Chapter 8
Mediation Analyses in Partial Least Squares Structural Equation Modeling: Guidelines and Empirical Examples

Gabriel Cepeda Carrión, Christian Nitzl, and José L. Roldán

Abstract Partial least squares structural equation modeling (PLS-SEM) is one of the options used to analyze mediation effects. Over the past few years, the methods for testing mediation have become more sophisticated. However, many researchers continue to use outdated methods to test mediation effects in PLS-SEM, which can lead to erroneous results in some cases. One reason for the use of outdated methods is that PLS-SEM tutorials do not draw on the newest statistical findings. This chapter illustrates how to perform modern procedures in PLS-SEM by challenging the conventional approach to mediation analysis and providing better alternatives.

These novel methods offer a wide range of testing options (e.g., multiple mediators) that go beyond simple mediation analysis alternatives, helping researchers to discuss their studies in a more accurate way. This chapter seeks to illustrate and help to operationalize the mediation in Nitzl et al.'s (Indus Manag Data Syst 116:1849–1864, 2016) paper about mediation in PLS, published in *Industrial Management & Data Systems*, with examples of two potential mediations: a multiple mediation with two mediators and a multistep multiple mediation.

8.1 Introduction

Partial least squares structural equation modeling (PLS-SEM) is a variance-based structural equation modeling technique that has been used to model latent variables, specifically composites, and the relationships between them (Henseler 2017). Therefore, it is a useful tool for testing hypotheses and answering research questions.

G.C. Carrión (✉) • J.L. Roldán
Faculty of Economics and Business, Department of Business Administration and Marketing, Universidad de Sevilla, Av. Ramón y Cajal 1, 41018 Seville, Spain
e-mail: gabi@us.es; jlroldan@us.es

C. Nitzl
Institute for Finance, Risk Management, and Management Accounting, University of the German Armed Forces Munich, Werner-Heisenberg-Weg 39, 85577 Neubiberg, Germany
e-mail: christian.nitzl@unibw.de

H. Latan, R. Noonan (eds.), *Partial Least Squares Path Modeling*,
DOI 10.1007/978-3-319-64069-3_8

One of these research questions investigates mediation. Mediation considers the presence of an intermediate variable or mechanism that transmits the effect of an antecedent variable to an outcome (Aguinis et al. 2017). For instance, mediation usually appears when the effect of reputation on customer loyalty is transmitted by customer satisfaction, such that reputation impact on customer satisfaction in turn influences customer loyalty (Hair et al. 2017). Hence, mediation refers to underlying effects that link antecedent and consequences variables. Despite the continuous use of mediation testing, studies in PLS-SEM often do not consider mediation effects in their hypotheses and therefore do not analyze the relevance in relevant structural models (Hair et al. 2017). In the worst case, researchers focus only on direct relationships and overlook mediation effects.

While there is a large body of literature on methods for testing mediation effects (Hayes and Scharkow 2013), the analytical tools that researchers have used in PLS-SEM studies to test mediation effects have generally been outdated compared to those for other statistical methods. Nitzl et al. (2016) have recently shown the misapplication of Baron and Kenny's procedure in the PLS-SEM field. Whereas researchers studying covariance-based structural equation modeling (CB-SEM) have often considered the latest findings when testing mediation (e.g., Iacobucci et al. 2007; Hair et al. 2010), most PLS-SEM researchers fail to do so, and in fact, they often avoid carrying out this kind of analysis. This is somewhat surprising because state-of-the-art applications for testing the significance of a mediator are also very suitable for PLS-SEM.

Therefore, we can state that one of the key reasons authors do not assess mediation effects in PLS path models is the lack of illustrative guidelines on conducting state-of-the-art mediation analysis with PLS-SEM. Furthermore, because these publications on PLS-SEM have been subjected to several recent changes (Henseler et al. 2016; Nitzl et al. 2016), an adequate illustration of these new guidelines related to mediation is badly needed.

Therefore, the objective of our chapter is to provide researchers with a nice illustration to implement mediation models in PLS-SEM. Thus, we offer complete examples and guidelines on how to conduct mediation analysis using PLS-SEM, inspired by Nitzl et al. (2016).

Our chapter is structured as follows: We first describe an advanced procedure for mediation analysis in PLS-SEM. We then list different types of mediation. Next, we offer illustrative examples of how to perform and discuss a mediation analysis with PLS. We also offer detailed guidelines for carrying out this type of analysis in PLS. Finally, we summarize our chapter and highlight potential avenues for future research.

8.2 Advanced Procedure for Mediation Analysis in PLS-SEM

8.2.1 The Mediation Effect

The core characteristic of a mediating effect (i.e., indirect effect or mediation) is that it involves a third variable that plays an intermediate role in the relationship between the independent and dependent variables. Technically speaking, the effect of the independent variable X on the dependent variable Y is mediated by a third variable, M, called the mediating variable or mediator (see Fig. 8.1). Thus, when we formulate mediation hypotheses, we focus on "how, or by what means, an independent variable (X) affects a dependent variable (Y) through one or more potential intervening variables, or mediators (M)" (Preacher and Hayes 2008). The researcher's objective in mediation analysis is mainly explanation (Henseler et al. 2016), although some scholars have also recently added the purpose of prediction (Shmueli et al. 2016).

Figure 8.1a shows the total effect c of the causal relationship between variables X and Y, and Fig. 8.1b shows a mediated effect in which X exerts an indirect effect $a \times b$ through M on Y.

Once we have defined the mediation effect, we briefly describe the procedure developed by Nitzl et al. (2016) to test mediation effects on PLS-SEM and also define the different types of mediation that researchers can find in their analysis. The procedure considers five important statements for testing mediating effects in PLS:

1. Testing the indirect effect $a \times b$ provides researchers with all the information they need to assess the significance of a mediation. Therefore, it is not necessary to conduct separate tests for paths a and b by applying PLS-SEM.

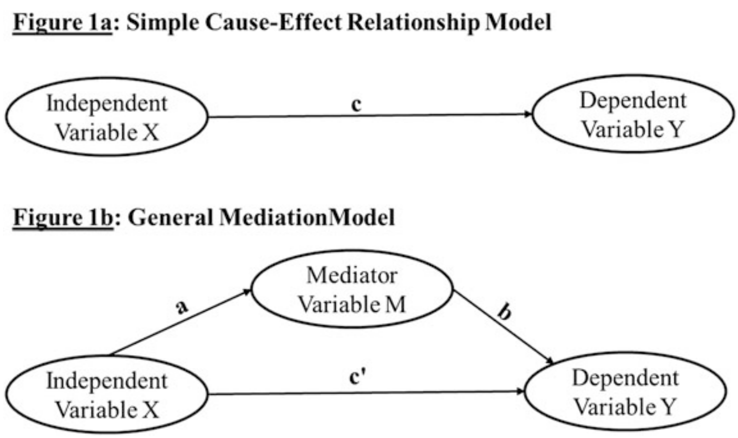


Fig. 8.1 (**a**) Simple cause-effect relationship and (**b**) general mediation model

2. The strength of the indirect effect $a \times b$ should determine the size of the mediation. Therefore, it is also not necessary to test the difference between c and c'.
3. A significant indirect effect $a \times b$ is the only prerequisite for establishing a mediation effect.
4. A bootstrap test should be used to test the significance of the indirect effect $a \times b$.
5. The significance of the direct effect (c') has to be tested in order to determine the type of effect and/or mediation.

These important statements are summarized in the procedure described by Nitzl et al. (2016). The procedure has two main steps (see Nitzl et al. (2016) for a more detailed description).

Step 1: Determining the significance of indirect effects and their magnitude
The indirect effect $a \times b$ must be significant in step 1 to establish a mediation effect. When testing mediation effects in PLS-SEM, researchers should bootstrap the sample of the indirect effects in order to obtain necessary information about the population distribution, in accordance with the nonparametric PLS-SEM method where bootstrap procedures are typically used for inference statistics, such as the calculation of the so-called pseudo t-value and confidence intervals (Henseler et al. 2009). The bootstrapping procedure is a nonparametric inferential technique that randomly withdraws several subsamples (e.g., 5000) with replacement from the original dataset. PLS-SEM uses each of the subsamples to estimate the underlying PLS path model.

