

# 6

## ASSESSING PLS-SEM RESULTS PART III

### Evaluation of the Structural Model

#### CASE STUDY ILLUSTRATION—HOW ARE PLS-SEM STRUCTURAL MODEL RESULTS REPORTED?

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We continue with the extended corporate reputation model as introduced in Chapter 5. If you do not have the PLS path model readily available in SmartPLS 4, download the file *Corporate Reputation.zip* from the <https://www.pls-sem.net> website and save it on your hard drive. Then, 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. Thereafter, 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*. Alternately, you see in the main screen of the *Workspace* view, under *Sample projects*, 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 to open.

The assessment of the structural model builds on the results from the standard model estimation, the bootstrapping routine, and the PLS<sub>predict</sub> proce-

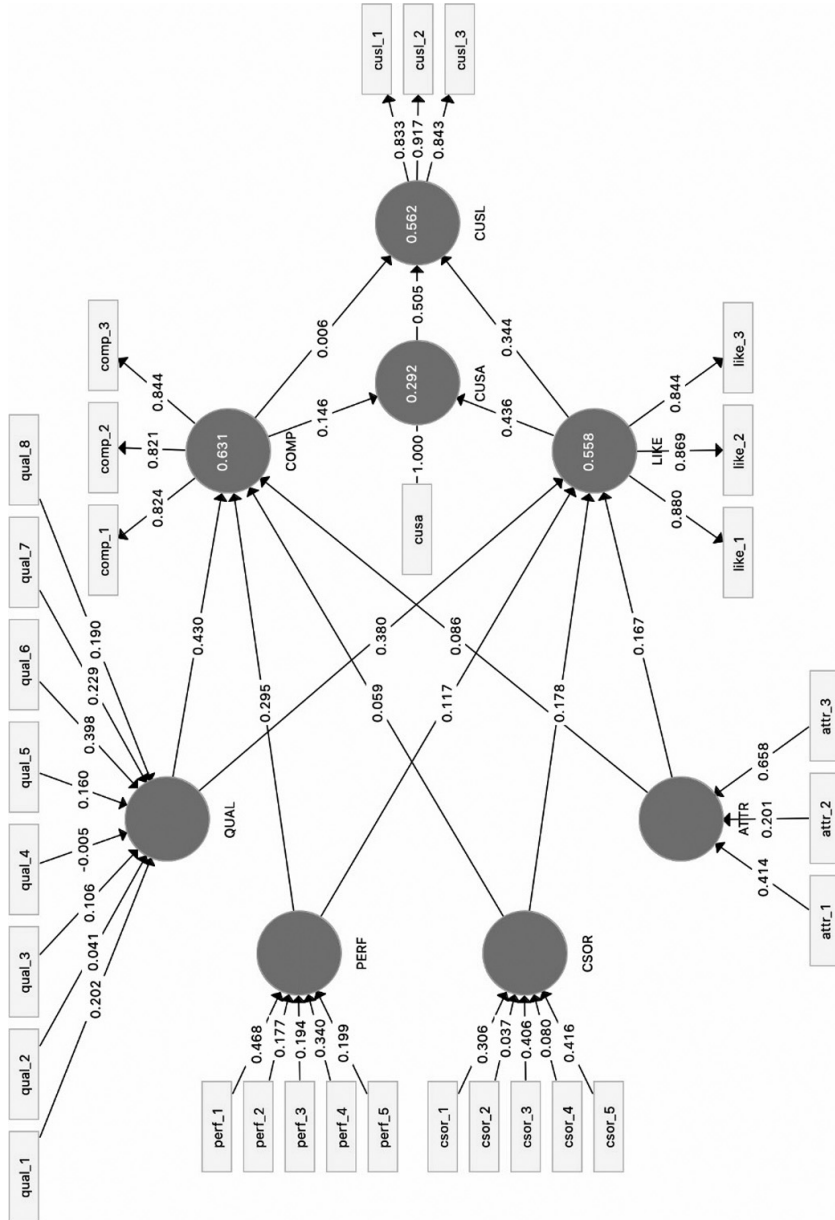
ture. After running the PLS-SEM algorithm using the same algorithm and missing values settings as in the previous chapters, SmartPLS shows the key results of the model estimation in the *Modeling window* (Exhibit A6.1). Per default, we see the path coefficients as well as the  $R^2$  values of the endogenous constructs (shown in the circles).

