Mediation Analysis

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Abstract

Mediating variables are prominent in psychological theory and research. A mediating variable transmits the effect of an independent variable on a dependent variable. Differences between mediating variables and confounders, moderators, and covariates are outlined. Statistical methods to assess mediation and modern comprehensive approaches are described. Future directions for mediation analysis are discussed.

Contents

INTRODUCTION

Mediating variables form the basis of many questions in psychology:

- Will changing social norms about science improve children's achievement in science?
- If an intervention increases secure attachment among young children, do behavioral problems decrease when the children enter school?
- Does physical abuse in early childhood lead to deviant processing of social information that leads to aggressive behavior?
- Do expectations start a self-fulfilling prophecy that affects behavior?
- Can changes in cognitive attributions reduce depression?
- Does trauma affect brain stem activation in a way that inhibits memory?
- Does secondary rehearsal increase image formation, which increases word recall?

Questions like these suggest a chain of relations where an antecedent variable affects a mediating variable, which then affects an outcome variable. As illustrated in the questions, mediating variables are behavioral, biological, psychological, or social constructs that transmit the effect of one variable to another variable. Mediation is one way that a researcher can explain the process or mechanism by which one variable affects another.

One of the primary reasons for the popularity of mediating variables in psychology is the historical dominance of the stimulus organism response model (Hebb 1966). In this model, mediating mechanisms in the organism translate how a stimulus leads to a response. A second related reason for the importance of mediating variables is that they form the basis of many psychological theories. For example, in social psychology, attitudes cause intentions, which then cause behavior (Fishbein & Ajzen 1975), and in cognitive psychology, memory processes mediate how information is transmitted into a response. A newer application of the mediating variable framework is in prevention and treatment research, where interventions are designed to change the outcome of interest by targeting mediating variables that are hypothesized to be causally related to the outcome.

A third reason for interest in mediation is methodological. Mediation represents the consideration of how a third variable affects the relation between two other variables. Although the consideration of a third variable may appear simple, three-variable systems can be very complicated, and there are many alternative explanations of observed relations other than mediation. This methodological and statistical challenge of investigating mediation has made methodology for assessing mediation an active research topic.

This review first defines the mediating variable and the ways in which it differs from other variables, such as a moderator or a confounder. Examples of mediating variables used in psychology are provided. Statistical methods to assess mediation in the single-mediator case are described, along with their assumptions. These assumptions are addressed in sections describing current research on the statistical testing of mediated effects, longitudinal mediation models, models with moderators as well as mediators, and causal inference for mediation models. Finally, directions for future research are outlined.

Definitions

Most research focuses on relations between two variables, X and Y, and much has been written about two-variable relations, including conditions under which X can be considered a possible cause of Y. These conditions include randomization of units to values of X and independence of units across and within values of X. Mediation in its simplest form represents the addition of a third variable to this X → Y relation, whereby X causes the mediator, M, and M causes Y, so X→ M → Y. Mediation is only one of several relations that may be present when a third variable, Z (using Z to represent the third variable), is included in the analysis of a two-variable system. One possibility is that Z causes both X and Y, so that ignoring Z leads to incorrect inference about the relation of X and Y; this would be an example of a confounding variable. In another situation, Z may be related to X and/or Y, so that information about Z improves prediction of Y by X, but does not substantially alter the relation of X to Y when Z is included in the analysis; this is an example of a covariate. Z may also modify the relation of X to Y such that the relation of X to Y differs at different values of Z; this is an example of a moderator or interaction effect. The distinction between a moderator and mediator has been an ongoing topic of research (Baron & Kenny 1986, Holmbeck 1997, Kraemer et al. 2001). A mediator is a variable that is in a causal sequence between two variables, whereas a moderator is not part of a causal sequence between the two variables. More detailed definitions of these variables in a three-variable system may be found in Robins & Greenland (1992).

The single-mediator model is shown in **Figure 1**, where the variables X, M, and Y are in rectangles and the arrows represent relations among variables. **Figure 1** uses the notation most widely applied in psychology, with a representing the relation of X to M, b representing the relation of M to Y adjusted for X, and c' the relation of X to Y adjusted for M. The symbols e_2 and e_3 represent residuals in the M and Y variables, respectively. The equations and coefficients corresponding to **Figure 1** are discussed below. For now, note that there is a direct effect relating X to Y and a mediated effect by which X indirectly affects

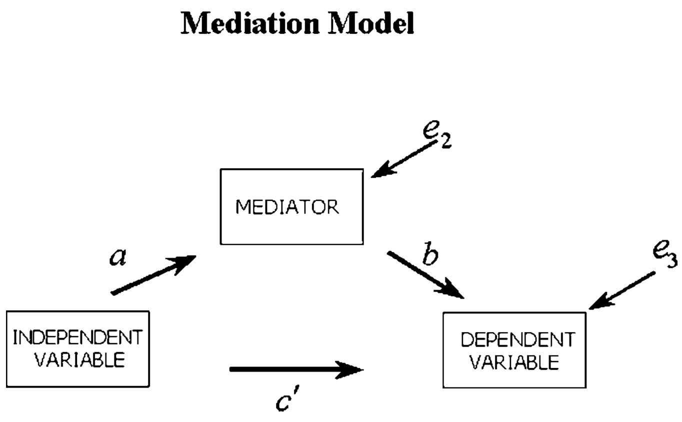

Figure 1

Mediation model.

Table 1 Subject area coverage in current mediation research

Subject area	# Articles cited
Social psychology	98
Clinical psychology	70
Health psychology	29
Developmental psychology	27
IO psychology	24
Cognitive psychology	18
Quantitative psychology (methods)	12
Program evaluation	8
Educational psychology	3
Environmental psychology	1
Evolutionary psychology	1

Y through M. Given that most prior mediation research has applied this single-mediator model, this review starts with this model. Limitations and extensions of the model are described in subsequent sections.

