The Importance of Indirect Effects in Media Effects Research: Testing for Mediation in Structural Equation Modeling

R. Lance Holbert and Michael T. Stephenson

This essay addresses the need for media effects researchers to decompose their structural equation models. We highlight the importance of studying specific indirect effects within a conditional effects framework and discuss how the lack of analysis of this type of effect in structural equation modeling does not fit well with the discipline’s theoretical foundations. We summarize several classes of mediation formulas and make recommendations for the estimation and testing of mediating relationships. Finally, an argument is made that the study of mediation is a necessary but not sufficient condition for better understanding media influence.

Empirical media effects research is a diverse field that continues to expand its theoretical, methodological, and analytical boundaries. As McLeod, Kosicki, and Pan (1996) have stated, “more complex models of media effects and more sophisticated statistical methods are being explored and used to connect previously isolated communication processes” (p. 241). One advanced multivariate statistical technique recently employed by media scholars is covariance-based structural equation modeling (SEM). We explore the underutilization of this technique by media effects scholars. In particular, we focus on the absence of indirect effects in media research and why the failure to move beyond the study of direct effects is inconsistent with some of the basic theoretical foundations of mass communication.

Once an adequate fit of the data has been obtained for a structural equation model, researchers are afforded the opportunity to study three types of influence: direct, indirect, and total effects (Bollen, 1987). A direct effect, the influence of one variable on another, is represented in a structural model by a single path. An indirect effect assesses the impact of one variable on another as that variable’s influence...
works through one or more intervening variables (Hoyle & Kenny, 1999). In addition, researchers can disaggregate a total indirect effect that works through multiple intervening variables into specific indirect effects (Brown, 1997; Fox, 1980). Each specific indirect effect isolates and assesses the role of a single intervening variable in a given relationship. The total effect of one variable on another is the sum of its direct and indirect effects.

Indirect effects are generally overlooked in most empirical research (Alwin & Hauser, 1975). This state of affairs is worrisome given that, “if an indirect effect does not receive proper attention, the relationship between two variables of interest may not be fully considered” (Raykov & Marcoulides, 2000, p. 7). Even though researchers have understood for some time the importance of media’s indirect effects (e.g., McGuire, 1986), a recent critical assessment reveals that the study of indirect effects via SEM is woefully inadequate across the communication sciences (Holbert & Stephenson, 2002). Holbert and Stephenson found that only 14.4% of communication studies using SEM from 1995 through 2000 analyze indirect effects in even the most cursory fashion.

This essay stresses that media effects research needs to systematically decompose its structural equation models into direct, indirect, specific indirect, and total effects. The conditional model of media influence states that media can (and most often do) act as mediators in a given process, or alternatively, media can work through one or more mediators before having an influence on a particular dependent variable (McLeod & Reeves, 1980). We begin by formally linking the study of mediation to media effects research, and then isolate the mass communication subfields of political and health communication to provide examples of how mediation is central to the discipline. Several different formulas for testing mediation have been offered by various researchers (MacKinnon, Lockwood, Hoffman, West, & Sheets, 2002), and three classes of mediation formulas are summarized. We isolate how SEM software packages test for indirect effects and assess how well this procedure performs relative to other formulas. We isolate one mediation formula as being particularly promising, and provide an example of its use to reveal its simplicity and utility. A series of recommendations for the assessment of total and specific indirect effects is offered. Finally, we reemphasize that the systematic study of mediation in media effects research is a necessary but not sufficient condition for better understanding the role of media influence in a host of contexts.

Mediation in Media Effects Research

Conditional Effects Model

McLeod and Reeves (1980) explain that the conditional effects approach acknowledges that media do not have universal influence on all individuals and/or societies. They argue that media research has been needlessly encumbered by “a lack of
uniformity and clarity as to the labels and meaning of the role of various third
‘conditional’ variables . . . affecting the relationship between exposure to media and
effect of that exposure” (p. 19). Mediating variables exist at every stage of the media
effects process, whether we are studying “who is affected, what is changing, [or] how
the process takes place” (p. 18). McLeod and Reeves conclude that it is not just
important for mass communication studies to include mediating variables but that
specific relationships between media, potential mediators, and various outcome
variables be hypothesized and systematically tested in order to place the role of
media in its proper context.

