Mediation Analysis

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Learning Objectives

After reading this chapter, you should:

1. Understand the basic concepts of mediation in a PLS-SEM context
2. Know how to execute a mediation analysis
3. Comprehend how to interpret the results
4. Learn to distinguish between a single and a multiple mediation analysis
5. Acquire the capability to use SEMinR to conduct a mediation analysis based on the corporate reputation example

7.1 Introduction

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Mediation occurs when a construct, referred to as **mediator construct**, intervenes between two other related constructs. More precisely, a change in the exogenous construct causes a change in the mediator construct, which, in turn, results in a change in the endogenous construct in the PLS path model. When such an effect is present, **mediation** can be a useful statistical analysis, if supported by theory and carried out properly.

Consider ■ Fig. 7.1 for an illustration of a **mediating effect** in terms of direct and indirect effects. A **direct effect** describes the relationships linking two constructs with a single arrow. Indirect effects are those structural model paths that involve a sequence of relationships with at least one intervening construct involved. Thus, an **indirect effect** is a sequence of two or more direct effects and is represented visually by multiple arrows. ■ Figure 7.1 shows both a direct effect p_3 between Y_1 and Y_3 and an indirect effect of Y_1 on Y_3 in the form of a $Y_1 \rightarrow Y_2 \rightarrow Y_3$ sequence. The indirect effect, computed as the product $p_1 \cdot p_2$, represents the mediating effect of the construct Y_2 on the relationship between Y_1 and Y_3 . Finally, the sum of the direct and indirect effect is referred to as the **total effect** (i.e., $p_1 \cdot p_2 + p_3$ in ■ Fig. 7.1).

Many PLS path models include mediation effects but are often not explicitly hypothesized and tested (Hair et al., 2022). Only when the possible mediation is theoretically considered and also empirically tested is it possible to fully and accurately understand the nature of the cause–effect relationship. Again, theory is always the foundation of empirical analyses, including mediation. Nitzl, Roldán, and Cepeda Carrión (2016) as well as Cepeda Carrión, Nitzl, and Roldán (2017) and Memon, Cheah, Ramayah, Ting, and Chuah (2018) provide detailed explanations of mediation analysis in PLS-SEM.

■ Fig. 7.1 Mediation model.
(Source: Hair, Hult, Ringle, & Sarstedt, 2022, Chap. 7; used with permission by Sage)

7.2 Systematic Mediation Analysis

A systematic mediation analysis builds on a theoretically established model and hypothesized relationships, including the mediating effect. To begin, it is important to estimate and assess the model, which includes all considered mediators. The next steps are the characterization of the mediation analysis' outcomes and testing of the mediating effects. We address these three steps in the following sections.

7.2.1 Evaluation of the Mediation Model

Evaluating a **mediation model** requires all quality criteria of the measurement and structural models to be met, as discussed in ► Chaps. 4, 5, and 6. The analysis begins with the assessment of the reflective and formative measurement models. For example, a lack of reliability for one or more reflective mediator constructs will have a meaningful impact on the estimated relationships in the PLS path model (i.e., the indirect paths can become considerably smaller than expected). For this reason, it is important to ensure that the reflectively measured mediator constructs exhibit a high level of reliability.

After establishing the reliability and validity of measurement models for the mediator as well as the other exogenous and the endogenous constructs, it is important to consider all structural model evaluation criteria. For instance, high collinearity must not be present since it is likely to produce biased path coefficients. For example, as a result of collinearity, the direct effect may become nonsignificant, suggesting the absence of mediation even though, for example, complementary mediation may be present (see the next section). Likewise, high collinearity levels may result in unexpected sign changes, rendering any differentiation between different mediation types problematic. Moreover, a lack of the mediator construct's discriminant validity with the exogenous or endogenous construct might result in a strong and significant but substantially biased indirect effect, consequently leading to incorrect implications regarding the existence or type of mediation. After meeting the relevant assessment criteria for reflective and formative measurement models, as well as the structural model, the actual mediation analysis follows.

7.2.2 Characterization of Outcomes

The question of how to test mediation has attracted considerable attention in methodological research. Decades ago, Baron and Kenny (1986) presented a mediation analysis approach, referred to as causal step approach, which many researchers still routinely draw upon (Rasoolimanesh, Wang, Roldán, & Kunasekaran, 2021). More recent research, however, concludes there are conceptual and methodological problems with Baron and Kenny's (1986) approach (e.g., Hayes, 2018). Against this background, our description builds on Zhao, Lynch, and Chen (2010), who offer a synthesis of prior research on mediation analysis and corresponding guidelines for future research (Nitzl et al., 2016).