The bootstrap routines of PLS-SEM software often provide results for at least direct effects (e.g., path a and path b). However, for a more detailed analysis of mediation, particularly in more complex model structures (e.g., multiple mediators), it is often necessary to compute the bootstrapping results for the indirect effects with the help of a spreadsheet application, such as Microsoft Excel or CALC in Open Office. For each bootstrapping subsample, the results of path a must be multiplied by path b to create the product term $a \times b$ of the indirect effect in a new column. For example, the computation of $k = 5000$ bootstrapping subsamples entails the generation of $k = 5000$ products $a \times b$ in a new column. The information about the characteristics of the distribution of mediation effects is obtained by calculating a ci% confidence interval for $a \times b$. For that, the subsamples (k) for $a \times b$ from the bootstrapping procedure must be arranged from smallest to largest (Hayes 2009). In the next step, a researcher has to select a specific alpha error; for example, for a probability of error of 5%, a 95% confidence interval must be determined with a 2.5% probability of error at each tail when conducting a two-sided test. The lower bound of $a \times b$ is in the $k \times (.5 - \text{ci}\%/2)$th ordinal position of the ordered list; for example, if one uses $k = 5000$ subsamples and a 95% confidence interval, the lower bound is the $5000 \times (.5 - 0.95/2) = 125$th ordinal position. Similarly, the $(1 + k \times (.5 + \text{ci}\%/2))$th ordinal determines the upper bound of the bootstrap confidence, which is the $1 + 5000 \times (.5 + 0.95/2) = 4876$th in the previous example. If *zero* is not included in the confidence interval, a researcher can assume that there is a significant indirect effect $a \times b$.

Another problem often occurs when the mean of the bootstrapped distribution for the indirect effect $a \times b$ is not equal to the estimated indirect effect $a \times b$ (Chernick 2011). As a result, researchers must correct for this bias in PLS-SEM. This can be accomplished by calculating the difference between the estimated indirect effect $a_{\mathrm{PM}} \times b_{\mathrm{PM}}$ from the path model (PM) and the mean value of the indirect effect $a_B \times b_B$ from the bootstrap sample (B). Consequently, the bias-corrected ci% confidence interval for an indirect effect $a \times b$ can be defined as

$$\begin{aligned}&[(k \times (.5 - \mathrm{ci}\%/2))\ \mathrm{th} + (a_{\mathrm{PM}} \times b_{\mathrm{PM}} - a_B \times b_B)\,;\\&(1 + k \times (.5 + \mathrm{ci}\%/2))\ \mathrm{th} + (a_{\mathrm{PM}} \times b_{\mathrm{PM}} - a_B \times b_B)]\,.\end{aligned} \tag{8.1}$$

Hayes and Scharkow (2013) show that the bias-corrected bootstrap confidence interval is the best approach for detecting mediation effects when a mediation effect is present (i.e., Type II error or power). Conversely, the percentile bootstrap confidence interval that is not bias corrected is a good compromise if a researcher is also concerned about Type I errors (Hayes and Scharkow 2013). Thus, the bias-corrected bootstrap confidence interval is the most reliable test if power is of the utmost concern, while the percentile bootstrap confidence interval provides a good compromise.

Step 2: Determining the type of effect and/or mediation
Step 2 involves defining the type of effect and/or mediation. A mediating effect always exists when the indirect effect $a \times b$ in step 1 is significant. The current mediation literature discusses two different types of mediation, full and partial mediation. Partial mediation can be subdivided into complementary and competitive partial mediation. We also discuss two effects that occur when the indirect effect is not significant, which means that only the direct effect is significant and no effect at all is significant. The latter cases do not represent a mediating effect in the narrow sense.

8.2.2 Full Mediation

A full mediation is indicated in the case where the direct effect c' is not significant, whereas the indirect effect $a \times b$ is significant. This means only the indirect effect via the mediator exists. In other words, full mediation means that the effect of the variable X on Y is completely transmitted with the help of another variable M. It also means the condition Y completely absorbs the positive or negative effect of X. In this way, it can completely pass an effect, or it can completely hinder the effect in terms of another effect. Technically speaking, the variable X extracts its influence only under a certain condition of M on Y. However, in the case of small samples, a researcher is to exercise some caution when talking about full mediation. As Rucker et al. (2011) showed, "the smaller the sample, the more likely mediation (when present) is to be labeled full as opposed to partial, because c' is more easily rendered non-significant" (p. 364). Hence, it is advisable to ensure that the sample size is great enough so that the necessary power of 0.8 for an alpha level of 0.05 for detecting effects in a PLS path model is obtained. For a simple mediation model, the necessary sample size can be quite low. Notwithstanding, a medium and small effect size would require a bigger sample. In contrast, in many cases, it can be observed that some small direct effects, c', remain even though the mediating effect is quite high in relation to the mediated direct effect. However, when this relation of the direct effect to the mediating effect becomes low but nevertheless stays significant, it can also be seen as full mediation. A researcher could indicate this with the help of the variance accounted for (VAF) value, which we will discuss in more detail below in our example. Conversely, when the absolute value of the indirect path $a \times b$ is larger than the absolute value of the total effect $(a \times b) + c'$, there is a suppressor effect (Cheung and Lau 2008); this situation could also be defined as full mediation (Hair et al. 2017).

8.2.3 Partial Mediation

All other situations under the condition that both the direct effect c' and the indirect effect $a \times b$ are significant represent partial mediation. Two types of partial mediation can be distinguished.

8.2.3.1 Complementary Partial Mediation

In a complementary partial mediation, the direct effect c' and indirect effect $a \times b$ point in the same (positive or negative) direction (Baron and Kenny 1986). It is an often observed result that $a \times b$ and c' are significant and $a \times b \times c'$ is positive, which indicates that a portion of the effect of X on Y is mediated through M, while X still explains a portion of Y that is independent of M. This complementary mediation hypothesis suggests that the intermediate variable explains, possibly confounds, or falsifies the relationships between the independent and dependent variables.

8.2.3.2 Competitive Partial Mediation

In a competitive partial mediation, the direct effect c' and indirect effect $a \times b$ point in a different direction. A negative $a \times b \times c'$ value indicates the presence of competitive mediation in step 2. As mentioned above, this indicates that a portion of the effect of X on Y is mediated through M, while X still explains a portion of Y that is independent of M. In the past, researchers often focused only on complementary mediation (Zhao et al. 2010). In the competitive partial mediation hypothesis, it is assumed that the intermediate variable will reduce the magnitude of the relationship between the independent and dependent variables. However, it is possible that the intermediate variable could increase the magnitude of the relationship between the independent and dependent variables. Competitive partial mediation has often been called a "negative confounding" or an "inconsistent" model. Thus, other types of mediation beyond complementary mediation should be considered in a PLS path model.

PLS researchers might also be interested in evaluating the strength (portion) in the case of a partial mediation. Mediation analyses regularly involve partial mediation, and therefore it can be helpful to have further information on the mediated portion. One approach for this is calculating the ratio of the indirect to total effect. This ratio is also known as the variance accounted for (VAF) value. VAF determines the extent to which the mediation process explains the dependent variable's variance. For a simple mediation, the proportion of mediation is defined as

$$\mathrm{VAF} = \frac{a \times b}{(a \times b) + c'}. \tag{8.2}$$

8.2.4 No Mediation

When the indirect effect is not significant, we can find another two situations. Although these cannot be considered mediation cases in a narrow sense, two types of effects can be distinguished.