When thinking of mediation, it is helpful to understand that two models exist: One is theoretical, corresponding to unobservable relations among variables, and the other is empirical, corresponding to statistical analyses of actual data (MacCorquodale & Meehl 1948). The challenging task of research is to infer the true state of mediation from observations. There are qualifications even to this simple dichotomy, and in general, it will take a program of research to justify concluding that a third variable is a mediating variable.

Mediation in Psychological Research

In order to ascertain how often mediation is used in psychology, a search was conducted using the *PsycInfo* search engine for articles containing the word "mediation" in the title and citing the most widely cited article for mediation methods, Baron & Kenny (1986). This search yielded 291 references. Of these articles, 80 came from American Psychological Association (APA) journals. Publications earlier than the year 2000 were primarily APA sources, but there was a surge in non-APA articles after that time. The majority of these sources (239 citations) examined mediation alone, and 52 investigated both mediation and moderation effects. These studies included a mix of cross-sectional and longitudinal data, and ordinary least squares regression and structural equation modeling were the primary analytic methods. The articles covered a wide range of substantive areas, including social psychology (98 articles) and clinical psychology (70); a complete breakdown is listed in **Table 1**.

Mediation studies, such as those discussed above, are of two general but overlapping types. One type consists of investigating how a particular effect occurs. These studies usually occur after an observed X → Y relation is found. This approach stems from the elaboration methodologies outlined by Lazarsfeld (1955) and Hyman (1955). In this framework, a third variable is added to the analysis of an X → Y relation in order to improve understanding of the relation or to determine if the relation is spurious. A mediating variable improves understanding of such a relation because it is part of the causal sequence of X → M → Y. For example, physical abuse in early childhood is associated with violence later in life. One explanation of this pattern is that children exposed to physical violence acquire deviant patterns of processing social information that lead to later violent behavior. Dodge et al. (1990) found evidence for this theoretical mediating process because social processing measures explained the relation between early childhood physical abuse and later aggressive behavior.

The second type of study uses theory regarding mediational processes to design experiments. Some of the best examples of this approach are found in the evaluation of treatment and prevention programs. In this research, an intervention is designed to change mediating variables that are hypothesized to be causally related to a dependent variable. If the hypothesized relations are correct, a prevention or treatment program that substantially changes the mediating variables will in turn change the outcome. Primary prevention programs, such as drug prevention programs, are designed to increase resistance skills, educate, and change norms to reduce drug use. Secondary prevention programs such as campaigns to increase screening rates for serious illness (Murray et al. 1986) educate and change norms regarding health to increase screening rates. In both of these examples, a mediator that transmits the effect of an independent variable on a dependent variable is first identified by theory and later tested in an experiment. Researchers from many fields have stressed the importance of assessing mediation in treatment and prevention research (Baranowski et al. 1998; Donaldson 2001; Judd & Kenny 1981a,b; Kraemer et al. 2002; MacKinnon 1994; Shadish 1996; Weiss 1997). First, mediation analysis provides a check on whether the program produced a change in the construct it was designed to change. If a program is designed to change norms, then program effects on normative measures should be found. Second, mediation analysis results may suggest that certain program components need to be strengthened or measurements need to be improved, as failures to significantly change mediating variables occur either because the program was ineffective or the measures of the mediating construct were not adequate. Third, program effects on mediating variables in the absence of effects on outcome measures suggest that program effects on outcomes may emerge later or that the targeted constructs were not critical in changing outcomes. Fourth, mediation can sometimes be used to discover proximal outcomes that can be used as a surrogate for an ultimate outcome. For example, in medical studies to reduce death owing to a disease, instead of waiting until death, a more proximal outcome such as disease symptoms may be identified. Finally, and most importantly, mediation analysis generates evidence for how a program achieved its effects. Identification of the critical ingredients can streamline and improve these programs by focusing on effective components.

Experimental Approaches to Mediation

Many psychological studies investigating mediation use a randomized experimental design, where participants are randomized to levels of one or more factors in order to demonstrate a pattern of results consistent with one theory and inconsistent with another theory (MacKinnon et al. 2002a, Spencer et al. 2005, West & Aiken 1997). Differences in means between groups are then attributed to the experimental manipulation of the mediator. The results of the randomized study along with the predictions of different theories are used to provide evidence for a mediation hypothesis and suggest further studies to localize and validate the mediating process. For example, a researcher may randomize individuals to conditions that will or will not induce cognitive dissonance. In one such study, Sherman & Gorkin (1980) randomly assigned subjects to solve either (*a*) a sex-role related brainteaser, or (*b*) a brainteaser not related to sex roles. The sexist brainteaser condition was designed to evoke cognitive dissonance in the self-identified feminist subjects, while the nonsex-role related condition was not. Participants were then asked to judge the fairness of a legal decision made in an affirmative action trial. The results were consistent with the prediction that participants with strong feminist beliefs were more likely to make extreme feminist judgments in the trial if they failed the sexist brainteaser task, in an attempt to reduce cognitive dissonance. Although results of this experiment were taken as evidence of a cognitive dissonance mediation relation, the mediating variable of cognitive conflict was not measured to obtain more information on the link between the manipulation, cognitive dissonance, and feminist judgments.

