7

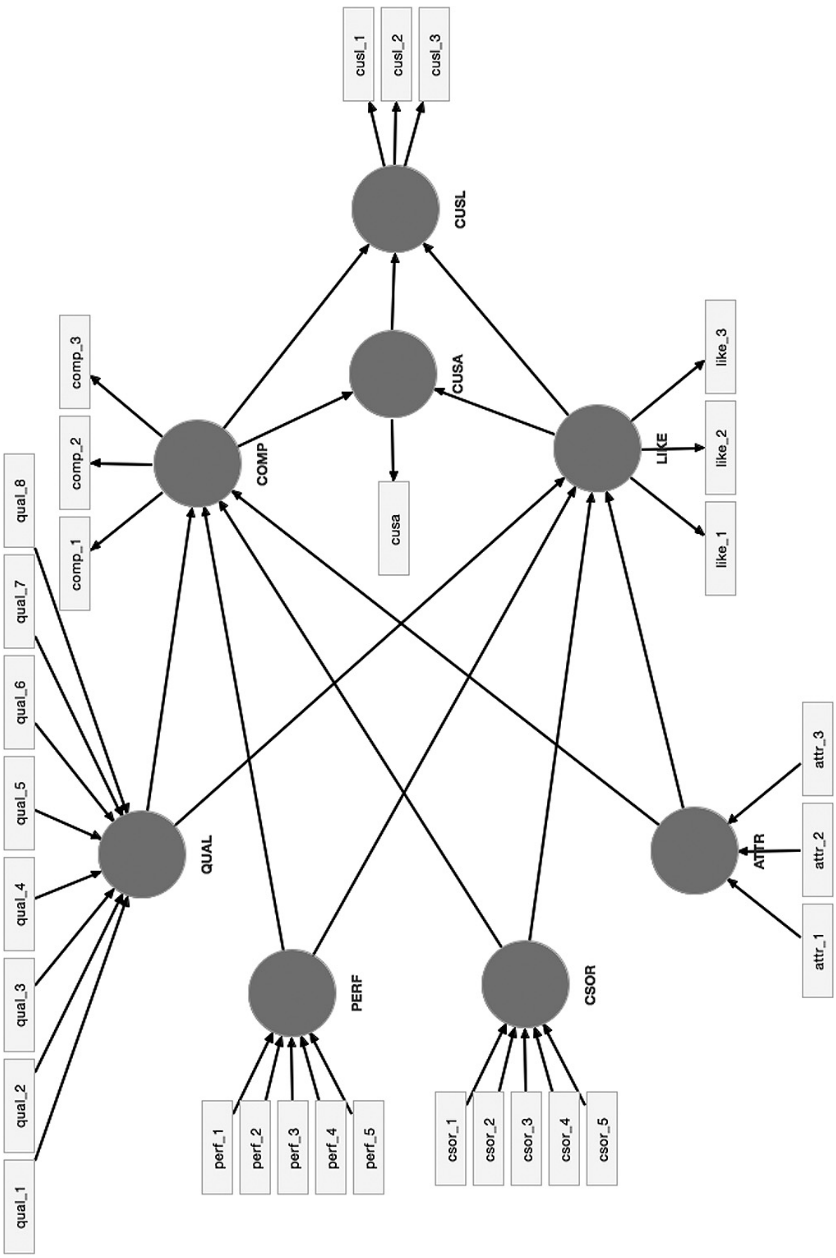
MEDIATION AND MODERATION ANALYSIS

Case Study Illustration—Mediation

To illustrate the estimation of mediating effects, let us, again, consider the extended corporate model in the SmartPLS software. If you do not have the model readily available, please go back to the case study in the previous chapter and import the SmartPLS *Project* file *Corporate Reputation.zip* by going to *Files → Import project from backup file* in the SmartPLS menu. Alternatively, you see in the main screen next to 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 will open. The model shown in Exhibit A7.1 will appear in the *Modeling* window.

