiently large (e.g., 10,000). In terms of the measurement models, we can compare the *t* values shown in Exhibit A5.12 with the critical values from the standard normal distribution to decide whether the coefficients are significantly different from zero. For example, the critical values for significance levels of 1% (α = 0.01) and 5% (α = 0.05) probability of error are 2.57 and 1.96 (two-tailed), respectively.

Alternatively, you can choose to display *p* values, as shown in Exhibit A5.13, in the combo box under *Inner model* on the top of the *Modeling* window. These correspond to the *t* values; for example, a *t* value of 1.96 translates into a *p* value of 0.05. The *p* values in the formative measurement models displayed in Exhibit A5.13 must be lower than 0.05 to establish significant outer weights at a significance level of 5% (i.e., α = 0.05). Finally, you can also let SmartPLS display *t* or *p* values in conjunction with the path coefficients.

By going to the bootstrapping results report, we get a more detailed overview of the results. The table under *Final results → Outer weights* provides an overview of results, including standard errors, bootstrap mean values, *t* values, and *p* values (Exhibit A5.14). The original estimate of an outer weight (shown in the second column, Original sample (O); Exhibit A5.14) divided by the bootstrap standard error (column: *Standard (STERR)*) for that outer weight results in its empirical *t* value as displayed in the second to last column in Exhibit A5.14. The *t* values translate into *p* values as shown in the last column.

The bootstrapping results report also provides bootstrap confidence intervals. Clicking on the *Confidence intervals* tab in the bootstrapping results report shows the confidence intervals as derived from the percentile method (Exhibit A5.15), which come in two forms: with and without bias correction. While the results differ only marginally (i.e., at the third decimal place), we focus on the percentile-based *Confidence intervals bias corrected*. Finally, you can access all bootstrap sample-specific estimates by clicking the *Samples* tab.

Exhibit A5.16 summarizes the results for the formatively measured constructs *ATTR, CSOR, PERF,* and *QUAL* by showing the original outer weights estimates, *t* values, *p* values, and the confidence intervals derived from the percentile method.

Looking at the significance levels, we find that all formative indicators are significant at a 5% level, except *csor_2, csor_4, qual_2, qual_3,* and *qual_4.* The results report of the SmartPLS software also provides their outer loadings, *t* values, and *p* values in the results table for the outer loadings. Using this information, we note that the lowest outer loading of these five formative indicators occurs for *qual_2* (0.570). Furthermore, the *p* values of the five indicator loadings (i.e., *csor_2, csor_4, qual_2, qual_3,* and *qual_4*) are clearly