Double randomization. In some designs it may be possible to investigate a mediational process by a randomized experiment to investigate the X → M relation and a second randomized experiment to investigate the M → Y relation (MacKinnon et al. 2002a, Spencer et al. 2005, West & Aiken 1997). Spencer et al. (2005) recently summarized two experiments reported by Word et al. (1974) that executed this design in a study of self-fulfilling prophecy for racial stereotypes. In study 1, white participants were randomly assigned to interview a black or white confederate. Using measures from the participants, black applicants received less immediacy, higher rates of speech errors, and shorter interviews than did white confederates. This part of the study demonstrated that race of applicant (X) significantly affected interview quality (M). In study 2, confederate white interviewers interviewed the participants from study 1. The confederate interviewers either gave interviews like white applicants were given in study 1 or they interviewed applicants with less immediacy, higher rates of speech errors, and shorter amounts of interviewer time, like black applicants. Here the M variable, type of interview, was randomized and the behavior of the applicants, the Y variable, was measured. The results of study 2 indicated that participants treated like blacks in study 1 performed less adequately and were more nervous in the interview than participants treated like whites in study 1. Although this type of experiment does much to reduce alternative explanations of the mediation hypothesis, it may be difficult to implement double randomization in other research contexts. Generally, the most difficult aspect of the design is the ability to randomly assign participants to the levels of the mediator so that the M → Y relation can be studied experimentally.

SINGLE-MEDIATOR MODEL

Mediation Regression Equations

Experimental studies in psychology rarely involve both manipulation of the mediator and measurement of mediating variables. If a research study includes measures of a mediating variable as well as the independent and dependent variable, mediation may be investigated statistically (Fiske et al. 1982). In this way, mediation analysis is a method to increase information obtained from a research study when measures of the mediating process are available.

There are three major approaches to statistical mediation analysis: (*a*) causal steps, (*b*) difference in coefficients, and (*c*) product of coefficients (MacKinnon 2000). All of these methods use information from the following three regression equations:

$$\mathrm{Y} = i_1 + c\mathrm{X} + e_1, \quad 1.$$

$$\mathrm{Y} = i_2 + c'\mathrm{X} + b\mathrm{M} + e_2, \quad 2.$$

$$\mathrm{M} = i_3 + a\mathrm{X} + e_3, \quad 3.$$

where i_1 and i_2 and i_3 are intercepts, Y is the dependent variable, X is the independent variable, M is the mediator, c is the coefficient relating the independent variable and the dependent variable, c' is the coefficient relating the independent variable to the dependent variable adjusted for the mediator, b is the coefficient relating the mediator to the dependent variable adjusted for the independent variable, a is the coefficient relating the independent variable to the mediator, and e_1, e_2, and e_3 are residuals. Equations 2 and 3 are depicted in **Figure 1**. Note that the mediation equations may be altered to incorporate linear as well as nonlinear effects and the interaction of X and M in Equation 2, as described later in this review.

The most widely used method to assess mediation is the causal steps approach outlined in the classic work of Baron & Kenny (1986; also Kenny et al. 1998) and Judd & Kenny (1981a, 1981b). Four steps are involved in the Baron and Kenny approach to establishing mediation. First, a significant relation of the independent variable to the dependent variable is required in Equation 1. Second, a significant relation of the independent variable to the hypothesized mediating variable is required in Equation 3. Third, the mediating variable must be significantly related to the dependent variable when both the independent variable and mediating variable are predictors of the dependent variable in Equation 2. Fourth, the coefficient relating the independent variable to the dependent variable must be larger (in absolute value) than the coefficient relating the independent variable to the dependent variable in the regression model with both the independent variable and the mediating variable predicting the dependent variable. This causal steps approach to assessing mediation has been the most widely used method to assess mediation. As discussed below, there are several limitations to this approach.

The mediated effect in the single-mediator model (see **Figure 1**) may be calculated in two ways, as either $\hat{a}\hat{b}$ or $\hat{c} - \hat{c}'$ (MacKinnon & Dwyer 1993). The value of the mediated or indirect effect estimated by taking the difference in the coefficients, $\hat{c} - \hat{c}'$, from Equations 1 and 2 corresponds to the reduction in the independent variable effect on the dependent variable when adjusted for the mediator. To test for significance, the difference is then divided by the standard error of the difference and the ratio is compared to a standard normal distribution.

The product of coefficients method, involves estimating Equations 2 and 3 and computing the product of $\hat{a}$ and $\hat{b}$, $\hat{a}\hat{b}$, to form the mediated or indirect effect (Alwin & Hauser 1975). The rationale behind this method is that mediation depends on the extent to which the program changes the mediator, a, and the extent to which the mediator affects the outcome variable, b. To test for significance, the product is then divided by the standard error of the product and the ratio is compared to a standard normal distribution.

The algebraic equivalence of the $\hat{a}\hat{b}$ and $\hat{c} - \hat{c}'$ measures of mediation was shown by MacKinnon et al. (1995) for normal theory ordinary least squares and maximum likelihood estimation of the three mediation regression equations. For multilevel models (Krull & MacKinnon 1999), logistic or probit regression (MacKinnon & Dwyer 1993), and survival analysis (Tein & MacKinnon 2003), the $\hat{a}\hat{b}$ and $\hat{c} - \hat{c}'$ estimators of the mediated effect are not always equivalent, and a transformation is required for the two to yield similar results (MacKinnon & Dwyer 1993).

Plotting the Mediation Equations

The quantities in Equations 1–3 can also be presented geometrically, as shown in **Figure 2** (MacKinnon 2007; R. Merrill, unpublished dissertation). Artificial data are plotted in **Figure 2**, where the independent variable, X, is dichotomous (to simplify the plot), the mediator, M, is on the horizontal axis, and the dependent variable, Y, is on the vertical axis. The two slanted lines in the plot represent the relation of M to Y in each X group, one line for the control group and one line for the treatment group. The two lines are parallel (note that if there were an XM interaction in Equation 2, then the slopes would not be parallel), with the slope of each line equal to the b coefficient ($\hat{b} = 0.91, se_{\hat{b}} = 0.18$). The distance between the horizontal lines in the plots is equal to the overall effect of X on Y, c ($\hat{c} = 1.07, se_{\hat{c}} = 0.27$), and the distance between the vertical lines is equal to the effect of X on M, a ($\hat{a} = 0.87, se_{\hat{a}} = 0.23$). The mediated effect is the change in the regression line relating M to Y for a change in M of a units as shown in the graph. The indirect effect, $\hat{a}\hat{b}$, is equal to $\hat{c} - \hat{c}'(\hat{c}' = 0.23, se_{\hat{c}'} = 0.24)$. Plots of the mediated effect may be useful to investigate the distributions of data for outliers and to improve understanding of relations among variables in the mediation model.