8.2.4.1 Only Direct Effect

If the indirect effect $a \times b$ is not significant while the direct path c' is, the mediator variable has no impact; this indicates that a direct, non-mediating effect is present. In this case, the study was perhaps searching for a wrong mediation relationship. However, it is possible that an unrecognized mediation relationship still exists and another mediation variable is present that mediates an effect between X and Y (Shrout and Bolger 2002). Thus, a researcher should rethink his theoretical basis when he has not found the expected mediation relationship (cf. Zhao et al. 2010).

8.2.4.2 No Effect

There is no effect if neither the indirect effect $a \times b$ nor the direct effect c' is significant. The total effect can still be significant. First of all, in this case, a researcher should check if the sample size has enough power to show an effect when there is an effect. Putting the last two cases together—the indirect effect $a \times b$ is not significant and the direct path c' is or is not—frequently indicates a problematic or flawed theoretical framework (Zhao et al. 2010). In this case, a researcher has to thoroughly examine the hypothesized model. When, for example, the total effect c is significant, it can indicate that the mediation variable should be deleted because it brings no further degree of explanation. In the case where the mediation variable M has no real effect, it only dilutes the effect of the direct variable X and should be deleted.

8.2.5 Multiple Mediation

PLS is regularly applied in complex path models. There may be multiple relationships between one or more independent variables, one or more mediator variables, and one or more dependent variables. For instance, a complementary mediation variable (M_1) may mitigate the independent variable (X) to a dependent variable (Y), and at the same time, a competitive mediation variable (M_2) may also exist. From a naïve perspective, someone can assume that the independent variable is not relevant because there is no relevant total effect c. However, when one of the mediator variables has a strong influence in a certain situation, the independent variable also wins in terms of relevance. Such areas can become very challenging, for example, when analyzing which process improves or hinders the influence of the external pressure to work on the outcome in a PLS path model. However, when more than one mediating effect is present, the abovementioned differentiation between direct and indirect effects for detecting mediation relationships remains applicable, and the above recommendations are inalterable (Hayes 2009).

Figure 8.2 presents an example of a PLS path model with two mediators. The total effect is equal to the direct effect of X on Y, in addition to the sum of the indirect effects of M_1 and M_2. A given meditator's indirect effect is referred to as a specific indirect effect (e.g., through M_1). The sum of the two specific indirect effects is the complete indirect effect. Thus, the total effect is the sum of the direct effect and the complete indirect effects (i.e., the sum of the specific indirect effects includes the relationship between M_1 and M_2). For the example in Fig. 8.3, the calculation of the total effect is

$$c = c' + (a_1 \times b_1) + (a_2 \times b_2) . \tag{8.3}$$

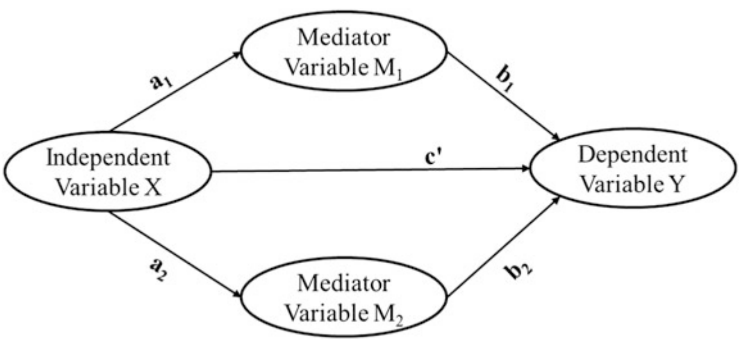


Fig. 8.2 Multiple mediator model

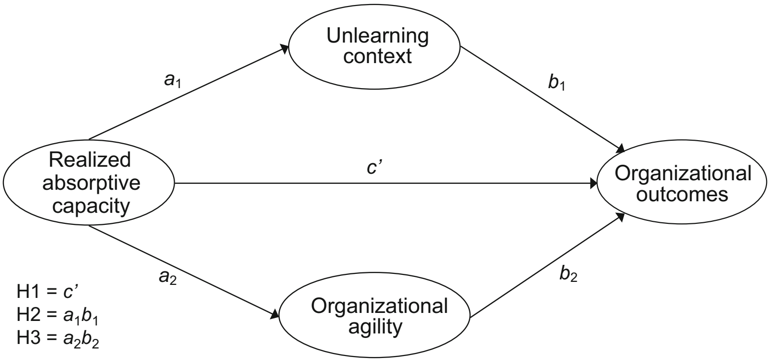


Fig. 8.3 An example of a multiple mediator model. Source: Roldán et al. (2014)

An interesting situation occurs when $a_1 \times b_1$ and $a_2 \times b_2$ in Eq. (8.2) have an opposite sign; this indicates that one effect functions as a complementary effect and the other functions as a competitive mediator effect. Such a model is called an inconsistent mediation model (MacKinnon et al. 2007). Consequently, even though significant specific indirect effects exist, the complete indirect effect [e.g., $(a_1 \times b_1) + (a_2 \times b_2)$] may not be significant.

Preacher and Hayes (2008) argue that the incorporation of multiple mediators and the comparison of their specific mediating effects are also useful for comparing different competing theories. Given this background, researchers are interested in comparing the strengths of specific mediating effects [e.g., $(a_1 \times b_1)$ and $(a_2 \times b_2)$] in complex models (Williams and MacKinnon 2008). For example, a researcher could test for two complementary mediator variables if mediator (M_1) has a stronger mediator effect than mediator (M_2). The previous explanation of how to compute bootstrap confidence intervals in PLS can be extended to test the significance of the difference between two specific mediating effects (Lau and Cheung 2012). For that purpose, a researcher must calculate the following equation:

$$D_{\mathrm{M}} = M_1 - M_2, \tag{8.4}$$

where M_1 and M_2 are the specific indirect effects and $\mathrm{D_M}$ is the difference between these two specific indirect effects. In this way, we test whether two specific indirect effects are equal or if they amount to zero. In the case examined in this study, the equation for Fig. 8.2 would be $D_{\mathrm{M}} = (a_1 \times b_1) - (a_2 \times b_2)$. Again, researchers can calculate the equation using a spreadsheet application to build a confidence interval with the help of the bootstrapping results of the PLS program (cf. Chin et al. 2013; Rodríguez-Entrena et al. 2016).

A frequently encountered case is that in which two mediators are connected to each other. This indicates an additional relationship between M_1 and M_2 in Fig. 8.2. Next, we provide examples of how to test such multiple mediation relationships in a PLS path model. In such a case, the total effect c can be calculated as follows: $c = c' + (a_1 \times b_1) + (a_2 \times b_2) + (a_1 \times a_3 \times b_2)$, where a_3 stands for the relation between M_1 and M_2. An interesting case in this situation is when a_2, b_2, and c' are not significantly different from zero, but the indirect effect $(a_1 \times a_3 \times b_2)$ is (e.g., when M_1 is the causal predecessor of M_2); this would mean that M_1 fully mediates the direct effect between X and M_2 and that M_2 fully mediates the direct effect between M_1 and Y, thus establishing a direct causal chain $X \rightarrow M_1 \rightarrow M_2 \rightarrow Y$ (Mathieu et al. 2008). Next, we illustrate this in our second example.

8.3 Illustrative Examples

8.3.1 A Case of a Multiple Mediator Model

In this first example, we take data from Roldán et al. (2014). This research examines the relationship between a key component of the absorptive capacity, the realized absorptive capacity (RACAP), and the organizational outcomes, this link being mediated by the unlearning context and the organizational agility (Fig. 8.3). These connections are examined through an empirical investigation of 112 large companies.

8.3.1.1 Data Collection and Measures

The population of this study consists of Spanish organizations that use Editran ™ and which have more than 100 employees. Editran™ is a software used to enhance communications over different platforms and is a de facto standard in the Spanish banking system. This population is suitable for our study, because these businesses are more familiar with knowledge and technology management. There were 464 companies identified from the SABI (Sistema de Análisis de Balances Ibéricos) database and invited to participate in the study, and 121 companies agreed. A total of 112 valid and completed questionnaires were collected.

