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Mediation analysis in partial least squares path modeling: Helping researchers discuss more sophisticated models

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Abstract

Purpose – Indirect or mediated effects constitute a type of relationship between constructs that often occurs in partial least squares (PLS) path modeling. Over the past few years, the methods for testing mediation have become more sophisticated. However, many researchers continue to use outdated methods to test mediating effects in PLS, which can lead to erroneous results. One reason for the use of outdated methods or even the lack of their use altogether is that no systematic tutorials on PLS exist that draw on the newest statistical findings. The paper aims to discuss these issues.

Design/methodology/approach – This study illustrates the state-of-the-art use of mediation analysis in the context of PLS-structural equation modeling (SEM).

Findings – This study facilitates the adoption of modern procedures in PLS-SEM by challenging the conventional approach to mediation analysis and providing more accurate alternatives. In addition, the authors propose a decision tree and classification of mediation effects.

Originality/value – The recommended approach offers a wide range of testing options (e.g. multiple mediators) that go beyond simple mediation analysis alternatives, helping researchers discuss their studies in a more accurate way.

Keywords Structural equation modelling, Partial least squares, Bootstrapping, Indirect effects, Mediation analysis, Multiple mediation

Paper type Research paper

1. Introduction

Partial least squares (PLS) is a variance-based structural equation modeling (SEM) technique that has become very popular in management and social sciences in recent years. Current discussions about PLS emphasis its capability to model both composites and factors (Henseler *et al.*, 2016) and its prediction orientation (Shmueli *et al.*, 2016). In addition to these reasons, PLS is a useful tool for testing hypotheses especially in complex path models in an explorative manner (Chin, 2010; Wold, 1980). Nevertheless, with complex path models, it is much easier to overlook the occurrence of effects that do not directly manifest their influence (cf. Hair *et al.*, 2012; Nitzl, in press). In a naïve manner, researchers focus only on direct relationships and ignore mediating effects completely. This focus can heavily bias the interpretation of the results when a variable has no direct effect because its effect is mediated by another variable. In the worst case, researchers assume that a variable is not relevant for answering their research question at all.

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Despite an increasing use and awareness of mediation effects, studies in PLS often do not consider mediating effects explicitly in their hypotheses and also do not analyze mediating effects in their path models (Hair *et al.*, 2013). Only a third of the PLS studies published in top-tier marketing and management accounting journals and only 20 percent of the PLS-SEM studies published in the *MIS Quarterly* journal conducted an explicit mediator analysis (Hair *et al.*, 2012; Ringle *et al.*, 2012; Nitzl, in press). In their review of five leading organization studies journals, Wood *et al.* (2008b) reported that 92 of 102 studies using mainly covariance-based structural equation modeling (CB-SEM) tested mediating effects. Their review illustrates the prevalence of mediation analysis for SEM.

To understand the relevance of testing mediating effects in a PLS-SEM, it is first necessary to understand what mediating effects are. The core of mediation analysis is that it assumes a sequence of relationships in which an antecedent variable affects a mediating variable, which then affects a dependent variable. In this way, "mediation is one way that a researcher can explain the process or mechanism by which one variable affects another" (MacKinnon *et al.*, 2007). Understanding mediation questions are important for researchers in several ways: they are the foundations of many management topics that can, for example, explain how certain process factors improve or hinder the influence of success drivers (e.g. Cepeda and Vera, 2007; Castro and Roldán, 2013); there is a methodological challenge, that is to say, the inclusion of a third variable that plays an intermediate role in the relationship between two variables in a model.