Standard Error of the Mediated Effect

Sobel (1982, 1986) derived the asymptotic standard error of the indirect effect using the multivariate delta method (Bishop et al. 1975) in Equation 4. This is the most commonly used formula for the standard error of the

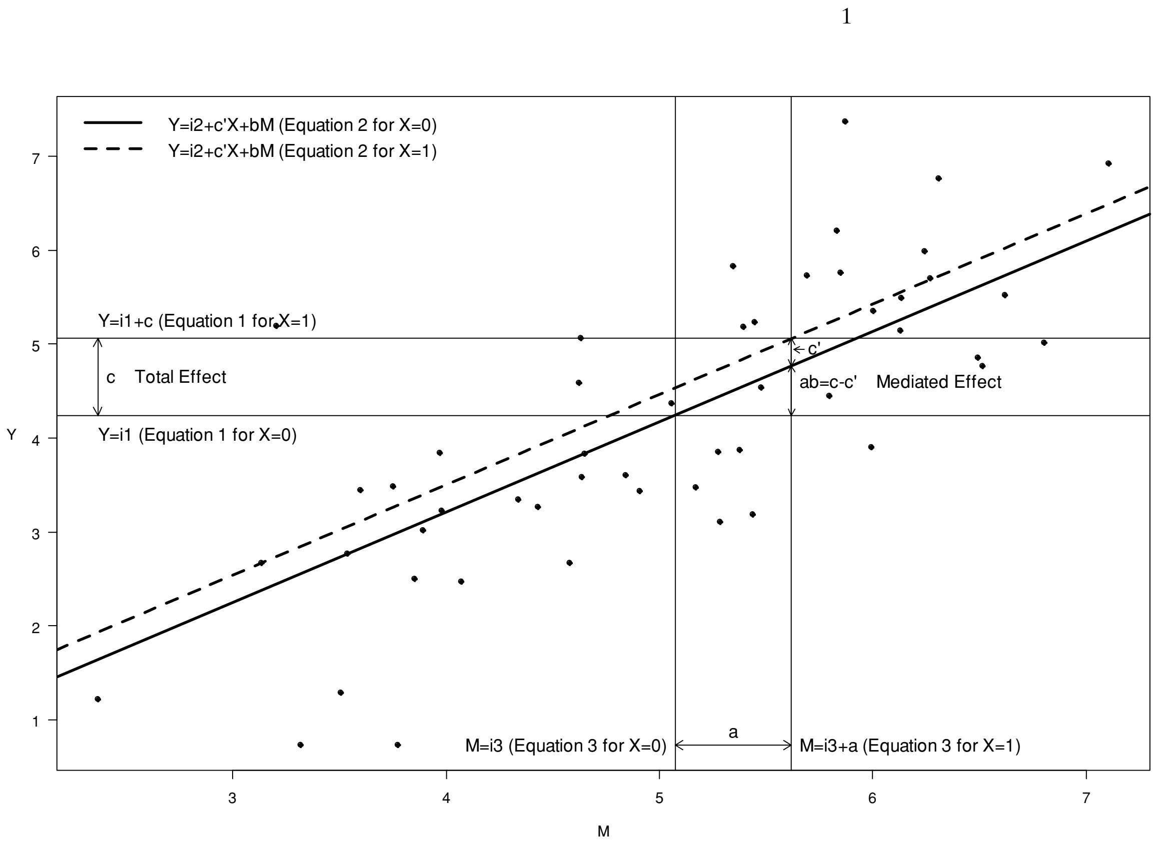

Figure 2

Plot of the mediated effect. To simplify figure, no hats are included above coefficient estimates.

mediated effect.

$$\sigma_{\hat{a}\hat{b}} = \sqrt{\sigma_{\hat{a}}^2 \hat{b}^2 + \sigma_{\hat{b}}^2 \hat{a}^2} \qquad 4.$$

Other formulas for the standard error of $\hat{a}\hat{b}$ and $\hat{c} - \hat{c}'$ are described in MacKinnon et al. (2002a).

Simulation studies indicate that the estimator of the standard error in Equation 4 shows low bias for sample sizes of at least 50 in single-mediator models (MacKinnon et al. 1995, 2002a). In models with more than one mediator, the standard error is accurate for minimum sample sizes of 100–200 (Stone & Sobel 1990). Similar results were obtained for standard errors of negative and positive path values, and larger models with multiple mediating, independent, and dependent variables (MacKinnon et al. 2002a, 2004; J. Williams, unpublished dissertation).

Confidence Limits for the Mediated Effect

The standard error of $\hat{a}\hat{b}$ can be used to test its statistical significance and to construct confidence limits for the mediated effect as shown in Equation 5:

$$\hat{a}\hat{b} \pm z_{1-\omega/2}{}^{*}\sigma_{\hat{a}\hat{b}}. \qquad 5.$$

Confidence limits based on the normal distribution for the mediated effect are often inaccurate as found in simulation studies (MacKinnon et al. 1995, 2002a; Stone & Sobel 1990) and from bootstrap analysis of the mediated effect (Bollen & Stine 1990, Lockwood

& MacKinnon 1998). These mediated effect confidence intervals tend to lie to the left of the true value of the mediated effect for positive mediated effects and to the right for negative mediated effects (Bollen & Stine 1990, MacKinnon et al. 1995, Stone & Sobel 1990). Asymmetric confidence limits based on the distribution of the product and bootstrap estimation have better coverage than these tests (MacKinnon et al. 2004).