In the following discussion, we will further explore the relationship between the two dimensions of corporate reputation (i.e., *COMP* and *LIKE*) and the target construct customer loyalty (i.e., *CUSL*). According to Festinger's (1957) theory of cognitive dissonance, customers who perceive that a company has a favorable reputation are likely to show higher levels of satisfaction in an effort to avoid cognitive dissonance. At the same time, previous research has demonstrated that customer satisfaction is the primary driver of customer loyalty. Therefore, we expect that customer satisfaction mediates the two relationships between likeability and customer loyalty as well as competence and customer loyalty. To analyze these two mediation relationships in the corporate reputation model in more detail, we apply the procedure shown in Exhibit 7.5.

Exhibit A7.1 ■ Extended Model in SmartPLS



To begin the mediation analysis, we test the significance of the indirect effects. The indirect effect from *COMP* via *CUSA* to *CUSL* is the product of the path coefficients from *COMP* to *CUSA* and from *CUSA* to *CUSL* (mediation path 1). Similarly, the indirect effect from *LIKE* via *CUSA* to *CUSL* is the product of the path coefficients from *LIKE* to *CUSA* and from *CUSA* to *CUSL* (mediation path 2). To test the significance of these path coefficients' products, we run the bootstrap routine. To do so, go to *Calculate → Bootstrapping* in the SmartPLS menu or click on the *Calculate* icon, above the *Modeling* window, 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 the PLS-SEM algorithm and the missing value treatment as before by selecting *10,000* subsamples, *Two tailed* testing, and a significance level of *0.05*. In addition, make sure to select *Do parallel processing*, *Most important (faster)*, and *Fixed seed*. Next, we click *Start calculation* making sure you have previously ticked *Open report* at the bottom of the dialog box.

After running the bootstrapping procedure, SmartPLS opens the bootstrapping results report. The table under *Final results → Specific indirect effects* provides us with an overview of results, including standard errors, bootstrap mean values, *t* values, and *p* values. Clicking on the *Confidence intervals bias corrected* tab in the bootstrapping results report shows the confidence interval as derived from the percentile method (with bias correction). Similarly, the table under *Final results → Path coefficients* offers the corresponding results for the direct effects, which we need in the further analysis. Exhibit A7.2 summarizes the bootstrapping results for the relationships between *COMP* and *CUSL* as well as *LIKE* and *CUSL*. Alternatively, if you are interested in the results for indirect effects of a serial or a joint mediation, open the bootstrapping report *Total indirect effects*.

We find that both indirect effects are significant, since neither of the 95% confidence intervals includes zero (see Chapter 5 for how to use confidence intervals for hypothesis testing). When reporting the confidence intervals, it is not necessary to also report the *t* values and *p* values. The next step of the mediation analysis focuses on the significance of the direct effects from

Exhibit A7.2 ■ Analysis of the Direct and Indirect Effects

	Direct Effect	95% Confidence Interval (With Bias Correction) of the Direct Effect	Significance ($p < 0.05$)?	Indirect Effect (via *CUSA*)	95% Confidence Interval (With Bias Correction) of the Indirect Effect	Significance ($p < 0.05$)?
COMP → CUSL	0.006	[–0.100, 0.114]	No	0.074	[0.006, 0.145]	Yes
LIKE → CUSL	0.344	[0.236, 0.451]	Yes	0.220	[0.153, 0.292]	Yes

COMP to *CUSL* and *LIKE* to *CUSL*. As determined in Chapter 6 and shown in Exhibit A7.2, the relationship from *COMP* to *CUSL* is very weak (0.006) and statistically nonsignificant. Following the mediation analysis procedure in Exhibit 7.5, we conclude that *CUSA* fully mediates the *COMP* to *CUSL* relationship. On the contrary, *LIKE* exerts a pronounced (0.344) and significant ($p \leq 0.05$) effect on *CUSL*. We therefore conclude that *CUSA* partially mediates the relationship since both the direct and the indirect effects are significant and meaningful (Exhibit 7.5). To further substantiate the type of partial mediation, we next compute the product of the direct effect and the indirect effect. Since the direct and indirect effects are both positive, the sign of their product is also positive (i.e., $0.344 \cdot 0.220 = 0.076$). Consequently, *CUSA* represents complementary mediation of the relationship from *LIKE* to *CUSL*.

