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Mediation Analysis in Social Psychology: Current Practices and New Recommendations

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Abstract

A key aim of social psychology is to understand the psychological processes through which independent variables affect dependent variables in the social domain. This objective has given rise to statistical methods for mediation analysis. In mediation analysis, the significance of the relationship between the independent and dependent variables has been integral in theory testing, being used as a basis to determine (1) whether to proceed with analyses of mediation and (2) whether one or several proposed mediator(s) fully or partially accounts for an effect. Synthesizing past research and offering new arguments, we suggest that the collective evidence raises considerable concern that the focus on the significance between the independent and dependent variables, both before and after mediation tests, is unjustified and can impair theory development and testing. To expand theory involving social psychological processes, we argue that attention in mediation analysis should be shifted towards assessing the magnitude and significance of indirect effects.

Understanding the psychological processes by which independent variables affect dependent variables in the social domain has long been of interest to social psychologists. Although moderation approaches can test competing psychological mechanisms (e.g., Petty, 2006; Spencer, Zanna, & Fong, 2005), mediation is typically the standard for testing theories regarding process (e.g., Baron & Kenny, 1986; James & Brett, 1984; Judd & Kenny, 1981; MacKinnon, 2008; MacKinnon, Lockwood, Hoffman, West, & Sheets, 2002; Muller, Judd, & Yzerbyt, 2005; Preacher & Hayes, 2004; Preacher, Rucker, & Hayes, 2007; Shrout & Bolger, 2002). For example, dual process models of persuasion (e.g., Petty & Cacioppo, 1986) often distinguish among competing accounts by measuring the postulated underlying process (e.g., thought favorability, thought confidence) and examining their viability as mediators (Tormala, Briñol, & Petty, 2007). Thus, deciding on appropriate requirements for mediation is vital to theory development.

Supporting the high status of mediation analysis in our field, MacKinnon, Fairchild, and Fritz (2007) report that research in social psychology accounts for 34% of all mediation tests in psychology more generally. In our own analysis of journal articles published from 2005 to 2009, we found that approximately 59% of articles in the *Journal of Personality and Social Psychology* (*JPSP*) and 65% of articles in *Personality and Social Psychology Bulletin* (*PSPB*) included at least one mediation test. Consistent with the observations of MacKinnon et al., we found that the bulk of these analyses continue to follow the causal steps approach outlined by Baron and Kenny (1986).

The current article examines the viability of the causal steps approach in which the significance of the relationship between an independent variable (X) and a dependent variable (Y) are tested both before and after controlling for a mediator (M) in order to examine the validity of a theory specifying mediation. Traditionally, the X → Y relationship is tested prior to mediation to determine whether there is an effect to mediate, and it is also tested after introducing a potential mediator to determine whether that mediator fully or partially accounts for the effect. At first glance, the requirement of a significant X → Y association prior to examining mediation seems reasonable. If there is no significant X → Y relationship, how can there be any mediation of it? Furthermore, the requirement that X → Y become nonsignificant when controlling for the mediator seems sensible in order to claim 'full mediation'. What is the point of hypothesizing or testing for additional mediators if the inclusion of one mediator renders the initial relationship indistinguishable from zero? Despite the intuitive appeal of these requirements, the present article raises serious concerns about their use.

Overview

Although there is value in testing the total effect of X on Y, we propose that overemphasizing the X → Y relationship before or after controlling for a mediator can lead to misleading, or even false, conclusions in theory testing. Here we concur with recent writings on mediation (Hayes, 2009; MacKinnon, Krull, & Lockwood, 2000; MacKinnon et al., 2002; Shrout & Bolger, 2002; Zhao, Lynch, & Chen, 2010) and also provide new evidence and arguments to bolster this point. Furthermore, we highlight the importance of considering suppression effects in mediation analyses in social psychology. Finally, we suggest that researchers interested in understanding intervening effects in proposed theoretical models should shift attention to testing the mediation effect itself and not constrain themselves by placing undue emphasis on the significance of the X → Y relationship.