For a more detailed assessment, we need to examine the SmartPLS results report. Following the structural model assessment procedure (Exhibit 6.1), we first need to check the structural model for collinearity issues by examining the VIF values of all sets of predictor constructs in the structural model. To do so, go to *Quality criteria* → *Collinearity statistics (VIF)* and click on the *Inner model* tab. The results table that opens (Exhibit A6.2) shows the VIF values of all combinations of endogenous constructs (represented by the columns) and corresponding exogenous (i.e., predictor) constructs (represented by the rows). Specifically, we assess the following sets of (predictor) constructs for collinearity: (1) *ATTR*, *CSOR*, *PERF*, and *QUAL* as predictors of *COMP* (and *LIKE*); (2) *COMP* and *LIKE* as predictors of *CUSA*; and (3) *COMP*, *LIKE*, and *CUSA* as predictors of *CUSL*. As can be seen in Exhibit A6.2, all VIF values are clearly below the threshold of 5 and with two exceptions (i.e., the *QUAL* predictor) below 3. Since the two exceptions are close to 3, we conclude that collinearity among the predictor constructs is not a critical issue in the structural model, and we can continue examining the results report.

The second step of the structural model assessment procedure (Exhibit 6.1) involves assessing the significance and relevance of the structural model relationships. Starting with the relevance assessment, go to *Final results* → *Path coefficients*, where we find the path coefficients as shown in the modeling window in three formats: matrix, list and bar charts. Looking at the relative importance of the driver constructs for the perceived competence (*COMP*), one finds that the customers' perception of the company's quality of products and services (*QUAL*) is most important, followed by its performance (*PERF*). In contrast, the perceived attractiveness (*ATTR*) and degree to which the company acts in socially conscious ways (*CSOR*) have very little bearing on *COMP*. These two drivers are, however, of increased importance for establishing a company's likeability (*LIKE*). Moving on in the model, we also find that likeability is the primary driver for the customers' satisfaction and loyalty, as illustrated by the increased path coefficients compared with those of *COMP*.

More interesting, though, is the examination of total effects. Specifically, we can evaluate how strongly each of the four formative driver constructs (*ATTR*, *CSOR*, *PERF*, and *QUAL*) ultimately influences the key target variable *CUSL* via the mediating constructs *COMP*, *LIKE*, and *CUSA*. Total effects are shown under *Final results* → *Total effects* in the results report. We read the table shown in Exhibit A6.3 column to row. That is, each column represents a target construct, whereas the rows represent predecessor constructs. For example, with regard to loyalty, we can see that among the four

**Exhibit A6.1 ■ Results in Modeling Window**



**Exhibit A6.2 ■ VIF Values in the Structural Model**

	ATTR	COMP	CSOR	CUSA	CUSL	LIKE	PERF	QUAL
ATTR		2.122				2.122		
COMP				1.686	1.716			
CSOR		2.083				2.083		
CUSA					1.412			
CUSL								
LIKE				1.686	1.954			
PERF		2.889				2.889		
QUAL		3.487				3.487		

**Exhibit A6.3 ■ Total effects**

	ATTR	COMP	CSOR	CUSA	CUSL	LIKE	PERF	QUAL
ATTR		0.086		0.085	0.101	0.167		
COMP				0.146	0.079			
CSOR		0.059		0.086	0.105	0.178		
CUSA					0.505			
CUSL								
LIKE				0.436	0.564			
PERF		0.295		0.094	0.089	0.117		
QUAL		0.430		0.228	0.248	0.380		

exogenous driver constructs, quality has the strongest total effect on loyalty (0.248), followed by corporate social responsibility (0.105), attractiveness (0.101), and performance (0.089). Therefore, it is advisable for companies to focus on marketing activities that positively influence the customers' perception of the quality of their products and services. By also taking the construct's indicator weights into consideration, we can even identify which specific element of quality needs to be addressed. Looking at the outer weights (*Final results* → *Outer weights*) reveals that *qual\_6* has the highest outer weight (0.398). This item relates to the survey question “[the company] is a reliable partner for customers.” Thus, marketing managers should try to enhance the customers' perception of the reliability of their products and services by means of marketing activities.