We modeled RACAP and unlearning context as multidimensional constructs (composites). We measured RACAP by two first-order dimensions (composites): transformation and exploitation. The unlearning context variable was assessed using three first-order dimensions (composites): the examination of lens fitting (ELF), the framework for changing individual habits (CIH), and the framework for consolidation of emergent understandings (CEU). The example's constructs were estimated in Mode A, and the characteristics of the scales are the following:

(a) RACAP. Items were measured using a seven-point Likert scale from the study by Jansen et al. (2008). RACAP includes the transformation and exploitation of new external knowledge. The final cleansed scale consists of four items for the transformation dimension and three items for the exploitation dimension.

(b) Unlearning context. At the organizational level, it is viewed as memory elimination in general and as changing beliefs, norms, values, procedures, and routines in particular. As described above, the unlearning context has three dimensions: the consolidation of emergent understandings, the examination of lens fitting, and the framework for changing individual habits. The measures relating to consolidation of emergent understandings consisted of six items taken from a scale designed by Cegarra and Sanchez (2008). Five items were used to measure the examination of lens fitting. Finally, we measured the framework for changing individual habits using seven items.
(c) Organizational agility. A business-wide capability to deal with changes that often arise unexpectedly in business environments via rapid and innovative responses that exploit changes as opportunities to grow and prosper. The indicators of organizational agility are based on the measures of organizational agility used by Lu and Ramamurthy (2011). The scale was composed of six items.
(d) Organizational outcomes. It is understood as an assessment of the global performance of the business. The scale for organizational outcomes consisted of ten reflective items adapted from Quinn and Rohrbaugh (1983).

8.3.1.2 Hypotheses Development

Once the conceptual framework is shown, the next step is hypotheses development. The research model depicted in Fig. 8.3 includes one direct and two mediating hypotheses:

H1: RACAP is positively associated with organizational outcomes.
H2: The relationship between RACAP and organizational outcomes is positively mediated by the unlearning context.
H3: The relationship between RACAP and organizational outcomes is positively mediated by organizational agility.

8.3.1.3 PLS-SEM Practical Considerations

This chapter's goal is not to illustrate the complete data analysis with PLS, but to focus on the structural model, specifically on how to test this mediation model with PLS. Guidelines for a complete analysis with PLS can be found in Henseler et al. (2016) and Hair et al. (2017).

Significance of Direct and Indirect Effects

We assess the significance of one direct (c') and two indirect effects ($a_1 \times b_1$ and $a_2 \times b_2$). The critical issue is that if the significance of each indirect effect cannot be

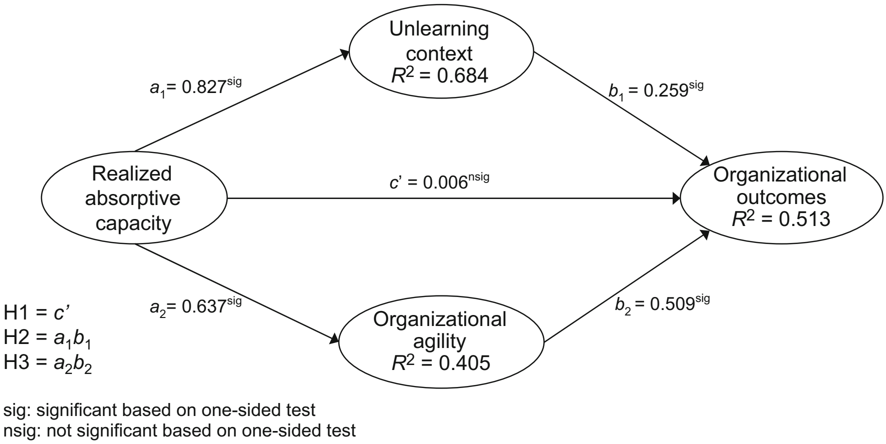


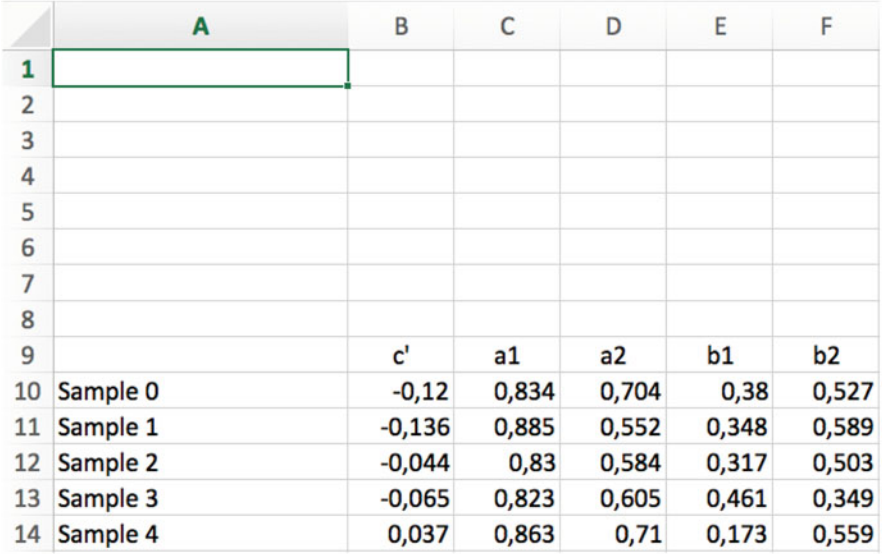
Fig. 8.4 An example of a multiple mediator model. Results. Source: Roldán et al. (2014)

established, there is no mediating effect. Consequently, having a significant indirect effect is the key to determining the type of mediation effect and its magnitude. Considering that our hypotheses have been formulated with direction (+), we will use a one-sided test. Accordingly, we will estimate 90% confidence intervals (CI).

Nitzl et al. (2016) suggested a procedure using a spreadsheet and multiplying the bootstrapping outputs (i.e., $a_1 \times b_1$ and $a_2 \times b_2$) to calculate the percentile and the bias-corrected confidence intervals. Therefore, once we run the model, we next perform the bootstrapping procedure with 5000 subsamples and no sign changes. In Fig. 8.4 we can see the estimates for direct effects.

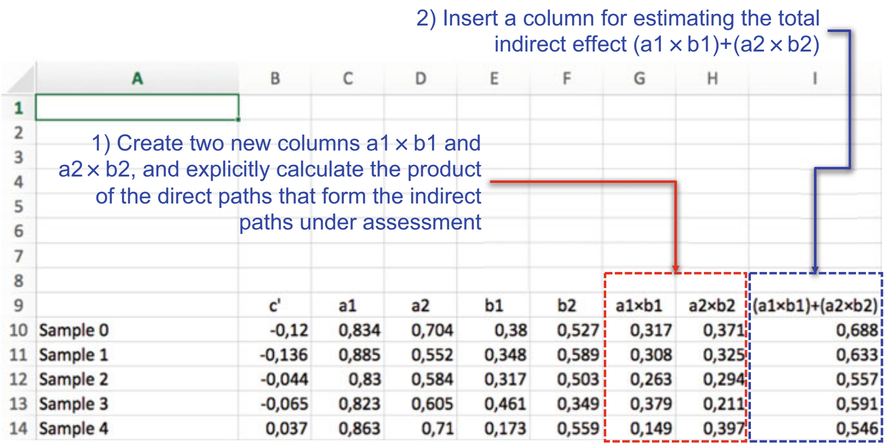
In order to calculate the specific indirect effects and the different confidence intervals, we use a spreadsheet application (i.e., Excel or CALC) to obtain the significance of mediator effects ($a_1 \times b_1$ and $a_2 \times b_2$) in the relationship between RACAP and organizational outcomes. We suggest carrying out the following steps:

1. Take the 5000 sets of path coefficients from all direct effects created by the bootstrap procedure and copy and paste into a spreadsheet's columns (Fig. 8.5).
2. Create a new column for each indirect effect under assessment. In this case, we generate two new columns ($a_1 \times b_1$ and $a_2 \times b_2$) and explicitly calculate the product of the direct paths that form such indirect paths. In addition, we include another column for estimating the total indirect effect $(a_1 \times b_1) + (a_2 \times b_2)$ (Fig. 8.6).
3. Copy the original values (O) provided by PLS for the direct effects. Then calculate the product of the direct paths that form each indirect path. In the line below, calculate the mean (M) for each column of the paths obtained with the bootstrapping process (Fig. 8.7).
4. Insert a new line where you estimate the bias as original (O) − mean (M) for each column (Fig. 8.8).



	c'	a1	a2	b1	b2
Sample 0	-0,12	0,834	0,704	0,38	0,527
Sample 1	-0,136	0,885	0,552	0,348	0,589
Sample 2	-0,044	0,83	0,584	0,317	0,503
Sample 3	-0,065	0,823	0,605	0,461	0,349
Sample 4	0,037	0,863	0,71	0,173	0,559

Fig. 8.5 Example 1. Step 1



	c'	a1	a2	b1	b2	a1×b1	a2×b2	(a1×b1)+(a2×b2)
Sample 0	-0,12	0,834	0,704	0,38	0,527	0,317	0,371	0,688
Sample 1	-0,136	0,885	0,552	0,348	0,589	0,308	0,325	0,633
Sample 2	-0,044	0,83	0,584	0,317	0,503	0,263	0,294	0,557
Sample 3	-0,065	0,823	0,605	0,461	0,349	0,379	0,211	0,591
Sample 4	0,037	0,863	0,71	0,173	0,559	0,149	0,397	0,546

Fig. 8.6 Example 1. Step 2

5. Estimate the percentile bootstrap CI for each column using the function PERCENTILE (range, *k*), *k* being the percentile value between 0 and 1. In our case, given our hypotheses are postulated with direction (+), we will use one-sided test, and we will estimate 90% CI (Fig. 8.9).
6. Estimate the bias-corrected CI adding the bias to the previously calculated percentile CI (Fig. 8.10).

1) Copy the original values (O) provided by PLS for the direct effects.

2) Calculate the product of the direct paths that form the indirect paths

3) estimating the total indirect effect =G2+H2

G2 =C2*E2

	A	B	C	D	E	F	G	H	I
1		c'	a1	a2	b1	b2	a1×b1	a2×b2	(a1×b1)+(a2×b2)
2	Original (O)	0,006	0,827	0,637	0,259	0,509	0,214	0,324	0,538
3	Mean (M)	0,008	0,826	0,640	0,251	0,518	0,207	0,332	0,540
4									
5									
6	4) Calculate the mean (M) for each column, =AVERAGE(range).								
7	E.g. for c', =AVERAGE(B10:B5009)								
8									
9		c'	a1	a2	b1	b2	a1×b1	a2×b2	(a1×b1)+(a2×b2)
10	Sample 0	-0,12	0,834	0,704	0,38	0,527	0,317	0,371	0,688
11	Sample 1	-0,136	0,885	0,552	0,348	0,589	0,308	0,325	0,633
12	Sample 2	-0,044	0,83	0,584	0,317	0,503	0,263	0,294	0,557
13	Sample 3	-0,065	0,823	0,605	0,461	0,349	0,379	0,211	0,591
14	Sample 4	0,037	0,863	0,71	0,173	0,559	0,149	0,397	0,546

Fig. 8.7 Example 1. Step 3

B4 =B2-B3

	A	B	C	D	E	F	G	H	I
1		c'	a1	a2	b1	b2	a1×b1	a2×b2	(a1×b1)+(a2×b2)
2	Original (O)	0,006	0,827	0,637	0,259	0,509	0,214	0,324	0,538
3	Mean (M)	0,008	0,826	0,640	0,251	0,518	0,207	0,332	0,540
4	Bias (O - M)	-0,002	0,001	-0,003	0,008	-0,009	0,007	-0,008	-0,001
5	Calculate the Bias: Original (O) – Mean (M)								
6									
7									
8									
9		c'	a1	a2	b1	b2	a1×b1	a2×b2	(a1×b1)+(a2×b2)
10	Sample 0	-0,12	0,834	0,704	0,38	0,527	0,317	0,371	0,688
11	Sample 1	-0,136	0,885	0,552	0,348	0,589	0,308	0,325	0,633
12	Sample 2	-0,044	0,83	0,584	0,317	0,503	0,263	0,294	0,557
13	Sample 3	-0,065	0,823	0,605	0,461	0,349	0,379	0,211	0,591
14	Sample 4	0,037	0,863	0,71	0,173	0,559	0,149	0,397	0,546

Fig. 8.8 Example 1. Step 4

7. If the confidence interval (CI) for a mediation effect (products) does not include 0 value, it means the mediating effect is significantly different from 0. In our example, both indirect effects are significant. In addition, the total indirect effect is also significant (Table 8.1).

The key point to determine a mediation effect is the evaluation of the significance of the indirect effect (Table 8.1). In our example, both indirect effects are significant; therefore, H2 and H3 are supported. However, the direct effect is not significant; consequently H1 is not supported.

Percentile LOWER (5%) for *c'* =PERCENTILE(B10:B5009,0,05)
Percentile LOWER (95%) for *c'* =PERCENTILE(B10:B5009,0,95)

	A	B	C	D	E	F	G	H	I
1		c'	a1	a2	b1	b2	a1×b1	a2×b2	(a1×b1)+(a2×b2)
2	Original (O)	0,006	0,827	0,637	0,259	0,509	0,214	0,324	0,538
3	Mean (M)	0,008	0,826	0,640	0,251	0,518	0,207	0,332	0,540
4	Bias (O - M)	-0,002	0,001	-0,003	0,008	-0,009	0,007	-0,008	-0,001
5	Percentile LOWER (5%)	-0,189	0,757	0,509	0,022	0,365	0,018	0,217	0,373
6	Percentile UPPER (95%)	0,194	0,884	0,748	0,474	0,670	0,396	0,459	0,715
7									
8									
9		c'	a1	a2	b1	b2	a1×b1	a2×b2	(a1×b1)+(a2×b2)
10	Sample 0	-0,12	0,834	0,704	0,38	0,527	0,317	0,371	0,688
11	Sample 1	-0,136	0,885	0,552	0,348	0,589	0,308	0,325	0,633
12	Sample 2	-0,044	0,83	0,584	0,317	0,503	0,263	0,294	0,557
13	Sample 3	-0,065	0,823	0,605	0,461	0,349	0,379	0,211	0,591
14	Sample 4	0,037	0,863	0,71	0,173	0,559	0,149	0,397	0,546

Fig. 8.9 Example 1. Step 5

B7 *fx* =B5+B4

	A	B	C	D	E	F	G	H	I
1		c'	a1	a2	b1	b2	a1×b1	a2×b2	(a1×b1)+(a2×b2)
2	Original (O)	0,006	0,827	0,637	0,259	0,509	0,214	0,324	0,538
3	Mean (M)	0,008	0,826	0,640	0,251	0,518	0,207	0,332	0,540
4	Bias (O - M)	-0,002	0,001	-0,003	0,008	-0,009	0,007	-0,008	-0,001
5	Percentile LOWER (5%)	-0,189	0,757	0,509	0,022	0,365	0,018	0,217	0,373
6	Percentile UPPER (95%)	0,194	0,884	0,748	0,474	0,670	0,396	0,459	0,715
7	BC: P. LOWER (5%) + Bias	-0,191	0,758	0,506	0,030	0,356	0,025	0,208	0,372
8	BC: P. UPPER (95%) + Bias	0,192	0,885	0,745	0,482	0,661	0,403	0,451	0,714
9		c'	a1	a2	b1	b2	a1×b1	a2×b2	(a1×b1)+(a2×b2)
10	Sample 0	-0,12	0,834	0,704	0,38	0,527	0,317	0,371	0,688
11	Sample 1	-0,136	0,885	0,552	0,348	0,589	0,308	0,325	0,633
12	Sample 2	-0,044	0,83	0,584	0,317	0,503	0,263	0,294	0,557
13	Sample 3	-0,065	0,823	0,605	0,461	0,349	0,379	0,211	0,591
14	Sample 4	0,037	0,863	0,71	0,173	0,559	0,149	0,397	0,546

