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MEDIATION ANALYSIS IN CONSUMER PSYCHOLOGY

Models, Methods, and Considerations

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The field of consumer psychology seeks to understand *how* and *why* individual and social factors affect consumers' thoughts, perceptions, and behavior. For example, research in consumer psychology has examined the relationship between mood and persuasion (Petty, Schumann, Richman, & Strathman, 1993), interruptions and behavioral intentions (Kupor & Tormala, 2015), as well as communicator power and the content of word-of-mouth communications (Dubois, Rucker, & Galinsky, 2016). Central to each of the research endeavors is a desire to understand both the causal relationship between an independent variable and a dependent variable (i.e., the how) and to offer a psychological explanation for the observed relationship (i.e., the why).

To illustrate, Petty and colleagues (1993) found, under high elaboration conditions, mood had a positive influence on persuasion. Participants placed into a positive mood were more persuaded by an advertisement relative to participants in a neutral mood condition. Moreover, Petty and colleagues demonstrated that the influence of mood on persuasion could be explained by the fact that positive mood biased the nature of people's thoughts: People in a positive mood were more likely to generate favorable thoughts, and these more favorable thoughts led to more persuasion. In common vernacular, Petty and colleagues (1993) demonstrated that the positive influence of mood on persuasion was *mediated* by participants' thoughts. In a similar vein, Dubois and colleagues (2016) found that high-power communicators were more like to persuade high-power audiences because they used arguments that emphasized competence (i.e., capabilities and skills), but low-power communicators were more likely to persuade low-power audiences because they used arguments that emphasized warmth (e.g., arguments that stressed trustworthiness and sincerity). Kupor and Tormala (2015) demonstrated that interruptions during message reception increased consumers' curiosity, which increased favorable thoughts in response to strong arguments, which in turn increased persuasion.

In each of these examples, evidence for the psychological process was obtained via the measurement of the mechanism (e.g., thoughts, type of arguments, curiosity). Indeed, a common means to examine evidence for a psychological process is to measure the proposed mediator. Once measured, researchers can apply statistical tests to assess the viability of a variable as a mediator (Baron & Kenny, 1986; MacKinnon, 2008; Preacher, Rucker, & Hayes, 2007; Rucker, Preacher, Tormala, & Petty, 2011; Shrout & Bolger, 2002). Although alternative means to test for psychological processes exist (Spencer, Zanna, & Fong, 2005), the measurement of a mediator and the subsequent statistical tests remain widespread tools in the social sciences and consumer psychology more specifically (see Pieters, 2017; Zhao, Lynch, & Chen, 2010).

In this chapter, we offer a concise primer on the use of mediation analyses with an emphasis on consumer psychology. Our intended audience comprises those who seek to understand, or seek to refresh themselves on, the basic mechanics of mediation analysis. We begin with a discussion of simple mediation models and terminology followed by a discussion of methods to test mediation. Subsequently, we examine how mediation models can become more complicated and extend our discussion to understand how to test such models. Finally, we discuss additional considerations when planning and conducting mediation analyses. Although the statistical approach to mediation analysis in consumer psychology is identical to that in other social sciences, we emphasize examples that align with topics and experiments of general relevance to consumer psychologists.

Simple Mediation Models and Terminology

Simple mediation models take the form of an independent variable (X) proposed to affect a dependent variable (Y) through a specified mediator variable or mediator (M); see Figure 20.1. This simple model can be further understood via the specific pathways at play. The relationship between the independent variable (X) and the mediator (M) is specified as the *a* path. The relationship between the mediator (M) and the dependent variable (Y), controlling for X, is specified as the *b* path. Finally, the relationship between the independent variable (X) and the dependent variable (Y) is specified as *c* prior to the inclusion of the mediator (M) and *c'* after the inclusion of the mediator.