The authors characterize three types of mediation:

- **Complementary mediation:** the indirect effect and the direct effect are significant and point in the same direction.
- **Competitive mediation:** the indirect effect and the direct effect are significant but point in opposite directions.
- **Indirect-only mediation:** the indirect effect is significant, but not the direct effect.

In addition, they identify two types of non-mediation:

- **Direct-only non-mediation:** the direct effect is significant, but not the indirect effect.
- **No-effect non-mediation:** neither the direct nor the indirect effect is significant.

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As a result, a mediation analysis may show that mediation does not exist at all (i.e., direct-only non-mediation and no-effect non-mediation) or, in case of a mediation effect, the mediator construct accounts either for some (i.e., complementary and competitive mediation) or for all of the observed relationship between two latent variables (i.e., indirect-only mediation). In that sense, the Zhao et al. (2010) procedure closely corresponds to Baron and Kenny's (1986) concepts of **partial mediation** (i.e., complementary mediation), **suppressor effect** (i.e., competitive mediation), and **full mediation** (i.e., indirect-only mediation).

Testing for the type of mediation in a model requires running a series of analyses, which ■ Fig. 7.2 illustrates. The first step addresses the significance of the indirect effect ($p_1 \cdot p_2$) via the mediator construct (Y_2) as shown in ■ Fig. 7.1. If the indirect effect is not significant (right-hand side of ■ Fig. 7.2), we conclude that Y_2 does not function as a mediator in the tested relationship. While this result may seem disappointing at first sight, as it does not provide empirical support for a

■ Fig. 7.2 Mediation analysis procedure. (Source: authors' own figure; Zhao et al., 2010)

hypothesized mediating relationship, further analysis of the direct effect p_3 can point to as yet undiscovered mediators. Specifically, if the direct effect is significant, we could conclude it is possible that there is an omitted mediator, which potentially explains the relationship between Y_1 and Y_3 (direct-only non-mediation). If the direct effect is also nonsignificant (no-effect non-mediation), however, we must conclude that our theoretical framework is flawed. In this case, we should go back to theory and reconsider the path model setup. Note that this situation can occur despite a significant total effect of Y_1 on Y_3 ($p_1 \cdot p_2 + p_3$ in ■ Fig. 7.1).

We may, however, find general support for a hypothesized mediating relationship in our initial analysis based on a significant indirect effect (left-hand side of ■ Fig. 7.2). As before, our next interest is with the significance of the direct effect p_3 . If the direct effect is not significant, we face the situation of indirect-only mediation. This situation represents the best-case scenario, as it suggests that our mediator fully complies with the hypothesized theoretical framework. If the direct effect p_3 is significant, we still find support for the hypothesized mediating relationship. However, the total effect between the two constructs Y_1 and Y_3 stems partially from the direct effect p_3 and partially from the indirect effect $p_1 \cdot p_2$. In this situation, we can distinguish between complementary and competitive mediation.

Complementary mediation describes a situation in which the direct effect and the indirect effect $p_1 \cdot p_2$ point in the same direction. In other words, the product of the direct effect and the indirect effect (i.e., $p_1 \cdot p_2 \cdot p_3$) is positive (■ Fig. 7.2). On the contrary, in competitive mediation – also referred to as **inconsistent mediation** (MacKinnon, Fairchild, & Fritz, 2007) – the direct effect p_3 and either indirect effect p_1 or p_2 have opposite signs. In other words, the product of the direct effect and the indirect effect $p_1 \cdot p_2 \cdot p_3$ is negative (■ Fig. 7.2). It is important to note that in competitive mediation, the mediating construct acts as a suppressor effect, which substantially decreases the magnitude of the total effect of Y_1 on Y_3 . Therefore, when competitive mediation occurs, researchers need to carefully analyze the theoretical substantiation of all effects involved.

7.2.3 Testing Mediating Effects

Prior testing of the significance of mediating effects relied on the Sobel (1982) test, which should no longer be used (Hair et al., 2022, Chap. 7). Instead of using the Sobel (1982) test, researchers should bootstrap the sampling distribution of the indirect effect (Preacher & Hayes, 2004; Preacher & Hayes, 2008a). Bootstrapping (see ► Chap. 5) makes no assumptions about the shape of the variables' distribution or the sampling distribution of the statistics and can be applied to small sample sizes with more confidence. Even though bootstrapping has been introduced for the mediation analysis in regression models, the approach is perfectly suited for the PLS-SEM method as well. In addition, bootstrapping the indirect effect yields higher levels of statistical power compared to the Sobel (1982) test (Zhao et al., 2010).

