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Research Articles

Conducting Mediation Analysis in Marketing Research

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Marketing researchers frequently conduct mediation analysis to enrich their understanding of a focal causal relationship by examining its underlying mechanism. The main purpose of this review is to provide an overview of what mediation analysis means, which approaches exist to establish mediation, and how to conduct mediation analysis with the state-of-the-art methodology. In the first part of the paper we review conceptual considerations of mediation for the most commonly used mediation model groups. We further discuss the suitability of different mediation analysis approaches, focusing on the bootstrapping approach. The second part of the paper is organized as a tutorial. Based on an example from the marketing field, we illustrate how to specify, estimate, and interpret mediation models with a tool for SPSS and SAS called PROCESS (Hayes 2017). We recommend a hierarchical procedure in which simple mediation models are examined first, followed by more complex models.

1. Introduction

Researchers in marketing and other fields are often interested in the causal effect of a predictor on an outcome variable. Mediation analysis adds to the understanding of such an effect by examining how well the effect can be explained by another variable, called a mediator (Iacobucci 2008). Thus, mediation analysis reveals how the predictor indirectly affects the outcome through the mediator. A prominent marketing example comes from research on advertising effectiveness, which revealed that the effect of ad liking on purchase intent is mediated by brand liking (MacKenzie et al. 1986). Mediation analysis is therefore especially relevant for those interested in grasping the underlying mechanism of a focal effect (Preacher 2015).

While common as a concept, an actual methodology of how to analyze mediation had not been established until Baron and Kenny (1986) proposed causal steps a researcher should apply to support a mediation hypothesis. The causal steps approach is based on the idea of inferring mediation from a series of separate regression models (Baron and Kenny 1986; James and Brett 1984; Judd and Kenny 1981). Another approach for analyzing mediation that was becoming increasingly popular at the time is structural equation modeling (SEM; Bagozzi and Yi 1988; Bollen 1989). Due to its ability to simultaneously

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estimate all model paths (Iacobucci et al. 2007), SEM is superior to the causal steps method. However, as its relative sophistication poses a number of problems and pitfalls (Anderson and Gerbing 1988), there have been calls for alternatives that are easy to use while also being equivalent to SEM.

Recent developments indicate that regression-based bootstrap approaches could be that alternative (Preacher and Hayes 2004, 2008). In particular, sophisticated mediation analysis has been simplified by Hayes' provision of the mediation analysis macro PROCESS, which is available for SPSS and SAS (Hayes 2017), as well as the accompanying textbook (Hayes 2013). Due to these advances, regression-based mediation analysis now allows the same reliability in estimation as SEM does (Hayes and Scharkow 2013). Therefore, applications of regression-based mediation analysis with novel methodology (Hayes 2013; Preacher and Hayes 2004, 2008) have been garnering increasing interest. The growing number of citations of the respective methodology papers reflects the relevance of mediation analysis as a means of theory development and testing in marketing research (see *Fig. 1*). *Fig. 1* displays how many times the most influential mediation publications (i. e., Baron and Kenny 1986; Hayes 2013; Preacher and Hayes 2004, 2008; Sobel 1982) have been cited in the top-tier marketing outlets *Journal of Consumer Research*, *Journal of Consumer Psychology*,[1] *Journal of Marketing*, *Journal of Marketing Research*, and *Marketing Science* since the publication of Baron and Kenny's (1986) causal steps approach. As can be seen from *Fig. 1*, interest in mediation analysis has increased substantially in the last decade.

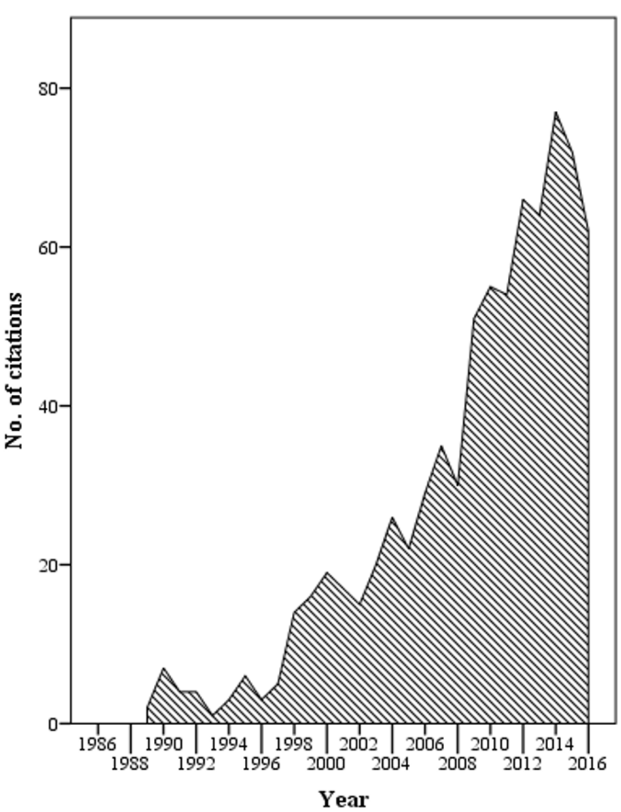


Fig. 1: Citation trend of influential mediation analysis publications

Although there is now a well-established body of literature advancing the methodology of mediation analysis since Baron and Kenny (1986), this technical literature has not fully "diffused to practicing researchers" (Zhao et al. 2010, p. 197). As a result, researchers often diverge in how they conduct tests of mediation (Hayes and Scharkow 2013). This paper contributes to existing literature by concisely integrating theoretical and practical knowledge in order to help in applying mediation analysis. Our main goal is to provide an overview of what mediation analysis means and which approaches exist to establish mediation, followed by a tutorial that demonstrates how to apply the state-of-the-art methodology. In the tutorial we illustrate how to specify, interpret, and report results using PROCESS (Hayes 2017). The analyses are conducted with examples from the marketing context.

2. Characteristics of mediation

Central to the concept of mediation is the so-called *mediator*. Extending a simple causal inference where a predictor X causes an outcome Y, the mediator M intervenes within this relationship. A mediator M is therefore a variable that is influenced by the predictor X and in turn influences the outcome Y: $X \rightarrow M \rightarrow Y$. When conducting mediation analysis, the researcher is primarily interested in this intervention process, namely the *indirect effect*, because it reveals something about how the causal relationship works (Iacobucci 2008). Therefore, examining the indirect effect is the focal element of theory testing with mediation analysis (Hayes 2013).

However, to estimate the extent to which the mediation process explains the relationship between the predictor X and the outcome Y, it is also necessary to consider the so-called *direct effect*. The direct effect represents the causal influence of X on Y that is not explained by the mediator M (James and Brett 1984). As we will outline in Section 2.3, examining the direct effect is particularly useful for further theory building (Zhao et al. 2010).

2.1. Indirect effect: Key to establishing mediation

In a first step, a researcher is often interested in *whether* a proposed mediator M can explain an effect of X on Y at all. This question is addressed by estimating the indirect effect through the mediator M (Hayes 2013). Hence, interpreting the indirect effect is the foundation for inference about a mediation hypothesis (Baron and Kenny 1986). In the following, we discuss how the indirect effect can be interpreted. It is important to note that the interpretation of the indirect effect is dependent on the model structure, especially the number of variables in the model and their interrelationships. While there is a multitude of possible mediation models, in this paper we focus

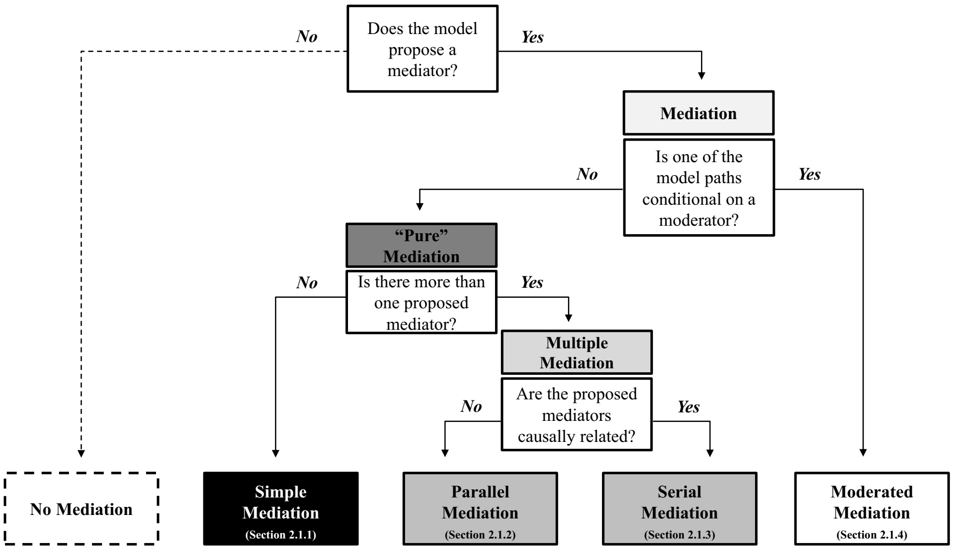


Fig. 2: Typology of mediation model groups

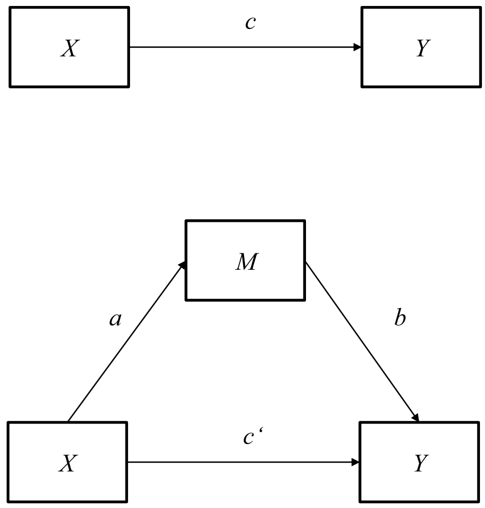
on four prototype model groups (Hayes 2013). Three of these model groups entail mediation only; hence we refer to them as models of "pure" mediation: (i) *simple mediation*, (ii) *parallel mediation*, and (iii) *serial mediation*. Aside from these "pure" mediation model groups, there are models that additionally contain moderator variables, referred to as *moderated mediation* models. *Fig. 2* illustrates the prototype model groups.

Simple mediation captures the standard $X \rightarrow M \rightarrow Y$ causal system, which means that there is exactly one mediator. In case of two or more mediators in the model, one can speak of multiple mediation (Hayes 2013). If the multiple mediators are causally unrelated, this is called *parallel mediation*, while *serial mediation* is present if at least two of the mediators in the model are causally related (i. e., one mediator affects another one and they form a causal chain). *Moderated mediation* means that at least one mediation path is linearly dependent on another variable. Each mediation model group is discussed in greater detail in the following section.