Our findings provide empirical support for the mediating role of customer satisfaction in the reputation model. More specifically, customer satisfaction represents a mechanism that underlies the relationship between competence and customer loyalty. Competence leads to customer satisfaction, and customer satisfaction in turn leads to customer loyalty. For the relationship between likeability and customer loyalty, customer satisfaction serves as a complementary mediator. Higher levels of likeability increase customer loyalty directly, but also increase customer satisfaction, which, in turn, leads to customer loyalty. Hence, some of likeability's effect on loyalty is explained by satisfaction.

Case Study Illustration—Moderation

To illustrate the estimation of moderating effects, let's consider the extended corporate model again, as shown in Exhibit A7.1 earlier in this chapter. In the following discussion, we focus on the relationship between customer satisfaction and customer loyalty. Specifically, we introduce switching costs as a moderator variable that can be assumed to negatively influence the relationship between satisfaction and loyalty. The higher the perceived switching costs, the weaker the relationship between these two constructs. We use an extended form of Jones, Mothersbaugh, and Beatty's (2000) scale and measure switching costs reflectively using four indicators (*switch_1* to *switch_4;* Exhibit A7.3), each measured on a 5-point Likert scale (1 = *fully disagree,* 5 = *fully agree*).

Exhibit A7.3 ■ Indicators for Measuring Switching Costs

switch_1	It takes me a great deal of time to switch to another company.
switch_2	It costs me too much to switch to another company.
switch_3	It takes a lot of effort to get used to a new company with its specific "rules" and practices.
switch_4	In general, it would be a hassle switching to another company.

We first need to extend the original model by including the moderator variable. To do so, enter a new construct in the model (see Chapter 2 for detailed explanations) and name it *SC* (i.e. switching costs). Next, we need to assign the indicators *switch_1, switch_2, switch_3*, and *switch_4* to the *SC* construct. Please note that in case of only one moderator variable, like income or age, you would use a single-item construct (i.e., a construct with only one indicator variable that serves as a moderator; see Chapters 2 and 4).

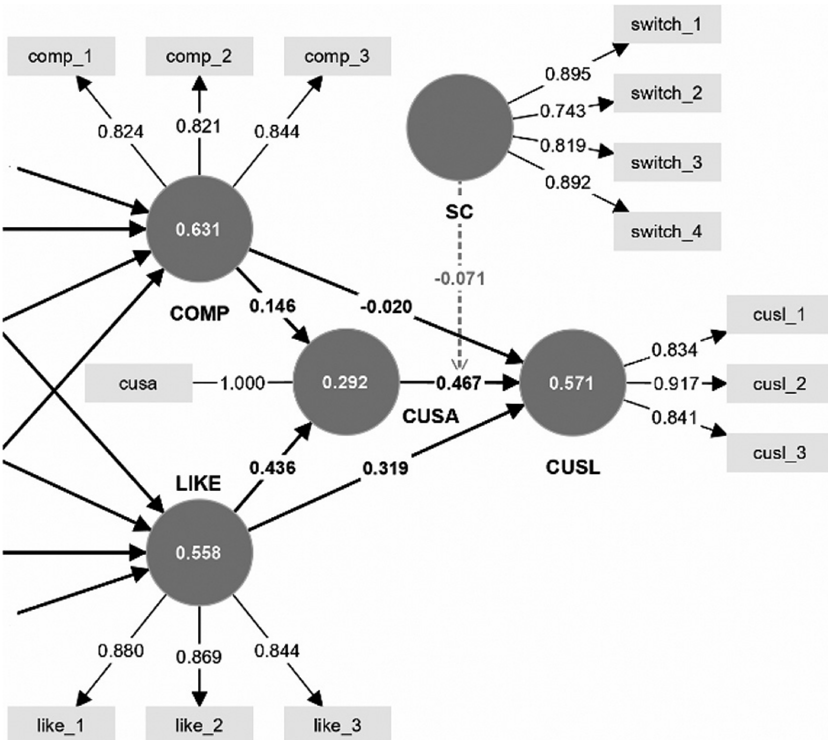
In the next step, we need to add a moderating relationship from *SC* to the path relationship between *CUSA* and *CUSL*. To do so, click on the *Moderating effect* button in the toolbar. Next, left-click on the moderator (*SC*) and move the cursor on the directional arrow that connect *CUSA* with *CUSL*. Exhibit A7.4 shows the model with *SC* as a moderator. When calculating the results, SmartPLS automatically adds a relationship from the moderator to the dependent variable of the moderated relationship, regardless of whether the relationship was included in the model or not (as in Exhibit A7.4).