Over the past few years, these technical challenges have already constituted a vibrant research topic in the quantitative methods domain, such as multiple regression analysis and CB-SEM (Hayes and Scharkow, 2013; Preacher and Hayes, 2008; Rucker *et al.*, 2011). For example, Zhao *et al.* (2010) demonstrated the misapplication of Baron and Kenny's (1986) procedure in the multiple regression analysis field. CB-SEM researchers often consider the latest findings when testing mediation such as testing the indirect effects with the help of bootstrapping (e.g. Iacobucci *et al.*, 2007; Hair *et al.*, 2010), whereas a number of PLS researchers still fail to do so (some current examples are Chi *et al.*, 2015; Jiang and Zhao; 2014; Yu *et al.*, 2015). Nitzl (in press) illustrates that almost all PLS-SEM in management accounting research uses more or less the outdated causal-step approach by Baron and Kenny (1986). This finding is somewhat surprising because state-of-the-art applications for testing the significance of a mediator are very suitable for PLS as well.

Even though initial and early updated proposals have been made for testing mediating effects in studies that applied PLS (cf. Chin, 2010; Sosik *et al.*, 2009; Streukens *et al.*, 2010), they have not found their way to broader application so far. One reason for this seems to be the lack of established knowledge on procedures as well as consolidated guidelines on conducting state-of-the-art mediation analysis. Hence, our contribution is a reaction to the call of Henseler *et al.* (2016) for new guidelines related to all aspects of PLS for serving as a suitable technique.

The objective of our contribution is to bridge this void by providing researchers with the necessary information to implement mediation models in PLS. We offer complete guidelines on how to conduct mediation analysis using PLS. Inspired by Zhao *et al.*'s (2010) paper, we use modern literature on mediation in quantitative methods (i.e. regression and CB-SEM) and transfer it to the PLS domain. We provide a typology of mediation and a decision tree as guidelines. We also factor the characteristics of PLS into consideration.

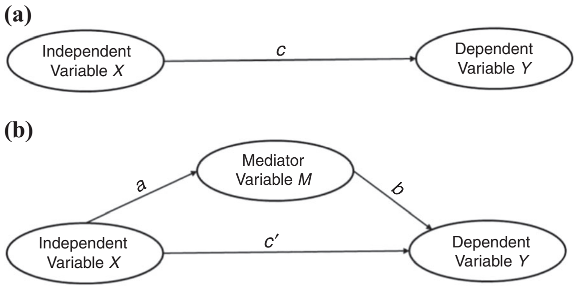
Our paper is structured as follows. After we define mediating effects, we describe Baron and Kenny's (1986) approach for testing mediation in Section 2. Their approach is our starting point because it is well known and researchers in PLS often pursue strategies that are in line with it. We discuss certain drawbacks to Baron and Kenny's (1986) approach, including the separate examination of direct, indirect, and total effects. Based on this, in Section 3, we provide a decision tree and classification of approaches suitable for PLS. In Section 4, we discuss additional aspects of the assessments of mediation in the context of PLS. Thereafter, we describe an important extension testing multiple mediations. Finally, in Section 6, we summarize our findings.

2. The mediating effect and Baron and Kenny's procedure and beyond

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 Figure 1). Figure 1(a) shows the total effect c of the causal relationship between variables X and Y, and Figure 1(b) shows a mediated effect in which X exerts an indirect effect $a \times b$ through M on Y. Thus, when we formulate mediation hypotheses, we focus on how an independent variable (X) affects a dependent variable (Y) by an intervening variable (M) (Baron and Kenny, 1986). The researcher's aim in mediation analysis is chiefly explanation because the main subject of mediation is to understand the development of processes (Henseler *et al.*, 2016; Iacobucci *et al.*, 2007). However, mediation analysis could also play an important role in prediction (Shmueli *et al.*, 2016).

Most scholars followed a procedure similar to that proposed by Baron and Kenny (1986) for multiple regression analysis in PLS. Preacher and Hayes (2008) summarized this approach as follows: "Variable M is a mediator if X significantly accounts for variability in M, X significantly accounts for variability in Y, M significantly accounts for variability in Y when controlling for X, and the effect of X on Y decreases substantially when M is entered simultaneously with X as a predictor of Y." Baron and Kenny's (1986) method assumes that testing the difference between c and c' is equal to testing whether the strength of the indirect path $a \times b$ is significantly different from 0, and this is the main criterion for determining mediation (Iacobucci *et al.*, 2007).