These specific pathways are the source of several pieces of terminology used in mediation analysis: *total effect, indirect effect*, and *direct effect*. The total effect refers to the overall influence of the independent variable (X) on the dependent variable (Y) and can be represented as either *c* or the sum $a \times b + c'$. These are equivalent because *c* represents the relationship between X and Y when no mediators are introduced, whereas $a \times b + c'$ consists of the independent effect of M and whatever effect of X on Y is left. The indirect effect reflects any portion of the relationship between X and Y that is accounted for by M; the indirect effect is captured by the product $a \times b$. Finally, the direct effect refers to any influence of X on Y that is not accounted for by M; the direct effect is represent as *c'*.

To illustrate the use of this terminology, consider the previously referenced research on mood and persuasion (Petty et al., 1993).[1] Petty et al. (1993; see Experiment 2) asked participants to complete an experiment that was described as being about college students' attitudes towards different television programs. Participants were told they would select a gift from a set of products, one of which would be advertised during the television program. Next, participants saw a television program designed to induce either a neutral or positive mood. Subsequently, participants saw an advertisement for the target product, a pen. Finally, participants' attitudes and thoughts towards the pen were measured. Petty et al. found that participants placed into a positive mood, as opposed to a neutral mood, had more favorable attitudes towards the pen. Moreover, participants in the positive mood condition had more favorable thoughts, which in turn predicted differences in attitudes.

As illustrated in Figure 20.2, participants' mood (X) had an effect on their attitudes (Y), and this effect was mediated by participants' favorable thoughts (M). In this example, the *indirect effect* is the product of the effect of mood on positive thoughts and the effect of positive thoughts on attitudes ($a \times b$).

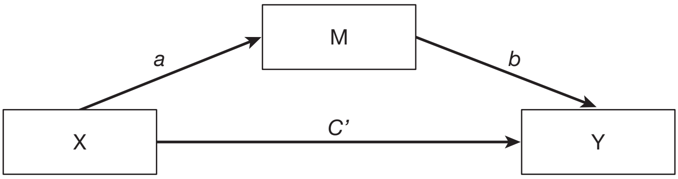

Figure 20.1 A Simple Mediation Model.

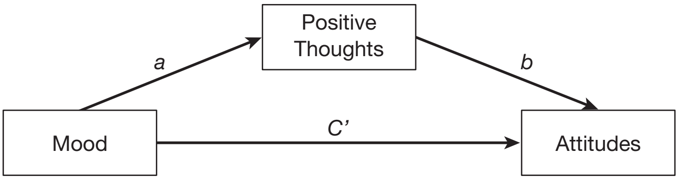

Figure 20.2 An Illustrative Example of Mediation.

The *direct effect* is the influence of mood on attitudes (c') controlling for positive thoughts. Finally, the *total effect* is the sum of the indirect effect and the direct effect (that is, $a \times b + c'$).

Testing Mediation

How does one gauge whether one's data are supportive of mediation? Over the last three decades, scholars have put forth several criteria for quantifying and testing mediation. Here we review three related approaches: The causal steps approach, the delta method, and bootstrapping.

The Causal Steps Approach

A landmark paper on mediation was the work of Baron and Kenny (1986). Baron and Kenny introduced a causal-steps approach to mediation. Step 1 of this approach is to conduct a regression analysis to test for a significant relationship between the independent variable (X) and the dependent variable (Y). This first step was deemed necessary because, if no relationship exists between the independent variable (X) and the dependent variable (Y), then no effect presumably exists that can be mediated. Step 2 involves a regression of the mediator (M) onto the independent variable (X); the logic for this step is that a mediator cannot explain a relationship between X and Y if Y is not causally impacted by the independent variable. Step 3 involves a regression of Y onto both X and M; that is, one predicts Y from X, while controlling for M. This final step provides an estimate of the relationship between M and the dependent variable (the b path). Mediation is observed when the a (Step 1), b (Step 2), and c (Step 3) paths are non-zero, and $c >$ than c' (see Baron & Kenny, 1986; Judd & Kenny, 1981).

