

# PATH MODEL ESTIMATION

# CASE STUDY ILLUSTRATION—PLS PATH MODEL ESTIMATION (STAGE 4)

To illustrate and explain PLS-SEM, we will use a single data set throughout the book and the SmartPLS 4 software (Ringle, Wende, & Becker, 2022). The representative data set is taken from prior research on the interplay of corporate reputation, customer satisfaction, and customer loyalty, as introduced in Chapter 2. The data set (i.e., the *Corporate reputation data.csv* file) and the ready-to-use SmartPLS project (i.e., the *Corporate Reputation.zip* file) for this case study are available at https://www.pls-sem.net.

### Model Estimation

To estimate the corporate reputation model in SmartPLS, you need to create a new project, import the indicator data (i.e., *Corporate reputation data.csv*), and draw the model as explained in the case study of Chapter 2. Alternatively, you can import the SmartPLS project from a backup file (i.e., *Corporate Reputation.zip*). The procedures to import projects into the SmartPLS software and to open a model are explained in Chapter 2 (i.e., you see the PLS path model in the software).

Before estimating the PLS path model, you may want to adjust the estimation mode of the outer weights used to compute the construct scores. The default setting for computing the construct scores is Mode A for reflective measurement models and Mode B for formative measurement models. However, by double-clicking on a latent variable, a dialog box opens, which allows you to change this default setting. However, the default setting rarely needs to be adjusted. Next, you need to navigate to *Calculate*  $\rightarrow$  *PLS-SEM algorithm*, which you can find at the top of the SmartPLS screen. Alternatively, you can left-click on the wheel symbol in the tool bar labeled *Calculate*, followed by *PLS-SEM algorithm*.

SmartPLS opens a dialog box that allows you to customize the algorithm settings (Exhibit A3.1). Make sure to retain the default weighting scheme setting by selecting Path (i.e., the path weighting scheme; the Factor and PCA alternatives represent special cases which are usually not applied). Further below, you can select the Type of results to be issues by the PLS-SEM algorithm. While in the majority of cases, the analysis should produce Standardized results, some research settings may call for the provision of Unstandardized and Mean-centered results. For instance, unstandardized results facilitate the interpretation in that structural model results can be interpreted in terms of changes in the construct values (rather than standard deviations). However, this setting is only reasonable when all indicators are measured on the same scale (e.g., a 7-point Likert scale). For all measurement model relationships, SmartPLS uses a default value of 1.0 to initialize the PLS-SEM algorithm. Alternatively, you can configure a specific weight for each indicator in the model. When selecting the option Individual in the Initial weight box, you can change the weight of each indicator in the list that opens below. You can also change the weight of all indicators by entering a weight in the box Min located under the list and click on Apply for all indicators button. If you want to return to the initial weight of the indicators, click on the Reset button. In this example, we use the default settings as shown in Exhibit A3.1.

Next, click on the *Data* tab at the top of the dialog box (Exhibit A3.2). In the dialog box that opens, you choose how to treat missing values (*Missing value algorithm*), select a *Weighting vector*, and select among data groups to be analyzed—provided that these have been defined before.

In terms of missing value treatment, neither of the indicator variables in the *Simple model* of our corporate reputation example has more than 5% missing values (specifically, the maximum number of missing values [four missing values; 1.16%] is in *cusl\_2*; see Chapter 2). Thus, we can use the mean value replacement option by selecting the corresponding menu function. SmartPLS also allows you to define *Data groups* in the *Data view*. You can then select these *Group data sets* for group-specific PLS-SEM analyses and a multigroup analysis (MGA), which er explain in detail in the book on the advanced PLS-SEM issues (Hair, Sarstedt, Ringle & Gudergan, 2024).

Under *Weighting vector*, you can specify a weighting variable that assigns the observations different weights in the estimation process to offset imbalances in the sample structure (compared to the population of interest). In the corporate reputation example, we do not specify a weighting variable, so we can retain the *None* default setting. Before initiating the model estimation,

Exhibit A3.1  PLS-SEM Algorithm Settings				
PLS-SEM algorithm		×		
The partial least squares struct estimator of latent variable stru a sequence of partial regressio	ural equation modeling (PLS-SEM) is a composite-based ctural equation models. Essentially, the PLS-SEM algorithm is ns.	More info		
Weighting scheme	Sactor  Path PCA			
Type of results	Standardized	•		
Initial weight	Default	•		
Default actings		Open report		
Delauit Settings	Close Start calcu	lation		

make sure to check the box *Open report* in the lower corner of the dialog box. Next, click on *Start calculation*. SmartPLS then computes the results for a maximum number of 3,000 iterations and as stop criterion of 1.0E-7 (i.e., 0.0000001). These settings cannot be changed in SmartPLS 4.

Occasionally, the algorithm does not start, and a message appears indicating a *Singular data matrix* problem. There are two potential reasons for this issue. First, an indicator is a constant (i.e., the indicator has same value such as "1" for all responses) and thus has zero variance. Second, an indicator is entered twice or is a linear combination of another indicator (e.g., one indicator is a multiple of another such as sales in units and sales in thousands of units).