The Use of the X → Y Relationship in Mediation Analyses

Figure 1 depicts the framework for a simple mediation model. X represents the independent variable, Y the dependent measure, and M the intervening or mediating variable. The top portion of the figure represents the total effect of X → Y, whereas the bottom portion represents the introduction of the mediator. In this figure, c represents the *total effect* of X → Y (i.e., the unstandardized slope of the regression of Y on X), whereas c' represents the *direct effect* of X → Y after controlling for the proposed mediator. The effect of the independent variable on the mediator is represented by a, and

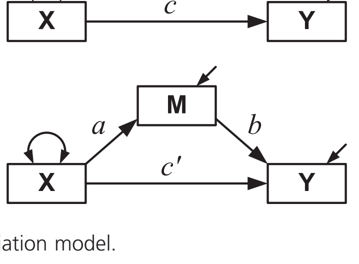

Figure 1 Schematic of a simple mediation model.

the effect of the mediator on the dependent variable, controlling for the independent variable, is represented by b. Finally, the *indirect effect* is the product $a \times b$. In general, $a \times b$ is equivalent to $c - c'$, the difference between the total effect and the direct effect, but it is easier to test the significance of $a \times b$ because these coefficients are drawn from a single model, whereas c and c' are drawn from two separate models. Indeed, most tests of mediation (e.g., Sobel, 1982) quantify the effect as $a \times b$. Significance testing often proceeds by comparing zero to the sampling distribution of $a \times b$, with specific approaches differing mainly in how the properties of the sampling distribution are obtained.

Most germane to the current concerns, significance testing of the X $\rightarrow$ Y relationship has been portrayed as critical in two stages of the causal steps approach. First, Baron and Kenny (1986) argue that a critical starting point for mediation analysis is a significant relationship between X and Y. From this perspective, a significant c coefficient can be viewed as a necessary condition for testing mediation. Without a significant c, the causal steps approach leads to the conclusion that an indirect effect does not exist because there is no overall effect to mediate. Second, the significance of X $\rightarrow$ Y also is used *after* the total effect has been found to be significant and a proposed mediator has been introduced and statistically controlled, in which case X $\rightarrow$ Y is known as the direct effect and labeled c'. After finding a significant indirect effect, if there is no longer a significant direct effect of X on Y, researchers typically report that the mediator *perfectly*, *completely*, or *fully* mediates the X $\rightarrow$ Y effect. In contrast, if there remains a significant direct X $\rightarrow$ Y effect after controlling for the mediator, researchers typically report that the mediator only *partially* mediates the X $\rightarrow$ Y effect. This practice is common in the reporting of mediation analyses. Among all articles in *JPSP* and *PSPB* employing a test of mediation from 2005 to 2009, approximately 36% (*JPSP*) and 38% (*PSPB*) used one or more of these terms in reporting the results of a mediation analysis.

The distinction between full and partial mediation has been influential in theory testing and the development of social psychological knowledge. In a simple mediation model with one mediator, full mediation suggests that a researcher has completely explained the process by which X influences Y and there is no need to test for further indirect effects. In the case of partial mediation, there is a clear implication that other indirect effects could (and probably should) be examined and tested empirically. Thus, conclusions of partial and full mediation can have implications for theory building as they suggest the plausibility of additional mechanisms. Practically, partial versus full mediation might be viewed as an indication of the importance of an intermediate variable in explaining the total effect (Preacher & Kelley, forthcoming).

In short, researchers rely upon the significance test of the X $\rightarrow$ Y relationship to (1) assess whether there is a significant total effect and thus decide whether it is appropriate to proceed with examining indirect effects, and (2) assess the extent, and therefore the importance or completeness, of any mediation observed. Consistent with emerging perspectives (Hayes, 2009; MacKinnon et al., 2002; Shrout & Bolger, 2002; Zhao et al., 2010), we question the requirement that a total X $\rightarrow$ Y effect be present before assessing mediation. Importantly, we also extend past work on this topic by questioning the emphasis on the significance of c' after including the proposed mediator, as well as the use of terms such as 'full' versus 'partial' mediation. Ultimately, we introduce new conceptual and empirical evidence highlighting the limitations of the causal steps approach and provide new recommendations for assessing mediation in social psychological research or in any research in which mediation is of interest.