2.1.1. Simple mediation

Mediation extends simple regression by introducing an explaining variable, the mediator (see *Fig. 3*). When there is exactly one mediator M intervening in the causal relationship of X on Y, this is called simple mediation. Conceptually, simple mediation means that a change in X leads to change in M (path a), and that change in M leads to change in Y (path b). The indirect effect is depicted as path ab because it is the product of the two paths that connect the predictor X to the mediator M (path a) and the mediator M to the outcome Y (path b). If the indirect effect ab is greater or smaller than zero (i. e., if it is statistically significant), one can claim that some form of mediation takes place (Zhao et al. 2010).

Simple mediation is the most basic form of mediation and allows one to make inferences about the underlying mechanism that connects an independent with a dependent variable. If the underlying process involves more than one mediator, so-called multiple mediation models are used. We discuss two forms of multiple mediation – parallel and serial mediation – in the following sections.



X: predictor variable
M: mediator
Y: outcome variable

a: effect of X on M
b: effect of M on Y

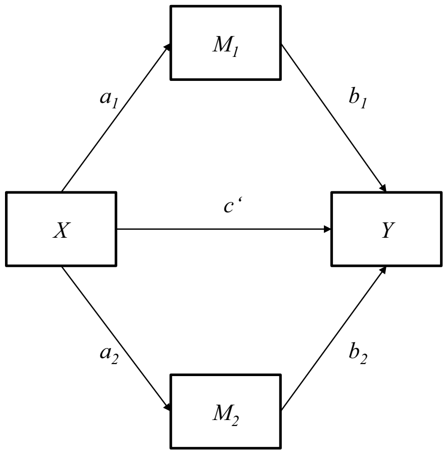
ab: indirect effect of X on Y
c': direct effect of X on Y

c: total effect of X on Y $= ab + c'$

Fig. 3: Simple mediation model as an extension of a simple causal relationship (based on Preacher and Hayes 2004, p. 718)

2.1.2. Parallel mediation

In some cases there are alternative theories to explain an effect of X on Y. In such cases, investigating the role of only one mediator is not enough. For example, while one theory might propose a mediator M_1, another theory might propose a different mediator M_2 for the same relationship (Hayes 2009). Considering two or more mediators that are not causally interrelated is the most basic extension of the simple mediation model; it is called parallel mediation (Hayes 2013). Parallel mediation models enable researchers to probe different mediation theories simultaneously in a model (e. g., Guevarra and Howell 2015). The example of two mediators would lead to a conceptual model structure like the one shown in *Fig. 4*.



X: predictor variable
M_1: mediator 1
M_2: mediator 2
Y: outcome variable

a_1b_1: specific indirect effect of X on Y through M_1
a_2b_2: specific indirect effect of X on Y through M_2

c': direct effect of X on Y
total indirect effect: $a_1b_1 + a_2b_2$

Fig. 4: Parallel mediation model with two mediators (based on Hayes 2013, p. 126)

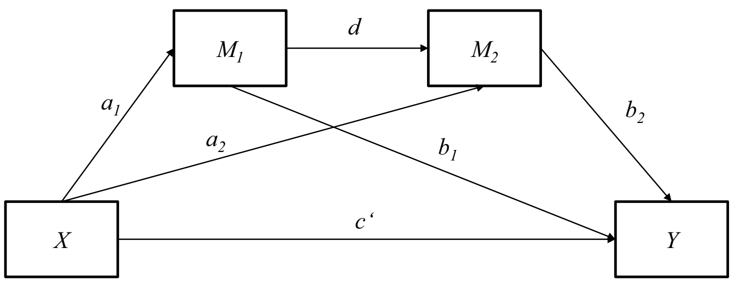
In models with more than one mediator, several *specific indirect effects* exist that can be attributed to one of the mediators. In the example displayed in *Fig. 4*, there are two specific indirect effects a_1b_1 and a_2b_2. If the aim of the researcher is to compare these two mediation processes, it is useful to assess the importance of each specific indirect effect. To do so, the researcher could check which of the proposed parallel mediations (i. e., specific indirect effects) is significant and then compare the magnitude of those specific indirect effects by testing whether they are equal in size (Preacher and Hayes 2008).

All specific indirect effects sum up to the *total indirect effect*, which expresses the extent to which all mediators together can explain the relationship between X and Y. We note that there are cases in which specific indirect effects with different signs cancel each other out, leading to an insignificant total indirect effect, despite having significant specific indirect effects (Rucker et al. 2011). Such a finding would be valuable, as it identifies two antagonistic mechanisms and thus offers deeper insight into the relationship between X and Y (Hayes 2009). This implies that finding a non-significant total indirect effect does not automatically mean that the conceptual model is flawed.

2.1.3. Serial mediation

Whenever the researcher hypothesizes that two or more mediators in a model influence each other, this is called serial mediation. In contrast to parallel mediation, serial mediation means that the mediators themselves are in a hierarchical causal relationship. Serial mediation is especially useful for investigating fine-grained causal chains of mediation (Hayes 2013) and is commonly employed in the marketing field (e. g., Hur et al. 2015; Winterich and Zhang 2014). *Fig. 5* depicts an example in which one mediator affects another mediator.

Similarly to parallel mediation, the indirect effect in a serial mediation model is split up into several specific indirect effects. In the two-mediator example, three specific indirect effects can be distinguished. First, there is the *long-way mediation*, which involves both mediators: a_1db_2. The long-way mediation represents a causal chain of mediators and is therefore the foundation of the serial mediation hypothesis. Second, there are two *shortcut mediations*, which each involve only one mediator: a_1b_1 and a_2b_2. If the long-way mediation is significant, serial mediation can be claimed. If the long-way mediation is not significant, this indicates that one of the other forms of mediation is more likely: if both shortcut mediations are significant, this indicates parallel mediation (as in *Fig. 4*); and only one significant shortcut mediation indicates simple mediation (as in *Fig. 3*). As in parallel mediation, the sum of all indirect effects constitutes the total indirect effect. The total indirect effect indicates the extent to which the long-way and all shortcut mediations together explain the effect of X on Y.



X: predictor variable
M_1: mediator 1
M_2: mediator 2
Y: outcome variable

a_1db_2: long-way specific indirect effect of X on Y through M_1 and M_2
a_1b_1: shortcut specific indirect effect of X on Y through M_1 only
a_2b_2: shortcut specific indirect effect of X on Y through M_2 only

c': direct effect of X on Y

total indirect effect: $a_1db_2 + a_1b_1 + a_2b_2$

Fig. 5: Serial mediation model with two mediators (based on Hayes 2013, p. 145)

2.1.4. Moderated mediation

Researchers often are not only interested in detecting a particular process (which would be tackled by a "pure" mediation analysis) but also want to investigate the conditions under which this process is active (e. g., Blanchard et al. 2016). Examining such conditions (also called *boundary conditions* of the focal effect) offers valuable information that helps assess whether indirect effects are conditional on different groups of respondents, contexts, or – more generally – on another variable (Preacher et al. 2007). For example, a proposed mediation might exist for one subgroup of the sample but not for another subgroup. Aside from this example of switching the mediation on and off, the so-called moderator variable might also strengthen or weaken the mediation or switch the mediation's direction (represented by a change in sign).

Whenever the mediation process is dependent on another variable, this is called moderated mediation (James and Brett 1984; Muller et al. 2005). Moderated mediation analysis works similarly to moderated regression analysis, with the exception that an indirect effect is altered. In moderated mediation, the moderator influences either one or both of the two paths of the indirect effect (*a* and *b*; Hayes 2013). Most moderated mediation models propose that the moderator alters the relationship of *X* on *M* (so-called *first-stage moderated mediation*, panel A of *Fig. 6*). However, it is also possible that the moderator conditions how the mediator *M* influences the outcome variable *Y* (so-called *second-stage moderated mediation*, panel B of *Fig. 6*). Furthermore, one or more moderators could also impact both paths of the indirect effect (panels C and D of *Fig. 6*).

The influence of the moderator is not necessarily limited to the indirect effect and can include the direct effect (panel E of *Fig. 6*). Further extensions, such as higher-order interactions (panel F of *Fig. 6*), are also possible. The myriad of potential combinations makes it necessary to reason a priori about conditional processes and develop a model based on the specific theorizing.

As moderated mediation is about inferring whether an indirect effect is linearly conditioned by a moderator, the most central result of such a model would be the so-called *conditional indirect effect* of *X* on *Y* (Iacobucci 2008). Although many authors have conceptually referred to moderated mediation (Baron and Kenny 1986; James and Brett 1984; Muller et al. 2005), an appropriate procedure for examining a conditional indirect effect was offered only recently (Hayes 2015). The procedure involves a formal test of the conditional nature of proposed mediators called the *index of moderated mediation* (Hayes 2015).

2.2. Direct effect: Key to assessing the importance of the mediation

While a significant indirect effect of *X* on *Y* through *M* answers the question of *whether* a proposed mediation exists, a researcher might also be interested in understanding to *what extent* the mediator can explain the relationship between *X* and *Y* (Rucker et al. 2011). In mediation analysis, this is determined by the direct effect of *X* on *Y*, which represents the influence of *X* on *Y* that is unrelated to change in *M*. Given a significant indirect effect but an insignificant direct effect, the mediation fully explains the variation of *Y* by *X*. In this case, researchers speak of *full mediation* (Baron and Kenny 1986; Zhao et al. 2010). However, if the direct effect is significant, the mediator *M* only partially explains the effect of *X* on *Y* and the term *partial mediation* is used (James and Brett 1984; Zhao et al. 2010). While some authors claim full mediation to be the gold standard, most articles that use mediation analysis report only partial mediation (Iacobucci 2008). In the following, we examine how distinguishing partial from full mediation may offer implications for theory building.