Exhibit A5.12   ■   Bootstrapping *t* Values in the Modeling Window
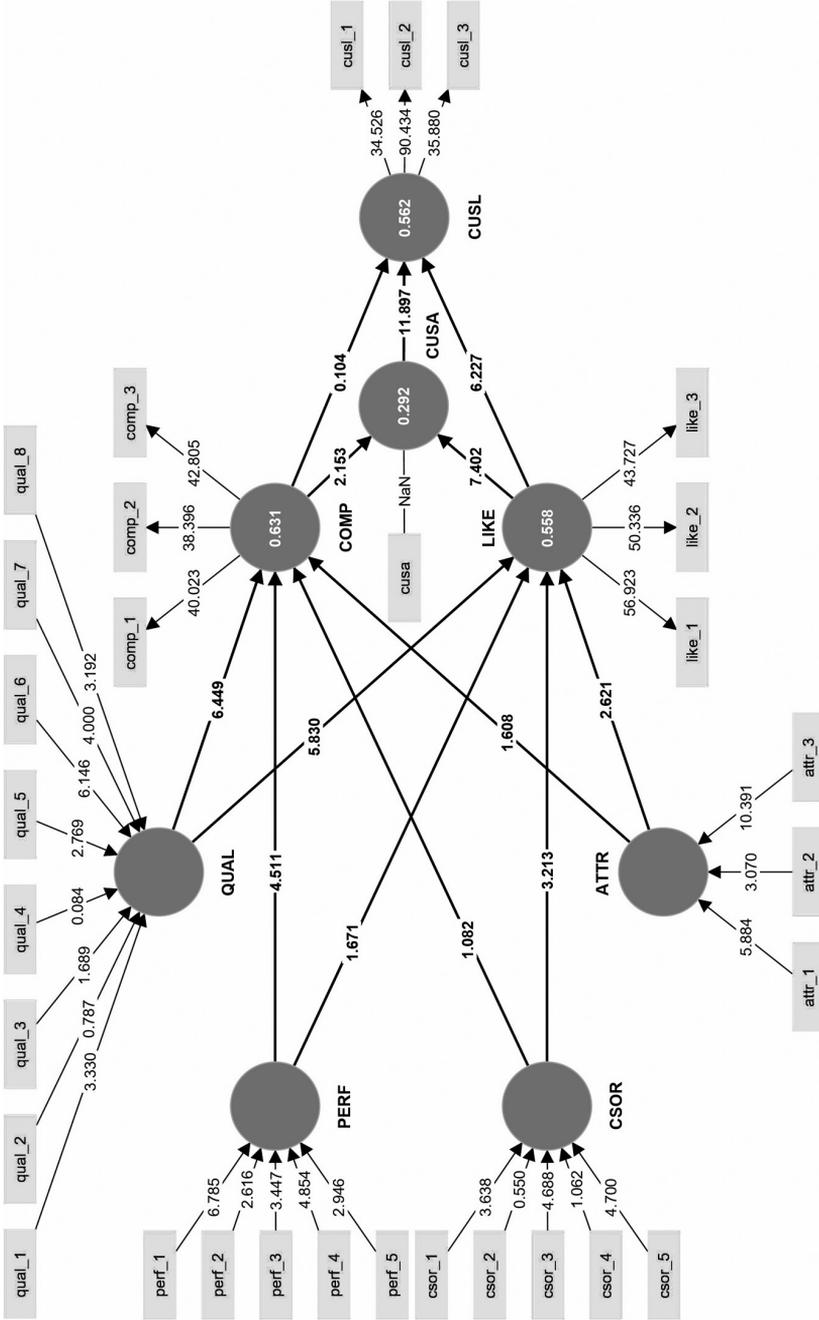
Exhibit A5.13 ■ Bootstrapping *p* values in the Modeling Window
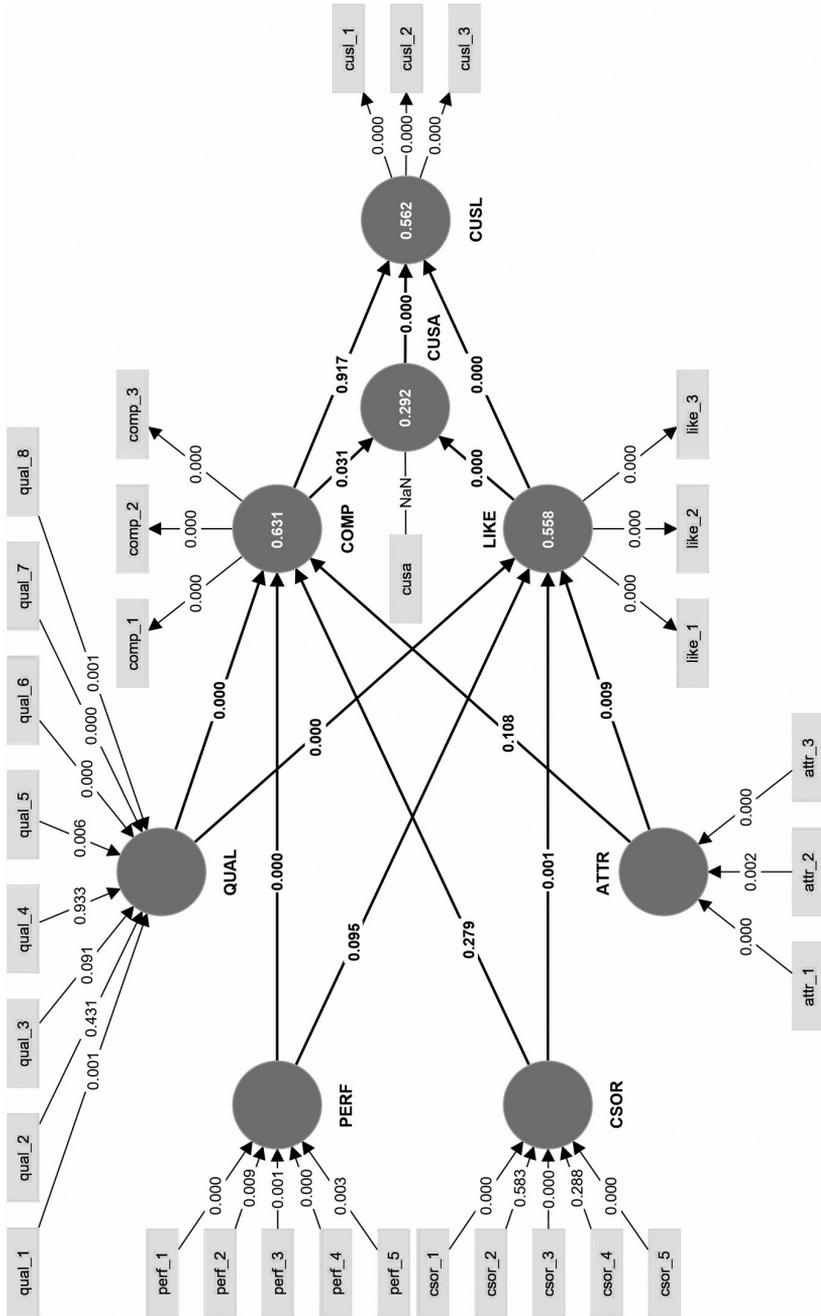
Exhibit A5.14 ■ Bootstrapping Results for Outer Weights