The analysis of the structural model relationships shows that several path coefficients (e.g., *COMP* → *CUSL*) have rather low values. To assess whether these relationships are significant (Exhibit 6.1), we run the bootstrapping procedure. The extraction of bootstrapping results for the structural model

estimates is analogous to the descriptions in the context of formative measurement model assessment (Chapter 5). To run the bootstrapping procedure, go to *Calculate* → *Bootstrapping* in the SmartPLS menu or go to the *Modeling* window and click on the *Calculate* icon, followed by *Bootstrapping* (note that you first may need to go back to the *Modeling* window before the *Calculate* icon appears). We retain all settings for missing value treatment and the PLS-SEM algorithm as in the initial model estimation and select *Do parallel processing* option, 10,000 bootstrap samples and select the *Complete (slower)* option. In the *BT setup* we choose *Percentile Bootstrap* as a *Confidence interval method*, *Two tailed* testing, a significance level of 0.05, and select *Fixed seed*. Next, we click *Start calculation*.

After running the procedure, SmartPLS shows the bootstrapping results for the measurement models and structural model in the *Modeling* window. Using the combo boxes available on the screen under the menu, you can choose whether SmartPLS should display *t* values or *p* values in the *Modeling* window. Exhibit A6.4 shows *p* values for the structural model relationships as resulting from the bootstrapping procedure.

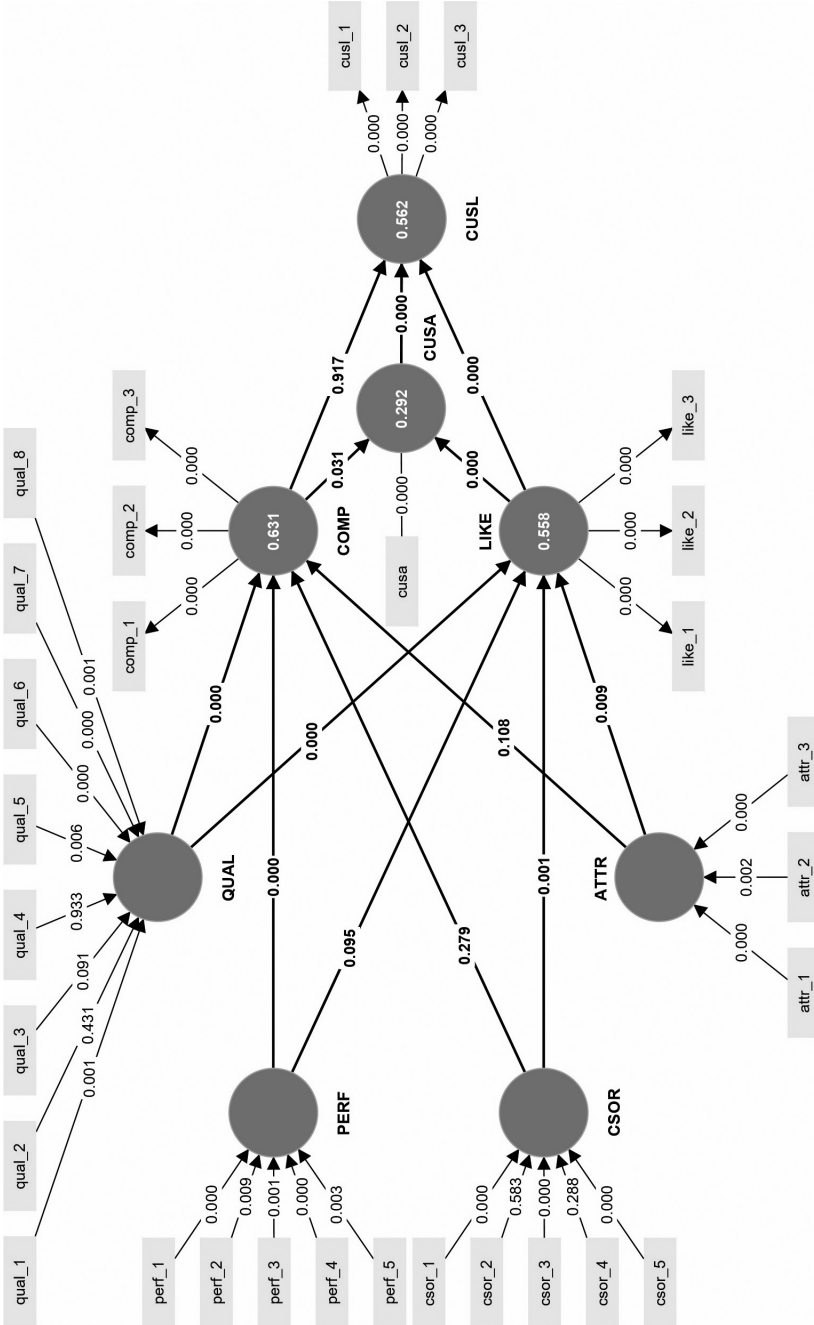
By going to the bootstrapping report, we get a more detailed overview of the results. The table under *Final results* → *Path coefficients* provides us with an overview of results, including standard errors, bootstrap mean values, *t* values and *p* values. Clicking on the *Confidence intervals* tab in the bootstrapping results report shows the confidence interval as derived from the percentile method without and with bias correction. Exhibit A6.5 shows the latter result.