- There is no need for researchers to use the PROCESS routine (Hayes, 2018) proposed for regression models to analyze mediation effects in PLS-SEM (i.e., in a subsequent tandem analysis, by using the latent variable scores obtained by PLS-SEM to run a regression model in PROCESS), since bootstrapping in PLS-SEM provides all relevant results with more accuracy and precision than PROCESS (Sarstedt, Hair, Nitzl, Ringle, & Howard, 2020).

7.3 Multiple Mediation Models

In the previous sections, we considered the case of a single mediator construct, which accounts for the relationship between an exogenous and an endogenous construct. Analyzing such a model setup is also referred to as **single mediation analysis**. More often, however, when evaluating structural models, exogenous constructs exert their influence through more than one mediating variable. This situation requires running **multiple mediation analyses** for the hypothesized relationships via more than one mediator in PLS-SEM (Cepeda Carrión et al., 2017; Nitzl et al., 2016). As an example of multiple mediation with two mediators, consider ■ Fig. 7.3. In this model, p_3 represents the direct effect between the exogenous construct and the endogenous construct. The **specific indirect effect** of Y_1 on Y_3 via mediator Y_2 is quantified as $p_1 \cdot p_2$. For the second mediator Y_4 , the specific indirect effect is given by $p_4 \cdot p_5$. In addition, we can consider the specific indirect effect of Y_1 on Y_3 via both mediators, Y_2 and Y_4 , which is quantified as $p_1 \cdot p_6 \cdot p_5$. The **total indirect effect** is the sum of the specific indirect effects (i.e., $p_1 \cdot p_2 + p_4 \cdot p_5 + p_1 \cdot p_6 \cdot p_5$). Finally, the total effect of Y_1 on Y_3 is the sum of the direct effect and the total indirect effects (i.e., $p_3 + p_1 \cdot p_2 + p_4 \cdot p_5 + p_1 \cdot p_6 \cdot p_5$).

To test a **multiple mediation model**, such as the one shown in ■ Fig. 7.3, researchers may be tempted to run a set of separate single mediation analyses, one for each proposed mediator (in this case, Y_2 and Y_4) separately. However, as Preacher and Hayes (2008a, 2008b) point out, this approach is problematic for at least two reasons. First, one cannot simply add up the indirect effects calculated in several single mediation analyses to derive the total indirect effect, as the mediators in a multiple mediation model typically will be correlated. As a result, the specific indirect effects, estimated using several single mediation analyses, will be biased

■ Fig. 7.3 Multiple mediation model. (Source: Hair et al., 2022, Chap. 7; used with permission by Sage)

and will not sum to the total indirect effect through the multiple mediators. Second, hypothesis testing and confidence intervals calculated for specific indirect effects may not be accurate due to the omission of other, potentially important, mediators. By considering all mediators at the same time in one model, we gain a more complete picture of the mechanisms through which an exogenous construct affects an endogenous construct (Sarstedt et al., 2020). Hence, we recommend including all relevant mediators in the model and, thus, analyzing their hypothesized effects simultaneously. In a multiple mediation model, a specific indirect effect can be interpreted as the indirect effect of Y_1 on Y_3 through a given mediator, while controlling for all other included mediators.

The analysis of a multiple mediation model also follows the procedure shown in ■ Fig. 7.2. That is, we should test the significance of the indirect effects (i.e., each specific and total indirect effects) and the direct effect between the exogenous construct and the endogenous construct. In addition, we should test whether the total indirect effect is significant. To assess the significance of the specific indirect effects, the total indirect effect, and the direct effect, we should use the results of the bootstrap routine. Similar to the path coefficient significance test (► Chap. 6), we should select 10,000 (or more) bootstrap subsamples and report the 95% percentile bootstrap confidence intervals for the final result reporting. On this basis, the analysis and result interpretation of a multiple mediation follow the same procedure as a single mediation analysis. Nitzl et al. (2016) as well as Cepeda Carrión et al. (2017) and Sarstedt et al. (2020) provide additional insights on multiple mediation analysis in PLS-SEM.