Recognition of the importance of indirect effects does not originate with the
conditional effects approach, but is a holdover from the two-step model of media
influence that ushered in the limited effects paradigm (e.g., Lazarsfeld, Berelson, &
Gaudet, 1948). Lazarsfeld and colleagues argued that media work through opinion
leaders to indirectly influence the general population. Thus, the fact that media
effects can be indirect has been a fundamental concept of mass communication
research for more than a half century (e.g., Klapper, 1960). Indeed, the importance
of mediating variables in media research is evident in the discussion of various
conditional influences found in some of the most influential theories or metacon-
cepts that drive mass communication research today (e.g., McCombs & Reynolds,
2002; Petty, Priester, & Briñol, 2002; Shrum, 2002).

Not only are mass communication researchers encouraged to study mediators in
the relationship between media and various criterion variables, but how various
forms of media use act as mediating variables as well. The uses and gratifications
perspective identifies several factors that influence why people turn to media and
what they take away from a given mediated communication experience (e.g., Katz,
states that “uses and gratifications rests on a mediated view of communication
influence, which stresses how individual differences constrain direct media effects”
(p. 526). The uses and gratifications framework argues that there are several pre-
media use variables that affect patterns of media use, and this approach has been
used in coordination with analyses of media influence on a given set of criterion
variables (e.g., Holbert, Kwak, & Shah, 2003; Holbert, Shah, & Kwak, 2003; Shah,
1998). Thus, media use has the potential to act as a mediating variable in relation-
ships between various pre-media use items and criterion variables that exist in
post-media use.

Role of Mediation in Mass Communication Subfields

The study of mass media effects has as its core the study of mediation. We wish to
isolate two particular subfields, political and health communication, which are
intricately linked to the study of intervening variables. These two exemplars provide
evidence for our argument that effects-based mass communication scholars envision
the study of media to be driven by processes that involve mediation.
Political communication. McLeod, Kosicki, and McLeod (2002) state that political communication scholarship “no longer looks for direct media effects” on voting (p. 236). Instead, political mass communication scholars study a wide range of dependent variables that intervene in the relationship between media and voting: vote likelihood, voters’ information levels about candidate issue positions, voters’ perceptions of the personal qualities of various candidates (e.g., Ansolabehere & Iyengar, 1995, Holbert, Benoit, Hansen, & Wen, 2002; McLeod, Scheufele, & Moy, 1999; Pfau, Holbert, Szabo, & Kaminski, 2002).² McLeod et al. (2002) state that the vast majority of political communication scholarship turns its attention to the study of dependent variables that are thought to be affected by various media depictions and that have some effect on voting. In short, the basis for much of today’s mass communication study of political campaigns is built on a foundation of mediation; political communication scholarship tends to focus on dependent variables that are potential mediators in the relationship between media and vote choice.

Health communication. In many ways, the study of mass media health campaigns parallels research in political campaigns. At their essence, health campaigns feature a message with the intent of changing or reinforcing a specific health outcome (MacKinnon & Dwyer, 1993). The “gold standard” for many health campaigns is a change in behavior such as quitting smoking or practicing safe sex (e.g., Hornik, 2002). But where most public health practitioners are ultimately focused in the behavior change, communication specialists invest their efforts into developing the messages for these campaigns targeting critical intervening variables (e.g., Rice & Atkin, 2001). Indeed the “mass media have a unique capacity to restructure the attitudes, expectations, and perceived social environments” (Worden & Flynn, 2002, p. 31) in order to facilitate a change in the desired health behavior.

The impact of a health communication campaign on both mediating and outcome variables is illustrated in an adolescent-smoking prevention campaign conducted by Worden and Flynn (2002). Media and school-based prevention messages employed the principles of social learning theory to create anti-smoking messages. To achieve the desired behavioral outcome, the prevention of adolescent smoking, the intervention messages focused primarily on four intervening variables: a negative view of smoking, a positive view of nonsmoking, refusal skills, and social norms for not smoking. Hence, the interventions seek to influence these intervening variables, which in turn propagate adolescent nonsmoking. Others target intervening variables as well. Cappella, Fishbein, Hornik, Ahern, and Sayeed (2001) identify a host of beliefs worthy of targeting in drug prevention messages. Maibach and Cotton (1995) focus on how knowledge, skills, and self-efficacy can be employed to tailor HIV-prevention messages in order to maximize the opportunity for behavior change. These examples, as well as many others not identified here, indicate how health campaign messages heavily target intervening variables in order to achieve or facilitate change in health behaviors.