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
attr_1 -> ATTR	0.414	0.412	0.070	5.884	0.000
attr_2 -> ATTR	0.201	0.200	0.065	3.070	0.002
attr_3 -> ATTR	0.658	0.656	0.063	10.391	0.000
comp_1 <- COMP	0.469	0.468	0.022	21.804	0.000
comp_2 <- COMP	0.365	0.365	0.017	21.372	0.000
comp_3 <- COMP	0.372	0.373	0.014	26.581	0.000
csor_1 -> CSOR	0.306	0.303	0.084	3.638	0.000
csor_2 -> CSOR	0.037	0.037	0.068	0.550	0.583
csor_3 -> CSOR	0.406	0.403	0.087	4.688	0.000
csor_4 -> CSOR	0.080	0.078	0.075	1.062	0.288
csor_5 -> CSOR	0.416	0.414	0.088	4.700	0.000
cusa <- CUSA	1.000	1.000	0.000	0.000	0.000
cusl_1 <- CUSL	0.369	0.369	0.016	22.562	0.000
cusl_2 <- CUSL	0.420	0.421	0.014	29.363	0.000
cusl_3 <- CUSL	0.365	0.364	0.016	23.433	0.000
like_1 <- LIKE	0.419	0.419	0.015	28.730	0.000
like_2 <- LIKE	0.374	0.374	0.013	27.917	0.000
like_3 <- LIKE	0.363	0.363	0.014	25.971	0.000
perf_1 -> PERF	0.468	0.466	0.069	6.785	0.000
perf_2 -> PERF	0.177	0.180	0.068	2.616	0.009
perf_3 -> PERF	0.194	0.191	0.056	3.447	0.001
perf_4 -> PERF	0.340	0.337	0.070	4.854	0.000
perf_5 -> PERF	0.199	0.197	0.067	2.946	0.003
qual_1 -> QUAL	0.202	0.203	0.061	3.330	0.001
qual_2 -> QUAL	0.041	0.040	0.052	0.787	0.431
qual_3 -> QUAL	0.106	0.104	0.063	1.689	0.091
qual_4 -> QUAL	-0.005	-0.004	0.054	0.084	0.933
qual_5 -> QUAL	0.160	0.158	0.058	2.769	0.006
qual_6 -> QUAL	0.398	0.395	0.065	6.146	0.000
qual_7 -> QUAL	0.229	0.227	0.057	4.000	0.000
qual_8 -> QUAL	0.190	0.190	0.060	3.192	0.001

below 0.01, suggesting that all loadings are significant at a level of 1%. Moreover, prior research and theory also provide support for the relevance of these indicators for capturing the corporate social responsibility and quality dimensions of corporate reputation (Eberl, 2010; Sarstedt, Wilczynski, & Melewar, 2013; Schwaiger, 2004; Schwaiger, Sarstedt, & Taylor, 2010). Thus, we retain the indicators in the formative constructs, even though their outer weights are not significant.

The analysis of outer weights concludes the evaluation of the formative measurement models. Considering the results from Chapters 4 and 5 jointly, all reflective and formative constructs exhibit satisfactory levels of quality. Thus, we can proceed with the evaluation of the structural model (Chapter 6).