However, in recent years, Baron and Kenny's (1986) causal-step approach for determining mediating effects has been challenged considerably by authors such as



Notes: (a) Simple cause-effect relationship; (b) general mediation model

Figure 1.
Simple cause-effect relationship and general mediation model

Shrout and Bolger (2002), Preacher and Hayes (2004, 2008) and Zhao *et al.* (2010), who call for a reconsideration of Baron and Kenny's (1986) method and suggest applying new procedures. For example, Shrout and Bolger (2002) argued that Baron and Kenny's (1986) first condition, that X needs to show a significant effect c on Y in the first step means an effect c should exist at all and that something can be mediated, should not be a requirement for the existence of mediation. Initially, it seems unnecessary to further investigate whether there is a mediated effect if there is no effect c; however, this argument holds only when complementary mediation occurs in a research model (Zhao *et al.*, 2010), which is the case only when path c has the same effect direction (i.e. positive or negative) as that of the indirect path $a \times b$. In the case of competitive mediation, where the effect of the indirect path $a \times b$ differs from that of path c, this requirement no longer holds. In complex SEMs, this can become critical because different types of mediation can occur in the same model at once. In such a case, it is possible that the direct effect c is not significant even if mediation exists and is therefore misleading as a precondition for mediation analysis. Furthermore, calculating the direct effect c is also problematic because it would require estimating the path coefficient of the model in a step-wise approach in different estimated path models in PLS. In the simplest form of mediation, this would mean first calculating a model with only the total effect c such as that shown in Figure 1(a). Thereafter, the mediation variable has to be included in the SEMs such as the one shown in Figure 1(b) (for a practical example, cf. Nitzl and Hirsch, 2016). Similar to other methods for analyzing mediating effects, in PLS, the estimation of the loadings or weights of the measurements of latent variables could depend on the variables that are considered in a research model. Because of these measurement differences that could occur in the casual step approach when including a new variable, this workaround could cause biases in the estimation of the path coefficients. Hence, this possible path difference can bias the evolution of mediating effects. However, in contrast to regression analysis, this step-wise approach is not necessary as PLS is able to test mediating effects in a single model at once.

Based on these shortcomings and the growing array of alternative approaches, state-of-the-art guidelines have to consider the following points for testing mediating effects in PLS (Preacher and Hayes, 2008; Shrout and Bolger, 2002; Zhao *et al.*, 2010):

First, testing the indirect effect $a \times b$ provides researchers with all information for testing mediation.

Second, the strength of the indirect effect $a \times b$ should determine the size of the mediation.

Third, a bootstrap test should be used to test the significance of the indirect effect $a \times b$.

In the following section, we discuss these elements in more detail and how they should be used to detect and define mediating effects in PLS.

3. Advanced procedure for mediation analysis in PLS

As shown, PLS researchers have to start by testing the indirect effect $a \times b$ when analyzing mediating effects. The indirect effect can also be formulated as the difference between the total and direct effect:

$$\text{Indirect effect}(a \times b) = \text{total effect}(c) - \text{direct effect}(c') \tag{1}$$

In Formula (1), c represents the total effect and not the effect to be mediated. Consequently, c does not constrain the size of a and b or their product (Hayes, 2009);