2.3. Mediation types and their implications for theory building

Zhao et al. (2010) developed a typology of mediation based on the interpretation of the indirect and direct ef-

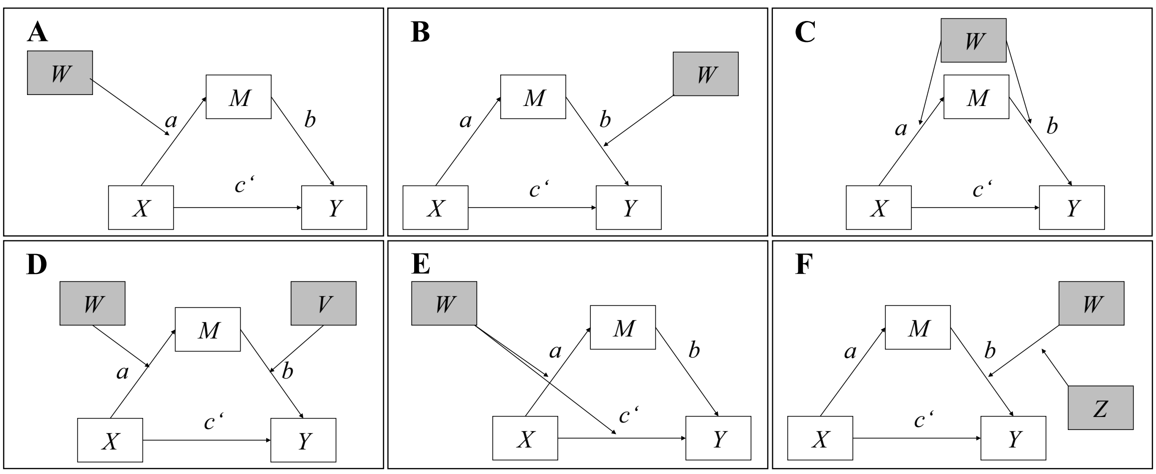
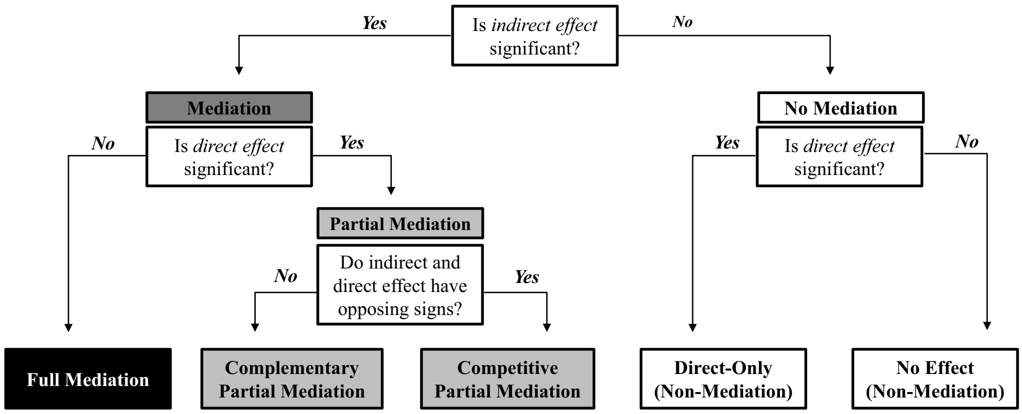


Fig. 6: Selection of variants of a moderated mediation model (own illustration based on Hayes 2013, p. 14)



	Full Mediation	Complementary Partial Mediation	Competitive Partial Mediation	Direct-Only (Non-Mediation)	No Effect (Non-Mediation)
Results Consistent with Proposed Framework?	**Yes**	**Yes**	**Yes**	No	No
Likely to Find an Omitted Mediator?	No	**Yes**	**Yes**	**Yes**	No
Most Likely Sign of this Omitted Mediator?		**Same sign as the existing mediator**	**Opposing sign to the existing mediator**	**Same sign as the direct effect**	

Fig. 7: Mediation types and their implications for theory building (own illustration based on Zhao et al. 2010, p. 201)

fects. *Fig. 7* illustrates this approach of distinguishing different mediation types (including non-mediation) and the associated implications for theory building.

As previously stated, a significant indirect effect combined with an insignificant direct effect reflects full mediation (Baron and Kenny 1986). In the case of full mediation, the underlying process is adequately captured and there is no need to search for additional explanatory elements (e. g., another mediator). In contrast, partial mediation implies that the researcher could find other mediators that have thus far been omitted in the analysis (Rucker et al. 2011). Following Zhao et al. (2010), the partial mediation concept is divided into two subtypes: *complementary partial mediation* and *competitive partial mediation*. Complementary partial mediation occurs when the indirect effect and the direct effect have the same sign. This means that there could be another potential mediator with the same sign as the existing mediator “hidden” in the direct effect. In contrast, competitive partial mediation takes place when the indirect effect and the direct effect have opposing signs. Competitive partial mediation implies that the “hidden” potential mediator and the existing mediator have opposing signs (Zhao et al. 2010).

Besides pointing to omitted mediators, partial mediation may also indicate that an important moderator has not been taken into account (Shrout and Bolger 2002). This could mean that the proposed mediation might only apply for a certain group or under a certain condition (omitted moderated mediation). If the moderator is not considered, there is a risk of underestimating the importance of the mediation process (Shrout and Bolger 2002), such as inferring partial mediation when in reality there is full mediation.

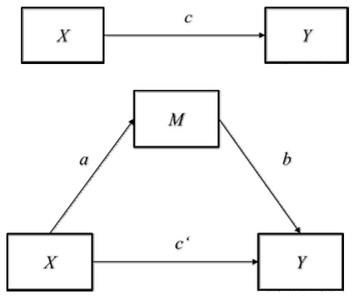
An insignificant indirect effect suggests non-mediation (Zhao et al. 2010). In this case, the same conclusions as before apply: if the direct effect is significant, there is a chance that the true mediator has been omitted. We note that in such a case, examination of paths *a* and *b* is particularly informative. If path *a* or *b* is not significant or very small in magnitude, this could explain the insignificance of the indirect effect as a whole, and it can guide future modification of the inconsistent conceptual framework. If both the indirect and direct effects are insignificant, *X* and *Y* are apparently unconnected.

3. Approaches to examine mediation

In the marketing field there are three dominant approaches to examining mediation: the *causal steps method* proposed by Baron and Kenny (1986), the *normal theory approach* introduced by Sobel (1982, 1986), and the regression-based *bootstrapping approach* put forth by Preacher and Hayes (2004, 2008). While the first two approaches are often used in conjunction and represent the traditional way of testing for mediation, bootstrapping is a more recent approach in mediation analysis.

3.1. Traditional approaches

Traditionally, the most influential approach in probing mediation has been the causal steps approach. Though Judd and Kenny (1981) as well as James and Brett (1984) already discussed the technique, it was finally proposed by Baron and Kenny (1986) and is therefore known as the *Baron-and-Kenny approach* (Kenny 2008). The basic principle of the causal steps approach is that it does not test the indirect effect itself, but logically infers mediation from testing all paths of the model separately

Step	Tested path	Regression equation*	Visualization
Step (i)	*c* path (total effect of *X* on *Y*)	$Y = i_1 + \boldsymbol{cX} + \varepsilon_Y$	
Step (ii)	*a* path (effect of *X* on *M*)	$M = i_2 + \boldsymbol{aX} + \varepsilon_M$	
Step (iii)	*b* path (effect of *M* on *Y*)	$Y = i_3 + c'X + \boldsymbol{bM} + \varepsilon_Y$	
Step (iv)	*c'* path (direct effect of *X* on *Y*)	$Y = i_3 + \boldsymbol{c'X} + bM + \varepsilon_Y$	

Notes: * Bold terms symbolize the tested parameters.

Tab. 1: Steps of the Baron-and-Kenny approach (own illustration based on Müller 2009, p. 247)

in four steps (Baron and Kenny 1986).[2] The approach involves analyses of (i) the total effect of *X* on *Y*, (ii) the effect of *X* on *M*, (iii) the effect of *M* on *Y*, and (iv) the direct effect of *X* on *Y* (see *Tab. 1*). Baron and Kenny (1986) propose that one can only claim mediation if all effects in the first three steps turn out to be significant. Given this prerequisite, one can claim full mediation if the direct effect in the fourth step is non-significant and partial mediation if it the direct effect is smaller than the total effect.

The Baron-and-Kenny approach has been criticized for several reasons. The most critical issues are its lack of power (which means that it often cannot uncover a genuine mediation process) as well as its failure to test the indirect effect *ab* (Hayes 2013; MacKinnon et al. 2002; Preacher and Hayes 2004, 2008). In addition, the requirements for steps (i) and (iv) seem overly restrictive and are unnecessary for establishing mediation (Hayes 2009; Rucker et al. 2011; Zhao et al. 2010). Due to these limitations, the Baron-and-Kenny approach no longer seems to be recommended (Hayes 2013; MacKinnon et al. 2002).

The normal theory approach (Sobel 1982, 1986), also called the *Sobel test*, addresses one weakness of the Baron-and-Kenny approach by establishing a formal test of the indirect effect *ab*. The Sobel test uses a logic for the inference of the indirect effect similar to that usually used for the estimation of direct effects. To conduct the test, one calculates the product of the coefficients *a* and *b*, divides this product by an estimate of the standard error of *ab*, se_{ab}, and compares this empirical z-score to a critical value from the standard normal distribution (Sobel 1982):

$$Z = \frac{ab}{se_{ab}} \tag{1}$$

Several methodological variations of the Sobel test exist, each varying in the way that se_{ab} is estimated. The simplest estimation approach (Baron and Kenny 1986; Sobel 1982), also referred to as first-order delta solution, encompasses the squared coefficients *a* and *b* and their squared standard errors:

$$se_{ab} = \sqrt{a^2 se_b^2 + b^2 se_a^2} \tag{2}$$

More complex estimation approaches include an additional product term of both squared standard errors, with this term either added to Equation (2) (Aroian 1947; so-called second-order delta solution) or subtracted (Goodman 1960; so-called unbiased delta solution). As all methods yield very similar results (Hayes and Scharkow 2013; MacKinnon et al. 1995), the simple first-order delta solution seems to be the most straightforward approach. Nevertheless, the following remarks hold for all variants of the Sobel test.

The Sobel test's shortcomings result from its normality assumption of the sampling distribution in the indirect effect *ab*. This assumption is usually only met in very large sample sizes (i. e., $n > 1{,}000$; Kisbu-Sakarya et al. 2014), while in smaller samples the sampling distribution of *ab* tends to be asymmetric (Bollen and Stine 1990; Stone and Sobel 1990). Although this limitation becomes less problematic with increasing effect sizes (e. g., a sample size of $n = 100$ seems sufficient to detect medium-sized mediation effects; MacKinnon et al. 2002), the Sobel test has specific weaknesses in detecting mediation when either path *a* or path *b* is weak. Therefore, the Sobel test has low power in detecting indirect effects and thus tends to be overly conservative. This means that the Sobel test might indicate that there is no indirect effect, while in reality there is mediation (Shrout and Bolger 2002). Hence, there is some risk of overlooking a genuine indirect effect in the data when using the Sobel test, unless the effect size or sample size is large (for details regarding mediation effect size and required sample size, see Fritz and MacKinnon 2007). Due to these limitations, use of (any variant of) the Sobel test is not recommend (Hayes and Scharkow 2013).

3.2. Bootstrapping approach

Bootstrapping is a non-parametric approach that bypasses the problem of questionable distributional assumptions of traditional techniques and enables an accurate test of the indirect effect (Bollen and Stine 1990; Shrout and Bolger 2002), even in small samples (Preacher and Hayes 2008). Importantly, bootstrapping provides more power in detecting indirect effects, but it does not show a higher type-I-error tendency (i. e., claiming me-

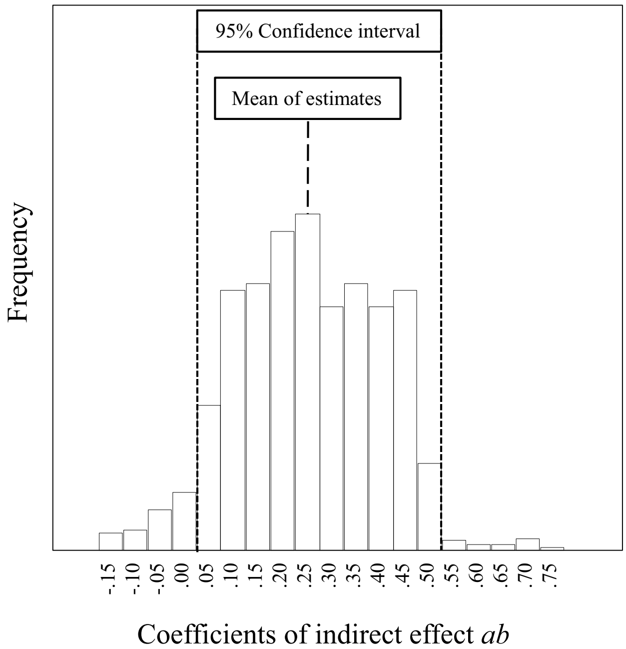


Fig. 8: Hypothetical example of a bootstrapped sampling distribution of the indirect effect ab (own illustration based on Preacher and Hayes 2004, p. 721)

diation although there is none) than the traditional methods (Hayes and Scharkow 2013). Because one can easily employ bootstrapping for mediation analysis via macros such as PROCESS (Preacher and Hayes 2004, 2008), the approach is being applied increasingly.