The causal steps approach has been extremely popular, perhaps in part because of its intuitive and straightforward nature. However, several scholars have pointed to inherent limitations in the causal steps approach. For example, the final step in the causal steps approach is to examine whether $c > c'$. However, it is possible to observe very small differences between c and c' and still conclude that mediation exists. For example, c could be significant (e.g., $p = .049$) and c' could be non-significant (e.g., $p = .051$), and one may conclude mediation is present even though this difference is trivial. In addition, it is also possible to observe rather large differences between c and c' and conclude little or no evidence for mediation. For example, if the sample size (N) is large, both c and c' might be highly significant. In addition, the causal steps approach is also known to suffer from low power (see MacKinnon, Lockwood, Hoffman, West, & Sheets, 2002; Pituch, Whittaker, & Stapleton, 2005).

Perhaps most importantly, none of the individual regression equations tests the hypothesis of interest. That is, central to the question of mediation is whether or not an indirect path exists; that is, is the $a \times b$ product term significant? Notably, aspects of the causal steps approach test the independent significance of a and b, but no single regression equation allows a direct test of the indirect effect, which is the hypothesis of interest in mediation analyses. In fact, scholars have noted that a focus on the piecemeal process ignores the fact that a significant relationship between the independent variable (X) and the dependent variable (Y) is not required to observe or test for indirect effects (see Rucker et al., 2011; Shrout & Bolger, 2002). Put simply, the significance of $a \times b$ does not depend on the significance of the c or c' path.

The Delta Method

In their discussion of the causal steps approach, Baron and Kenny (1986) were aware of the limitation of focusing on each piecemeal path in a test of mediation. Specifically, a means to test for the significance of the indirect effect (i.e., the $a \times b$ path) is to obtain the approximate standard error (SE) of *ab*. Specifically, the $\mathrm{SE}_{\mathrm{ab}}$ can be obtained via the delta method, as follows:

$$SE_{ab} = \sqrt{\hat{a}^2 s_b^2 + \hat{b}^2 s_a^2}$$

In this equation, the s^2 terms are sampling variances of the coefficients (squared SEs). Sobel's test (Sobel, 1982) involves dividing $a \times b$ by $\mathrm{SE}_{\mathrm{ab}}$ and treating the result as a z-test that can then be used to gauge the statistical significance of the $a \times b$ pathway. For example, imagine an advertiser wants to test whether the use of an emotional versus a cognitive ad campaign will increase consumers' purchases of the product because it leads to better memory for the product. In this experiment, the type of advertising is the independent variable (X), consumers' purchase is the dependent variable (Y), and memory for the product is the mediator (M). Assume the advertiser obtains the following results from the test: $a = .228$; $b = .390$; $SE_{\mathrm{a}} = .0477$; $SE_{\mathrm{b}} = .0891$.

From these values, it is possible to compute both the point estimate of $a \times b$ and the SE_{ab}.

Point estimate: $a \times b = (.228 \times .390) = .089$

Standard error: $SE_{ab} = \sqrt{\hat{a}^2 s_b^2 + \hat{b}^2 s_a^2} = \sqrt{.228^2 \times .0891^2 + .390^2 \times .0477^2} = .0275$

Sobel's test: $z = \dfrac{a \times b}{SE_{ab}} = \dfrac{.089}{.0275} = 3.24$

The result of the Sobel test (z = 3.24) exceeds the critical value of statistical significance and therefore suggests that attitude (M) mediates the effect of an emotional advertisement versus cognitive advertisement (X) on purchase (Y).

Although the delta method is an improvement over the causal steps strategy, it has several limitations. First, the delta method tends to require large samples to justify treating it as a z-test. Second, the delta method is prone to either underestimated or inflated Type I error. Part of the concern that arises with the delta method is that it assumes that the numerator in Sobel's test—the $a \times b$ term—is normally distributed. However, this assumption is not often met in practice, especially when N is small.

Bootstrapping

One means to overcome the problem that the $a \times b$ term is not normally distributed is through the use of asymmetric confidence interval (CI) methods. Perhaps the most common approach among such methods is bootstrapping (Bollen & Stine, 1990; Efron & Tibshirani, 1994; Preacher & Hayes, 2004, 2008; Shrout & Bolger, 2002). Bootstrapping makes no distributional assumptions and thus avoids the assumption of normality required by the delta method.