7.4 Case Study Illustration: Mediation Analysis

We now perform a deeper investigation of the relationship between the two dimensions of corporate reputation (*LIKE* and *COMP*) on the key construct customer loyalty (*CUSL*). The theory of cognitive dissonance (Festinger, 1957) proposes that 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. Previous research has demonstrated, however, that customer satisfaction is the primary driver of customer loyalty (Anderson & Fornell, 2000). Therefore, we expect that customer satisfaction mediates the relationship between likeability and customer loyalty as well as competence and customer loyalty (■ Fig. 7.4). To test these hypothesized effects, we will apply the procedure shown in ■ Fig. 7.2.

To begin the mediation analysis, we need to ensure that all construct measures are reliable and valid and that the structural model meets all quality criteria. As we have conducted these evaluations in ► Chaps. 5 and 6 and found the model to be satisfactory, we can now move directly to the mediation analysis. If your model has not yet been thoroughly assessed, please do so before conducting the mediation analysis.

As illustrated in ■ Fig. 7.2, we first need to test for significance of the relevant indirect effects in the extended corporate reputation model (■ Fig. 7.4). 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, dashed line

■ **Fig. 7.4** Extended corporate reputation model with highlighted mediation effects. (Source: authors' own figure)

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in ■ Fig. 7.4). 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, dotted line in ■ Fig. 7.4). To test for significance of these path coefficients' products, we first need to estimate and bootstrap the model and summarize the results (see ► Chaps. 5 and 6 for details and thorough explanation).

```
# Load the SEMinR library
library(semnr)

# Load the data
corp_rep_data <- corp_rep_data

# Create measurement model
corp_rep_mm_ext <- constructs(
  composite("QUAL", multi_items("qual_", 1:8), weights = mode_B),
  composite("PERF", multi_items("perf_", 1:5), weights = mode_B),
  composite("CSOR", multi_items("csor_", 1:5), weights = mode_B),
  composite("ATTR", multi_items("attr_", 1:3), weights = mode_B),
  composite("COMP", multi_items("comp_", 1:3)),
  composite("LIKE", multi_items("like_", 1:3)),
  composite("CUSA", single_item("cusa")),
  composite("CUSL", multi_items("cusl_", 1:3))
)
```



```

# Create structural model
corp_rep_sm_ext <- relationships(
  paths(from = c("QUAL", "PERF", "CSOR", "ATTR"), to = c("COMP",
"LIKE")),
  paths(from = c("COMP", "LIKE"), to = c("CUSA", "CUSL")),
  paths(from = c("CUSA"), to = c("CUSL"))
)

# Estimate the model
corp_rep_pls_model_ext <- estimate_pls(
  data = corp_rep_data,
  measurement_model = corp_rep_mm_ext,
  structural_model = corp_rep_sm_ext,
  missing = mean_replacement,
  missing_value = "-99"
)

# Summarize the results of the model estimation
summary_corp_rep_ext <- summary(corp_rep_pls_model_ext)

# Bootstrap the model
boot_corp_rep_ext <- bootstrap_model(
  seminr_model = corp_rep_pls_model_ext,
  nboot = 1000,
  cores = parallel::detectCores(),
  seed = 123
)

# Summarize the results of the bootstrap
summary_boot_corp_rep_ext <- summary(boot_corp_rep_ext, alpha =
0.05)

```

The results for total indirect effects can be found by inspecting the **total_indirect_effects** element within the **summary_corp_rep_ext** object, **summary_corp_rep_ext\$total_indirect_effects**. Specific indirect paths can be evaluated for significance, by using the **specific_effect_significance()** function. This function takes a bootstrapped model object, an antecedent construct name, and an outcome construct name as arguments and returns the bootstrap confidence interval for the total indirect paths from the antecedents to the outcome construct (■ Table 7.1).

We use the **specific_effect_significance()** function on the **boot_corp_rep_ext** object and specify the indirect path using the **from** and **to** arguments. A separate path must be specified for *COMP*, through *CUSA*, to *CUSL*, and another for *LIKE*, through *CUSA*, to *CUSL*:

Table 7.1 A list of arguments for the `specific_effect_significance()` function

Argument	Value
<i>boot_seminr_model</i>	The bootstrapped SEMinR model containing the estimated paths
<i>from</i>	The antecedent construct name
<i>through</i>	A vector of all mediating construct names
<i>to</i>	The outcome construct name
<i>alpha</i>	The statistical power in percentage to be used for determining confidence intervals. The default is 0.05 (5%) for a two-tailed test