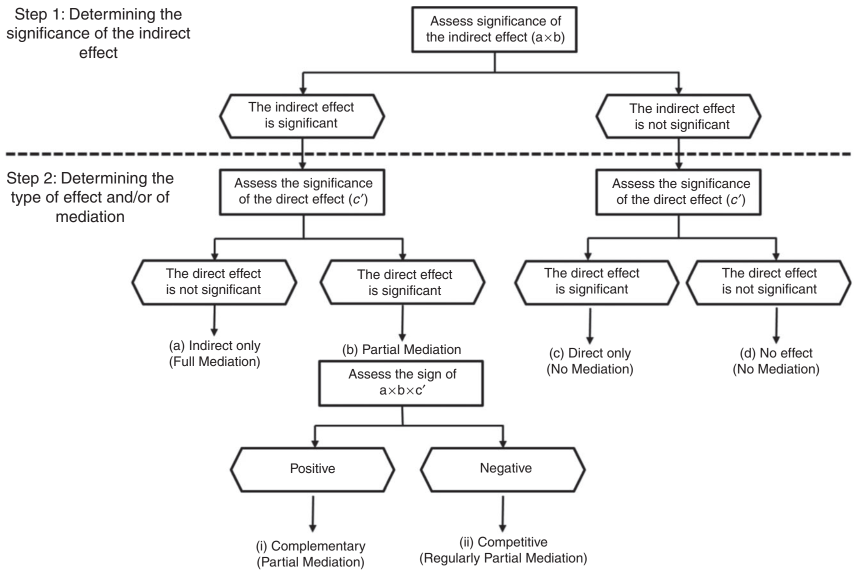
this indicates that it is no longer necessary to test a separate model to obtain the total effect c in a PLS model (Figure 1(a)). Although researchers should regularly include the direct effect c' in their PLS to control and determine the type of mediating effect.

Figure 2 shows a decision tree that can used to determine the type of mediation analysis. It includes two steps that reflect the abovementioned recommendations for state-of-the-art mediation analysis. In the following, we describe these two steps in detail.

Step 1. Determining the significance of indirect effects

In Step 1, the indirect effect is tested for significance. In the simplest form of mediation, the indirect effect is the product $a \times b$ of the two paths from the source construct X to the mediator construct M (path a) and from the mediator construct M to the target construct Y (path b). PLS researchers have often applied the parametric Sobel (1982) test for testing indirect effects (e.g. Helm *et al.*, 2010; Nitzl and Hirsch, 2016). Preacher and Hayes (2004, 2008) show that the Sobel test is not appropriate for analyzing indirect effects because the parametric assumptions (i.e. normality) of paths a and b do not hold for the product term of the two paths (i.e. $a \times b$) if one assumes that a and b are normal distributed. This bias is especially relevant for small sample sizes, which is often the case in PLS (Shrout and Bolger, 2002). Alternatively, researchers should apply bootstrap routines to test the significance of the indirect effect $a \times b$.

The bootstrapping procedure is a non-parametric inferential technique that randomly draws several subsamples (e.g. 5,000) with replacement from the original data set. Bootstrapping a data sample of an indirect effect is necessary to obtain information about the population distribution, which is then the basis for hypotheses testing. Hence, bootstrapping routines do not require assumptions about the shape of the variable distribution (cf. Chin, 2010). In the first step in a PLS, the data for each item of the measurement are bootstrapped. In the next step, the bootstrapped results are



Source: cf. Zhao *et al*. (2010)

Figure 2.
Mediator analysis procedure in PLS

separately used to estimate the underlying PLS path model. The different model estimations provide the distribution of the path coefficients for the inner path model.

The bootstrap routines in the PLS software often provide bootstrap results for at least direct effects (e.g. paths a and 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 combination of $a \times b$ of a certain indirect effect with the help of a spreadsheet application, such as Microsoft Excel or CALC in OpenOffice. 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 $k = 5{,}000$ bootstrapping subsamples entails the generation of $k = 5{,}000$ products $a \times b$ in a new column. Thereafter, the standard deviation, which is equivalent to the standard error (SE) in bootstrapping (Chernick, 2011), can be computed for the new column of the indirect effect $a \times b$ to determine the SE of its distribution. Hair *et al.* (2016) explain this procedure in detail and provide an example that shows how to conduct these computations. Using the SE of $a \times b$ derived from the bootstrap statistic, a pseudo t-test can be calculated to test whether the indirect effect $a \times b$ is significantly different from 0. Furthermore, based on the pseudo t-value, one can also calculate the p value.