The core idea behind bootstrapping is to generate a sampling distribution of the indirect effect by treating one's sample as a population and drawing a large number of resamples (e.g., 20,000). Each of these "resamples" is then used to estimate $a \times b$. This results in a sampling distribution of $a \times b$ that does not have to be normal or even symmetric. This sampling distribution can be used to produce a CI around the direct effect. Specifically, for a 95% bootstrap interval, we would locate the values of $a \times b$ that cut off the lower and upper 2.5%. An indirect effect is considered significant if this 95% CI does not contain zero.

Complex Mediation Models

The core principles discussed in simple mediation models can be extended to more complex mediation models. In particular, mediation models can involve multiple mediators, moderator variables, and specialized cases such as nonlinear mediation, longitudinal mediation, and multilevel data.

Multiple Mediator Models

Multiple mediator models extend basic mediation models through the inclusion of one or more additional mediators. In particular, multiple mediator models can take the form of serial or parallel mediation.

Serial mediation involves two or more mediators that are proposed to operate in sequence (see Figure 20.3, top panel). That is, the independent variable (X) is proposed to affect a first mediator (M1) that affects a second mediator (M2) that affects the dependent variable (Y). As an illustrative example, Kupor and Tormala (2015, Experiment 3) explored the relationship between interruptions (X) and behavioral intentions (Y). Specifically, the researchers demonstrated that individuals who were interrupted during the processing of product information became more curious about the content (M1), which led them to pay more attention and generate more favorable thoughts (M2) that produced more favorable behavioral intentions (Y). One limitation of serial mediation is that one must be all the more careful with claims of causality because both mediators are measured. We examine this issue subsequently in our discussion of general recommendations for mediation.

Parallel mediation involves two or more mediators that are proposed to operate in parallel to explain the effects of an independent variable (X) on a dependent variable (Y; see Figure 20.3, bottom panel). To illustrate, Tormala, Briñol, and Petty (2007) examined the relationship between the number of positive thoughts participants were requested to generate (IV) and their attitudes (DV).

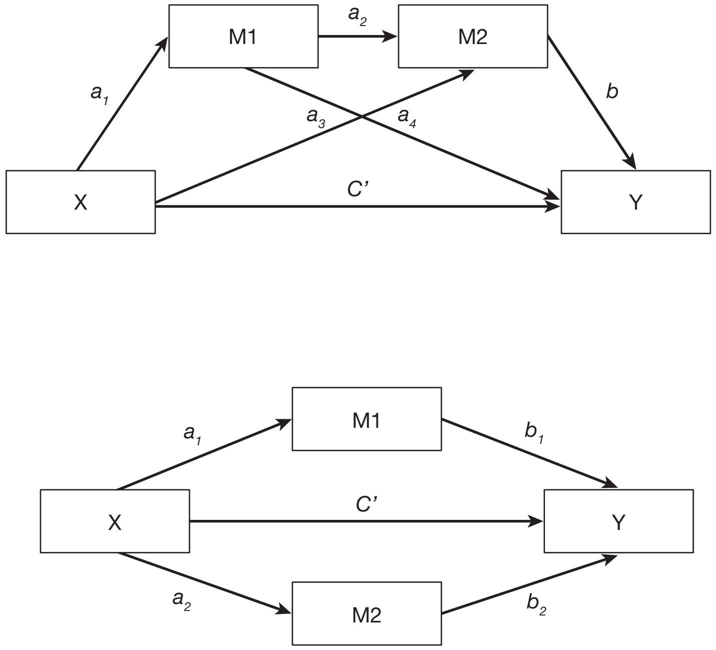

Figure 20.3 Multiple Mediator Models of Serial Mediation (Top Panel) and Parallel Mediation (Bottom Panel).

Specifically, Tormala et al. (2007) hypothesized that individuals' attitudes would become more negative when they were asked to generate a larger number of positive thoughts. They reasoned this would occur for two reasons. First, generating a large number of positive thoughts is difficult and would reduce their confidence in their positive thoughts (M1). Second, generating a large number of positive thoughts would ironically lead participants to generate unrequested negative thoughts (M2). Consistent with this perspective, Tormala et al. found evidence of parallel mediation.