Fig. 8.10 Example 1. Step 6

Type of Mediation and Magnitude

Once we have determined the significance of the two mediation effects, we can go for the second step to determine the type of mediation and its magnitude. Table 8.1 shows the point estimate for the direct effect (c'), the indirect effects ($a_1 \times b_1$, $a_2 \times b_2$), and the total indirect effect [$(a_1 \times b_1) + (a_2 \times b_2)$]. Given that c' is not significant and both the indirect and the total indirect effects are significant, a full mediation can be defended. In addition, we can calculate VAF to assess the magnitude for each mediation. It can be said that almost 99% of the total effect is

Table 8.1 Example 1. Summary of mediating effects tests

Direct effects	Coefficient	Bootstrap 90% CI Percentile		BC	
H1: c'	0.006^{nsig}	−0.189	0.194	−0.191	0.192
a_1	0.827^{sig}	0.757	0.884	0.758	0.885
a_2	0.637^{sig}	0.509	0.748	0.506	0.745
b_1	0.259^{sig}	0.022	0.474	0.030	0.482
b_2	0.509^{sig}	0.365	0.670	0.356	0.661

Indirect effects	Point estimate	Percentile		BC		VAF
H2: $a_1 \times b_1$	0.214^{sig}	0.018	0.396	0.025	0.403	39.3%
H3: $a_2 \times b_2$	0.324^{sig}	0.217	0.459	0.208	0.451	59.6%
Total indirect effect	0.538^{sig}	0.373	0.715	0.372	0.714	98.9%

Notes: *sig* significant, *nsig* not significant, *BC* bias corrected, *VAF* variance accounted for

due to two mediation effects jointly. Because the VAF exceeds 80%, this implies an additional argument for a full mediation.

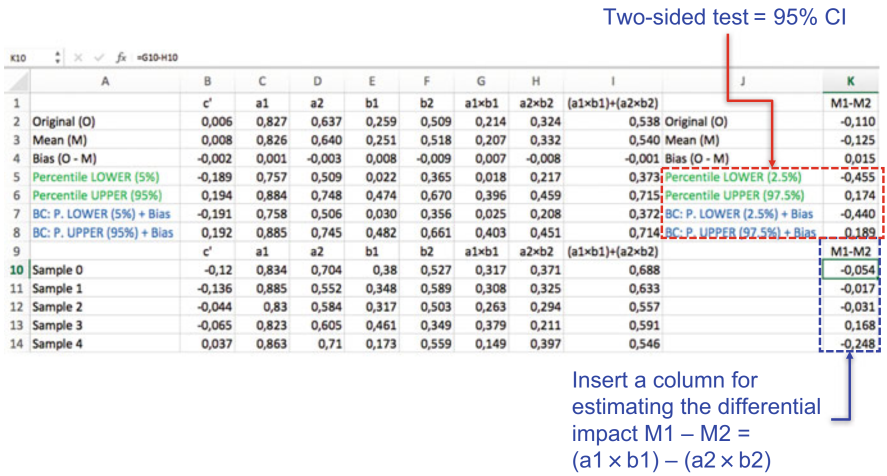
Comparison of Mediating Effects

When we evaluate a multiple mediator model, we can go further comparing the different mediating effects. In our example, we want to test whether the unlearning context (M_1) has a stronger mediator effect than the organizational agility (M_2) variable. With this aim in mind, we will assess the potential statistical difference between $a_1 \times b_1$ and $a_2 \times b_2$ following the guidelines provided by Chin et al. (2013) and Rodríguez-Entrena et al. (2016). Thus, we will include a new column where we estimate the difference between $a_1 \times b_1$ and $a_2 \times b_2$ and calculate percentile and bias-corrected CI. Because we have not postulated any hypothesis about the differential impact of both indirect effects, we will carry out a two-sided test (95% CI) (Fig. 8.11).

The test (Table 8.2) shows there is not a differential impact between M_1 and M_2 since both CIs contain the zero value. Accordingly, we cannot state that the unlearning context (M_1) has a stronger mediator effect than the organizational agility (M_2) variable and vice versa.

8.3.2 An Example of a Multistep Multiple Mediator Model

Our second example has been extracted from Roldán et al. (2017). This study examines post-adoption behaviors (i.e., frequency of use, routinization, and infusion) and their effects on the sense of community in the domain of social network



K10 =G10-H10

	A	B	C	D	E	F	G	H	I	J	K
1		c'	a1	a2	b1	b2	a1×b1	a2×b2	(a1×b1)+(a2×b2)		M1-M2
2	Original (O)	0,006	0,827	0,637	0,259	0,509	0,214	0,324	0,538	Original (O)	-0,110
3	Mean (M)	0,008	0,826	0,640	0,251	0,518	0,207	0,332	0,540	Mean (M)	-0,125
4	Bias (O - M)	-0,002	0,001	-0,003	0,008	-0,009	0,007	-0,008	-0,001	Bias (O - M)	0,015
5	Percentile LOWER (5%)	-0,189	0,757	0,509	0,022	0,365	0,018	0,217	0,373	Percentile LOWER (2.5%)	-0,455
6	Percentile UPPER (95%)	0,194	0,884	0,748	0,474	0,670	0,396	0,459	0,715	Percentile UPPER (97.5%)	0,174
7	BC: P. LOWER (5%) + Bias	-0,191	0,758	0,506	0,030	0,356	0,025	0,208	0,372	BC: P. LOWER (2.5%) + Bias	-0,440
8	BC: P. UPPER (95%) + Bias	0,192	0,885	0,745	0,482	0,661	0,403	0,451	0,714	BC: P. UPPER (97.5%) + Bias	0,189
9		c'	a1	a2	b1	b2	a1×b1	a2×b2	(a1×b1)+(a2×b2)		M1-M2
10	Sample 0	-0,12	0,834	0,704	0,38	0,527	0,317	0,371	0,688		-0,054
11	Sample 1	-0,136	0,885	0,552	0,348	0,589	0,308	0,325	0,633		-0,017
12	Sample 2	-0,044	0,83	0,584	0,317	0,503	0,263	0,294	0,557		-0,031
13	Sample 3	-0,065	0,823	0,605	0,461	0,349	0,379	0,211	0,591		0,168
14	Sample 4	0,037	0,863	0,71	0,173	0,559	0,149	0,397	0,546		-0,248

Fig. 8.11 Example 1. Comparison of mediating effects. Spreadsheet illustration

Table 8.2 Example 1. Comparison of mediating effects

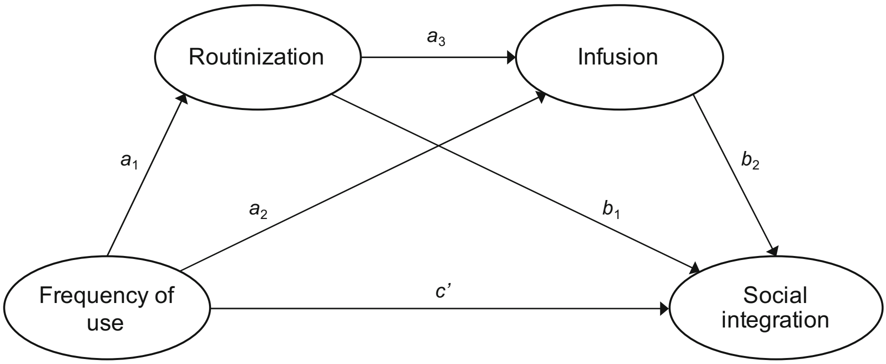
Differential effect	Coefficient	Bootstrap 95% CI			
		Percentile		BC	
$M_1 - M_2 = (a_1 \times b_1) - (a_2 \times b_2)$	−0.110	−0.455	0.174	−0.440	0.189

sites. Specifically, this contribution formulates a multistep mediator model where frequency of use affects social integration via routinization and infusion (Fig. 8.12). The data was collected from 278 users of Tuenti, a popular social network site among the Spanish college student population during the period 2006–2012.