MacKinnon *et al.* (2004) and Wood (2005) stated that more valid information about the characteristics of the distribution of mediating effects is received by calculating a confidence interval (CI) for $a \times b$ than with a pseudo t-value. For calculating a CI, the subsamples (k) for $a \times b$ from the bootstrapping procedure must be arranged from smallest to largest (Hayes, 2009). A researcher has to select a specific α error; for example, for a probability of error of 5 percent, a 95 percent CI must be determined with a 2.5 percent probability of error at each tail when conducting a two-sided test. The lower bound of $a \times b$ is in the $k \times (0.5–\mathrm{CI}\%/2)$th ordinal position of the ordered list; for example, if one uses $k = 5{,}000$ subsamples and a 95 percent CI, the lower bound is the $5{,}000 \times (0.5–0.95/2) = 125$th ordinal position. Similarly, the $(1 + k \times (0.5 + \mathrm{CI}\%/2))$th ordinal determines the upper bound of the bootstrap confidence, which is the $1 + 5{,}000 \times (0.5 + 0.95/2) = 4{,}876$th in the previous example. If 0 is not included in the CI, 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 (i.e. sample mean in most applications of the software tools (M)) for the indirect effect $a_M \times b_M$ is not equal to the estimated indirect effect (i.e. original sample in most of the software tools (O)) $a_O \times b_O$ (Chernick, 2011). As a result, researchers must correct for this bias in PLS, which can be accomplished by calculating the difference between the estimated indirect effect $a_O \times b_O$ from the path model and the mean value of the indirect effect $a_M \times b_M$ from the bootstrap sample. Consequently, the bias-corrected CI% for an indirect effect $a \times b$ can be defined as:

$$\left[\left(k \times \left(0.5–\mathrm{CI}\%/2\right)\right)\mathrm{th} + (a_O \times b_O – a_M \times b_M);\right.$$

$$\left.\left(\left(1 + k \times \left(0.5 + \mathrm{CI}\%/2\right)\right)\mathrm{th} + (a_O \times b_O – a_M \times b_M)\right)\right] \quad (2)$$

Hayes and Scharkow (2013) show that the bias-corrected bootstrap CI is the best approach for detecting mediating effects when a mediating effect is present (i.e. Type-II error or power). Conversely, the percentile bootstrap CI that is not bias-corrected is a good compromise if a researcher is also concerned about Type-I errors (Hayes and Scharkow, 2013).

Some researchers revert to Preacher and Hayes's (2004) macro and use the latent variable scores from a PLS program to test indirect effects. This type of workaround is problematic in the context of PLS. As mentioned above, PLS uses each bootstrap subsample to estimate the underlying PLS path model. The bootstrap bases are the measurements of each construct: for a measurement with five items, a separate bootstrap for each of these five items is performed. Using the latent variables scores directly for the bootstrap procedure means fixing the bootstraps of the measurement model and therefore not considering their variance. Hence, using Hayes's macro is less conservative. Therefore, to also fully consider the variance in the measurement of a PLS path model estimation, researchers must directly rely on the bootstrapping results from the PLS software when testing direct effects for significance (Sosik *et al.*, 2009; Chin, 2010).

Step 2. Determining the type of effect and/or of mediation

Step 2 (Figure 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 divided again 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.

(a) 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, which means only the indirect effect via the mediator exists. In other words, full mediations means that the effect of the variable X to Y is completely transmitted with 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. As an example, Nitzl and Hirsch (2016) show that in the trust relationship between a superior and a subordinate, the effect of the organization setting (X) to trust belief (Y) is fully mediated by the trustworthiness (M) of the subordinate. This finding shows that even in an organization setting (X) that may influence the trust relation between a superior and his/her subordinate in a positive way, the superior will not trust the subordinate when he/she is not trustworthy. Technically speaking, the variable X extracts his influence only under a certain condition of M on Y. However, in the case of small samples, a researcher have 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 nonsignificant" (p. 364).