Finally, clicking on the *Samples* tab in the bootstrapping results report shows the results of each bootstrap run as shown in Exhibit A6.6. The displayed table includes the estimates of all the path coefficients for all 10,000 subsamples. These estimates are used to compute the bootstrapping mean values, standard errors, *t* values, and *p* values of all the path coefficients, shown in the *Mean, STDEV, T values, and P values* table of the bootstrapping results report.

Exhibit A6.7 provides a summary of the path coefficient estimates, *t* values, *p* values, and confidence intervals. Again, researchers usually report either the *t* values (and their significance levels) or the *p* values or the confidence intervals. We find that all criteria come to the same outcome for the significance of path coefficients. Otherwise, we recommend relying on the bootstrap confidence intervals for significance testing (see Chapter 5 for details). Exhibit A6.7 shows all results only for illustrative purposes.

Assuming a 5% significance level, we focus on the 95% bootstrap confidence interval obtained by the percentile approach with bias correction and find that all relationships in the structural model are significant, except *PERF* → *LIKE*, *ATTR* → *COMP*, *CSOR* → *COMP*, and *COMP* → *CUSL* (Exhibit A6.7). These results suggest that companies should concentrate their marketing efforts on enhancing their *LIKE* (by strengthening *QUAL*) rather than their *COMP* to maximize *CUSL*.

**Exhibit A6.4 ■ Bootstrapping *p* values in the Modeling Window**



### Exhibit A6.5 ■ Percentile Confidence Intervals (with Bias Correction) for the Path Coefficients

	Original sample (O)	Sample mean (M)	Bias	2.5%	97.5%
ATTR -> COMP	0.086	0.086	-0.000	-0.016	0.195
ATTR -> LIKE	0.167	0.162	-0.005	0.044	0.292
COMP -> CUSA	0.146	0.144	-0.001	0.012	0.279
COMP -> CUSL	0.006	0.006	-0.000	-0.100	0.114
CSOR -> COMP	0.059	0.063	0.004	-0.048	0.164
CSOR -> LIKE	0.178	0.179	0.000	0.067	0.284
CUSA -> CUSL	0.505	0.505	-0.000	0.420	0.584
LIKE -> CUSA	0.436	0.437	0.001	0.316	0.545
LIKE -> CUSL	0.344	0.345	0.001	0.236	0.451
PERF -> COMP	0.295	0.298	0.002	0.162	0.418
PERF -> LIKE	0.117	0.121	0.004	-0.022	0.252
QUAL -> COMP	0.430	0.430	0.000	0.299	0.558
QUAL -> LIKE	0.380	0.387	0.007	0.246	0.500