Evidence for Significant Indirect Effects when Total or Direct Effects are Absent

In this article, we seek to provide systematic evidence that significant indirect effects can occur in the absence of significant total or direct effects. Common to both the scenarios is that the lack of an effect, whether it be total or direct, does not preclude the possibility of observing indirect effects. To start, we use a new simulation study to demonstrate that significant indirect effects can be detected even when c is not statistically significant and an empirical example to demonstrate that additional indirect effects can be detected even when c' is not statistically significant.

Simulation study

First, via simulation, we examined the probability of observing significant indirect effects even when c is not significant. To do so, we set population values of a and b to .4 in all conditions, and varied the population value of c (.2, .3, .4, .5, .6) and the sample size N (25, 50, 100, 200) to span common values found in social psychological research. We generated 5000 samples per cell in this 5 (c) × 4 (N) design and tested the significance of the indirect effect using bias-corrected bootstrap 95% confidence intervals (CIs). As seen in Table 1, when c is underpowered (i.e., weaker) relative to a and b, significant indirect effects can be observed in the absence of a significant total effect. Cell contents in Table 1 represent the proportion of those trials in a given cell for which $a \times b$ was significant but c was not (i.e., if a cell produces 3963 trials with nonsignificant c coefficients, the proportion is from these trials). As the relative power of the test of c increases, this tendency is reduced and eventually eliminated. These results suggest that detecting indirect effects in the absence of a total effect can be quite frequent – nearly half the time – in sample sizes typical of social psychology research.

Experimental results

To illustrate that additional mediation can be observed when c' is no longer statistically significant, we present an example from Tormala, Falces, Briñol, and Petty (2007) that contrasted two theoretical accounts for the ease of retrieval effect described by Schwarz et al. (1991). In the original work, participants rated themselves as more assertive when they recalled few (easy) as opposed to many (difficult) examples of assertiveness. In a conceptual replication of this effect in persuasion, Tormala et al. (2007) found that

Table 1 Proportion of significant indirect effects in the absence of a significant total effect as a function of varying values of c and N

c	N = 25	N = 50	N = 100	N = 200
.20	.243	.482	.445	.191
.30	.202	.274	.126	.009
.40	.130	.111	.011	.000
.50	.062	.020	.000	.000
.60	.016	.001	.000	.000

c = total effect of X on Y; N = sample size; coefficients a (the effect of X on M) and b (the effect of M on Y controlling for X) are held constant at .40 for varying levels of c and N.

participants' attitudes were more favorable when they listed 2 (easy) rather than 10 (difficult) positive thoughts about an issue.

Tormala et al. (2007) tested two theories for why this effect occurred. On the basis of the self-validation hypothesis (Petty, Briñol, & Tormala, 2002), they reasoned that when it was more difficult to generate positive thoughts (i.e., a larger number was requested), participants should have less confidence in the positive thoughts generated, and less confidence in positive thoughts should lead to less favorable attitudes (see Tormala, Petty, & Briñol, 2002). A second possible account, however, was that as it became difficult to generate the number of positive thoughts requested, participants might spontaneously generate unrequested negative thoughts as well, and more negative thoughts should lead to less favorable attitudes. To test these possibilities, Tormala et al. measured both thought confidence (M1) and the number of unrequested negative thoughts (M2) that came to mind for participants.

Tormala et al. started with a simple mediation model. In this analysis, number of positive thoughts requested (i.e., X) significantly affected both M1 ($a_1 = -1.25$, $p < .01$) and attitudes ($c = -1.18$, $p = .03$).[1] Participants reported less confidence in their positive thoughts and less positive attitudes when asked to generate 10 (difficult) versus 2 (easy) positive thoughts. When both X and M1 were included as predictors of attitudes, M1 remained significant ($b_1 = .56$, $p < .01$), whereas X did not ($c' = -.47$, $p = .36$). A bias-corrected bootstrap 95% CI indicated that the indirect effect through M1 was significant, $a_1 \times b_1 = -.71$, 95% CI: [−1.48, −.14].