To compute the moderation results, SmartPLS performs the two-stage approach, which allows to disclose the significance of a moderating effect (which is usually the case in PLS-SEM applications). Furthermore, the two-stage approach is the most versatile approach, as it also works when the exogenous construct or the moderator are measured formatively.

The evaluation of the moderator variable's measurement model shows that the construct measures are reliable and valid. All indicator loadings are above 0.70, and the convergent validity assessment yields an AVE of 0.705, providing support for convergent validity of the switching cost moderator (*SC*). The composite reliability ρ_A has a value of 0.858, indicating internal consistency reliability. In terms of discriminant validity, *SC* exhibits increased HTMT values only with *COMP* (0.850) and *LIKE* (0.802). A further analysis of these HTMT values uses Complete (slower) bootstrapping (percentile bootstrap, 10,000 subsamples, one-tailed testing with a 0.05 significance level, and standard settings for the PLS-SEM algorithm and missing value treatment). As discussed in Chapter 4, we assume the more conservative HTMT value of 0.85 for all relevant construct combinations except *COMP* and *LIKE* as well as *CUSA* and *CUSL*. For these pairs of constructs, we assume the higher 0.90 threshold because of their conceptual similarity. For the additional *SC* construct, we also consider conceptional similarity with *LIKE*, *COMP*, *CUSA* and apply a higher HTMT threshold such as 0.90 or even 1. The results show that the HTMT values are significantly lower ($p < 0.05$) than the critical cutoff values of 0.85, except for *SC* and *COMP* as well as *SC* and *LIKE*. However, as the corresponding HTMT values are significantly lower than 0.9 and 1, respectively, we conclude that inclusion of the *SC* moderator in the model does not entail discriminant validity problems.

Due to the inclusion of additional constructs in the path model (i.e., *SC* and the interaction term), the measurement properties of all other constructs in the path model will change (even though changes will likely be marginal).

Exhibit A7.4 ■ Moderator Analysis Results in SmartPLS

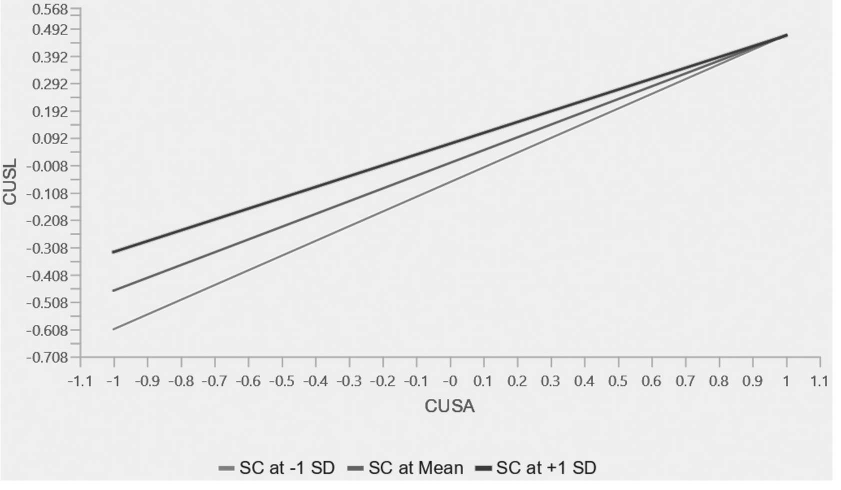


Reanalyzing all measurement models provides support for the measures' reliability and validity. Note that the measurement model results shown in the *Modeling window* stem from Stage 1 of the two-stage approach. The structural model results, however, stem from Stage 2 of the two-stage approach when all constructs are measured with single items.