Exhibit A3.2  Missing Values Dialog Box			
I PLS-SEM algorithm	X		
The partial least squares structural equation n estimator of latent variable structural equation a sequence of partial regressions.	nodeling (PLS-SEM) is a composite-based More info models. Essentially, the PLS-SEM algorithm is		
Missing values			
Missing value algorithm	Mean replacement -		
Weighting vector			
Weighting vector	None -		
Data groups			
Data groups	<ul> <li>✓ Base data set</li> <li>✓ Group data sets</li> <li>Contract plan</li> <li>Prepaid plan</li> </ul>		
	Open report		
Default settings	Close Start calculation		

Under these circumstances, PLS-SEM cannot estimate the model, and the researcher has to modify the model by excluding the problematic indicator(s).

## **Estimation Results**

After convergence, SmartPLS opens the default report, which shows the graphical output with the model estimates in the main window. The left side of the window shows a list of different results, classified into five categories:

- 1. Graphical,
- 2. Final results,
- 3. Quality criteria,
- 4. Algorithm, and
- 5. Model and data.

For example, under *Final results*, you can find the *Outer loadings* and *Outer weights* tables. It is important to note that the results for outer loadings and outer weights are provided by the software for all measurement models, regardless of whether they are specified as reflective or formative. If you have reflective measurement models, you interpret the outer loadings. In contrast, if you have formative measurement models, you primarily interpret the outer weights (note that the outer loadings may also be relevant in the interpretation of formative measurement models; see Chapter 5). The default report provides various other results menus of which the *Stop criterion changes* under *Algorithm* is of initial interest. Here, we can see the number of iterations the PLS-SEM algorithm ran. We will discuss these and further elements of the results report in later chapters.

Exhibit A3.3 shows the results report for the path coefficients in matrix format. The table reads from the row to column. For example, the value 0.504 in the *CUSA* row and the *CUSL* column is the standardized path coefficient of the relationship from *CUSA* to *CUSL*. The path coefficient estimates can also be shown in a list format by clicking on *Path coefficients*  $\rightarrow$ *List* (Exhibit A3.4). Clicking on *Path coefficients*  $\rightarrow$  *Bar chart* opens a bar chart (Exhibit A3.5), which visualizes the path coefficients for each model relationship. Each bar's height represents the strength of the relationship displayed at the bottom of each bar. The chart can be customized by clicking on the information button *customize this chart* on the yellow horizontal bar below the chart.

An initial overview of the results is offered in the *Graphical* output. Initially, SmartPLS provides three key results: (1) the outer loadings or outer

	СОМР	CUSA	CUSL	LIKE
СОМР		0.162	0.009	
CUSA			0.504	
CUSL				
LIKE		0.424	0.342	

#### Exhibit A3.3 Path Coefficients Report (Matrix Format)

Exhibit A3.4 Path Coefficients Report (List Forma
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	Path coefficients
COMP -> CUSA	0.162
COMP -> CUSL	0.009
CUSA -> CUSL	0.504
LIKE -> CUSA	0.424
LIKE -> CUSL	0.342

#### Exhibit A3.5 Path Coefficients Report (Bar chart)



weights for the measurement models, (2) the path coefficients for the structural model relationships, and (3) the  $R^2$  values of the endogenous constructs *CUSA* and *CUSL* (Exhibit A3.6).

The structural model results enable us to determine, for example, that *CUSA* has the strongest effect on *CUSL* (0.504), followed by *LIKE* (0.342) and *COMP* (0.009). Moreover, the three constructs explain 56.2% of the variance of the endogenous construct *CUSL* ( $R^2 = 0.562$ ), as indicated by the value in the circle. *COMP* and *LIKE* also jointly explain 29.5% of the variance of *CUSA* ( $R^2 = 0.295$ ). In addition to examining the sizes of the path coefficients, we must also determine if they are statistically significant. Based on their sizes, it would appear that the relationships *CUSA*  $\rightarrow$  *CUSL* and *LIKE*  $\rightarrow$  *CUSL* are significant. But it seems very unlikely that the hypothesized



path relationship  $COMP \rightarrow CUSL$  (0.009) is significant. As a rule of thumb, for sample sizes of up to about 1,000 observations, path coefficients with standardized values above 0.20 are usually significant, and those with values below 0.10 are usually not significant. Nevertheless, making definite statements about a path coefficient's significance requires determining the coefficient estimates' standard error, which is part of more detailed structural model results evaluations presented in Chapter 6.

At the top of the Graphical output, SmartPLS offers various options for displaying other results elements in, for example, the structural model (Inner model) and the measurement models (Outer model). In the list under Constructs, you can switch between the statistics Average variance extracted (AVE), Composite reliability (rho\_A), Composite reliability (rho\_C), Cronbach's alpha, *R-square*, and *R-square adjusted*, which we will discuss in the following chapters. Depending on the selected setting, SmartPLS will show the corresponding statistic in the center of the constructs in the Graphic output. Note that you can also left-click on the menu to select it and then use the upwards and downwards arrow keys on your keyboard to quickly switch between the alternative results options displayed for Constructs. Similarly, you can switch between different types of parameter estimates in the inner or the outer models. Finally, by clicking on the box under Highlight paths, you can highlight the estimates in the inner model (i.e., structural model) and outer models (i.e., measurement models). Based on the size of their estimated coefficients, the paths appear as thicker or thinner.

On the basis of the path coefficient estimates and their significance, you can determine whether the conceptual model along with its theoretical hy-

potheses are substantiated empirically. Moreover, by examining the relative sizes of the significant path relationships, it is possible to make statements about the relative importance of the exogenous latent variables in predicting an endogenous latent variable. In our simple example, *CUSA* and *LIKE* have moderate to strong effect on *CUSL*, whereas *COMP* does not explain *CUSL* at all.