By conventional standards, M1 fully mediated the ease of retrieval effect. Nevertheless, Tormala et al. tested whether the second psychological process, the presence of unrequested negative thoughts (M2), also operated. A simultaneous regression with X and M1 as predictors of M2 revealed that X affected M2 ($a_2 = 1.58$, $p = .01$), but M1 did not ($e = -.20$, $p = .31$). Following this analysis, Tormala et al. examined whether M2 mediated the effect of X on attitudes, even after controlling for M1 (see Figure 2 for a schematic representation). Both M2 ($b_2 = -.46$, $p < .001$) and M1 ($b_1 = .47$, $p < .01$) predicted attitudes, but X did not ($c' = .26$, $p = .59$). Moreover, the indirect effect through M2 was significant even after controlling for the indirect effect of M1, $a_2 \times b_2 = -.84$, 95% CI: [−1.49, −.42].

In short, although the first test met the requirements for 'full mediation', evidence for a second theoretically meaningful process was produced. These findings speak to the current issues by demonstrating that additional significant indirect effects can be observed

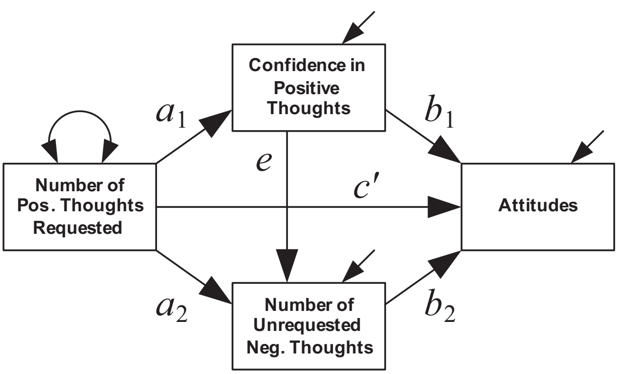

Figure 2 Conceptual diagram of the model fit by Tormala et al. (2007).

even if c' is not significant following an initial indirect effect. This raises serious concerns as to whether and when researchers should or even can claim full mediation.

Asymmetries in Statistical Power for Detecting Indirect and Total/Direct Effects

One potential reason an indirect effect might be detected even when the total or direct effect is not significant is differential power for detecting these effects. In this section we examine why the statistical power to detect c or c' can be less than the power to detect the $a \times b$ pathway in the same sample or investigation.

Measurement precision

First, precision of estimation of a, b, and c (e.g., size of the standard error, width of the CI) can make the indirect and total effects differentially detectable. For instance, in Figure 1, if the test of c is underpowered but a and b are both fairly precise, or one of them compensates for imprecision in the other such that $a \times b$ is found to be significant, it could be easier to detect an indirect effect relative to a total effect. Such an outcome would be particularly likely to happen with moderately reliable X and Y but *highly* reliable M. This highly reliable M would increase power for any regression weight associated with it (a and b) but would do nothing for c. Similarly, measurement precision might affect whether additional mediation can be uncovered when c' is not significant. Indeed, if c is underpowered, c' might be rendered nonsignificant rather easily despite the existence of additional indirect effects. In this circumstance, if one has a second mediator measured with high reliability, it could be possible to show that the second indirect effect is significant despite a nonsignificant c'.

Strength of relationship

Second, an independent variable might exert a stronger influence on a mediator (path a) than on the dependent measure (path c), which could lead to a stronger indirect effect than total effect. Thus, the $a \times b$ path can be significant even when the c path is not. The same logic also holds after controlling for an initial mediator that renders c' nonsignificant. If the relationship between an independent variable and a second proposed mediator is stronger than path c', this type of relationship could produce a second indirect effect, despite finding c' to be nonsignificant after controlling for the first mediator.

Sample size

Mediation conclusions also are dependent on sample size. Keeping all other factors the same, as sample size increases one is more likely to find a significant total effect (c) if one is present. Similarly, as the terms are traditionally defined (e.g., see Baron & Kenny, 1986), determinations of partial versus full mediation rest on p-values associated with the direct effect (c') and, by implication, the sample size (N). The smaller the sample, the more likely mediation (when present) is to be labeled full as opposed to partial, because c' is more easily rendered nonsignificant.