8.3.2.1 Data Collection and Measures

Undergraduate students, users of the Tuenti social network, were recruited from social studies at a public university in Southern Spain. A total of 278 questionnaires were collected from members who responded to an offline survey.

Frequency of use is defined as the number of times that an individual uses a social network site (SNS). It was operationalized by two self-reported measures. Routinization describes the state in which SNS use is no longer perceived as out of the ordinary but becomes institutionalized, being associated with habitual and standardized usage, that is, the integrating of the SNS into daily routines. We measure it by adapting a scale developed by Sundaram et al. (2007). Infusion is conceptualized as the extent to which a person uses an SNS to its highest level to maximize its potential, implying the notion of a deeper use. We use an adaptation of the measure developed by Jones et al. (2002). Finally, social integration measures



H1 = Frequency of use → Social Integration = c'
H2 = Frequency of use → Routinization → Social Integration = a_1b_1
H3 = Frequency of use → Infusion → Social Integration = a_2b_2
H4 = Frequency of use → Routinization → Infusion → Social Integration = $a_1a_3b_2$

Fig. 8.12 An example of a model with a three-path mediated effect. Source: Roldán et al. (2017)

both the sense of belongingness to, and the identification with, the SNS and the social community's interactivity level. Consequently, social integration is modeled as a multidimensional construct composed of two dimensions: community participation and community integration. All variables have been estimated in Mode A.

8.3.2.2 Hypotheses Development

Considering the research model described in Fig. 8.12, we have postulated one direct and three mediating hypotheses, one of them proposing a three-path mediated effect:

H1: Frequency of use is positively related to social integration.
H2: The relationship between frequency of use and social integration is positively mediated by routinization.
H3: The relationship between frequency of use and social integration is positively mediated by infusion.
H4: The relationship between frequency of use and social integration is sequentially and positively mediated by routinization and infusion.

8.3.2.3 PLS-SEM Practical Considerations

We follow the guidelines described in the previous example. Therefore, we will show the final results of our analyses in order to avoid excessive redundancy in the explanation (Fig. 8.13).

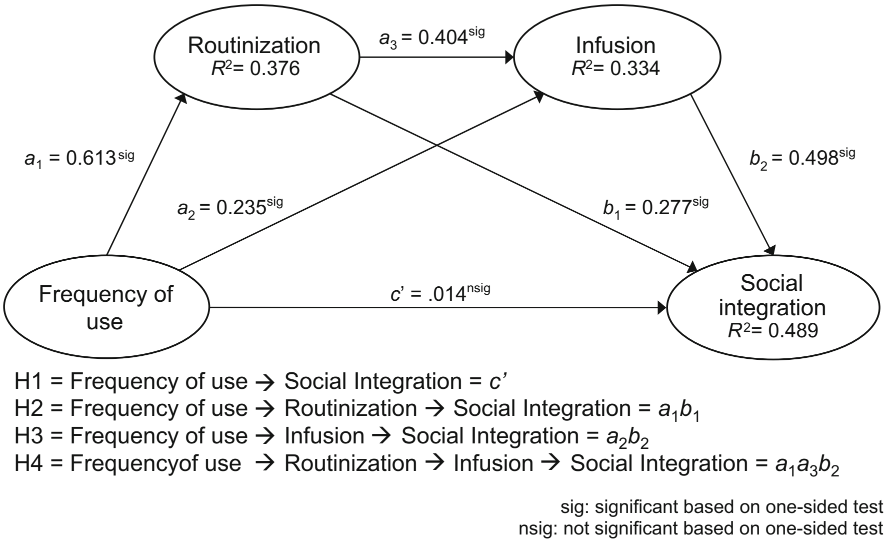


Fig. 8.13 An example of a model with a three-path mediated effect. Results. Source: Roldán et al. (2017)

	A	B	C	D	E	F	G	H	I	J	K
1		c'	a1	a2	a3	b1	b2	a1×b1	a2×b2	a1×a3×b2	(a1×b1)+(a2×b2)+(a1×a3×b2)
2	Original	0,014	0,613	0,235	0,404	0,277	0,498	0,170	0,117	0,123	0,410
3	Mean	0,015	0,614	0,235	0,404	0,277	0,498	0,170	0,117	0,124	0,411
4	Bias (O - M)	-0,001	-0,001	0,000	0,000	0,000	0,001	0,000	0,000	0,000	-0,001
5	Percentile LOWER (5%)	-0,073	0,548	0,132	0,286	0,165	0,408	0,101	0,063	0,080	0,343
6	Percentile UPPER (95%)	0,107	0,672	0,339	0,521	0,386	0,584	0,240	0,176	0,172	0,479
7	BC: P. LOWER (5%) + Bias	-0,074	0,547	0,131	0,286	0,166	0,408	0,101	0,063	0,079	0,343
8	BC: P. UPPER (95%) + Bias	0,106	0,671	0,339	0,521	0,386	0,584	0,240	0,176	0,171	0,478
9		c'	a1	a2	a3	b1	b2	a1×b1	a2×b2	a1×a3×b2	(a1×b1)+(a2×b2)+(a1×a3×b2)
10	Sample 0	0,049	0,531	0,228	0,515	0,290	0,480	0,154	0,109	0,131	0,395
11	Sample 1	0,011	0,589	0,210	0,441	0,287	0,434	0,169	0,091	0,113	0,373
12	Sample 2	-0,058	0,670	0,228	0,466	0,432	0,407	0,290	0,093	0,127	0,509
13	Sample 3	-0,003	0,565	0,407	0,295	0,252	0,504	0,143	0,205	0,084	0,431
14	Sample 4	0,089	0,622	0,261	0,372	0,264	0,488	0,164	0,127	0,113	0,404

Fig. 8.14 Example 2. Final spreadsheet with the estimation of indirect effects and confidence intervals

The evaluation of our research model involves estimating the significance of one direct (c') and the three indirect effects ($a_1 \times b_1$, $a_2 \times b_2$, and $a_1 \times a_3 \times b_2$). Considering that our hypotheses have been formulated with direction (+), we will use a one-sided test, calculating 90% confidence intervals (Fig. 8.14).

Significance of Direct and Indirect Effects

Frequency of use has no significant direct effect on social integration (H1: c') (Table 8.3). Therefore, H1 is not supported. On the other hand, all the indirect effects of

Table 8.3 Example 2. Summary of mediating effects tests

Direct effects	Coefficient	Bootstrap 90% CI			
		Percentile		BC	
H1: c'	0.014 ^{nsig}	−0.073	0.107	−0.074	0.106
a_1	0.613^{sig}	0.548	0.672	0.547	0.671
a_2	0.235^{sig}	0.132	0.339	0.131	0.339
a_3	0.404^{sig}	0.286	0.521	0.286	0.521
b_1	0.277^{sig}	0.165	0.386	0.166	0.386
b_2	0.498^{sig}	0.408	0.584	0.408	0.584

Indirect effects	Point estimate	Percentile		BC		VAF
H2: $a_1 \times b_1$	0.170	0.101	0.240	0.101	0.240	40.0%
H3: $a_2 \times b_2$	0.117	0.063	0.176	0.063	0.176	27.6%
H4: $a_1 \times a_3 \times b_2$	0.123	0.080	0.172	0.079	0.171	29.0%
Total indirect effect	0.410	0.343	0.479	0.343	0.478	96.6%

Notes: *sig* significant, *nsig* not significant, *BC* bias corrected, *VAF* variance accounted for

frequency of use on social integration are significant. This means that H2–H4 have been supported. Thus, routinization positively mediates the relationship between frequency of use and social integration (H2: $a_1 \times b_1$). Likewise, infusion mediates the path between frequency of use and social integration (H3: $a_2 \times b_2$). Finally, we find that frequency of use is positively associated with higher routinization and infusion, which relates to higher levels of social integration (H4: $a_1 \times a_3 \times b_2$).