Bootstrapping relies on resampling of the data (Efron 1982), whereby one draws a large number (e. g., 10,000) of new samples of size *n* with replacement from the original sample. The model parameters are estimated for each new sample, resulting in a large number of estimates for each parameter. The estimates can then be ordered by size to draw a probability density distribution for each path parameter (Preacher and Hayes 2004). *Fig. 8* shows a hypothetical example for such a density distribution of the indirect effect *ab*.

The mean of all bootstrap estimates is calculated for the point estimate of the indirect effect *ab* (see *Fig. 8*). Because a non-normal distribution of parameters precludes the calculation of *t*- and *p*-values, the significance of the indirect effect *ab* is inferred from the confidence interval of its bootstrap distribution. If the confidence interval does not include zero, one can be statistically confident that the effect is different from zero.

In the basic form, called *percentile bootstrap*, the confidence interval is determined by two percentile cutoffs of the sampling distribution (e. g., 2.5 % and 97.5 % in the case of $\alpha = .05$). In the example of 10,000 bootstraps illustrated in *Fig. 8*, the 250^{th} highest (.05) and 9751^{st} highest score (.50) define the 95 % confidence interval. The results of the percentile bootstrap in *Fig 8* indicate that the proposed indirect effect is significantly different from zero, as the confidence interval does not include zero (meaning it does not encompass positive and negative values). Therefore, one can say with 95 % confidence that mediation is present (Preacher and Hayes 2004).

The percentile bootstrap is especially suitable in circumstances where robustness of the estimation is important, such as when samples include potential outliers (Creedon and Hayes 2015), when either the *a* or *b* path is large and the other path is zero (Koopman et al. 2015), or when facing small sample size ($n < 50$; Koopman et al. 2015). In case of larger sample sizes it is recommendable to use an alternative form called *bias-corrected bootstrap*. This procedure generally results in slightly more liberal bootstrap confidence intervals because it adjusts the confidence interval for bias in the bootstrap sample distribution (Efron 1987). Such bias may result from non-symmetric bootstrap sample distributions and is not accounted for by the percentile bootstrap (Efron and Tibshirani 1993). The differences across forms of bootstrapping are usually small, but they can sometimes influence the inference. While percentile bootstrapping may be reasonable in adverse situations (such as small sample size), bias-corrected bootstrap today is the standard form in mediation analysis.

Although percentile bootstrap and bias-corrected bootstrap differ slightly in their estimates, both outperform the Sobel test and Baron-and-Kenny approach remarkably with regard to statistical power (Hayes and Scharkow 2013) and propensity to type I error (MacKinnon et al. 2002). Hence, among the methods that are commonly used, reliable, and easy to conduct, bootstrapping seems to be the most promising approach for mediation analysis. After two seminal papers and add-ons about the bootstrapping approach in mediation analysis (Preacher and Hayes 2004, 2008), Hayes (2013, 2017) released a macro for SPSS and SAS called PROCESS, which combines the functionality of the preceding add-ons. In the following, we demonstrate how to conduct and interpret mediation analysis following the bootstrapping approach with PROCESS. The tutorial illustrates the specification of the different model groups and the interpretation of respective results with an example from advertising effectiveness.

4. Tutorial: Estimating mediation models with PROCESS

PROCESS (which can be downloaded from the developer's website; Hayes 2017) is specialized for mediation analysis, moderation analysis, and combinations of both procedures using the regression-based bootstrapping approach. PROCESS provides a dialog box-style graphical user interface as well as a syntax-based form, which makes it easy for researchers to specify and estimate models. The macro works with predefined models numbered from model 1 to model 76, all assigned to one special conceptual structure of the focal mediation model and thus enabling it to estimate the most commonly used theoretical model structures.[3] PROCESS requires

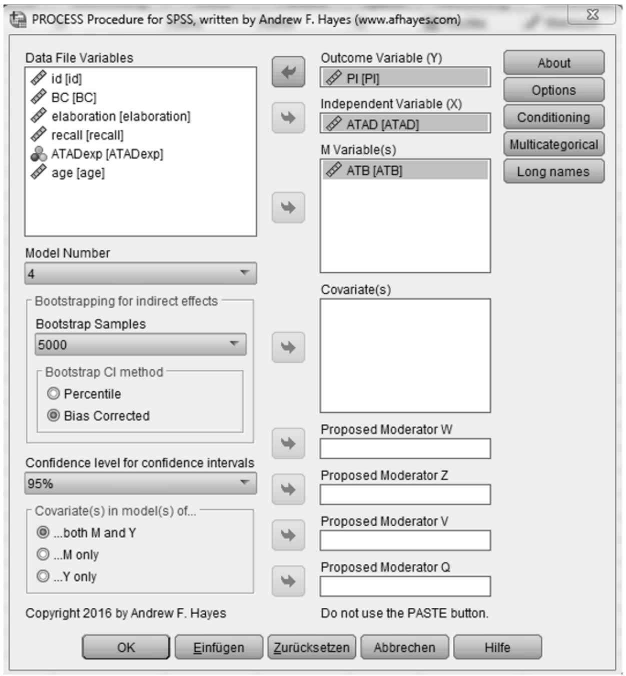


Fig. 9: Screenshot of the PROCESS v 2.16 graphical user interface in IBM SPSS Statistics 24

specification of (i) the model [number] that is to be estimated (a conceptual reasoning that must be clarified a priori and then reflected by the model number one can find in the templates document provided at the PROCESS website) and (ii) the variables included in the model and their associated roles (e. g., independent variable, dependent variable, and mediator). *Fig. 9* shows the graphical user interface (for SPSS) which can be found under ANALYZE→REGRESSION→PROCESS after installing the macro (see Hayes 2013).

In this section, we illustrate how to specify the examples of the four mediation model groups introduced in Section 2 with hypothetical experimental data.[4] The context of our example is advertising effectiveness, which represents a classic topic in marketing research and provides a suitable framework for testing different forms of mediation models. Specifically, research has suggested processes that are in line with simple mediation (MacKenzie et al. 1986), parallel or serial mediation (Brown and Stayman 1992), and moderated mediation (MacKenzie and Spreng 1992). To facilitate understanding the underlying process, we recommend a hierarchical procedure in which a simple model is considered first, followed by a gradual increase in model complexity. We employ the hierarchical procedure in this tutorial as well and begin with an examination of a simple mediation model, followed by parallel and serial mediation models, and ending with moderated mediation analysis.

The illustration focuses on the *purchase intent of the product advertised* (*PI*) and how it is influenced by *attitude toward the ad* (hereafter A_{Ad}; MacKenzie et al. 1986). The example data set also includes variables that are potentially important for the underlying process, namely *attitude toward the brand* (A_{Brand}), *product recall* (*recall*), and the *elaboration of the ad* (*elabo*). All variables were measured on 7-point Likert scales (with 7 = "completely agree"), except *elabo* which was experimentally manipulated (with the levels 1 = *high* and 2 = *low*). Finally, the data set includes the control variable *age*. With these variables, we will provide guidance on how to interpret the PROCESS output; suggestions for reporting results for each of the four mediation models are summarized in the appendix.

4.1.1. Simple mediation

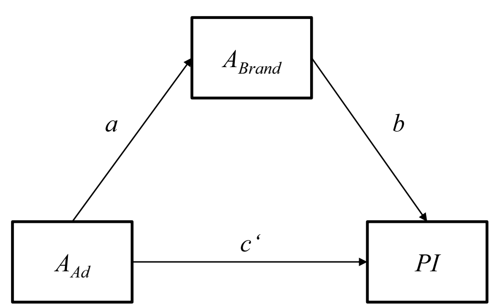
First, we might be interested in answering the question of whether A_{Brand} mediates the effect of A_{Ad} on *PI*. This corresponds to a simple mediation model, as proposed by MacKenzie et al. (1986) and illustrated in *Fig. 10*.

Translating the simple mediation model to PROCESS means that we have to choose the model number 4 in the PROCESS template (see Hayes 2013) and specify the necessary variables. The associated syntax command must be specified as follows:[5]

```
process vars = A_Ad A_Brand PI/y = PI/x = A_Ad/m
= A_Brand/model = 4.
```

The syntax command first defines that the procedure "*process*" shall be used. Next, after the "*vars* =" argument, all model variables are listed and assigned to their roles as *X*, *M*, or *Y* in the model. The final specification assigns the appropriate model number, "*/model = 4*." After running the syntax, PROCESS generates an output, which is divided into different sections, separated by lines of stars (see *Fig. 11*).

Just below the header, the model specification and sample size is presented. The second and third sections plot the simple regression results for paths *a* and *b*, respectively. The section 4, titled "*Direct and indirect effects*,"



A_{Ad}: predictor variable
A_{Brand}: mediator
PI: outcome variable

a: effect of A_{Ad} on A_{Brand}
b: effect of A_{Brand} on *PI*

ab: indirect effect of A_{Ad} on *PI* through A_{Brand}

c': direct effect of A_{Ad} on *PI*

c: total effect of A_{Ad} on *PI* $= ab + c'$

Fig. 10: Simple mediation example (PROCESS model 4)

Header

```
************* PROCESS Procedure for SPSS Release 2.16.1 ******************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2013). www.guilford.com/p/hayes3

**************************************************************************
```

Section 1

```
Model = 4
    Y = PI
    X = A_Ad
    M = A_Brand

Sample size
        100

**************************************************************************
```

Section 2

```
Outcome: A_Brand

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,4504      ,2029     2,8855    24,9409     1,0000    98,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1,9893      ,4648     4,2797      ,0000     1,0669     2,9117
A_Ad          ,4878      ,0977     4,9941      ,0000      ,2939      ,6816   — path a

**************************************************************************
```

Section 3

```
Outcome: PI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,7587      ,5756     1,3432    65,7783     2,0000    97,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      ,8107      ,3455     2,3466      ,0210      ,1250     1,4964
A_Brand       ,6325      ,0689     9,1767      ,0000      ,4957      ,7692   — path b
A_Ad          ,1500      ,0746     2,0100      ,0472      ,0019      ,2981

******************** DIRECT AND INDIRECT EFFECTS *************************
```

Section 4

```
Direct effect of X on Y
     Effect         SE          t          p       LLCI       ULCI
      ,1500      ,0746     2,0100      ,0472      ,0019      ,2981        — path c′

Indirect effect of X on Y
              Effect    Boot SE   BootLLCI   BootULCI
A_Brand        ,3085      ,0864      ,1596      ,4919                     — indirect effect ab

******************** ANALYSIS NOTES AND WARNINGS *************************
```

Section 5

```
Number of bootstrap samples for bias corrected bootstrap confidence intervals:
     5000

Level of confidence for all confidence intervals in output:
    95,00
```

Fig. 11: PROCESS output for simple mediation example (model 4)

is the central part of the mediation analysis output. The last section entails information about the number of bootstrap samples and the level of confidence for all confidence intervals reported in the output.