Hence, it is advisable to ensure that the sample size is sufficiently large that the necessary power of 0.8 for an α level of 0.05 for detecting effects in a PLS path model is obtained (Roldán and Sánchez-Franco, 2012; Nitzl, in press). For a simple mediation model such as that shown in Figure 1(b), the necessary sample size is quite low, starting with 30 cases to detect strong effects, which is often the case in the context of experimental research (small sample per group and analyzing strong effects). Notwithstanding, a medium and small effect size would require a sample of 66 and 481 cases, respectively. In contrast, in many cases, it can be observed that some small direct effect c' remains 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 accountant for (VAF) value, which we will discuss in more detail below. 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.*, 2016).

(b) 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 mediations can be distinguished:

(i) 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, whereas 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. Complementary partial mediation is often called a "positive confounding" or a "consistent" model (Zhao *et al.*, 2010). For example, Nitzl and Hirsch (2016) showed, in addition to the abovementioned full mediating effect, that 30 percent of the trust disposition (X) of a superior is mediated through the organizational (M) setting. Thus, the superior with a higher trust disposition (X) perceives the organizational context to be more positive, which in turn positively influences whether a subordinate will be perceived as trustworthy (Y).

(ii) 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 (Figure 2). As mentioned above, this indicates that a portion of the effect of X on Y is mediated through M, whereas 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.

For example, McFatter (1979) suggested that intelligence (X) has a positive influence on individual performance (Y); however, this effect could be suppressed by the task boredom variable (M) because intelligence (X) leads to greater task boredom (M), and this variable has a negative effect on individual performance (Y). In this vein, complementary and competitive mediation are equally likely to occur, and each has the potential to deliver theoretically interesting findings (MacKinnon *et al.*, 2007). Thus, other types of mediation beyond complementary mediation should be considered in a PLS path model.

(c) Only direct effect

If the indirect effect $a \times b$ is not significant (i.e. the right path in the Figure 2 decision tree) whereas 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 the model's theoretical basis if the expected mediation relationship cannot be found (cf. Zhao *et al.*, 2010).

(d) 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, the researcher should determine whether the sample size has enough power to show an effect when there is an effect (Roldán and Sánchez-Franco, 2012; Nitzl, in press). 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, the researcher should 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. If the mediation variable M has no real effect, it only dilutes the effect of the direct variable X and should be deleted.

4. Additional aspects for assessing mediation models fit and strength in PLS

Before the background that mediation analysis mainly deals with explanation, a discussion of the use of goodness-of-fit indices is appropriate. The goodness-of-fit of a model is the ability of a PLS path model to reproduce the data. Iacobucci *et al.* (2007) emphasize that a good fit is required before interpreting mediation analysis in a structural model in the context of CB-SEM, which is in line with the general suggestion of Henseler *et al.* (2016) for PLS that it should also become customary for PLS to determine the model fit. According to Wood *et al.* (2008b), many authors inferred full mediation when a model excluding direct effect c' exhibited a better fit than a model including both direct c' and the indirect effects $a \times b$.

In the past, there were no valid criteria for evaluating the global fit of a PLS path model (Henseler and Sarstedt, 2013). Recently, to fill this gap, Henseler *et al.* (2014) introduced the fit index standardized root mean square residual (SRMR) for the context of PLS. A value below 0.08 indicates that a PLS path model provides a sufficient fit of the empirical data (cf. Hu and Bentler, 1998). Williams and MacKinnon (2008) argue that the CIs from resampling methods are a possible solution to the distributional irregularities of the mediated effect. Therefore, it is good practice to report the upper quantile of the CI of the bootstrap distribution of the SRMR, which Henseler *et al.* (2016) propose as an exact test of the model fit. Other indices that can be used for testing the exact fit are the geodesic discrepancy (d_G) and the unweighted least squares discrepancy (d_{ULS}) (Dijkstra and Henseler, 2015). Hence, the analysis of a mediation model in a PLS path model should start with the evolution of the global fit to verify that all relevant effects are included in the structural model. Furthermore, in line with the abovementioned practice, a PLS researcher can use SRMR, for example, for inferring a full mediation when a model excluding direct effect c' exhibits a better fit than a model including both direct c' and indirect effects $a \times b$.