As with simple mediation models, it is possible to test multiple mediation models with bootstrapping techniques (Hayes, Preacher, & Myers, 2011; Preacher & Hayes, 2008). It is also possible to specify *specific indirect effects* of interest. For example, in the serial mediation model depicted in Figure 20.3, top panel, one can test whether a specific indirect effect exists in the form of the independent variable (X) affecting a first mediator (M1), which affects a second mediator (M2), which affects the dependent measure of interest (Y); that is, one can test the a_1a_2b path. Alternatively, researchers could explore other specific indirect effects of interest in this same model. For example, a researcher could also estimate and test the specific indirect effects a_1a_4 or a_3b. In a parallel mediation model, such as the one depicted in Figure 20.3, bottom panel, one can also test specific indirect pathways such as a_1b_1 or a_2b_2.

Moderated Mediation Models

Moderated mediation models involve a baseline mediation effect that is moderated by at least one other variable (W) in some capacity. A large number of distinct moderated mediation models are possible. One example of moderated mediation includes a variable (W) that moderates the relationship between the independent variable (X) and the dependent variable (Y; see Figure 20.4, Image 1). Another example of moderated mediation includes a moderator (W) that influences the relationship between the mediator (M) and the dependent variable (Y; see Figure 20.4, Image 2). It is also possible for a moderator (W) to influence both the relationship between the independent variable (X) and the mediator variable (M) as well as the relationship between the mediator (M) and the dependent variable (Y; see Figure 20.4, Image 3).

As one example of moderated mediation, consider work by Dubois et al. (2016). These authors explore the relationship between the psychological state of power of a communicator and how persuaded an audience was by the message generated by the communicator. Dubois et al. found that communicator power (X) affected the competence of the arguments (M), which affected the audience's attitudes (Y). However, Dubois et al. reported that the relationship between the competence of the arguments (M) and the audience's attitude (Y) was moderated by the audience's own power (W). Specifically, competence arguments were more persuasive to audiences in a high-power state compared with a low-power state.

As an example of an alternative and distinct form of moderated mediation, we revisit the work on mood and persuasion explored in our discussion of simple mediation. Recall that Petty and colleagues (1993) found that individuals in a positive (vs. neutral) mood state were more likely to generate positive thoughts and thus had more positive attitudes about an advertised product. However, Petty and colleagues proposed that this mediation would be observed only under high elaboration conditions—that is, when people were paying sufficient attention to generate thoughts in the first place. Under low elaboration conditions, Petty and colleagues suggested that mood would not affect participants' thoughts but would affect attitudes in a direct fashion via an affective cue.

To test this moderated mediation hypothesis, Petty and colleagues manipulated how involved consumers were with the focal advertisement based on what free gift participants were told to expect at the end of the experiment. Although the target advertisement always featured a pen, participants in the high-involvement condition were told they would receive a pen, which made the advertisement for the pen extremely relevant to them. In contrast, participants in the low-involvement condition were told they would receive instant coffee, which made the advertisement for the pen less relevant to