A general conclusion can be reached that the study of mediation is essential to better understanding the role of media in a host of contexts. However, very few direct
tests of mediation have been provided by recent mass communication scholarship employing SEM, a multivariate statistical technique that affords the opportunity to test several mediating relationships simultaneously. We wish to address the testing of mediation more formally and offer a series of recommendations for the analysis of these types of relationships via SEM.

Mediation

Baron and Kenny (1986) highlight the basic S-O-R model first popularized by Woodworth (1928) and reemphasized by Markus and Zajonc (1985) as a perfect example of a theoretical framework that focuses on the study of mediation. Media scholars have pointed to this same model as best representing the process of media influence (e.g., McLeod et al., 2002). The importance of the O-S-O-R model of mass communication influence serves to reinforce our claim that the study of media effects must involve the testing of mediation (e.g., McLeod et al., 1996).

There are more than a dozen distinct methods used in extant empirical scholarship to test for mediation. MacKinnon et al. (2002) collapse these methods into three groups: causal step, differences in coefficients, and product of coefficients.3 We will detail each of these broad classifications, highlight which existing mediation equations fall into each classification, and then summarize recent Monte Carlo simulation analyses that compare how well the various formulas perform in terms of statistical power and Type I error rates. It is important to detail each of these classifications given that “there is no firm consensus across disciplines as to the definition of an intervening variable effect” (MacKinnon et al., 2002, p. 84).

Causal Step

The most popular example of the causal step approaches is that of Baron and Kenny (1986), which is a slight derivative of earlier discussions for mediation offered by Judd and Kenny (1981a, 1981b). As MacKinnon et al. (2002) state, “the overall purpose of the causal steps methods was to establish the conditions for mediation rather than a statistical test of the indirect effect” (p. 87). Kenny, Kashy, and Bolger (1998) detail four criteria for complete mediation. First, the independent variable should have a significant influence on the dependent variable. Second, the independent variable must be significantly related to the potential mediator. Third, the mediator must have a significant relationship with the dependent variable. Finally, the initially significant relationship between the independent and dependent variable becomes zero once the role of the mediator is accounted for in the process. If only steps one through three are met, then partial mediation is established. This approach works well for the assessment of a single potential intervening variable (e.g., Stephenson, Benoit, & Tschida, 2001), but does not provide much utility when there is more than one intervening variable in a given model (MacKinnon, 2000; West &
Aiken, 1997). This weakness is particularly troublesome for the testing of structural equation models, which allow for the testing and evaluation of several potential mediators simultaneously (Bollen, 1987; see also MacKinnon, Krull, & Lockwood, 2000; Stephenson, 2003).

**Differences in Coefficients**

The equations in this category compare the relationship between an independent and outcome variable before and after accounting for the role of a potential mediator (see Clogg, Petkova, & Shihadeh, 1992; Freedman & Schatzkin, 1992; Olkin & Finn, 1995). These equations provide an estimate of an intervening variable and a standard error associated with that estimate (MacKinnon et al., 2002). Thus, this category provides a more formal statistical test of mediation than that offered by the causal steps processes outlined above. With this stated, MacKinnon et al. (2002) stress several potential weaknesses with these equations. These equations are seen as only pseudo-direct tests of mediation, not nearly as accurate as the product of coefficient tests detailed in the next section. Inaccuracies stem from these equations comparing the relationship between the independent variable and dependent variable rather than a direct test of the mediating relationship itself. The difference of coefficient mediation tests are the least used in the social sciences and each formula has been created to compare a particular type of statistic (e.g., simple correlation, partial correlation, regression coefficient). Thus, the equations in this category are not generalizable to the broad testing of mediation across different types of analyses.