We can determine whether mediation exists by interpreting the indirect effect of A_{Ad} on *PI* through A_{Brand} (depicted in the output section 4 as "indirect effect *ab*"). Using the bootstrap sample distribution explained above (see Section 3.2.), PROCESS reports the point estimate of the indirect effect ("*Effect*") and its standard error ("*Boot SE*"). This is followed by the upper and lower limits of the bootstrap confidence interval ("*BootLLCI*" and "*BootULCI*"). As can be seen from the output, the bootstrap confidence interval (*CI*) is (.16 to .49). As the 95 % confidence interval does not include zero, we can infer significant mediation of A_{Ad}'s effect on *PI* through A_{Brand} at $\alpha = .05$. Next, the importance of the mediation can be assessed by interpreting A_{Ad}'s direct effect on *PI* (depicted as path *c'*). In the example, the *p*-value of the direct effect is .047 and can therefore be considered significant. Using the framework depicted in *Fig. 7*, we can conclude complementary partial mediation (Zhao et al. 2010). In addition to the direct and indirect effects of the independent variable, PROCESS plots the estimates for the single paths of the model. For the simple mediation model, these can be derived from the results of two regressions underlying the model: one having mediator A_{Brand} and one having *PI* as outcome variable. As the indirect effect consists of two single effects, path $A_{Ad} \rightarrow A_{Brand}$ and path $A_{Brand} \rightarrow PI$, one can inspect them to reveal that attitude toward the ad impacts purchase intent because it increases attitude toward the brand (effect: .49, $p < .001$; depicted as path *a*), while the latter increases purchase intent (effect: .63, $p < .001$; depicted as path *b*). Note that the point estimate of the indirect effect *ab* equals the product of $a \times b$: $.31 = .49 \times .63$.

4.1.2. Parallel mediation

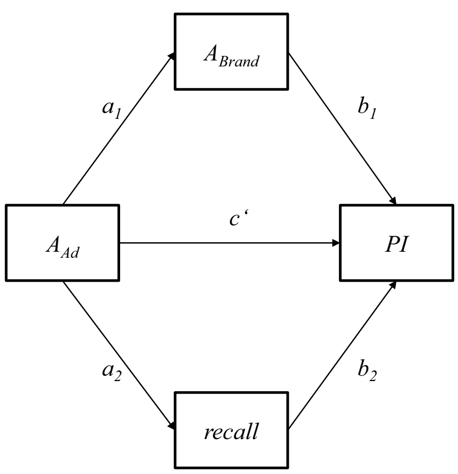
Extending the simple mediation situation, *recall* could be another potential mediator between A_{Ad} and *PI* (Brown and Stayman 1992), which would lead to a conceptual model structure like the one shown in *Fig. 12*.

When comparing two proposed mediations it may be of interest to assess whether the corresponding specific indirect effects differ in magnitude. In PROCESS, the "*contrast = 1*" command provides a significance test that can carry out this comparison. If enabled, PROCESS estimates bootstrap confidence intervals for a pairwise comparison of specific indirect effects. It is expressed by a confidence interval because it is based on the bootstrap sampling distributions of both specific indirect effects. If the confidence interval does not entail zero, it implies that the two specific indirect effects are statistically different from each other (if it does include zero, difference between the effects cannot be assumed). It is important to note that this test can only be interpreted as a comparison of effect size when both effects have the same sign. Compared to the simple mediation example, the syntax command is changed in two ways. First, the variable *recall* is entered and assigned the role of (second) mediator ("*m = recall*"). Second, the pairwise comparison option for the specific indirect effects is enabled with "*contrast = 1*."

```
process vars = A_Ad A_Brand PI recall/y = PI/x =
A_Ad/m = A_Brand recall/model = 4/contrast = 1.
```

The PROCESS output summary in *Fig. 13* looks similar to the one-mediator case in *Fig. 11*. However, in this model there are now two specific indirect effects ($A_{Ad} \rightarrow A_{Brand} \rightarrow PI$ and $A_{Ad} \rightarrow recall \rightarrow PI$), which together constitute a total indirect effect. For the parallel mediation model, it is most important to interpret these specific indirect effects. In our example, A_{Brand} (indirect effect: .26; 95 % CI: .14 to .43) as well as *recall* (indirect effect: .08; 95 % CI: .02 to .17) are significant mediators. If a comparison of the two indirect effects is intended, the contrast bootstrap interval (see line C1, which means "contrast 1") is examined (depicted as contrast test). In the example, two positive mediations coexist in parallel and differ significantly in size, as the C1 bootstrap confidence interval does not encompass zero (difference: .17; 95 % CI: .01 to .36). This means that A_{Brand} can explain the effect of A_{Ad} on *PI* significantly better than *recall* does. Finally, the total indirect effect should only be interpreted if the researcher wants to investigate the extent to which all mediators together can explain the causal relationship between A_{Ad} and *PI* (depicted as total indirect effect). In the example, the total indirect effect is positive and significant (effect: .34; 95 % CI: .20 to .50). Next, we can interpret the direct effect (depicted as path *c'*). As the effect is insignificant (effect: .12; $p = .075$), we can infer full mediation (see *Fig. 7*).[6] It can also be an option to further investigate the detailed regression results (as in the previous section), but we do not illustrate this here.

Taken together, the analysis reveals that attitude toward the ad impacts purchase intent through both attitude toward the brand as well as product recall. However, the indirect effect through attitude toward the brand is greater in magnitude than that through product recall. This indicates that attitude toward the brand plays a greater role in explaining the effect of attitude toward the ad than product recall does.



A_{Ad}: predictor variable
A_{Brand}: mediator 1
recall: mediator 2
PI: outcome variable

a_1b_1: specific indirect effect of A_{Ad} on *PI* through A_{Brand}
a_2b_2: specific indirect effect of A_{Ad} on *PI* through *recall*

c': direct effect of A_{Ad} on *PI*
total indirect effect: $a_1b_1 + a_2b_2$

Fig. 12: Parallel mediation example (PROCESS model 4)

```
******************** DIRECT AND INDIRECT EFFECTS *************************

Direct effect of X on Y
     Effect         SE          t          p       LLCI       ULCI
      ,1206      ,0671     1,7982      ,0753     -,0125      ,2537

Indirect effect of X on Y
             Effect    Boot SE   BootLLCI   BootULCI
TOTAL         ,3379      ,0752      ,1975      ,5024
A_Brand       ,2553      ,0725      ,1373      ,4258
recall        ,0826      ,0369      ,0225      ,1712
(C1)          ,1727      ,0871      ,0093      ,3619

Specific indirect effect contrast definitions
(C1)   A_Brand    minus      recall
```

path *c'*
total indirect effect
specific indirect effects a_1b_1 and a_2b_2
contrast test

Fig. 13: PROCESS output summary of parallel mediation example (model 4)

4.1.3. Serial mediation

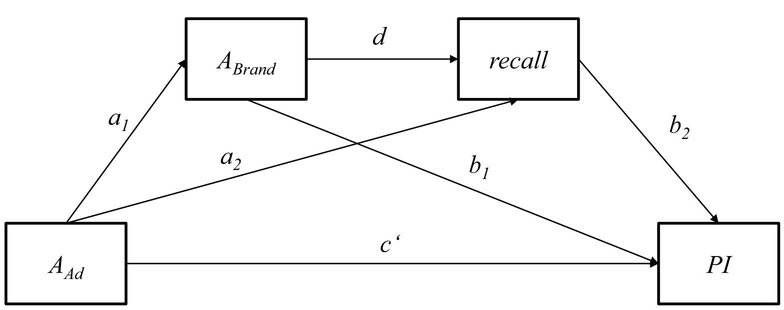
Transferring the perspective of serial mediation to our example, one can also hypothesize that the two mediator variables, A_{Brand} and *recall*, are causally related. One plausible assumption could be that A_{Brand} impacts *recall* (Brown and Stayman 1992), which would result in a conceptual model like the one depicted in *Fig. 14*.

When specifying serial mediation with model 6, it is particularly important to consider the order of the mediator variables in the "*m =*" list, as the variables listed earlier will be regarded causally prior to those listed later. We note that in our example no adjustment of the mediator order is necessary as it already complied with the proposed causal chain. Specifying the framework thus requires two changes to the parallel mediation syntax command: First, the model number must be changed to "*model = 6.*" Second, the *"contrast = 1"* option is no longer necessary, as the aim of serial mediation is not to compare the mediators. These changes result in the following model specification:

```
process vars = A_Ad A_Brand PI recall/y = PI/x =
A_Ad/m = A_Brand recall/model = 6.
```

Again, the most important part of the output is the summary section ("*Direct and indirect effects*"), displayed in *Fig. 15*. PROCESS plots each specific indirect effect as well as the total indirect effect. Central to the serial mediation hypothesis is the long-way mediation $A_{Ad} \rightarrow A_{Brand} \rightarrow recall \rightarrow PI$ (named "*Ind2*" in the output). If the long-way specific indirect effect is significant, serial mediation can be claimed (depicted as long-way specific indirect effect a_1db_2). Second, we investigate the shortcut indirect effects (depicted as shortcut specific indirect effects a_1b_1 and a_2b_2) and the direct effect (depicted as path *c'*) to better understand the character of the proposed mediation paths. As before, it can also be an option to further investigate the detailed regression results (which are not illustrated here).