### Exhibit A6.6 ■ Bootstrap Samples

	ATTR -> COMP	ATTR -> LIKE	COMP -> CUSA	COMP -> CUSL	CSOR -> COMP	CSOR -> LIKE	CUSA -> CUSL	LIKE -> CUSA	LIKE -> CUSL
Sample 0	0.139	0.200	0.174	-0.007	0.058	0.268	0.552	0.453	0.317
Sample 1	0.033	0.170	0.071	0.071	0.062	0.157	0.477	0.428	0.341
Sample 2	0.110	0.312	0.159	-0.008	0.080	0.055	0.512	0.429	0.387
Sample 3	0.060	0.179	0.097	0.052	0.057	0.176	0.446	0.419	0.386
Sample 4	0.129	0.169	0.198	0.003	0.067	0.206	0.483	0.327	0.380
Sample 5	0.088	0.159	0.148	0.075	0.004	0.253	0.472	0.349	0.340
Sample 6	0.080	0.202	0.304	-0.020	0.113	0.078	0.525	0.330	0.344
Sample 7	0.044	0.125	-0.036	-0.019	0.027	0.187	0.506	0.543	0.395
Sample 8	0.127	0.158	0.174	0.045	0.097	0.212	0.539	0.394	0.299
Sample 9	0.011	0.241	0.097	-0.150	0.130	0.226	0.571	0.438	0.389
Sample 10	-0.019	0.248	0.137	-0.049	0.082	0.199	0.527	0.413	0.359
Sample 11	0.093	0.197	0.045	0.047	0.128	0.088	0.537	0.567	0.273
Sample 12	0.042	-0.002	0.086	-0.018	0.031	0.284	0.571	0.506	0.282
Sample 13	0.158	0.161	0.081	0.029	0.020	0.124	0.499	0.507	0.342
Sample 14	0.147	0.206	0.114	0.005	0.108	0.138	0.526	0.450	0.288
Sample 15	0.168	0.108	0.126	0.116	-0.039	0.226	0.474	0.492	0.275
Sample 16	0.124	0.182	-0.027	-0.011	0.097	0.162	0.515	0.483	0.386
Sample 17	0.042	0.109	0.134	0.008	0.062	0.090	0.450	0.331	0.341
Sample 18	0.068	0.183	0.047	0.020	-0.038	0.083	0.506	0.481	0.319
Sample 19	0.068	0.193	0.147	-0.110	-0.054	0.198	0.525	0.469	0.390
Sample 20	0.054	0.272	0.092	0.111	0.054	0.203	0.521	0.505	0.276

**Exhibit A6.7 ■ Significance Testing Results of the Structural Model Path Coefficients**

	Path Coefficients	t Values	p Values	95% Confidence Intervals (With Bias Correction)	Significance <sup>a</sup> ( $p < 0.05$ )?
<i>ATTR</i> → <i>COMP</i>	0.086	1.579	0.114	[-0.016;0.195]	No
<i>ATTR</i> → <i>LIKE</i>	0.167	2.666	0.008	[0.044;0.292]	Yes
<i>COMP</i> → <i>CUSA</i>	0.146	2.173	0.030	[0.012;0.279]	Yes
<i>COMP</i> → <i>CUSL</i>	0.006	0.103	0.918	[-0.100;0.114]	No
<i>CSOR</i> → <i>COMP</i>	0.059	1.086	0.278	[-0.048;0.164]	No
<i>CSOR</i> → <i>LIKE</i>	0.178	3.200	0.001	[0.067;0.284]	Yes
<i>CUSA</i> → <i>CUSL</i>	0.505	11.960	0.000	[0.420;0.584]	Yes
<i>LIKE</i> → <i>CUSA</i>	0.436	7.381	0.000	[0.316;0.545]	Yes
<i>LIKE</i> → <i>CUSL</i>	0.344	6.207	0.000	[0.236;0.451]	Yes
<i>PERF</i> → <i>COMP</i>	0.295	4.457	0.000	[0.162;0.418]	Yes
<i>PERF</i> → <i>LIKE</i>	0.117	1.684	0.092	[-0.022;0.252]	No
<i>QUAL</i> → <i>COMP</i>	0.430	6.400	0.000	[0.299;0.558]	Yes
<i>QUAL</i> → <i>LIKE</i>	0.380	5.834	0.000	[0.246;0.500]	Yes