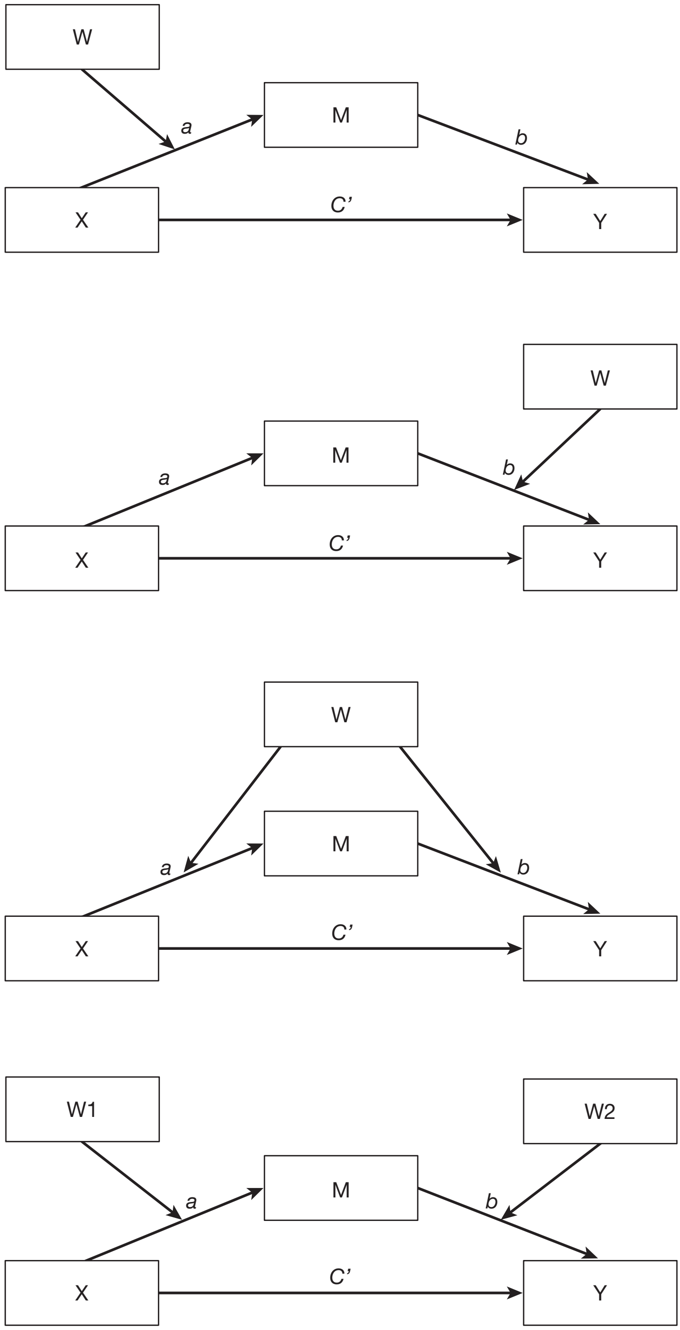

Figure 20.4 Moderated Mediation Models.

them. Petty and colleagues found that involvement moderated whether participants generated positive thoughts towards the message. Participants were more likely to generate thoughts when involvement was high compared with low. In mediation vernacular, involvement (W) moderated the relationship between mood (X) and positive thoughts (M), and positive thoughts (M) affected attitudes (Y).

In short, where Dubois et al. (2016) observed moderation of the *b* path, Petty et al. observed moderation of the *a* path. These represent but two examples of moderated mediation. It is also possible to develop even more complex moderated mediation models, such as those that combine multiple mediators and multiple moderators (Hayes, 2017). For example, one could have a moderated mediation model in which one moderator (W1) affects the relationship between the independent variable (X) and the mediator (M), and another moderator (W2) affects the relationship between the mediator (M) and the dependent variable (Y; see Figure 20.4, Image 4).

Specialized Mediation Models

A number of specialized mediation models have also arisen that reflect particular aspects of the data and/or the dependent measure. Indeed, the approach to mediation already discussed in this primer can be extended and adapted to address particular needs of consumer psychologists. For example, consumer psychologists often use experiments that involve a binary dependent measure, such as choice. In such cases, researchers can apply extensions of mediation models designed to handle binary or dichotomous outcomes (see Huang, Sivaganesan, Succop, & Goodman, 2004; MacKinnon & Dwyer, 1993). Similarly, researchers who have a within-subject design can use refinements in mediation models designed for such cases (see Judd, Kenny, & McClelland, 2001; Montoya & Hayes, 2017). Researchers might also have expectations that the relationship between either an independent variable (X) or a mediator (M) and a dependent variable (Y) is nonlinear in nature. In such cases, *instantaneous indirect effects* can be assessed (see Hayes & Preacher, 2010). In other cases, consumer psychologists might have longitudinal data (e.g., consumer brand preferences over time). Specialized models have been developed to model longitudinal data that involve repeated measurements of individuals over time (see Hoffman, 2014; Little, 2013). Finally, researchers might also be interested in testing mediation with clustered data (i.e., multilevel mediation), such as data from consumers who are "nested" within different demographic areas. Methods have been developed to estimate and test indirect effects in these contexts (see Lachowicz, Sterba, & Preacher, 2015; Preacher, Zyphur, & Zhang, 2010). In short, beyond the basic mediation and moderated mediation models discuss in this primer, a number of specialized models exist with a corpus of work that can be consulted for their specific application.