The output of the example in *Fig. 15* suggests that the long-way mediation $A_{Ad} \rightarrow A_{Brand} \rightarrow recall \rightarrow PI$ is significant (effect: .05; 95 % CI: .02 to .11), as is the indirect path $A_{Ad} \rightarrow A_{Brand} \rightarrow PI$ (effect: .25; 95 % CI: .13 to .41). In contrast, the indirect effect of $A_{Ad} \rightarrow recall \rightarrow PI$ is not significant (95 % CI: -.04 to .12). Like in the parallel mediation example, the direct effect is insignificant (*p* = .075). Taken together, the data support the serial mediation hypothesis: attitude toward the ad increases attitude toward the brand, which in turn increases product recall, which ultimately affects purchase intent. In addition, attitude toward the ad affects purchase intent via attitude toward the brand, without product recall being involved. This finding qualifies the result of the parallel mediation example: product recall does not act as an independent mediator but rather is part of a



A_{Ad}: predictor variable
A_{Brand}: mediator 1
recall: mediator 2
PI: outcome variable

a_1db_2: long-way specific indirect effect of A_{Ad} on *PI* through A_{Brand} and *recall*
a_1b_1: shortcut specific indirect effect of A_{Ad} on *PI* through A_{Brand} only
a_2b_2: shortcut specific indirect effect of A_{Ad} on *PI* through *recall* only

c': direct effect of A_{Ad} on *PI*

total indirect effect: $a_1db_2 + a_1b_1 + a_2b_2$

Fig. 14: Serial mediation example (PROCESS model 6)

```
******************** DIRECT AND INDIRECT EFFECTS *************************

Direct effect of X on Y
     Effect         SE          t          p       LLCI       ULCI
      ,1206      ,0671     1,7982      ,0753     -,0125      ,2537

Indirect effect(s) of X on Y
           Effect    Boot SE   BootLLCI   BootULCI
Total:      ,3379      ,0738      ,1979      ,4867
Ind1 :      ,2553      ,0721      ,1312      ,4120
Ind2 :      ,0532      ,0214      ,0199      ,1090
Ind3 :      ,0294      ,0411     -,0394      ,1225

Indirect effect key
 Ind1 :  A_Ad      ->     A_Brand  ->      PI
 Ind2 :  A_Ad      ->     A_Brand  ->      recall    ->      PI
 Ind3 :  A_Ad      ->     recall   ->      PI
```

path *c'*

shortcut specific indirect effect a_1b_1

long-way specific indirect effect a_1db_2

shortcut specific indirect effect a_2b_2

Fig. 15: PROCESS output summary of serial mediation example (model 6)

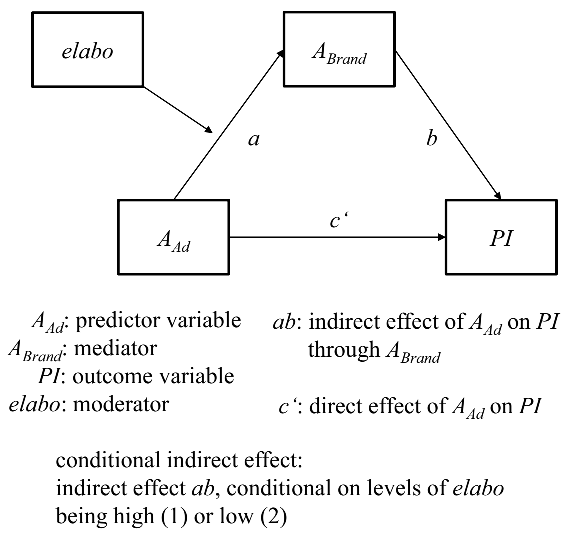


Fig. 16: Moderated mediation example (PROCESS model 7)

longer causal chain that involves attitude toward the brand.

4.1.4. Moderated mediation

Extending the "pure mediation" example, one could imagine that the test person's processing elaboration of the ad (*elabo*) might be a variable that determines whether the proposed mediation process $A_{Ad} \rightarrow A_{Brand} \rightarrow PI$ exists. Specifically, it is conceivable that in the case of low elaboration the proposed mediation works, while A_{Ad} does not lead to an increase in A_{Brand} in case of high elaboration (MacKenzie and Spreng 1992). In this case a first-stage moderated mediation model in PROCESS is suitable, as shown in its most basic form (model 7) in *Fig. 16*.

To specify such a model in PROCESS, one must adjust the syntax command of the simple mediation model to include the variable *elabo* and assign it the moderator role with "*/w = elabo.*" Moreover, the model number must be changed to "*model = 7.*"

```
process vars = A_Ad A_Brand PI elabo/y = PI/x =
A_Ad/m = A_Brand /model = 7/w = elabo.
```

The output shown in *Fig. 17* provides a summary of the direct and indirect effects. The indirect effect is now conditional on the values of the moderator (the subsection is therefore called "*Conditional indirect effect(s) of X on Y at values of the moderator(s)*").

To interpret the output, it is necessary to examine whether the proposed moderated mediation exists. This can be achieved by carrying out a formal test of moderated mediation called the *index of moderated mediation* (Hayes 2015), depicted as such in *Fig. 17*. The index represents the quantification of the linear association between the moderator and the indirect effect. Like before, it is a bootstrap confidence interval that is interpreted as support for the existence of moderated mediation if it does not include zero. As here the confidence interval does not include zero (95 % CI: .06 to .63), the hypothesis of moderated mediation is supported. This means that the indirect effect of *A_Ad* on *PI* through *A_Brand* depends on levels of *elabo*.

If the index of moderated mediation supports the existence of moderated mediation, one may wish to investigate the indirect effect at representative values of the moderator (depicted as conditional indirect effect) to further explore the conditions under which mediation does (not) exist (Preacher et al. 2007). This method is also called *spotlight analysis* (Fitzsimons 2008; Spiller et al. 2013). If the moderator is dichotomous, it results in exactly two conditional indirect effects. For a continuous moderator, by default the conditional indirect effects for the moderator mean and at values of one standard deviation above and below the mean are plotted. As in the examples before, the mediation type can be determined by additionally considering the direct effect (depicted as path *c'*). In the example we see that while there is a significant indirect effect for test persons with *low elaboration* (effect: .45; 95 % CI: .24 to .66), the effect is not significant in the *high-elaboration* group (95 % CI: -.07 to .34). The direct

```
******************** DIRECT AND INDIRECT EFFECTS *************************

Direct effect of X on Y
     Effect         SE          t          p       LLCI       ULCI
      ,1500      ,0746     2,0100      ,0472      ,0019      ,2981

Conditional indirect effect(s) of X on Y at values of the moderator(s):

Mediator
              elabo     Effect    Boot SE   BootLLCI   BootULCI
A_Brand      1,0000      ,1355      ,1044     -,0690      ,3427
A_Brand      2,0000      ,4479      ,1108      ,2395      ,6615

Values for quantitative moderators are the mean and plus/minus one SD from mean.
Values for dichotomous moderators are the two values of the moderator.

******************** INDEX OF MODERATED MEDIATION ************************

Mediator
              Index   SE(Boot)   BootLLCI   BootULCI
A_Brand       ,3124      ,1489      ,0573      ,6258

When the moderator is dichotomous, this is a test of equality of the
conditional indirect effects in the two groups.
```

path c'

conditional indirect effect

test of moderated mediation

Fig. 17: PROCESS output summary of moderated mediation example (model 7)

Goal	Description	Syntax statement
Control for the influence of other variables in the model by including covariates	Listing variables after *"process vars ="* without assigning roles makes PROCESS treat these variables as covariates.	"*process vars = [additionally include name of covariate]*"
Make bootstrap results reproducible and avoid variances in results due to resampling when repeating the same analysis	PROCESS output values always differ slightly due to the random resampling process. The statement is seeding the random number generator responsible for resampling with an arbitrary value, which leads to exactly reproducible results.	"*seed = [number]*"
Make the estimation of confidence intervals more precise	5,000 bootstrap resamples is the default in PROCESS. The higher the number of bootstraps, the more reliable the results become. 10,000 bootstraps are a good compromise between desired precision and required computation time.	"*boot = [number]*"
Change the bootstrapping approach from the default bias-correct bootstrap to percentile bootstrapping	Percentile bootstrapping is especially robust in small samples or adverse situations.	"*percent = 1*"
Save the estimated bootstraps of all paths of the model in a new SPSS data set to compare confidence intervals of parameters, for example.	Saving the bootstraps makes it possible to manually compare paths or function of paths (e. g., the indirect effect is a function of a and b). In the new data set, each row contains the coefficients from one bootstrap sample (e. g., i_1, a, i_2, b, c′ for the simple mediation model named COL1 to COL5).	"*save = 1*"
Perform mediation analysis with a multicategorical independent variable (e. g., two experimental conditions plus a control group coded "1 = control," "2 = treatment A," and "3 = treatment B")	Unlike continuous or dichotomous variables, multicategorical independent variables cannot just be included in mediation analysis without transformation (categorical independent variables with more than two levels are interpreted as linear, which leads to biased parameter estimates). PROCESS is able to recode such a multicategorical variable automatically via the command "/mcx = ", with "/mcx = 1" being the flag for dummy coding (for a detailed description of the analysis, see Hayes and Preacher 2014). Note that multicategorical independent variables are currently possible in simple mediation models only.	"*mcx = 1*"

Tab. 2: Additional statements of the PROCESS syntax

effect is significant (*p = .047)*, implying partial mediation. From a theory perspective, we can hence conclude that attitude toward the ad affects purchase intent via attitude toward the brand only when the ad is not elaborated deeply.

4.1.5. Further modifications of the mediation analysis

Besides the extensions discussed, PROCESS allows further syntax statements to modify the analysis according to the researcher's goals. In *Tab. 2* we describe other potential needs for modification of the default syntax command and how to address them.

The following syntax command shows an example application of these extensions based on the simple mediation syntax command for the control variable *age*, a seed starting the random number generator at position 100, and 10,000 bootstrap resamples using the percentile bootstrapping approach and a multicategorical independent variable:

```
process vars = A_Ad A_Brand PI age/y = PI/x = A_Ad/m = A_Brand/model = 4/seed = 100/boot = 10000/percent = 1/save = 1/mcx = 1.
```

5. Robustness assessment and complex model testing

In the last section, we examine two topics worth considering for a deeper understanding of how to conduct mediation analysis. Although there have been many advanced topics discussed in the recent literature, such as how to handle longitudinal data (Preacher 2015) or analyzing non-linear effects (Hayes and Preacher 2010), we limit the scope of this section to two basic topics: (i) the importance of making robust causal inference via correct specification and (ii) the use of structural equation modeling as an alternative for analyzing complex mediation models.

5.1. Assessing the robustness of the causal inference

As discussed in the context of partial mediation, a rigorous specification of the proposed model is of utmost importance in order to identify genuine mediation processes. We also examined the omitting of alternative mediators or moderators as examples of incomplete mediation findings. However, there are further misspecifications that could turn a genuine full mediation into a result of partial mediation or insignificance, such as non-linearity of causal relationships, measurement error, missing paths, or outliers (Creedon and Hayes 2015). To overcome these potential sources of misspecification, the standard means known from regression analysis should be applied (e. g., visual inspection, outlier detection, inspection of residuals).

Even in the case of a significant full mediation, the researcher should reflect upon the specification of the proposed model to ensure that the results are meaningful. If this is not done carefully, what has been identified as a mediator in the proposed model might in reality play a different causal role (MacKinnon et al. 2000; Stelzl 1986). For example, the proposed mediator *M* may not be a real causal mediator, but rather just a correlate of *X*, *Y*, or the true mediator that is not specified in the model at all. Therefore, inference about the proposed mediation cannot be based on a significant indirect effect alone; instead, significance of the mediation is just a necessary condition following a-priori conceptual reasoning (Fiedler et al. 2011). It is therefore important to make sure that one can conceptually and empirically justify the proposed model against rival explanations (Iacobucci et al. 2007). In this regard, it makes sense to test other possible model specifications and compare them to the focal model (and report the results accordingly). If one can rule out the potential sources of misspecification discussed above, this enhances confidence in the proposed theoretical framework.