To illustrate, we conducted a second simulation study. We set population values of a and b to .4 in all conditions, and varied the population value of c (.2, .3, .4, .5, .6) and the sample size N (25, 50, 100, 200). We generated 5000 samples per cell in this 5

(c) × 4 (N) design and tested the significance of the indirect effect using bias-corrected bootstrap 95% CIs. As expected, the proportion of trials in which mediation was significant increased with N and with the size of the c coefficient. Furthermore, as seen in Figure 3, the proportion of significant mediation effects that could be described as full decreased as sample size increased. Keeping all other factors the same, going from a significant c to a nonsignificant c' is more likely when N is small because the test of c' has less power as N decreases. These results suggest that moderate sample sizes might be optimal if one wishes to demonstrate full mediation via the causal steps approach. Moderate sample sizes give a researcher enough power to just detect the total effect, which would render virtually any mediation effect 'full'. A sample that is too small might be an obstacle to demonstrating the total effect (c), whereas a sample size that is too large makes it harder to rule out additional layers of mediation (because c' remains significant). Given their dependence on sample size, the meaningfulness and utility of the 'full' and 'partial' mediation labels is limited in our view.

Size of the total effect

The size of the total effect also matters. The smaller the total effect, the more likely it is that claims of full versus partial mediation will be made based on the significance of c' (Little, Card, Bovaird, Preacher, & Crandall, 2007). For example, any observed mediation for a total effect with an initial p-value of .05 likely will lead to claims of full mediation, because the p-value of the direct effect likely will be greater than .05 after controlling for

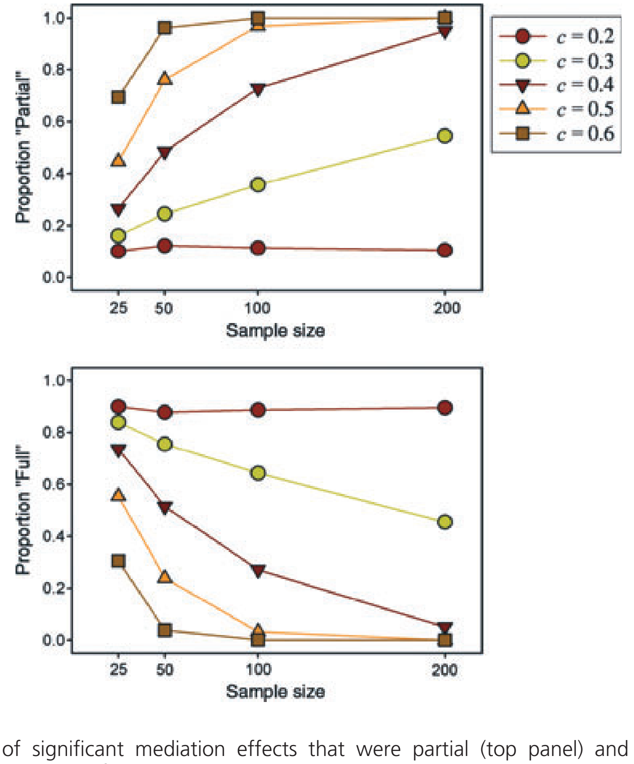

Figure 3 Proportion of significant mediation effects that were partial (top panel) and full (bottom panel) at different sample sizes and levels of c.

the mediator. Conversely, if the total effect is highly significant (e.g., $p < .001$), even a well-measured mediator and an objectively strong intervening process might yield claims of only partial mediation. Indeed, conventional practice suggests that a mediation effect could be labeled 'full' when the p-value for the total effect changes from .04 to a direct effect p-value of .06. By contrast, mediation would be labeled 'partial' if a total effect p-value of .001 changes to a direct effect p-value of .05. Thus, controlling for sample size, the significance level of the total effect can determine whether the same degree of mediation (i.e., an equivalent indirect effect) produces claims of full or partial mediation.