Type of Mediation and Magnitude

Table 8.3 indicates that c' is not significant and all postulated indirect effects are significant. Consequently, this means that routinization and infusion fully and jointly mediate the influence of frequency of use on social integration. This is also supported by applying the variance accounted for (VAF) index. When the VAF has an outcome above 80%, a full mediation can be assumed. This occurs when we assess the total indirect effect of frequency of use on social integration (VAF = 96.6%).

Comparison of Mediating Effects

Finally, we will test whether routinization (M_1) has a stronger mediator effect than infusion (M_2). As we did in the previous example, we evaluate the statistical difference between $a_1 \times b_1$ and $a_2 \times b_2$ (Table 8.4). In this case, we do not observe a significant difference between both indirect effects.

Table 8.4 Example 2. Comparison of mediating effects

Differential effect	Coefficient	Bootstrap 95% CI			
		Percentile		BC	
$M_1 - M_2 = (a_1 \times b_1) - (a_2 \times b_2)$	0.053	−0.067	0.175	−0.067	0.175

8.4 Conclusion

PLS-SEM is a statistical procedure for structural equation modeling that social science researchers can consider when conducting research. This chapter helps readers to understand how PLS-SEM can be applied in mediation analysis through two illustrative examples. PLS-SEM seems not to be "a panacea for flaws in research design or execution" (Rigdon 2016: 604), but research must not ignore the proper model assessment prior to drawing a conclusion. This kind of advanced modeling (i.e., mediation analysis) can be performed by PLS-SEM as illustrated by this chapter. The adoption of these guidelines is advised for researchers who use PLS-SEM, particularly when they tackle multiple mediation models.

References

Aguinis, H., Edwards, J. R., & Bradley, K. J. (2017). Improving our understanding of moderation and mediation in strategic management research. *Organizational Research Methods* (forthcoming).

Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic and statistical considerations. *Journal of Personality and Social Psychology, 51*(6), 1173–1182.

Cegarra, J. G., & Sánchez, M. T. (2008). Linking the individual forgetting context with customer capital from a seller's perspective. *The Journal of the Operational Research Society, 59*, 1614–1623.

Chernick, M. R. (2011). *Bootstrap methods: A guide for practitioners and researchers*. New York: Wiley.

Cheung, G. W., & Lau, R. S. (2008). Testing mediation and suppression effects of latent variables: Bootstrapping with structural equation models. *Organizational Research Methods, 11*(2), 296–325.

Chin, W. W., Kim, Y. J., & Lee, G. (2013). Testing the differential impact of structural paths in PLS analysis: A bootstrapping approach. In H. Abdi et al. (Eds.), *New perspectives in partial least squares and related methods*, *Springer proceedings in mathematics and statistics* (Vol. 56, pp. 221–229). New York: Springer.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis*. Upper Saddle River, NJ: Pearson/Prentice Hall.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). Thousand Oaks, CA: Sage.

Hayes, A. F. (2009). Beyond Baron and Kenny: Statistical mediation analysis in the new millennium. *Communication Monographs, 76*(4), 408–420.

Hayes, A. F., & Scharkow, M. (2013). The relative trustworthiness of inferential test of the indirect effect in statistical mediation analysis: Does method rally matter? *Psychological Science, 24*(10), 1918–1927.

Henseler, J. (2017). Bridging design and behavioral research with variance-based structural equation modeling. *Journal of Advertising, 46*(1), 178–192.

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. In R. R. Sinkovics & P. N. Ghauri (Eds.), *Advances in International Marketing* (Vol. 20, pp. 277–320). Bingley: Emerald.

Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: Updated guidelines. *Industrial Management & Data Systems, 116*(1), 2–20.

Iacobucci, D., Saldanha, N., & Deng, X. (2007). A mediation on mediation: Evidence that structural equation models perform better than regression. *Journal of Consumer Psychology, 17*(2), 140–154.

Jansen, J. J. P., George, G., van den Bosch, F. A. J., & Volberda, H. W. (2008). Senior team attributes and organizational ambidexterity: The moderating role of transformational leadership. *Journal of Management Studies, 45*(5), 982–1007.

Jones, E., Sundaram, S., & Chin, W. W. (2002). Factors leading to sales force automation use: A longitudinal analysis. *Journal of Personal Selling & Sales Management, 22*, 145–156.

Lau, R. S., & Cheung, G. W. (2012). Estimating and comparing specific mediation effects in complex latent variable models. *Organizational Research Methods, 15*(1), 3–16.

Lu, Y., & Ramamurthy, K. (2011). Understanding the link between information technology capability and organizational agility: An empirical examination. *MIS Quarterly, 35*(4), 931–954.

MacKinnon, D. P., Fairchild, A. J., & Fritz, M. S. (2007). Mediation analysis. *Annual Review of Psychology, 58*, 593–614.

Mathieu, J. E., DeShon, R. P., & Bergh, D. D. (2008). Mediational inferences in organizational research: Then, now, and beyond. *Organizational Research Methods, 11*(2), 203–223.

Nitzl, C., Roldan, J. L., & Cepeda-Carrion, G. (2016). Mediation analysis in partial least squares path modeling: Helping researchers discuss more sophisticated models. *Industrial Management & Data Systems, 116*(9), 1849–1864.

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods, 40*(3), 879–891.

Quinn, R. E., & Rohrbaugh, J. (1983). A spatial model of effectiveness criteria: Towards a competing values approach to organizational analysis. *Management Science, 29*(3), 363–377.

Rigdon, E. (2016). Choosing PLS path modeling as analytical method in European Management Research: A realist perspective. *European Management Journal, 34*(6), 598–605.

Rodríguez-Entrena, M., Schuberth, F., & Gelhard, C. (2016). Assessing statistical differences between parameters estimates in Partial Least Squares path modeling. *Quality and Quantity*, 1–13.

Roldán, J. L., Cegarra, J. G., & Cepeda, G. (2014). Building organisational agility through an unlearning Context. *European Conference on Knowledge Management, 2*, 834–842.

Roldán, J. L., Sanchez-Franco, M. J., & Real, J. C. (2017). From frequency of use to social integration: The mediation of routinization and infusion in Tuenti community. *European Research on Management and Business Economics, 23*(2), 63–69.

Rucker, D. D., Preacher, K. J., Tormala, Z. L., & Petty, R. E. (2011). Mediation analysis in social psychology: Current practices and new recommendations. *Social and Personality Psychology Compass, 5*(6), 359–371.

Shmueli, G., Ray, S., Estrada, J. M. V., & Chatla, S. B. (2016). The elephant in the room: Evaluating the predictive performance of PLS models. *Journal of Business Research, 69*(10), 4552–4564.

Shrout, P. E., & Bolger, N. (2002). Mediation in experimental and non-experimental studies: New procedures and recommendations. *Psychological Methods, 7*(4), 422–445.

Sundaram, S., Schwarz, A., Jones, E., & Chin, W. W. (2007). Technology use on the front line: How technology enhances individual performance. *Journal of the Academy of Marketing Science, 35*, 101–112.

Williams, J., & MacKinnon, D. P. (2008). Resampling and distribution of the product methods for testing indirect effects in complex models. *Structural Equation Modeling, 15*(1), 23–52.

Zhao, X., Lynch, J. G., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. *Journal of Consumer Research, 37*(2), 197–206. doi:10.1086/651257.