Beside the assessment of the model fit, PLS researchers might also be interested in evaluating the strength (portion) in case of a partial mediation. Mediation analysis regularly involves 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 VAF value. VAF determine the extent to which the mediation process explains the dependent variable's variance. For a simple mediation, the proportion of mediation is defined (Figure 1) as:

$$\mathrm{VAF} = \frac{a \times b}{a \times b \times c'} \tag{3}$$

Using VAF as classification for mediation portion is not uncritical. If the indirect effect is significant but does not mediate much of the total effect c, VAF would be low. As shown in Figure 2, a significant indirect effect $a \times b$ and insignificant direct effect c' would indicate a full mediation. Such differences between significance testing and VAF interpretation especially occur when samples sizes are small in terms of the power or a high multicollinearity between the constructs exists (Rucker *et al.*, 2011). A researcher should be aware that detecting a significant indirect effect $a \times b$ is always higher than detecting a direct effect c' (Cohen, 1988). The rule of thumb is if the VAF is less than 20 percent, one should conclude that nearly zero mediation occurs; a situation in which the VAF is larger than 20 percent and less than 80 percent could be characterized as a typical partial mediation (Hair *et al.*, 2016); and a VAF above 80 percent indicates a full mediation. However, in this situation, the VAF may amount to, for example, only 60 percent, in which case researchers should not assume full mediation.

Additionally, the interpretation of VAF is clear only for consistent or complementary mediating effects (i.e. c and $a \times b$ having the same effects positive or negative). In one case, VAF can be greater than 1 when the total effect c is smaller than the indirect effect $a \times b$; this is the case for a suppressor effect. In situations where the VAF is greater than 1 and the direct effect c' is not significant; there is no strong indication that suppression is present. In this situation, Shrout and Bolger (2002) suggest considering a VAF equal to 1 as representing a full mediation. In another case, one could consider inconsistent mediation (i.e. c and $a \times b$ having different effects) as yielding a negative VAF or a VAF tending to infinity as c approaches 0 (Hayes, 2009). Therefore, some researchers advise the calculation of VAF only when the absolute value of the standardized total effect $c = a \times b + c'$ is at least 0.2 (Hair *et al.*, 2016). Thus, in general, VAF may provide some deeper insights into mediation analysis but should be interpreted very cautiously given the background of the above mentioned limitations.

Some researchers measure the strength of mediation as its influence on the coefficient of determination R^2 (James and Brett, 1984). However, a change in R^2 says nothing about whether a mediator explains a portion of the relationship between an independent and a dependent variable (Wood *et al.*, 2008b) because the amount of reduction in the effect of an independent variable due to a mediator variable is not equivalent to either the change in R^2 or the change in the associated inferential statistics, such as the F value. The finding that R^2 is significantly greater after including a mediator indicates only an additive effect. Therefore, the methods for measuring the mediation's strength should be based on the indirect effect.

Furthermore, a researcher should not overlook important further aspects for the assessment of mediating effects in a PLS path model. An important precondition for analyzing mediating effects is that residuals (error terms) have to be uncorrelated;

otherwise, they can heavily bias the results of the estimations (McDonald, 1997). In CB-SEM, the correlations between residuals can be followed by identification problems that have to be resolved using an unrealistic constraint of the error term with 0. In contrast, PLS as a soft modeling approach does not suffer from identification problems in the case of correlated residuals (Falk and Miller, 1992). PLS can suffer from a problematic bias in the estimation of the direct effect c', which is similar to what Henseler (2012) shows for generalized structured component analysis. The size of the bias depends on the reliability of the mediating construct. Hence, researchers should recognize the need for valid and reliable measurements when testing mediating effects in PLS.