Recommendations in Mediation Analysis

In this final section, we provide several guidelines, recommendations, and best practices for the construction of mediation tests. In particular, we raise for consideration issues related to alternative models, claims of partial versus full mediation, and causality.

Alternative Models

In the case of complex mediation models, an issue that arises is that alternative models can be used to explain the same data. For example, with two measured mediators, one can model different serial mediation models, as well as serial versus parallel mediation. With two measured or manipulated moderators, one can also model different moderated mediation models. As the number of mediators and moderators increases, so does the number of potential models. For this reason, we suggest that it is important for researchers to emphasize the roles of theory and logic in mediation analyses. To illustrate, we consider two examples from consumer psychology—one a multiple mediator model and one a moderated mediation model—discussed previously in this chapter.

Kupor and Tormala (2015) report a case of serial mediation whereby interruptions (X) affect one's curiosity (M1) that in turn affects one's favorable thoughts (M2) that in turn affects one's behavioral intentions (Y). In this example, both mediators were measured. As such, one could test an alternative serial mediation model where interruptions (X) affect one's favorable thoughts (M2) that in turn affect one's curiosity (M1) that in turn affects one's behavioral intentions (Y). Because both models are saturated, and therefore have equivalent (and perfect) fit, how can one determine which model is better to represent the data? To answer this question, researchers must often make a case based on logic and prior theory. Indeed, Kupor and Tormala (2015) made a case for the observed serial mediation based on ample prior research in the domain of attitudes research. An alternative approach would be to manipulate different pieces of the model independently. For example, if one wanted to establish the relationship between curiosity (M1) and favorable thoughts (M2) in a causal fashion, one could seek to manipulate the mediator (for discussion of experimental methods, see Spencer et al., 2005). Of course, the establishment of a causal relationship via a manipulation of a mediator does not preclude the possibility that the reverse causal relationship may also sometimes occur.

Dubois et al. (2016), report a case of moderated mediation that can be explored via multiple models. Specifically, the authors found that communicator power (X) affected the degree to which the arguments emphasized competence (M), which affected the audience's attitudes (Y). Furthermore, moderated mediation was observed because the relationship between the degree to which the arguments emphasized competence (M) and the audience's attitude (Y) was moderated by the audience's own power (W). However, an alternative model that could have been examined is whether the audience's own power (W) moderated the relationship between communicator power (X) and the degree to which the arguments emphasized competence (M), which than affected the audience's attitude (Y). In this case, however, whereas an alternative model could fit the data, it did not make sense logically. Specifically, the communicators generated their message first and *independent of* knowledge of the audience's own power (W). As such, unless the communicators were clairvoyant, it seems unlikely that they could have adjusted the arguments they generated based on the audience. This example provides a case where the logic for a specified model can be helpful in separating out otherwise statistically equivalent models.

Given that multiple models can be fit to the same data, we strongly advocate that researchers take care in *both* the use of theory and experimental design when exploring mediation. Specifically, strong theory provides one means to separate out models that fit the data equally well (e.g., Kupor & Tormala, 2015; Pieters, 2017), longitudinal designs can afford greater confidence in claims of causal effects (e.g., Selig & Preacher, 2009), and experiments can also be constructed in ways to reduce the plausibility of alternative models (e.g., Dubois et al., 2016; see MacKinnon, Cheong, & Pirlott, 2012; MacKinnon, Lockhart, Baraldi, and Gelfand, 2013; Robins & Greenland, 1992).