Source: authors' own table

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```
# Inspect total indirect effects
summary_corp_rep_ext$total_indirect_effects

# Inspect indirect effects
specific_effect_significance(boot_corp_rep_ext,
  from = "COMP",
  through = "CUSA",
  to = "CUSL",
  alpha = 0.05)
specific_effect_significance(boot_corp_rep_ext,
  from = "LIKE",
  through = "CUSA",
  to = "CUSL",
  alpha = 0.05)
```

Tip

The `specific_effect_significance()` can be used for calculating the bootstrap mean, standard deviation, *t*-statistic, and bootstrap confidence intervals for paths involving multiple mediators. The `through` argument can take multiple mediating constructs as arguments (e.g., `through = c("construct1", "construct2")`). Therefore, this function can be used for testing models with serial mediation.

The results in Fig. 7.5 show that the total indirect effect of *COMP* on *CUSL* is **0.074**, and the total indirect effect of *LIKE* on *CUSL* is **0.220**. When inspecting the bootstrap confidence intervals, we conclude that – since the confidence interval does not include the zero for either effect – the effects are significant at the specified 5% level. Note that the confidence intervals will look slightly different in your analysis, as they are derived from bootstrapping, which is a random process.

```
~/seminr/
> # Inspect total indirect effects
> summary_corp_rep_ext$total_indirect_effects
  QUAL PERF CSOR ATTR COMP LIKE CUSA CUSL
QUAL 0.000 0.000 0.000 0.000 0.000 0.000 0.228 0.248
PERF 0.000 0.000 0.000 0.000 0.000 0.000 0.094 0.089
CSOR 0.000 0.000 0.000 0.000 0.000 0.000 0.086 0.105
ATTR 0.000 0.000 0.000 0.000 0.000 0.000 0.085 0.101
COMP 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.074
LIKE 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.220
CUSA 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000
CUSL 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000
> # Inspect indirect effects
> specific_effect_significance(boot_corp_rep_ext, from = "COMP", through = "CUSA", to = "CUSL", al
pha = 0.05)
  Original Est. Bootstrap Mean   Bootstrap SD      T Stat.      2.5% CI      97.5% CI
1 0.07350093    0.07443445    0.03651814    2.01272396    0.00296709    0.14620781
> specific_effect_significance(boot_corp_rep_ext, from = "LIKE", through = "CUSA", to = "CUSL", al
pha = 0.05)
  Original Est. Bootstrap Mean   Bootstrap SD      T Stat.      2.5% CI      97.5% CI
1 0.22001302    0.21993527    0.03687955    5.96571802    0.14917504    0.29318977
> |
```

■ Fig. 7.5 Results of total indirect effects and specific effect confidence intervals. (Source: authors' screenshot from R)

Following the mediation analysis procedure (■ Fig. 7.2), we can now ascertain if the direct effect is significant for each of the two mediation effects (i.e., *COMP* to *CUSL* and *LIKE* to *CUSL*). These paths can be accessed by inspecting the **paths** element of the **summary_corp_rep_ext** object. The confidence intervals for the direct effects can be evaluated by inspecting the **bootstrapped_paths** element of the **summary_boot_corp_rep_ext** object.

```
# Inspect the direct effects
summary_corp_rep_ext$paths

# Inspect the confidence intervals for direct effects
summary_boot_corp_rep_ext$bootstrapped_paths
```

The results in ■ Fig. 7.6 show that the direct effect from *COMP* to *CUSL* is **0.006** with a 95% confidence interval **[−0.104; 0.115]**. As this interval includes zero, this direct effect is not significant. According to the guidelines shown in ■ Fig. 7.2, we therefore conclude that the relationship between *COMP* and *CUSL* is fully mediated by *CUSA*. Next, we need to consider the direct relationship between *LIKE* and *CUSL*, which has a **0.344** path coefficient with a 95% confidence interval **[0.231; 0.449]**. As this confidence interval does not include zero, we conclude that *CUSA* partially mediates the effect of *LIKE* on *CUSL*. We now need to further evaluate if *CUSA* acts as a complementary or competitive mediator for the effect of *LIKE* on *CUSL*. To do so, we need to determine whether the product of the direct and indirect effects ($p_1 \cdot p_2 \cdot p_3$ in ■ Fig. 7.1) has a positive or negative sign. To show these paths, we use the path element