5. Handling multiple mediations

PLS is regularly characterized by complex path models (Hair *et al.*, 2012; Nitzl, in press). There may be multiple relationships between one or more independent variables, one or more mediator variables, or one or more dependent variables (for general SEM examples, see Wood *et al.*, 2008a). 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 using a PLS path model to analyze which process improves or hinders the influence of the external pressure to work on performance. 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 remain unchanged (Hayes, 2009).

Figure 3 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 effect 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 Figure 3, the calculation of the total effect is:

$$c = c' + a_1 \times b_1 + a_2 \times b_2 \tag{4}$$

An interesting situation occurs (see our example above) when $a_1 \times b_1$ and $a_2 \times b_2$ in Equation (4) have an opposite sign; this indicates that one effect functions as a

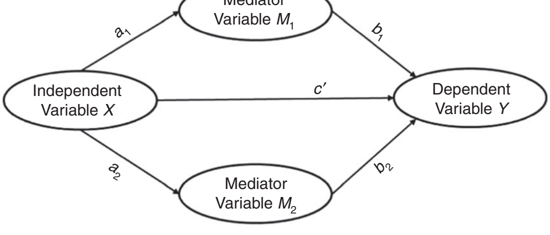


Figure 3. Multiple mediator model

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 CIs 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:

$$D_M = M_1 - M_2 \tag{5}$$

where M_1 and M_2 are the specific indirect effects and 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 0. In the case examined in this study, the equation for Figure 3 would be $D_M = a_1 \times b_1 - a_2 \times b_2$. Again, researchers can calculate the equation using a spreadsheet application to build a CI with the help of the bootstrapping results of a PLS program.

A frequently encountered case is one in which two mediators are connected to each other. This connection indicates an additional relationship between M_1 and M_2 in Figure 3. Castro and Roldán (2013) and Klarner *et al.* (2013) 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 0, 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).

6. Conclusion

PLS applications must routinely account for mediating effects and apply state-of-the-art procedures. For this reason, we propose an alternative procedure for mediation analysis in PLS. Several articles using PLS applied at least some form of mediation. Although a few PLS studies already used a modern approach to test mediation, no study has yet presented a systematic overview and guideline of how to perform and classify a mediation analysis in a PLS path model context. PLS researchers are keenly interested in testing mediational hypotheses. However, they have used (if any) Baron and Kenny's (1986) approach, which is often criticized. Therefore, we have systematically transferred the recent findings from different research areas on mediation analysis to PLS. We summarize the findings more comprehensively and also evaluate their applicability for PLS, resulting in adjusted recommendations for mediation analysis in the context of PLS.

We illustrate that the characteristics of PLS require special consideration when analyzing mediating effects. PLS makes it necessary to test the relevant effects in one single model and not to follow a causal-step approach for testing mediating effects, in which first a direct effect is tested and a mediator variable is included in the next step. Additional, the bootstrap results for testing indirect effects have to be used directly from the PLS software because of fixed measurement problems when using only the values from the latent constructs that are included in another program. Moreover, caution is necessary when mediation is indicated, however, in terms of additional assessments contradicting the classification guideline. The reasons for possible contradictions include small sample sizes or high multicollinearity.

With PLS, it is straightforward to estimate important extensions such as multiple mediators. With the help of the decomposition of total and indirect effects and testing these effects, a researcher can gain deep insight into mediation processes of a PLS, which should become a standard approach for PLS. For the sake of brevity, we do not include a concrete example where we show every aspect that we discuss. Nevertheless, we regularly refer to concrete examples relevant to our research. In general, good examples for mediation analysis can be found in Chin (2010) and Streukens *et al.* (2010). In summary, this paper provides researchers with a wide range of tools for performing advanced mediation analysis in PLS that may improve theory development in different research areas.

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