Partial versus Full Mediation

In mediation tests, it is common to see researchers use the terms "partial" and "full" mediation. For tests of simple mediation, these terms are used to reflect the significance of the direct effect (*c'*). *Partial mediation* is used to refer to cases in which the direct effect (*c'*) remains significant after a significant indirect effect has been found. In contrast, *full mediation*—also sometimes referred to as perfect or complete mediation—reflects cases in which the direct effect (*c'*) is no longer significant after a significant indirect effect has been found. At one level, this distinction has been used as a coarse means to capture how impressive or important the mediator is as an explanatory variable for the relationship between an independent variable and a dependent variable. However, Rucker et al. (2011) have discouraged the use of partial versus full mediation because it focuses on the p-value as opposed to the effect size. Indeed, with both empirical data and simulation analyses, Rucker et al. (2011) demonstrate that the determination of partial versus full mediation can be somewhat arbitrary, and such rough cuts can impede research.

As an example of how the use of the terms partial and full mediation can impede research, Rucker et al. (2011) note that full mediation suggests that the effect of the independent variable (X) on the dependent variable (Y) is accounted for entirely by the mediator. The conceptual implication of such a conclusion is severe: No other intermediate processes exist. However, Rucker et al. (2011) demonstrate that it is empirically possible to obtain evidence for other indirect effects, even when the conditions of "full mediation" are met. Moreover, suppressor variables—variables that reduce the relationship between X and Y—can also affect whether one concludes mediation is partial or full. Specifically, one might observe full mediation until a suppressor variable is identified (for more on suppressor variables, see Rucker et al., 2011). A solution to this is to move away from the terminology of partial versus full and instead focus on quantifying and reporting effect size. A number of effect sizes have been designed for use in mediation analysis; see Preacher and Kelley (2011) for an overview and Lachowicz, Preacher, and Kelley (2018) for recent developments.

A final notable problem with the use of partial and full mediation is that it does not even relate to the specific test of interest. That is, the quantity of primary interest in a simple mediation model—the $a \times b$ term—is logically separate from the significance of c' (for discussion, see Rucker et al., 2011). However, the terms partial and full derive from the significance of c'. Thus, the very basis on which "partial" and "full" are defined fail to even relate to the core hypothesis of interest in mediation tests.

Cautions Regarding Causal Inference

Many are familiar with the phrase "correlation does not imply causation." This phrase captures the idea that, whereas correlation may result from a causal relationship, correlation in and of itself is not sufficient to make causal claims. In simple mediation analyses—though similar arguments apply to more complicated mediation models—the weak link in the causal change occurs in the *b* path. Specifically, the *b* path reflects a relationship between the mediator (M) and the dependent measure (Y), which are both measured variables. As a consequence, it is possible that, rather than the mediator causing the dependent variable, the dependent variable might be the cause of the mediator. Alternatively, it is possible that a third variable explains the relationship between the mediator and the dependent variable that is not, in fact, the independent variable (IV).

Because the *b* path in a simple mediation model is based on correlation, it does warrant some caution to interpret it in a causal fashion. However, this limitation can be addressed, in part, via psychological theory and logic. For example, just as serial mediation has interpretive issues, as we discussed in the case of Kupor and Tormala (2015), such concerns are reduced when past theory or logic favors a particular causal relationship. In addition, alternative approaches to test the psychological mechanism, such as direct manipulation of the process, can be used to supplement mediation measurement approaches (see Spencer et al., 2005).

Pieters (2017), well aware of the correlational nature of the *b* path, has also offered a series of recommendations to assess whether a mediation model is meaningful. For example, Pieters suggests that the relationship between the mediator (M) and the dependent measure (Y) should not be too small or too large. If the coefficient for the *b* path is too small, researchers may lack the power to detect a significant relationship. If the coefficient for the *b* path is too large, it is possible that the mediator (M) and the dependent measure (Y) reflect measurements of the same—not different—underlying constructs.

Conclusion

Central to the endeavor of consumer psychology is the desire to understand the psychological mechanisms that explain how consumers think and behave. Mediation analysis facilitates such endeavors because it allows researchers to test for the presence of indirect effects in their data. However, tests of mediation are statistical tools that must be grounded in a proper understanding of how to conduct mediation tests, what such tests are able to tell us, and what the limitations of such tests are.

Note

1 Petty and colleagues suggest that this mediation model holds only under cases of high involvement. Thus, our example here focuses on this case. We explore the role of involvement, as studied by Petty et al., 1993, in our discussion of moderated mediation.

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