Suppression Effects Can Conceal Significant Total or Direct Effects

It is often possible that multiple indirect effects involving unmeasured variables explain a particular relationship. This observation is important because it provides another reason why there might be significant indirect effects in the absence of a total or direct effect. Specifically, *opposing* indirect effects can obscure a total effect as well as influence claims of partial versus full mediation. We posit that in cases in which current procedures would suggest the absence of mediation, examining multiple – potentially competing – indirect effects could enhance theory.

Consider suppression effects. MacKinnon et al. (2000) use the term *suppressor* to describe "a variable which increases the predictive validity of another variable (or set of variables) by its inclusion in a regression equation." Similarly, we describe a suppressor variable as one that undermines the total effect by its omission, meaning accounting for it in a regression equation enhances the predictive utility of the other variables in the equation. As depicted in Figure 4, the X → Y relationship can involve not only a mediating variable, M, but also a suppressing variable, S. Suppression occurs when an indirect effect has a sign that is *opposite* to that of the total effect, and thus omission of the suppressor might lead the total effect to appear small or nonsignificant. Evidence of suppression is found when including an intervening variable produces a value of c' that is greater in magnitude than c. In such a case, the X → Y relationship is actually strengthened, not weakened, by including an intervening variable (i.e., a suppressor).

McFatter (1979) offers an example of a suppression effect in examining the role of intelligence on task performance. Whereas intelligence (X) is expected to be associated with greater ability (M) and therefore enhance performance (Y), McFatter (1979) suggested that this relationship might be suppressed by intelligence leading to greater task boredom (S), because boredom harms performance. In this example, there is a mediating effect of ability as well as a suppressing effect of boredom. Before accounting for the suppressor variable, the total effect of intelligence on performance might appear to be zero,

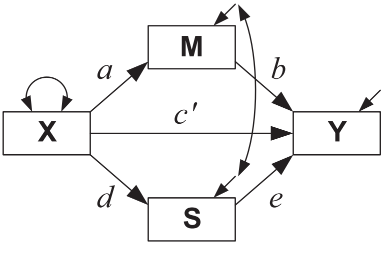

Figure 4 Schematic of a suppression effect.

but that would not be an accurate description of the effect of intelligence on the outcome.

Because a suppressor variable weakens the effect of X on Y by its omission, a suppressor can, unless controlled for, cause both total and direct effects to be nonsignificant. Controlling for the suppressor, in contrast, can render both effects significant. The implication is that a suppressor might lead researchers to believe there is no total effect or to claim they have demonstrated full mediation when actually there is a remaining effect that is being suppressed by an omitted variable. Whether a suppressor variable prevents observing a significant total effect or fosters an erroneous claim of full mediation depends on the size of the suppression effect relative to the size of the total effect. A large suppression effect reduces the likelihood that a researcher will detect a total effect and test mediation, whereas a smaller suppression effect might leave the total effect observable but lead researchers to false conclusions of full mediation. These findings underscore the importance of avoiding the terms 'full' or 'partial' when describing mediation.

Of course, suppressors can be of theoretical and practical importance as well. Consider an intervention designed to protect the self-esteem of members of stigmatized groups. This intervention might seek to boost self-esteem by training individuals to identify or recognize discrimination when present to preempt internal attributions for discrimination-based rejection. Reducing internal attributions for rejection should bolster self-esteem. If this intervention also reduces perceptions of group status, however, this might suppress its positive effect on self-esteem, making it appear as though the intervention offers no benefit (see Leonardelli & Tormala, 2003). By identifying this suppression effect, the intervention effect can be better understood and even improved.

Finally, it is worth acknowledging that tests of mediation and tests of suppression involve the same analytic methods (MacKinnon et al., 2000). The difference lies in the relationship between the indirect effect ($a \times b$) and the total effect (c). If the indirect effect has the same sign as the total effect, the intervening variable is viewed as a mediator. If an indirect effect has the opposite sign of the total effect, the intervening variable is a suppressor because it weakens the observed relationship by its omission.

Partial and Full Mediation: Indicators of Practical Importance or Effect Size?