Our next concern is with the size of the moderating effect. As can be seen in Exhibit A7.4, the interaction term has a negative effect on *CUSL* (–0.071), whereas the simple effect of *CUSA on CUSL is* 0.467. Jointly, these results suggest that the relationship between *CUSA* and *CUSL* is 0.467 for an average level of switching costs. For higher levels of switching costs (e.g., *SC* is increased by one standard deviation unit), the relationship between *CUSA* and *CUSL* decreases by the size of the interaction term (i.e., 0.467 – 0.071 = 0.396). On the contrary, for lower levels of switching costs (e.g., *SC* is decreased by one standard deviation unit), the relationship between *CUSA* and *CUSL* becomes 0.467 + 0.071 = 0.538. To better comprehend the results of the moderator analysis, go to *Final results → Simple slope analysis*. The simple slope plot that follows visualizes the two-way interaction effect (Exhibit A7.5).

The three lines shown in Exhibit A7.5 represent the relationship between *CUSA* (*x*-axis) and *CUSL* (*y*-axis). The middle line represents the relationship for an average level of the moderator variable *SC*. The other two lines represent the relationship between *CUSA* and *CUSL* for higher (i.e., mean value of *SC* plus one standard deviation unit) and lower (i.e., mean value of *SC* minus one standard deviation unit) levels of the moderator variable *SC*. As we can see, the relationship between *CUSA* and *CUSL* is positive for all three lines as indicated by their positive slope. Hence, higher levels of customer satisfaction go hand in hand with higher levels of customer loyalty.

Exhibit A7.5 ■ Simple Slope Plot in SmartPLS



In addition, we can analyze the moderating effect's slope in greater detail. The upper line, which represents a high level of the moderator construct *SC,* has a flatter slope while the lower line, which represents a low level of the moderator construct *SC,* has a steeper slope. This makes sense since the interaction effect is negative. As a rule of thumb and an approximation, the slope of the high level of the moderator construct *SC* is the simple effect (i.e., 0.467) plus the interaction effect (–0.071), while the slope of the low level of the moderator construct *SC* is the simple effect (i.e., 0.467) minus the interaction effect (–0.071). Hence, the simple slope plot supports our previous discussion of the negative interaction term: higher *SC* levels entail a weaker relationship between *CUSA* and *CUSL,* while lower levels of *SC* lead to a stronger relationship between *CUSA* and *CUSL*.

Next, we assess whether the interaction term is significant. For this purpose, we run bootstrapping with the *Percentile bootstrap* procedure, *10,000* Subsamples, *Two tailed* testing, and a significance level of *0.05*. In addition, make sure to select *Do parallel processing*, *Most important (faster)*, and *Fixed seed.* The analysis yields a p value of 0.024 for the path linking the interaction term *SC* × *CUSA* and *CUSL*. Similarly, the 95% percentile bootstrap bias corrected confidence interval of the interaction term's effect is [–0.134, –0.010]. As the confidence interval does not include zero, we conclude that the interaction effect is significant, providing support for the existence of a moderating effect. Overall, these results provide clear support that *SC* exerts a significant and negative effect on the relationship between *CUSA* and *CUSL*. The higher the switching costs, the weaker the relationship between customer satisfaction and customer loyalty.

For the completeness of the results representation, the final step addresses the moderator's f^2 effect size. Recall that Kenny (2018) defines interaction term effect sizes of 0.005, 0.01, and 0.025 as small, medium, and large. By going to *Quality criteria* → *f-square* in the SmartPLS algorithm results report, we learn that the f^2 effect size of the interaction term (i.e., *CUSA * SC*) has a value of 0.014 and, thus, a medium effect.