<sup>a</sup> We refer to the bootstrap confidence intervals for significance testing, as described in Chapter 5.

This is not surprising, considering that customers rated mobile network operators. As their services (provision of network capabilities) are intangible, affective judgments play a much more important role than cognitive judgments for establishing customer loyalty. Furthermore, we learn that *ATTR* and *CSOR* only influence *LIKE*, which is also not surprising since these two driver constructs are also more affective in nature.

To examine the bootstrapping results for the total effects, go to *Final results* → *Total effects*. Exhibit A6.8 summarizes the results for the total effects of the exogenous constructs *ATTR*, *CSOR*, *PERF*, and *QUAL* on the target constructs *CUSA* and *CUSL* taken from the *Mean*, *STDEV*, *T values*, *P values* table of the bootstrapping results report. As can be seen, all total effects are significant at a 5% level.

Next, we turn our attention to the assessment of the model's explanatory power as called for in the third step of the structural model assessment procedure (Exhibit 6.1). To do so, we go back to the SmartPLS results report as produced after running the PLS-SEM algorithm (not bootstrapping).



**Exhibit A6.8 ■ Significance Testing Results of the Total Effects**

	Total Effect	t Values	p Values	95% Confidence Intervals (With Bias Correction)	Significance <sup>a</sup> ( $p < 0.05$ )?
<i>ATTR</i> → <i>CUSA</i>	0.086	2.817	0.005	[0.029;0.149]	Yes
<i>ATTR</i> → <i>CUSL</i>	0.101	2.740	0.006	[0.030;0.176]	Yes
<i>COMP</i> → <i>CUSL</i>	0.074	2.117	0.034	[0.006;0.145]	Yes
<i>CSOR</i> → <i>CUSA</i>	0.086	3.142	0.002	[0.035;0.143]	Yes
<i>CSOR</i> → <i>CUSL</i>	0.105	3.107	0.002	[0.042;0.175]	Yes
<i>LIKE</i> → <i>CUSL</i>	0.220	6.282	0.000	[0.153;0.292]	Yes
<i>PERF</i> → <i>CUSA</i>	0.094	2.454	0.014	[0.016;0.168]	Yes
<i>PERF</i> → <i>CUSL</i>	0.089	2.034	0.042	[-0.001;0.174]	Yes
<i>QUAL</i> → <i>CUSA</i>	0.228	6.189	0.000	[0.155;0.301]	Yes
<i>QUAL</i> → <i>CUSL</i>	0.248	5.788	0.000	[0.160;0.331]	Yes

<sup>a</sup> We refer to the bootstrap confidence intervals for significance testing, as described in Chapter 5.

To start with, we examine the  $R^2$  values of the endogenous latent variables, which are available under *Quality criteria* → *R-square* (select the *Overview* tab for the matrix view). Following our rules of thumb, the  $R^2$  values of *COMP* (0.631), *CUSL* (0.562), and *LIKE* (0.558) can be considered moderate, whereas the  $R^2$  value of *CUSA* (0.292) is rather weak.