It is important to note that there are no formal means of examining the fit of a model (like the multiple fit indices known from SEM; see Section 5.2.) when using PROCESS. In situations where more than one model is both conceptually and empirically meaningful (e. g., significant and interpretable indirect effects in parallel and serial mediation analysis), we follow Hayes (2013) and recommend preferring those models which are less restricted in their assumptions. In the given example, this would mean preferring the serial model over the parallel model, as it allows both mediators to be connected, while the parallel model implicitly assumes that the mediators are unrelated (i. e., a correlation of exactly zero).

5.2. Testing complex mediation models with SEM

In this paper we have illustrated how to use regression-based mediation analysis via PROCESS for moderately complex mediation models. This approach is sufficient for most research settings, as simpler models with fewer variables are generally preferable to more complex ones (Cohen 1990). However, there might be situations that require complex mediation models that cannot be analyzed with PROCESS. For example, a requested model may contain more than one independent or dependent variable.

SEM offers a methodology for analyzing causal relationships between multiple latent variables (Bollen 1989; Iacobucci 2010). Hence, SEM allows the examination of complex nomological networks (Iacobucci 2008), such as serial mediation models with multiple dependent and independent (in SEM terminology: exogenous) variables. In addition to the number of structural relationships, SEM is also flexible regarding the type of relationships. For example, it is possible to model non-recursive relations of the form Y1⟵⟶Y2 (Iacobucci 2009).

Another advantage of SEM is that it explicitly considers latent variables with multiple indicators that are measured with error, whereas in regression-based research multi-item measurements of variables are typically collapsed to mean scores (Iacobucci 2009). If the items measure the latent construct inconsistently (i. e., factor loadings are not uniformly high), this simplification can reduce the likelihood of finding systematic relationships in regression-based mediation analysis (Danner et al. 2015). Iacobucci et al. (2007) demonstrate that inferring mediation from mean scores for *X*, *M*, and *Y* may lead to misleading results compared to full measurement models, especially when the mediation effect is small. In conclusion, it may be beneficial to consider measurement error if the measurement of variables is problematic (which can be identified via factor analysis or reliability analysis).

A third advantage of SEM is its provision of model fit indices (Hu and Bentler 1998; Iacobucci 2010). Fit indices can be used to assess the adequacy of a proposed model, but they also enable the comparison of different models. Formal comparison is useful because sometimes a researcher is unsure which theoretical model is most promising. For instance, the so-called χ^2 difference test is able to test whether two nested models significantly differ; the better fitting model is indicated by the smaller χ^2 value (for details on model comparison, see Danner et al. 2015). Furthermore, SEM allows one to constrain paths inside the structural model if there is theoretical reason to do so (e. g., to set them to zero or to set several paths to the same value). Such constrained models can also be compared to more parsimonious alternatives via fit indices that take into account the parsimony of the models (e. g., Bayesian Information Criterion; see Danner et al. 2015).

In the case of models that cannot be specified with PROCESS, using established SEM software like AMOS (Arbuckle 2016) or Mplus (Muthén and Muthén 1998–2015) appears to be a good choice. Such SEM programs offer bootstrapping as an estimation method (Cheung and Lau 2008), which we also recommend using in SEM because of the non-normal nature of the indirect effect. If bootstrapping is applied, SEM yields nearly the same results as PROCESS (for the four examples, the results in AMOS differ from the ones in PROCESS only on the third decimal). Despite the opportunities SEM presents for specifying mediation models, it also means more complexity in setup and analysis – for example, when comparing alternative models in the presence of contradicting fit indices (Iacobucci et al. 2007).

Furthermore, most of the SEM programs do not offer the full functionality of PROCESS regarding mediation analysis. For instance, while it is possible to test the total indirect effect in most of the SEM programs, parameters and confidence intervals of specific indirect effects in mediation models are usually not part of the output (exceptions are Mplus, Mx, and OpenMx; Macho and Ledermann 2011). Nonetheless, it is possible to manually implement some of the features. For example, there exists a methodology to estimate specific indirect effects in SEM programs such as AMOS, called the phantom model approach (Macho and Ledermann 2011). Macho and Ledermann's idea for estimating a specific indirect effect is to build a separate partial model (phantom model) that mimics the full model but only encompasses the paths of the specific effect (for detailed instruction on how to build a phantom model, see Macho and Ledermann 2011). Other examples in which SEM programs do not provide as much default features as PROCESS is in the interpretation of moderated mediation (e. g., they do not yet provide an index of moderated mediation) or mediation models with multicategorical independent variables (the so-called omnibus test; Hayes and Preacher 2014). Researchers interested in these specific features in complex model settings may prefer Mplus. The syntax-based nature of Mplus makes it possible to access code concerning such advanced mediation analysis features (e. g., code for complex moderated mediation models in Hayes and Preacher 2014).

In summary, SEM is a powerful approach that can enhance mediation analysis in several ways. However, one should keep in mind that its sophistication poses several challenges and therefore inexperienced researchers might face some error potential when using it. A decision rule would be that regression-based bootstrap approaches (such as those offered by PROCESS) are preferable unless the issues described in this section become crucial.

6. Summary

The goal of this paper was to give an overview of mediation analysis. To achieve this goal, we reviewed the basic concept of mediation as well as its main elements, and we discussed how to interpret mediation results based on indirect and direct effects. We focused on simple mediation, parallel mediation, serial mediation, and moderated mediation, which represent the most common mediation model groups in marketing research. After reviewing the conceptual background of mediation analysis, we turned our attention to the methodological aspects of mediation analysis. Here, we compared three different regression-based approaches of mediation analysis. In particular, we examined the rationale of the bootstrapping approach, discussed why it yields superior results compared to traditional approaches of mediation analysis, and argued that it is particularly suitable for estimating the indirect effect. While we concentrated on conceptual and methodological considerations in the first part of the paper, the second part is organized as a tutorial. Here, we illustrated how to conduct mediation analysis and interpret the output of the SPSS/SAS macro PROCESS.

In the tutorial, we presented a typical case of more than one model specification being theoretically meaningful and recommended a hierarchical procedure. Hereby one examines simple mediation models first and, step by step, extends those simple models to more complex models. Following such a stepwise approach, we opted for inspecting the indirect effect at each step to determine *whether* a proposed mediator can explain the proposed causal relationship. Moreover, we recommended inspecting the direct effect to reveal to *what extent* the causal relationship can be explained by the mediator. This information is useful for further conceptual reasoning, and we describe a suitable framework in Section 2.3. Besides inspecting the direct and indirect effect in simple and parallel mediation, we also illustrated how to test more sophisticated hypotheses of a serial mediation model and a moderated mediation model. For the serial mediation model, we emphasized the significance of the long-way specific indirect effect as most important. For the moderated mediation model we recommended to test whether the proposed indirect effect is conditional on levels of a moderator, revealed by the index of moderated mediation. After giving detailed information on how to specify the models with PROCESS syntax and interpret the relevant elements of the PROCESS output, in the appendix we illustrated how to report results. Concluding, we hope that this review and tutorial will contribute to a consistent and cognizant use of mediation analysis.

Notes

[1] Because consumer researchers frequently use mediation analysis, we added the *Journal of Consumer Psychology* to our list of top-tier journals.

[2] In their work, Baron and Kenny (1986) describe three regression equations and thus three steps. Because the third equation is used to draw two different inferences, we refer to them as separate steps.

[3] It is recommendable to also download the templates document from the website, which lists all the models PROCESS can specify (Hayes 2017). A full documentation of PROCESS is provided by Hayes (2013).

[4] The data can be downloaded from: https://rsw.beck.de/zeitschriften/marketing/current-issue

[5] One can find the specification for this model in the graphical user interface in *Fig. 9*. Note that the syntax will change with the release of PROCESS v3 (Hayes 2017).

[6] Some journals, including the *Journal of Consumer Research*, require reporting p-values between .05 and .10 as marginally significant (Journal of Consumer Research 2017). Although some researchers argue that marginally significant results should be dismissed (Iacobucci 2005), it frequently happens that marginally significant effects are treated as "almost (highly) significant." In the latter case, one would infer complementary partial mediation from the above results.

Appendix
Suggestions for reporting PROCESS results (based on the data examples)

Simple mediation

We used PROCESS model 4 (Hayes 2013) to test the proposed mediation. The data is consistent with the claim that A_{Ad} impacts A_{Brand}, which in turn increases *PI* (b = .31; 95 % CI = .16 to .49). The mediation partially explains the effect of A_{Ad} on *PI*; in addition A_{Ad} influences *PI* independently from the proposed mechanism (b = .15, *p* = .047). Hence, we infer complementary partial mediation (Zhao et al. 2010).

(The reader may refer to Schrift and Amar (2015) and Siddiqui et al. (2017) for further examples of reporting simple mediation results yielded from PROCESS in the marketing literature.)

Parallel mediation

We used PROCESS model 4 (Hayes 2013) to test the proposed mediations. Overall, we could establish a mediation of both proposed mediators, resulting in a significant mediation from A_{Ad} to *PI* through A_{Brand} (b = .26; 95 % CI: .14 to .43) and *recall* (b = .08; 95 % CI: .02 to .17). The proposed mediation through A_{Brand} is significantly stronger than the one through product recall (Δ_b = .17; 95 % CI: .01 to .36). There is an insignificant direct effect of A_{Ad} on *PI* (b = .12, *p* = .075). Taken together, the findings indicate full parallel mediation.

(The reader may refer to Hur et al. (2015) and Winterich and Zhang (2014) for further examples of reporting parallel mediation results yielded from PROCESS in the marketing literature.)

Serial mediation

Using PROCESS model 6 (Hayes 2013) we could establish a serial mediation from A_{Ad} through A_{Brand} through *recall* to *PI* (b = .05; 95 % CI: .02 to .11). In addition, A_{Ad} had an indirect effect on *PI* through A_{Brand} (b = .25, 95 % CI .13 to .41) but not through *recall* (b = .03, 95 % CI -.04 to .12). Finally, there is no direct effect of A_{Ad} on *PI* (b = .12, *p* = .075), indicating full serial mediation.

(The reader may refer to Hur et al. (2015) and Winterich and Zhang (2014) for further examples of reporting serial mediation results yielded from PROCESS in the marketing literature.)

Moderated mediation

We used PROCESS model 7 (Hayes 2013) to test the proposed moderated mediation. Overall, we could establish a moderated mediation from A_{Ad} through A_{Brand} to *PI*, dependent on *elaboration mode* (index of moderated mediation: .31; 95 % CI: .06 to .63). While for the low elaboration group there is a significant indirect effect of A_{Ad} on *PI* through A_{Brand} (b = .45, 95 % CI .24 to .66), the effect disappears when elaboration is high (b = .14, 95 % CI -.07 to .34).

(The reader may refer to Blanchard et al. (2016) and Hur et al. (2015) for further examples of reporting moderated mediation results yielded from PROCESS in the marketing literature.)