Exhibit A5.15 ■ Percentile Confidence Intervals (with Bias Correction) for Outer Weights

	Original sample (O)	Sample mean (M)	Bias	2.5%	97.5%
attr_1 -> ATTR	0.414	0.412	-0.003	0.275	0.551
attr_2 -> ATTR	0.201	0.200	-0.001	0.076	0.333
attr_3 -> ATTR	0.658	0.656	-0.002	0.527	0.773
comp_1 <- COMP	0.469	0.468	-0.001	0.432	0.518
comp_2 <- COMP	0.365	0.365	0.000	0.332	0.399
comp_3 <- COMP	0.372	0.373	0.001	0.344	0.399
csor_1 -> CSOR	0.306	0.303	-0.003	0.138	0.471
csor_2 -> CSOR	0.037	0.037	0.000	-0.090	0.175
csor_3 -> CSOR	0.406	0.403	-0.003	0.236	0.572
csor_4 -> CSOR	0.080	0.078	-0.002	-0.075	0.222
csor_5 -> CSOR	0.416	0.414	-0.002	0.241	0.588
cusa <- CUSA	1.000	1.000	0.000	1.000	1.000
cusl_1 <- CUSL	0.369	0.369	0.000	0.336	0.400
cusl_2 <- CUSL	0.420	0.421	0.000	0.396	0.453
cusl_3 <- CUSL	0.365	0.364	-0.000	0.334	0.396
like_1 <- LIKE	0.419	0.419	-0.000	0.394	0.452
like_2 <- LIKE	0.374	0.374	0.000	0.349	0.401
like_3 <- LIKE	0.363	0.363	0.000	0.335	0.390
perf_1 -> PERF	0.468	0.466	-0.002	0.324	0.596
perf_2 -> PERF	0.177	0.180	0.003	0.037	0.301
perf_3 -> PERF	0.194	0.191	-0.003	0.091	0.314
perf_4 -> PERF	0.340	0.337	-0.004	0.212	0.490
perf_5 -> PERF	0.199	0.197	-0.002	0.072	0.338
qual_1 -> QUAL	0.202	0.203	0.000	0.083	0.324
qual_2 -> QUAL	0.041	0.040	-0.001	-0.057	0.147
qual_3 -> QUAL	0.106	0.104	-0.001	-0.017	0.227
qual_4 -> QUAL	-0.005	-0.004	0.000	-0.107	0.104
qual_5 -> QUAL	0.160	0.158	-0.001	0.044	0.271
qual_6 -> QUAL	0.398	0.395	-0.003	0.272	0.527
qual_7 -> QUAL	0.229	0.227	-0.002	0.120	0.344
qual_8 -> QUAL	0.190	0.190	-0.000	0.075	0.308

Exhibit A5.16 ■	Formative Constructs Outer Weights Significance Testing Results					
Formative Constructs	Formative Indicators	Outer Weights (Outer Loadings)	*t* Value	*p* Value	95% Confidence Interval (With Bias Correction)	Significance[a] ($p < 0.05$)?
ATTR	attr_1	0.414 (0.755)	5.884	0.000	[0.275;0.551]	Yes
	attr_2	0.201 (0.506)	3.070	0.002	[0.076;0.333]	Yes
	attr_3	0.658 (0.891)	10.391	0.000	[0.527;0.773]	Yes
CSOR	csor_1	0.306 (0.771)	3.638	0.000	[0.138;0.471]	Yes
	csor_2	0.037 (0.571)	0.550	0.583	[-0.090;0.175]	No
	csor_3	0.406 (0.838)	4.688	0.000	[0.236;0.572]	Yes
	csor_4	0.080 (0.617)	1.062	0.288	[-0.075;0.222]	No
	csor_5	0.416 (0.848)	4.700	0.000	[0.241;0.588]	Yes
PERF	perf_1	0.468 (0.846)	6.785	0.000	[0.324;0.596]	Yes
	perf_2	0.177 (0.690)	2.616	0.009	[0.037;0.301]	Yes
	perf_3	0.194 (0.573)	3.447	0.001	[0.091;0.314]	Yes
	perf_4	0.340 (0.717)	4.854	0.000	[0.212;0.490]	Yes
	perf_5	0.199 (0.638)	2.946	0.003	[0.072;0.338]	Yes
QUAL	qual_1	0.202 (0.741)	3.330	0.001	[0.083;0.324]	Yes
	qual_2	0.041 (0.570)	0.787	0.431	[-0.057;0.147]	No
	qual_3	0.106 (0.749)	1.689	0.091	[-0.017;0.227]	No
	qual_4	–0.005 (0.664)	0.084	0.933	[-0.107;0.104]	No
	qual_5	0.160 (0.787)	2.769	0.006	[0.044;0.271]	Yes
	qual_6	0.398 (0.856)	6.146	0.000	[0.272;0.527]	Yes
	qual_7	0.229 (0.722)	4.000	0.000	[0.120;0.344]	Yes
	qual_8	0.190 (0.627)	3.192	0.001	[0.075;0.308]	Yes

[a] We refer to the bootstrap confidence intervals for significance testing, as recommended in this chapter.