To obtain the effect sizes  $f^2$  for all structural model relationships, go to *Quality criteria* → *f-square* (select the *Matrix* view). Exhibit A6.9 shows the  $f^2$  values for all combinations of endogenous constructs (represented by the columns) and corresponding exogenous (i.e., predictor) constructs (represented by the rows). For example, *LIKE* has a medium effect size of 0.159 on *CUSA* and of 0.138 on *CUSL*. On the contrary, *COMP* has no effect on *CUSA* (0.018) or *CUSL* (0.000). Please note these results differ from a manual computation of the  $f^2$  values by using the aforementioned equation with values for  $R^2_{\text{included}}$  and  $R^2_{\text{excluded}}$ . This difference results because SmartPLS uses the latent variable scores of the model that includes all latent variables and then internally excludes latent variables to obtain the  $R^2_{\text{excluded}}$ . On the contrary, when manually computing the  $f^2$  values by estimating the model with and without a latent variable, the model changes and, thus, so do the latent variable scores. Hence, the difference of the manually computed  $f^2$  values results from the changes in the latent variable scores due to a model modification which is, however, incorrect.

**Exhibit A6.9 ■  $f^2$  Effect Sizes**

	ATTR	COMP	CSOR	CUSA	CUSL	LIKE	PERF	QUAL
ATTR		0.009				0.030		
COMP				0.018	0.000			
CSOR		0.005				0.035		
CUSA					0.412			
CUSL								
LIKE				0.159	0.138			
PERF		0.082				0.011		
QUAL		0.143				0.094		

The fourth step of the structural model assessment procedure (Exhibit 6.1) requires assessing the model’s predictive power using  $PLS_{predict}$ . To initiate the procedure, go to *Calculate* → *PLSpredict/CVPAT* in the SmartPLS menu or go to the *Modeling* window and click on the *Calculate* icon, followed by *PLSpredict/CVPAT*. In the dialog box that opens, we retain the default settings. That is, we run  $PLS_{predict}$  with 10 folds and 10 repetitions and select the *Fixed seed* option. To initiate the analysis, click on *Start calculation*.

**Exhibit A6.10 ■  $PLS_{predict}$  Results Report**

	$Q^2_{predict}$	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE
comp_1	0.473	1.043	0.798	1.070	0.815
comp_2	0.364	1.099	0.881	1.110	0.872
comp_3	0.398	1.135	0.898	1.133	0.869
cusa	0.245	1.022	0.791	1.019	0.796
cusl_1	0.259	1.300	0.989	1.310	0.964
cusl_2	0.233	1.523	1.174	1.542	1.170
cusl_3	0.141	1.531	1.155	1.569	1.178
like_1	0.472	1.128	0.857	1.154	0.881
like_2	0.360	1.483	1.149	1.546	1.186
like_3	0.351	1.510	1.170	1.587	1.240

Exhibit A6.10 shows the  $PLS_{predict}$  results report. To access the PLS and LM benchmarks model’s results, go to *Final results* → *MV prediction summary* and select the *Overview* tab in the results report. We focus our analysis on the model’s key target construct *CUSL* and consider the RMSE as the default metric for interpreting the prediction error of the construct’s indicators. In an initial step, we interpret the  $Q^2_{predict}$  values. The analysis shows that all three

indicators (i.e., *cusl\_1*, *cusl\_2*, and *cusl\_3*) have  $Q^2_{\text{predict}}$  values larger than zero, suggesting that the PLS path model outperforms the most naïve benchmark. The following analyses require comparing the RMSE values produced by the PLS-SEM analysis with those produced by the naïve LM benchmark model.

Comparing the RMSE values, we find that the PLS-SEM analysis produces smaller prediction errors (i.e., smaller RMSE values) than the LM for all three *CUSL* indicators. Specifically, the analysis produces the following RMSE values (PLS-SEM vs. LM):

- *cusl\_1*: 1.300 vs. 1.310,
- *cusl\_2*: 1.523 vs. 1.542, and
- *cusl\_3*: 1.531 vs. 1.569.