It could be argued that using the terms 'partial' and 'full' helps convey the effect size or practical significance of a mediating process. A demonstration of full mediation implies that an underlying process can completely account for the X → Y relationship, whereas a demonstration of partial mediation implies that it cannot. Consequently, a partial mediation effect might be viewed as smaller or less important than a full mediation effect.

In response to this argument, we note that indirect effects vary in their size, but this point is missed when all effects that fall short of completely mediating a relationship are labeled 'partial'. If researchers wish to convey effect size, the size of an indirect effect can be directly computed, reported, and interpreted in its raw metric; $a \times b$ and c' are both changes in Y per unit change in X. Specifically, $a \times b$ is the amount by which Y is expected to change as a function of a change of size a in M (which, in turn, is the expected change in M per unit increase in X). There is no need to use words like partial, full, or complete if the goal is to suggest an effect size because the effect can be represented and understood using simply $a \times b$. Other methods for quantifying effect size in mediation are discussed by Preacher and Kelley (forthcoming).

Costs: Focusing on the Significance of c and c' Can Impede Research

The fact that indirect effects can be revealed in the absence of a total or direct effect suggests that focusing on the test of the total or direct effect can restrict research progress. In the case of the total effect, it might cause researchers to miss theorized relationships that are present in the data. In addition, the use of the terms 'partial' and 'full' based on the significance of the direct effect after controlling for a mediator can hinder theory development. Evidence for full mediation, for instance, would likely discourage researchers from examining other (theoretically motivated) indirect effects. Thus, claims of full mediation can unnecessarily constrain theory development, as when there might be additional mediating pathways. Also important, 'partial' mediation might be viewed as less impressive than 'full' mediation by researchers or reviewers. We submit that shedding light on a new indirect effect can be of theoretical and practical importance regardless of the size of the effect and regardless of whether or not it meets the standard criteria for full mediation. Given that there is always the possibility of additional mediation, the notion that partial mediation is somehow less impressive is unwarranted.

Recommendations for Practice

Abandon the emphasis on the significance of c and c'

In accord with others (e.g., Hayes, 2009; MacKinnon et al., 2000; Shrout & Bolger, 2002; Zhao et al., 2010), we submit that the requirement for a significant total $X \rightarrow Y$ effect prior to examining indirect effects be abandoned. Furthermore, the absence of a direct effect after controlling for an initial mediator should not lead to conclusions of 'full' mediation. Rather, we submit that researchers' exploration of mediation should be guided by theory. If there are theoretical reasons to predict the presence of an indirect effect, or multiple indirect effects, researchers should explore these effects regardless of the significance of the total or direct effect.[2]

Consider and assess suppression effects

There has not been a strong encouragement for researchers to consider suppressor variables in their models. This is important because the investigation of suppression effects provides an opportunity to acquire a deeper understanding of the relationships among variables. When researchers are preparing an experiment, for example, they should consider not only mediators linking the independent variable to the dependent variable, but also potential suppressors that might cloak this relationship. A theory that takes into account mediating and suppressing variables is more complete than a theory that examines only the former.

Focus on the size of indirect effects

We recommend that mediation analyses focus on examining the magnitude of *indirect* effects. Specifically, the $a \times b$ term is the amount by which Y is expected to change per a change of size a in M, which is the expected change in M per a change in one unit of X. Focusing on the presence and size of the indirect effect obviates reliance upon the significance of the $X \rightarrow Y$ relationship before and after mediation is assessed. Instead, emphasis is placed upon (1) whether there is evidence for an indirect effect (i.e., statistical significance) and (2) the size of that indirect effect. This is not license for researchers to exclude reporting the significance of the total effect; indeed, a significant X → Y effect would be important for theories explicitly stating that a total effect exists or that some intervention has a total effect. Rather, a significant total effect should not be viewed as a necessary step before examining hypothesized indirect effects. Furthermore, a nonsignificant direct effect (c') should not be viewed as a stopping rule in the search for additional mediators.