```

Console Terminal Jobs
~/seminr/
> # Inspect the direct effects
> summary_corp_rep_ext$paths
      COMP  LIKE  CUSA  CUSL
R^2      0.631 0.558 0.292 0.562
AdjR^2    0.627 0.552 0.288 0.558
QUAL      0.430 0.380      .      .
PERF      0.295 0.117      .      .
CSOR      0.059 0.178      .      .
ATTR      0.086 0.167      .      .
COMP      .      . 0.146 0.006
LIKE      .      . 0.436 0.344
CUSA      .      .      . 0.505
> # Inspect the confidence intervals for direct effects
> summary_boot_corp_rep_ext$bootstrapped_paths
      Original Est. Bootstrap Mean Bootstrap SD T Stat. 2.5% CI 97.5% CI
QUAL -> COMP      0.430      0.431      0.065  6.603  0.303  0.552
QUAL -> LIKE      0.380      0.384      0.067  5.699  0.253  0.514
PERF -> COMP      0.295      0.301      0.064  4.611  0.173  0.422
PERF -> LIKE      0.117      0.123      0.073  1.613 -0.011  0.261
CSOR -> COMP      0.059      0.059      0.054  1.084 -0.044  0.165
CSOR -> LIKE      0.178      0.177      0.056  3.205  0.065  0.282
ATTR -> COMP      0.086      0.084      0.055  1.565 -0.018  0.194
ATTR -> LIKE      0.167      0.165      0.065  2.573  0.034  0.291
COMP -> CUSA      0.146      0.147      0.071  2.047  0.007  0.281
COMP -> CUSL      0.006      0.006      0.055  0.104 -0.104  0.115
LIKE -> CUSA      0.436      0.435      0.062  7.069  0.312  0.555
LIKE -> CUSL      0.344      0.343      0.056  6.175  0.231  0.449
CUSA -> CUSL      0.505      0.505      0.042 12.074  0.420  0.586
>

```

■ **Fig. 7.6** Results of direct effects and confidence intervals for direct effects. (Source: authors' screenshot from R)

of `summary_corp_rep_ext`. We can subset this path's matrix to display the path from *LIKE* to *CUSA*, `summary_corp_rep_ext$paths["LIKE", "CUSA"]`. We need to repeat this step for each of the three paths in the mediation relationship and then multiply the paths.

```

# Calculate the sign of p1*p2*p3
summary_corp_rep_ext$paths["LIKE", "CUSL"] *
  summary_corp_rep_ext$paths["LIKE", "CUSA"] *
  summary_corp_rep_ext$paths["CUSA", "CUSL"]

```

The results in ■ **Fig. 7.7** show that the product of the three paths is positive (**0.076**). We therefore conclude that *CUSA* acts as a complementary partial mediator in the relationship between *LIKE* and *CUSL*.

```

Console Terminal x Jobs x
~/seminr/
> # Calculate the sign of p1*p2*p3
> summary_corp_rep_ext$paths["LIKE", "CUSL"] *
+ summary_corp_rep_ext$paths["LIKE", "CUSA"] *
+ summary_corp_rep_ext$paths["CUSA", "CUSL"]
[1] 0.07569007
>

```

■ Fig. 7.7 Results of calculating $p_1 \cdot p_2 \cdot p_3$. (Source: authors' screenshot from R)

Summary

Mediation occurs when a third variable, referred to as a mediator construct, intervenes between two other related constructs. More precisely, a change in the exogenous construct results in a change in the mediator construct, which, in turn, affects the endogenous construct in the model. After theoretically establishing a mediation model and its hypothesized relationships, a systematic mediation analysis includes the estimation and evaluation of the mediation model results, their characterization, and testing for the mediating effects. Analyzing the strength of the mediator construct's relationships with the other construct(s) enables the researcher to better understand the mechanisms that underlie the relationship between an exogenous and an endogenous construct. In the simplest form, the PLS-SEM analysis considers only one mediator construct, but the model also can involve multiple mediator constructs that need to be analyzed simultaneously.

? Exercise

We continue analyzing the influencer model as introduced in the exercise section of ► Chap. 3. In the model (► Fig. 3.10), SIC has a direct effect on *PI*, but also two indirect effects via *PL* and *PQ*. In the following, we turn our attention to the potential mediating effects of SIC on *PI*:

1. Is the indirect effect between SIC and *PI* via *PL* significant?
2. Is the indirect effect between SIC and *PI* via *PQ* significant?
3. Is the direct relationship between SIC and *PI* significant?
4. Which types of mediation effects are present?

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