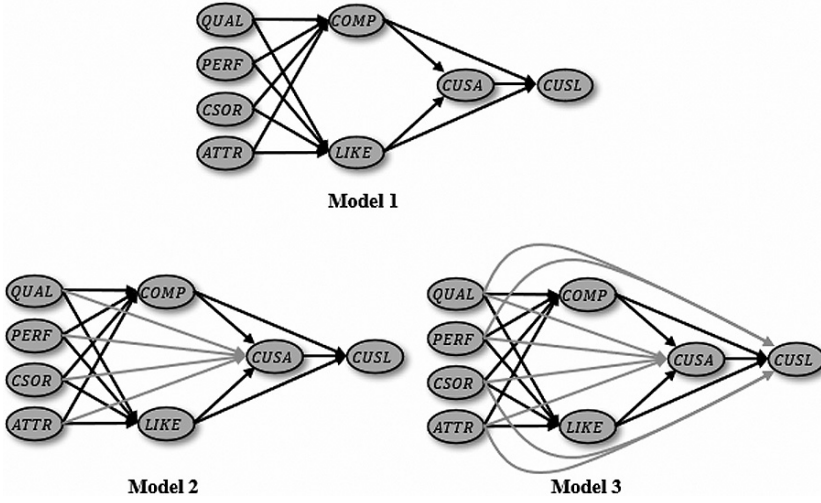
These results suggest the model has high predictive power as the PLS-SEM analysis outperforms the naïve LM benchmark model for all *CUSL* indicators. Note that the absolute size of the differences in RMSE values is of secondary importance for two reasons. First, the size of the RMSE values largely depend on the measurement scale of the indicators. As the *CUSL* indicators are measured on 7-point Likert scales, the range of possible RMSE differences is quite limited. Second, the RMSE values generated by  $PLS_{\text{predict}}$  are highly stable. Hence, even marginal differences in the RMSE values are typically significant.

The results report after running *PLSpredict/CVPAT* in SmartPLS also includes the CVPAT results under *Final results* → *CVPAT*. In both CVPAT results reports, *PLS-SEM vs. Indicator average (IA)* and *PLS-SEM vs. Linear model (LM)*, we obtain a negative average loss value difference for the *Overall* model. This means that PLS-SEM has a lower average loss than the IA and LM prediction benchmarks. Moreover, since the *p value* is below 0.05, we conclude that PLS-SEM's predictive capabilities are significantly better than those of these two prediction benchmarks. Hence, the CVPAT results support high predictive power of the PLS-SEM results for the corporate reputation model.

In a final step, we compare different configurations of the reputation model. Drawing on Danks, Sharma, and Sarstedt (2020) and Sharma et al. (2020), we compare the original model that serves as the basis for our prior analyses (Model 1), with two more complex variants in which the four driver constructs also relate to *CUSA* (Model 2) and *CUSL* (Model 3). Exhibit A6.11 shows the three models under consideration.

To compare the models, we estimate each model using the PLS-SEM algorithm and examine the BIC criterion, which can be accessed in the results report under *Quality criteria* → *Model selection criteria*. Exhibit A6.12 shows the BIC values for the five models under consideration.

**Exhibit A6.11. Model comparisons**



**Exhibit A6.12 ■ BIC values**

	Model 1	Model 2	Model 3
<b>BIC</b>	-261.602	-261.603	-245.038
<b>Akaike weights (relative model likelihoods)</b>	49.98%	50.01%	0.01%

Comparing the BIC values, we find that Model 2 yields the lowest BIC value, closely followed by Model 1 and, with a greater difference, Model 3. Considering the marginal difference in BIC values between Models 1 and 2, however, the evidence in favor of the more complex model, which relates all four driver constructs to *CUSA* is not very strong. To further explore the difference, we compute the BIC-based Akaike weights for the three models. To do so, we first compute each delta score, which gives 0.001 for Model 1, 0 for Model 2, and 16.565 for Model 3. We then compute  $e^{(-0.5 \cdot \text{delta})}$  for each model, which gives 0.9995 for Model 1, 1 for Model 2, and 0.0003 for Model 3. Dividing each value by (0.9995 + 1 + 0.0003) gives the Akaike weights shown in Exhibit A6.12. Comparing the weights, we find a marginally higher relative likelihood for Model 2 over Model 1. However, considering that Model 1 is more parsimonious, we would opt for this model rather than the more complex variant Model 2.