Significance Testing

A simulation study of 14 methods to assess the mediated effect found that the power to detect mediated effects using the most widely used causal step methods was very low, as were type I error rates (MacKinnon et al. 2002a, 2004). Low power was also observed for tests based on the normal distribution for mediated effect estimators (i.e., $\hat{a}\hat{b}$ and $\hat{c} - \hat{c}'$) divided by their respective standard errors (Hoyle & Kenny 1999). A joint test of the significance of $\hat{a}$ and $\hat{b}$ was a good compromise between type I and type II errors.

There are several explanations for the low power of most tests for mediation. First of all, the requirement that there be a significant X to Y relation in the Baron and Kenny causal steps test severely reduces power to detect mediation, especially in the case of complete mediation (i.e., direct effect is zero). There are many cases where significant mediation exists but the requirement of a significant relation of X to Y is not obtained. A recent study using empirical approaches to determine required sample size for 0.8 power to detect a mediated effect with small effect size values of the *a* and *b* path required approximately 21,000 subjects for the causal steps test (Fritz & MacKinnon 2007). As the size of the direct effect gets larger, the power to detect mediation using the causal steps approach approximates power to detect mediation by testing whether both the *a* and the *b* paths are statistically significant. It is important to note that the overall relation of X and Y represents important information for a research study, and in some studies it may be useful to require an overall X to Y relation. The point is that requiring an X to Y relation substantially reduces power to detect real mediation effects. An explanation for the low power of tests of mediation based on dividing an estimator, either $\hat{a}\hat{b}$ or $\hat{c} - \hat{c}'$, of the mediated effect by its corresponding standard error is that the resulting ratio does not always follow a normal distribution (MacKinnon et al. 2004). Resampling methods and methods based on the distribution of the product of *ab* address these sampling problems and are described below.

Distribution of the Product

The product of two normally distributed random variables is normally distributed only in special cases (Springer 1979), which explains the inaccuracy of methods of assessing statistical significance of mediation based on the normal distribution. For example, for two standard normal random variables with a mean of zero, the excess kurtosis is equal to six (Meeker et al. 1981) compared to an excess kurtosis of zero for a normal distribution. MacKinnon et al. (2002a, 2004a) showed that in comparison with commonly used methods, significance tests for the mediated effect based on the distribution of the product had more accurate type-I error rates and statistical power. A new program, PRODCLIN (MacKinnon et al. 2006a; program download available at **http://www.public.asu.edu/~davidpm/ripl/Prodclin/**), can now be used to find critical values of the distribution of the product and to compute confidence limits for the mediated effect.

Computer-Intensive Analysis

Computer-intensive methods use the observed data to generate a reference distribution, which is then used for confidence interval estimation and significance testing (Manly 1997, Mooney & Duval 1993, Noreen 1989). Programs to compute confidence limits of the mediated effect for bootstrap methods is described in Preacher & Hayes (2004) and Lockwood & MacKinnon (1998); the AMOS (Arbuckle 1997), EQS (Bentler 1997), LISREL (Jöreskog & Sörbom 1993), and Mplus (Muthén & Muthén 1998–2006) programs also conduct bootstrap resampling for the mediated effect.

Computer-intensive methods, also called resampling methods, for mediation are important for at least two reasons (Bollen & Stine 1990, MacKinnon et al. 2004, Shrout & Bolger 2002). First, these methods provide a general way to test significance and construct confidence intervals in a wide variety of situations where analytical formulas for quantities may not be available. Second, the methods do not require as many assumptions as other tests, which is likely to make them more accurate than traditional mediation analysis.

Assumptions of the Single-Mediator Model

There are several important assumptions for tests of mediation. For the $\hat{a}\hat{b}$ estimator of the mediated effect, the model assumes that the residuals in Equations 2 and 3 are independent and that M and the residual in Equation 2 are independent (McDonald 1997; R. Merrill, unpublished dissertation). It is also assumed that there is not an XM interaction in Equation 3, although this can and should be routinely tested. The assumptions of a correctly specified model include no misspecification of causal order (e.g., $Y \rightarrow M \rightarrow X$ rather than $X \rightarrow M \rightarrow Y$), no misspecification of causal direction (e.g., there is reciprocal causation between the mediator and the dependent variable), no misspecification due to unmeasured variables that cause variables in the mediation analysis, and no misspecification due to imperfect measurement (Holland 1988, James & Brett 1984, McDonald 1997). These assumptions may be difficult to test and may be untestable in most situations so that proof of a mediation relation is impossible. A more realistic approach is to incorporate additional information from prior research, including randomized experimental studies, theory, and qualitative methods to bolster the tentative conclusion that a mediation relation exists.

Complete Versus Partial Mediation

Researchers often test whether there is complete or partial mediation by testing whether the c' coefficient is statistically significant, which is a test of whether the association between the independent and dependent variable is completely accounted for by the mediator (see James et al. 2006). If the c' coefficient is statistically significant and there is significant mediation, then there is evidence for partial mediation. Because psychological behaviors have a variety of causes, it is often unrealistic to expect that a single mediator would be explained completely by an independent variable to dependent variable relation (Judd & Kenny 1981a).

Consistent and Inconsistent Models

Inconsistent mediation models are models where at least one mediated effect has a different sign than other mediated or direct effects in a model (Blalock 1969, Davis 1985, MacKinnon et al. 2000). Although knowledge of the significance of the relation of X to Y is important for the interpretation of results, there are several examples in which an overall X to Y relation may be nonsignificant, yet mediation exists. For example, McFatter (1979) described the hypothetical example of workers making widgets, where X is intelligence, M is boredom, and Y is widget production. Intelligent workers tend to get bored and produce less, but smarter workers also tend to make more widgets. Therefore, the overall relation between intelligence and widgets produced may actually be zero, yet there are two opposing mediational processes. A number of other resources provide examples of these inconsistent effects (Paulhus et al. 2004, Sheets & Braver 1999). Inconsistent mediation is more common in multiple mediator models where mediated effects have different signs. Inconsistent mediator effects may be especially critical in evaluating counterproductive effects of experiments, where the manipulation may have led to opposing mediated effects.