References

Anderson, J. C., & Gerbing, D. W. (1988). Structural Equation Modeling in Practice: A Review and Recommended Two-Step Approach. *Psychological Bulletin*, 103(3), 411–423.

Arbuckle, J. L. (2016). *IBM SPSS Amos 24 User's Guide*. Chicago: Amos Development Corporation.

Aroian, L. A. (1947). The Probability Function of the Product of Two Normally Distributed Variables. *The Annals of Mathematical Statistics*, 18(2), 265–271.

Bagozzi, R. P., & Yi, Y. (1988). On the Evaluation of Structural Equation Models. *Journal of the Academy of Marketing Science*, 16(1), 74–94.

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.

Blanchard, S. J., Carlson, K. A., & Hyodo, J. D. (2016). The Favor Request Effect: Requesting a Favor from Consumers to Seal the Deal. *Journal of Consumer Research*, 42(6), 985–1001.

Bollen, K. A. (1989). *Structural Equations with Latent Variables*. New York: Wiley.

Bollen, K. A., & Stine, R. (1990). Direct and Indirect Effects: Classical and Bootstrap Estimates of Variability. *Sociological Methodology*, 20(1), 15–140.

Brown, S. P., & Stayman, D. M. (1992). Antecedents and Consequences of Attitude Toward the Ad: A Meta-Analysis. *Journal of Consumer Research*, 19(1), 34–51.

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.

Cohen, J. (1990). Things I Have Learnt (So Far). *American Psychologist*, 45(12), 1304–1312.

Creedon, P. S., & Hayes, A. F. (2015). Small Sample Mediation Analysis: How Far Can We Push the Bootstrap? *Poster presented at Ohio State University*, Columbus, USA.

Danner, D., Hagemann, D., & Fiedler, K. (2015). Mediation Analysis with Structural Equation Models: Combining Theory, Design, and Statistics. *European Journal of Social Psychology*, 45(4), 460–481.

Efron, B. (1982). *The Jackknife, the Bootstrap and Other Resampling Plans*. Stanford: SIAM.

Efron, B. (1987). Better Bootstrap Confidence Intervals. *Journal of the American Statistical Association*, 82(397), 171–185.

Efron, B., & Tibshirani, R. J. (1993). *An Introduction to the Bootstrap*. New York: Chapman & Hall.

Fiedler, K., Schott, M., & Meiser, T. (2011). What Mediation Analysis Can (Not) Do. *Journal of Experimental Social Psychology*, 47(6), 1231–1236.

Fitzsimons, G. J. (2008). Death to Dichotomizing. *Journal of Consumer Research*, 35(1), 5–8.

Fritz, M. S., & MacKinnon, D. P. (2007). Required Sample Size to Detect the Mediated Effect. *Psychological Science*, 18(3), 233–239.

Goodman, L. A. (1960). On the Exact Variance of Products. *Journal of the American Statistical Association*, 55(292), 708–713.

Guevarra, D. A., & Howell, R. T. (2015). To Have in Order to Do: Exploring the Effects of Consuming Experiential Products on Well-Being. *Journal of Consumer Psychology*, 25(1), 28–41.

Hayes, A. F. (2009). Beyond Baron and Kenny: Statistical Mediation Analysis in the New Millennium. *Communication Monographs*, 76(4), 408–420.

Hayes, A. F. (2013). *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach*. New York: Guilford Press.

Hayes, A. F. (2015). An Index and Test of Linear Moderated Mediation. *Multivariate Behavioral Research*, 50(1), 1–22.

Hayes, A. F. (2017). *The PROCESS Macro for SPSS and SAS*. http://processmacro.org/index.html. Accessed 2 May 2017.

Hayes, A. F., & Preacher, K. J. (2010). Quantifying and Testing Indirect Effects in Simple Mediation Models When the Constituent Paths are Nonlinear. *Multivariate Behavioral Research*, 45(4), 627–660.

Hayes, A. F., & Preacher, K. J. (2014). Statistical Mediation Analysis with a Multicategorical Independent Variable. *British Journal of Mathematical and Statistical Psychology*, 67(3), 451–470.

Hayes, A. F., & Scharkow, M. (2013). The Relative Trustworthiness of Inferential Tests of the Indirect Effect in Statistical Mediation Analysis: Does Method Really Matter? *Psychological Science*, 24(10), 1918–1927.

Hu, L., & Bentler, P. M. (1998). Fit Indices in Covariance Structure Modeling: Sensitivity to Underparameterized Model Misspecification. *Psychological Methods*, 3(4), 424–453.

Hur, J. D., Koo, M., & Hofmann, W. (2015). When Temptations Come Alive: How Anthropomorphism Undermines Self-Control. *Journal of Consumer Research*, 42(2), 340–358.

Iacobucci, D. (2005). From the Editor: On *p*-Values. *Journal of Consumer Research*, 32(1), 6–11.

Iacobucci, D. (2008). *Mediation Analysis*. Thousand Oaks: Sage.

Iacobucci, D. (2009). Everything You Always Wanted to Know about SEM (Structural Equations Modeling) But Were Afraid to Ask. *Journal of Consumer Psychology*, 19(4), 673–680.

Iacobucci, D. (2010). Structural Equations Modeling: Fit Indices, Sample Size, and Advanced Topics. *Journal of Consumer Psychology*, 20(1), 90–98.

Iacobucci, D., Saldanha, N., & Deng, X. (2007). A Meditation on Mediation: Evidence that Structural Equations Models Perform Better than Regressions. *Journal of Consumer Psychology*, 17(2), 140–154.

James, L. R., & Brett, J. M. (1984). Mediators, Moderators, and Tests for Mediation. *Journal of Applied Psychology*, 69(2), 307–321.

Journal of Consumer Research (2017). *JCR Style Sheet*. http://www.ejcr.org/newstylesheet.pdf. Accessed 2 May 2017.

Judd, C. M., & Kenny, D. A. (1981). Process Analysis: Estimating Mediation in Treatment Evaluations. *Evaluation Review*, 5(5), 602–619.

Kenny, D. A. (2008). Reflections on Mediation. *Organizational Research Methods*, 11(2), 353–358.

Kisbu-Sakarya, Y., MacKinnon, D. P., & Mioèeviæ, M. (2014). The Distribution of the Product Explains Normal Theory Mediation Confidence Interval Estimation. *Multivariate Behavioral Research*, 49(3), 261–268.

Koopman, J., Howe, M., Hollenbeck, J. R., & Sin, H.-P. (2015). Small Sample Mediation Testing: Misplaced Confidence in Bootstrapped Confidence Intervals. *Journal of Applied Psychology*, 100(1), 194–202.

Macho, S., & Ledermann, T. (2011). Estimating, Testing, and Comparing Specific Effects in Structural Equation Models: The Phantom Model Approach. *Psychological Methods*, 16(1), 34–43.

MacKenzie, S. B., Lutz, R. J., & Belch, G. E. (1986). The Role of Attitude Toward the Ad as a Mediator of Advertising Effectiveness: A Test of Competing Explanations. *Journal of Marketing Research*, 23(2), 130–143.

MacKenzie, S. B., & Spreng, R. A. (1992). How Does Motivation Moderate the Impact of Central and Peripheral Processing on Brand Attitudes and Intentions? *Journal of Consumer Research*, 18(4), 519–529.

MacKinnon, D. P., Krull, J. L., & Lockwood, C. M. (2000). Equivalence of the Mediation, Confounding and Suppression Effect. *Prevention Science*, 1(4), 173–181.

MacKinnon, D. P., Lockwood, C. M., Hoffman, J. M., West, S. G., & Sheets, V. (2002). A Comparison of Methods to Test Mediation and Other Intervening Variable Effects. *Psychological Methods*, 7(1), 83–104.

MacKinnon, D. P., Warsi, G., & Dwyer, J. H. (1995). A Simulation Study of Mediated Effect Measures. *Multivariate Behavioral Research*, 30(1), 41–62.

Muller, D., Judd, C. M., & Yzerbyt, V. Y. (2005). When Moderation is Mediated and Mediation is Moderated. *Journal of Personality and Social Psychology*, 89(6), 852–863.

Müller, D. (2009). Moderatoren und Mediatoren in Regressionen. In S. Albers, D. Klapper, U. Konradt, A. Walter, & J. Wolf (Eds.), *Methodik der empirischen Forschung*, Wiesbaden: Gabler, 245–252.

Muthén, L. K., & Muthén, B. O. (1998–2015). *Mplus User's Guide* (7th ed.). Los Angeles: Muthén & Muthén.

Preacher, K. J. (2015). Advances in Mediation Analysis: A Survey and Synthesis of New Developments. *Annual Review of Psychology*, 66, 825–852.

Preacher, K. J., & Hayes, A. F. (2004). SPSS and SAS Procedures for Estimating Indirect Effects in Simple Mediation Models. *Behavior Research Methods*, 36(4), 717–731.

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.

Preacher, K. J., Rucker, D. D., & Hayes, A. F. (2007). Addressing Moderated Mediation Hypotheses: Theory, Methods, and Prescriptions. *Multivariate Behavioral Research*, 42(1), 185–227.

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.

Schrift, R. Y., & Amar, M. (2015). Pain and Preferences: Observed Decisional Conflict and the Convergence of Preferences. *Journal of Consumer Research*, 42(4), 515–534.

Shrout, P. E., & Bolger, N. (2002). Mediation in Experimental and Nonexperimental Studies: New Procedures and Recommendations. *Psychological Methods*, 7(4), 422–445.

Siddiqui, R. A., May, F., & Monga, A. (2017). Time Window as a Self-Control Denominator: Shorter Windows Shift Preference toward Virtues and Longer Windows toward Vices. *Journal of Consumer Research*, 43(6), 932–949.

Sobel, M. E. (1982). Asymptotic Confidence Intervals for Indirect Effects in Structural Equation Models. *Sociological Methodology*, 13, 290–312.

Sobel, M. E. (1986). Some New Results on Indirect Effects and Their Standard Errors in Covariance Structure Models. *Sociological Methodology*, 16, 159–186.

Spiller, S. A., Fitzsimons, G. J., Lynch, J. G., & McClelland, G. H. (2013). Spotlights, Floodlights, and the Magic Number Zero: Simple Effects Tests in Moderated Regression. *Journal of Marketing Research*, 50(2), 277–288.

Stelzl, I. (1986). Changing a Causal Hypothesis without Changing the Fit: Some Rules for Generating Equivalent Path Models. *Multivariate Behavioral Research*, 21(3), 309–331.

Stone, C. A., & Sobel, M. E. (1990). The Robustness of Estimates of Total Indirect Effects in Covariance Structure Models Estimated by Maximum Likelihood. *Psychometrika*, 55(2), 337–352.

Winterich, K. P., & Zhang, Y. (2014). Accepting Inequality Deters Responsibility: How Power Distance Decreases Charitable Behavior. *Journal of Consumer Research*, 41(2), 274–293.

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.

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Mediation Analysis, Mediator, Bootstrapping, PROCESS, Tutorial.