Some researchers might be uncomfortable with the idea that one cannot 'prove' full mediation. However, the reality is that to claim full mediation, one would have to have confidently measured – without error – all possible mediators and suppressors. Few, if any, variables are measured without error in psychology (Hoyle & Kenny, 1999). The impossibility of perfect measurement, in and of itself, suggests that one cannot ever claim to have established complete mediation. However, by focusing on effect sizes, researchers could talk about the magnitude of an effect, and might conclude that they have likely documented the primary mediator of interest in a given X → Y relationship and that the likelihood of any additional large mediators is remote.

Conclusion

As our desire to understand processes in social psychological phenomena has increased, so too has the sophistication of our tools. Nevertheless, some of the field's requirements and considerations regarding mediation analysis seem outdated. Indeed, focusing on the significance of the X → Y relationship before or after examining a mediator might be unnecessarily restrictive. We advocate a consideration of the significance of indirect effects and examination of effect sizes accompanying those effects in theory building and hypothesis testing.

Short Biographies

Derek D. Rucker received his B.A. in Psychology from the University of California, Santa Cruz, and his Ph.D. in Social Psychology from the Ohio State University in 2005. Upon graduation, he joined the Kellogg School of Management, Northwestern University, where is now an Associate Professor of Marketing. Dr. Rucker's primary research focuses on the study of attitudes, persuasion, power, and social influence. Much of his work in these domains aims to better understand the role of psychological states in individuals' response to persuasion and message attributes. His work on these topics has appeared in a number of leading journals spanning the psychology and marketing disciplines. He is currently the Richard M. Clewett Research Professor in Marketing and teaches Advertising Strategy.

Kristopher J. Preacher is an assistant professor in the Quantitative Psychology training program at the University of Kansas. He is also currently an associate of the KU Center for Research Methods and Data Analysis (CRMDA). His research is focused on bridging the gap between theory construction and model specification and assessment. Specific topics of interest include factor analysis, structural equation modeling (SEM), multilevel modeling (MLM), latent growth curve modeling (LGM), model fit, and the assessment of mediation and moderation effects. Dr. Preacher has taught courses on multilevel modeling, factor analysis, structural equation modeling, and nonparametric statistics. He received his Ph.D. in quantitative psychology from the Ohio State University in 2003 and completed a Postdoc at the University of North Carolina, Chapel Hill, before joining the University of Kansas.

Zakary L. Tormala is an Associate Professor of Marketing in the Graduate School of Business at Stanford University. He received his B.A. in Psychology from Arizona State University and his PhD in Social Psychology from Ohio State University in 2003. That year, Dr. Tormala started his career as an Assistant Professor in the Department of Psychological and Brain Sciences at Indiana University. He moved to Stanford in the summer of 2007. His research interests are in the areas of attitudes and social cognition. Much of his current work focuses on better understanding the role of metacognition in these domains. He has published numerous journal articles and chapters exploring the role of meta-cognitive factors in attitude formation, maintenance, and change.

Richard E. Petty is Distinguished University Professor of Psychology at Ohio State University. He received his B.A. from the University of Virginia and his Ph.D. from Ohio State. Petty's research focuses on the situational and individual factors responsible for changes in attitudes and behaviors. He has published eight books and over 300 articles and chapters. His current work emphasizes both implicit and meta-cognitive factors in social judgment. Petty is a fellow of the American Academy of Arts and Sciences, the American Association for the Advancement of Science, APA, and APS. His honors include the Scientific Impact Award from the Society of Experimental Social Psychology and the Distinguished Scientific Contribution Awards from the Societies for Personality and Social Psychology and Consumer Psychology. He is past editor of the *Personality and Social Psychology Bulletin* and former President of the Society for Personality and Social Psychology and the Midwestern Psychological Association.

Endnotes

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[1] Regression weights are represented by letters corresponding to those provided in Figure 2. Tormala et al. (2007) reported standardized regression weights and Sobel's test. We report unstandardized weights and bootstrap CIs, in line with current conventions in mediation analysis.

[2] If a total effect is never significant across a research program, this can be problematic, especially when a total effect is important to a theory, and might suggest the need to examine factors such as suppressors. We simply suggest that it should not be a prerequisite for any particular experiment.

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