Effect Size Measures of Mediation

The raw correlation for the *a* path and the partial correlation for the *b* path are effect size measures for mediation models. Standardized regression coefficients may also serve as effect size measures for individual paths in the mediated effect. There are other effect size measures of the entire mediated effect rather than individual paths. The proportion mediated, $1 - (\frac{\hat{c}'}{\hat{c}}) = \frac{\hat{a}\hat{b}}{(\hat{a}\hat{b}+\hat{c}')}$, is often used, but values of the proportion mediated are often very small and focusing on an overall proportion mediated may neglect additional mediating mechanisms (Fleming & DeMets 1996). The proportion mediated is also unstable unless sample size is at least 500 (Freedman 2001, MacKinnon et al. 1995). Alwin & Hauser (1975) suggest taking the absolute values of the direct and indirect effects prior to calculating the proportion mediated for inconsistent models. More work is needed on effect size measures for mediation.

EXTENSIONS OF THE SINGLE-MEDIATOR MODEL

Many important extensions have addressed limitations of the mediation approach described above. First, many studies hypothesize more complicated models including multiple independent variables, multiple mediators, and multiple outcomes. These models may include hypotheses regarding the comparison of mediated effects. Second, mediation in multilevel models may be especially important, as mediation relations at different levels of analysis are possible (Krull & MacKinnon 1999, 2001; Raudenbush & Sampson 1999). Third, mediation effects may differ by subgroups defined by variables both within the mediation model and outside the mediation model. Fourth, mediation requires temporal precedence from X to M to Y, and longitudinal mediation models have been developed (Gollob & Reichardt 1991, Kraemer et al. 2002). Finally, developments in the causal interpretation of research results (Holland 1988, Robins & Greenland 1992) provide a general framework to understand the limitations and strengths of possible causal inferences from a mediation study. Each of these extensions is described below.

Multilevel Mediation Models

Many studies measure data clustered at several levels, such as individuals in schools, classrooms, therapy groups, or clinics. If mediation analysis from these types of studies is analyzed at the individual level, ignoring the clustering, then type I error rates can be too high (Krull & MacKinnon 1999, 2001). These problems occur because observations within a cluster tend to be dependent so that the independent observations assumption is violated. The investigation of mediation effects at different levels of analysis also may be important for substantive reasons (Hofmann & Gavin 1998). For example, a mediated effect present at the therapy group level may not be present at the individual level. Similarly, it is possible that the mechanism that mediates effects at the school level, such as overall norms, may be different from the mechanism that mediates effects at the individual level.

Kenny et al. (2003) demonstrated that in some cases the *a* and the *b* paths may represent random effects. For example, assume that X, M, and Y are measured from individuals in schools and that the researcher is interested in the mediation effect, but the *a*, *b*, and c' coefficients may vary significantly across schools rather than having a single fixed effect. If *a* and *b* are random effects, they may covary, and an appropriate standard error and point estimate for the mediated effect must allow for this covariance between random effects to be applied. Kenny et al. used a resampling method to obtain a value for this covariance. Other methods that have been recently proposed to assess this covariance consist of combining Equations 2 and 3 into the same analysis (Bauer et al. 2006) and directly estimating the covariance among the random effects in the Mplus program (Muthén & Muthén 1998–2006).

Mediation with Categorical Outcomes

In some mediation analyses, the dependent variable is categorical, such as whether a person used drugs or not. In this case, Equations 1 and 2 must be rewritten for logistic or probit regression, where the dependent variable is typically a latent continuous variable that has been dichotomized in analysis. Because the residual in each logistic or probit equation is fixed, the parameters c, c', and b depend on the other independent variables in the model. Therefore, the $\hat{c} - \hat{c}'$ method of estimating mediation is incorrect because the parameter estimate of $\hat{c}'$ depends on the effect explained by the mediator and the scaling of Equations 1 and 2 (MacKinnon & Dwyer 1993). One solution to this problem is to standardize regression coefficients prior to estimating mediation (Winship & Mare 1983). If the mediator is treated as a continuous variable, a product of coefficients test of the mediated effect may be obtained using $\hat{a}$ from ordinary least squares regression and $\hat{b}$ from logistic regression. Again, better confidence limits and statistical tests are obtained if critical values from the distribution of the product or bootstrap methods are used (D.P. MacKinnon, M. Yoon, C.M. Lockwood, & A.B. Taylor, unpublished manuscript).

Multiple Mediators

Mediating processes may include multiple mediators, dependent variables, and/or independent variables. In school-based drug prevention, for example, prevention programs target multiple mediators such as resistance skills, social norms, attitudes about drugs, and communication skills. The multiple-mediator model is likely to provide a more accurate assessment of mediation effects in many research contexts. Models with more than one mediator are straightforward extensions of the single-mediator case (MacKinnon 2000). Several standard error formulas for comparing different mediated effects are given by MacKinnon (2000), and the methods are illustrated with data from a drug prevention study.

Longitudinal Mediation Models

Longitudinal data allow a researcher to examine many aspects of a mediation model that are unavailable in cross-sectional data, such as whether an effect is stable across time and whether there is evidence for one of the important conditions of causality, temporal precedence. Longitudinal data also bring challenges, including nonoptimal measurement times, omitted variables or paths, and difficult specification of the correct longitudinal mediated effect of interest (Cheong et al. 2003, Cole & Maxwell 2003, Collins et al. 1998).

There are three major types of longitudinal mediation models. The autoregressive model was described by Gollob & Reichardt (1991) and elaborated by Cole & Maxwell (2003). In the basic autoregressive model, relations that are one measurement occasion (wave) apart are specified, and the relation between the same variable over time is specified to assess stability, as are covariances among the variables at the first wave and the covariances among the residual variances of X, M, and Y at later waves. The covariances among X, M, and Y at the same wave of measurement reflect that the causal order of these measures is unknown. Only relations consistent with longitudinal mediation are estimated among the variables.

A second form of the autoregressive mediation model includes contemporaneous mediation relations among X, M, and Y, such that mediation can occur within the same wave in addition to longitudinal mediation across waves. Practically, this would occur if there were a change in the mediator that led to change in the outcome between the first and second wave of measurement. Still another form of the autoregressive longitudinal mediation model allows for cross-lagged relations among variables, where the direction of the relations among X, M, and Y are all free to vary. Freeing the directions of the relationships violates the temporal precedence specified by the mediation model but allows possible cross-lagged relations among variables to be investigated, making it a more reasonable model than assuming relations are zero among the variables. Limitations of the autoregressive models include the cross-lagged model where many true models may yield the same cross-lagged coefficients and the frequent exclusion of individual differences in mean level (see Dwyer 1983, Rogosa 1988).

Another model that can be used with longitudinal mediation data is the latent-growth modeling (LGM) or parallel-process model (Muthén & Curran 1997, Singer & Willet 2003). The LGM mediation model examines whether the growth in X affects the growth trajectory of M, which affects the growth trajectory of Y. As in the nonlatent framework, the relation between X and the growth trajectory of Y has two sources: the indirect effect via the growth of M and the direct effect. One limitation of the parallel-process model is that the mediation relation is correlational: the slope in X is correlated with the slope in M, and the slope in M is correlated with the slope in Y. The interpretation of this correlation is that change in M is related to change in Y at the same time, not that change in M is related to change in Y at a later time. An alternate way to specify the LGM mediation model is the two-stage piecewise parallel-process model (Cheong et al. 2003). In the two-stage parallel-process model, the growth of the mediator and the outcome process is modeled for earlier and later times separately, allowing the mediated effects to be investigated at different periods. Measurement invariance is very important in LGM, because changes in the measure over time will confound the interpretation of change over time.

In the difference score approach to longitudinal mediation, differences between the mediator and dependent variables scores are taken, as is the independent variable if it does not reflect assignment to treatment condition. These difference scores are then analyzed using the same equations as those used for cross-sectional models. The latent difference score (LDS) model can also be applied to three or more waves using a latent framework (Ferrer & McArdle 2003, McArdle 2001, McArdle & Nesselroade 2003). In the LDS model, fixed parameters and latent variables are used to specify latent difference scores, such that the model represents differences between waves as dynamic change. The LDS model can be especially useful in situations where it is expected there will be different predictors at different measurement occasions.

In addition to the autoregressive, LGM, and LDS models, other models can be used to analyze longitudinal mediation data, including a combination of the autoregressive and LGM models (Bollen & Curran 2004) and specification of model parameters in a continuous time metric to address the problem of different time intervals of measurement (Arminger 1986, Boker & Nesselroade 2002, Dwyer 1992).

Moderation and Mediation

The strength and form of mediated effects may depend on other variables. Variables that affect the hypothesized relation among a set of variables in such ways are known as moderators and are often tested as interaction effects (Aiken & West 1991, Baron & Kenny 1986). A nonzero XM interaction in Equation 2 discussed above is an example of a moderator effect that suggests that the *b* coefficient differs across levels of X. Different *b* coefficients across levels of X may reflect mediation as a manipulation and may alter the relation of M to Y. For example, a smoking prevention program may remove a relation between tobacco offers (M) and tobacco use (Y) because persons exposed to the program learned skills to refuse tobacco offers so that offers are significantly related to use in the control group but not in the program group (Judd & Kenny 1981a). The presence of moderator effects indicates that the modeled function changes across different levels of the moderator variable, where moderators may be either a manipulated factor in an experimental setting or a naturally occurring variable such as gender. The examination of these variables and their impact on mediation models is useful in psychological research to address the question of how an experiment achieved its effects. However, by also examining moderator effects, one is able to investigate whether the experiment differentially affects subgroups of individuals (Donaldson 2001, MacKinnon 2001, MacKinnon & Dwyer 1993, Sandler et al. 1997). Three potential models in which this examination may take place are (*a*) moderated mediation, (*b*) mediated moderation, and (*c*) mediated baseline by treatment moderation models.

Moderated mediation. The moderated mediation model is the simplest statistical model with moderator and mediation effects (Judd et al. 2001). In this model, a variable mediates the effect of an independent variable on a dependent variable, and the mediated effect depends on the level of a moderator. Thus, the mediational mechanism differs for subgroups of participants (e.g., across cohorts, ages, or sexes; James & Brett 1984).

The single-mediator version of this model consists of estimating the same mediation model for each subgroup and then comparing the mediated effect across subgroups. A statistical test of the equivalence of the mediated effect across groups was described in MacKinnon (2007), and tests of the equality of $\hat{a}$, $\hat{b}$, and $\hat{c}'$ can provide information on the invariance-of-action theory (how the program changes mediators) and conceptual theory (how mediators are related to the outcome) across groups.

The moderated mediation model is more complex when the moderator variable is continuous. Although the regression equations required to estimate the continuous moderated mediation model are the same as for the categorical case, the interpretation of results is complicated because of the large number of values of a continuous moderator. In this case, researchers may choose to analyze simple mediation effects (see Tein et al. 2004).

Mediated moderation. Mediated moderation (Baron & Kenny 1986, Morgan-Lopez & MacKinnon 2001) occurs when a mediator is intermediate in the causal sequence from an interaction effect to a dependent variable. For example, the effect of a prevention program may be greater for high-risk subjects, and the interaction effect of program exposure and risk-taking may then affect a mediating variable of social norms that then affects drug use. The purpose of mediated moderation is to determine the mediating variable(s) that explain the interaction effect. This model consists of estimating a series of regression equations where the main effect of a covariate and the interaction of the covariate and program exposure are included in both models. Morgan-Lopez & MacKinnon (2001) describe an estimator of the mediated moderator effect that requires further development and evaluation.

Mediated baseline by treatment moderation. The mediated baseline by treatment moderation model is a special case of the mediated moderation model. The substantive interpretation of the mediated effect in this model is that the mediated effect depends on the baseline level of the mediator. This scenario is a common result in prevention and treatment research, where the effects of an intervention are often stronger for participants who are at higher risk on the mediating variable at the time they enter the program

(Khoo 2001, Pillow et al. 1991). These treatment condition by baseline interactions have been found in numerous areas of research, ranging from universal prevention programs with elementary school children to selective prevention interventions with the various at-risk groups (e.g., Ialongo et al. 1999, Martinez & Forgatch 2001, Stoolmiller et al. 2000). Information provided in these models may indicate for whom an intervention is ineffective or even counterproductive and may be used to screen future participants into more effective programs based on their baseline characteristics. Various authors have outlined the equations and rationale for the mediated baseline by treatment moderator model (Baron & Kenny 1986, Morgan-Lopez & MacKinnon 2001, Tein et al. 2004).

To date, models with moderators and mediators have remained largely independent. This separation in their presentation has contributed to confusion in the understanding of each relative to the others. A critical goal of future research in this area will be to develop and test a general model in which each of the models is a special case. One such model is described in Muller et al. (2005). Another model is in development but has not yet been empirically tested in applied research (MacKinnon 2007):

$$Y = i + c'_1 X + c'_2 Z + c'_3 XZ + b_1 M + b_2 MZ + h XM + j XMZ + e. \qquad 6.$$

In this model, the XM and XMZ interactions are added to the individual mediation and moderation equations to form a general model that includes all effects (including additional c' and b effects). Here the h coefficient represents the test of whether the M to Y relation differs across levels of X, and the j coefficient represents the three-way interaction effect whereby the relations between Z and M and Y differ across levels of X. If a statistically significant j coefficient is found, further simple interaction effects and simple mediated effects are explored.

Causal Inference

Methods based on the observed regression approach to estimating mediation have been criticized based on causal analysis of the relations among variables. One of these criticisms addressed above is the equivalent model criticism. For example, if X, M, and Y are measured simultaneously, there are other models that would explain the data equally well (e.g., X is the mediator of the M to Y relationship or M and Y both cause X), and in many situations it is not possible to distinguish these alternatives without more information (Spirtes et al. 1993).

The case in which X represents random assignment to conditions improves causal interpretation of mediating variables (Holland 1988, Robins & Greenland 1992) because X precedes M and Y. Holland applied Rubin's (1974) causal model to a mediation and showed, under some assumptions, the typical regression coefficient for the group effect on test score, $\hat{c}$, and the group effect on number of hours studied, $\hat{a}$, are valid estimators of the true causal effect because of the randomization of units to treatment. The regression coefficient, $\hat{b}$, relating X to Y adjusted for M, is not an accurate estimator of the causal effect because this relation is correlational, not the result of random assignment. The estimator, $\hat{c}'$, is also not an accurate causal estimator of the direct effect.

Several new approaches to causal inference for mediation have begun to appear. One promising alternative is based on principal stratifications of the possible relations of X to M to Y where the mediated effect is estimated within these stratifications (Angrist et al. 1996, Frangakis & Rubin 2002). B. Jo (unpublished manscript) has proposed a latent class version of this model, and M.E. Sobel (unpublished manuscript) has proposed an enhancement of the Holland instrumental variable method.

The most important aspect of the causal inference methods is the illustration of the problems interpreting the M to Y relation as a causal relation. Researchers have several options in this situation. First, apply some of the new models to increase evidence for causal inference. Second, treat the results of the mediation analysis as descriptive information that may not reflect the true underlying causal mediation relation, especially for the M to Y relation, even when advanced causal inference models are applied. Third, future experimental studies (perhaps double randomization, described above) as well as qualitative and clinical information are required to validate a mediation relation. In particular, a program of research that sequentially tests predictors of the mediator theory provides the most convincing evidence for mediation.

SUMMARY AND FUTURE DIRECTIONS

There is broad and sustained interest in mediation analysis from many areas of psychology and other fields: Begg & Leung (2000), Botvin (2000), Kristal et al. (2000), Petrosino (2000). Tests for mediation differ considerably in type I error rates and statistical power (MacKinnon et al. 2002a, 2004). The recommended test of mediation assesses the statistical significance of the X to M relation, $\hat{a}$ path, and then the M to Y relation, $\hat{b}$ path. If both are statistically significant, there is evidence of mediation. Because confidence limits are important for understanding effects, confidence limits based on the distribution of the product or the bootstrap are recommended. This approach also applies to mediated effects in more complicated models. It is also important to consider opposing mediated effects and more complicated models such that overall relations may not be statistically significant yet mediation may still exist in a research study. These opposing effects or mediated effects that counteract each other resulting in a nonsignificant X to Y relation may be of substantive interest. Several effect size measures for mediation models have been proposed (A.J. Fairchild, D.P. MacKinnon, & M.P. Taborga, unpublished manuscript; Taborga et al. 1999), but these require more development.

Person-oriented approaches based on trajectory classes (Muthén & Muthén 2000) and staged responses across trials (Collins et al. 1998) represent new ways to understand mediational processes consistent with the goal of examining individual-level processes and group-level processes. Longitudinal data provide rich information for the investigation of mediation. In particular, latent growth curve and latent difference score models may be especially suited to the examination of mediation chains across multiple waves of data because of the ability to investigate the effect of prior change on later change. The usefulness of causal inference models and different alternatives to learning more about mediation are an important topic for future research. Additionally, experimental designs to investigate mediation require further development. Similarly, methods to combine qualitative as well as quantitative information about mediational processes should clarify mediation relations. These developments will advance our ability to answer mediation questions in psychology.

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