**Product of Coefficients**

These equations calculate the product of the paths leading from the independent variable to the intervening variable and the intervening variable to the dependent variable, divide this product by its standard error, and then make a comparison to the normal distribution. The three traditional product of coefficient formulas vary only slightly in their estimation of the standard error (e.g., Arloans, 1944; Goodman, 1960; Sobel, 1982). In addition to these traditional estimates, MacKinnon and colleagues have more recently offered a series of distinct product of coefficient equations to assess potential mediation (e.g., MacKinnon & Lockwood, 2001; MacKinnon, Lockwood, & Hoffman, 1998). The MacKinnon et al. alternatives have been introduced because the traditional product of coefficients equations have been shown to have low statistical power because the products of the path estimates are not normally distributed. Thus, each of the MacKinnon et al. alternatives attempts to create greater normality in the products of the path estimates in a given mediating relationship (see MacKinnon et al., 2002, for equations). We will discuss below how the MacKinnon et al. alternatives perform relative to the more traditional product of coefficient estimates.

Now that we have provided a summary of the strengths and weaknesses of the
various options offered for the testing of mediation, we turn to the multivariate technique of SEM. The major SEM software packages (e.g., LISREL, EQS, AMOS) are surprisingly unified in how they estimate indirect effects. However, no one statistical package formally tests for mediation in complex models (i.e., models with more than three variables). We wish to highlight what mass communication researchers need to concern themselves with regarding mediation and SEM, what various SEM software packages do not tell researchers about mediation, and make a set of formal recommendations concerning mediation to media effects scholars who are using SEM.

Mediation and SEM

Specific Indirect Effects

The most important type of effect for assessing mediation in structural equation models is the specific indirect effect (Brown, 1997). Once again, specific indirect effects represent the portion of the total indirect effect that works through a single intervening variable (Fox, 1980). Specific indirect effects are not calculated by the major SEM software packages. These software packages provide researchers with estimates for direct effects, the aggregate of the specific indirect effects (i.e., the total indirect effect), and total effects, but not the effect type that directly assesses mediation (i.e., the specific indirect effect).

Why is the study of specific indirect effects essential to the study of mediation? This can best be explained through an example (Rosenberg, 1968). Suppose a media effects researcher is testing a particular structural equation model and that a given set of relationships among four variables in that model can be isolated (see Figure 1). The model shows Variable A having an influence on all three variables to its right. The two intervening variables (Variables B and C) are also shown to have an influence on the dependent variable (Variable D).

![Four-Variable Potential Mediation Model](image-url)

Figure 1
Four-Variable Potential Mediation Model
The major SEM software packages provide the following effects estimates: the respective direct effects of Variables A, B, and C on Variable D; the total indirect effect of Variable A on Variable D; and the total effects for Variables A, B, and C on Variable D. There exists in the model two potential mediators in the relationship between Variables A and D (i.e., Variables B and C). Thus, the total indirect effect for Variable A on Variable D is the sum of two specific indirect effects. The first specific indirect effect runs through variable B, and the other through Variable C. It is essential that each specific indirect effect be isolated and tested to assess whether one or both of the intervening variables are mediators.

**Product of Coefficient Estimate and SEM**

The product of coefficient tests for mediation were designed specifically to address the multiple mediator scenario (Sobel, 1987). They allow for the most direct testing of specific indirect effects. Researchers can easily obtain the product of the path estimates that establish the specific indirect effect and then use one of the various equations to obtain a standard error for that specific indirect effect. The other two categories, causal steps and differences in coefficients, work best when a single mediator is being analyzed but prove to have limited utility for more complex models that involve multiple mediators. These more complex models (i.e., multiple mediator) are typical of structural equation models in mass communication (Dillard, 2002).

All of the major structural equation modeling software packages used by communication scientists (e.g., LISREL, EQS, and AMOS) employ a product of coefficient equation to assess indirect effects. Once again, these packages only estimate total indirect effects, not the specific indirect effects necessary for assessing mediation. More specifically, each of these programs use the Sobel (1982) equation to test for the statistical significance of the total indirect effects for the variables in a model. A recent Monte Carlo simulation testing the relative statistical power and Type I error rates of various mediation equations found the Sobel estimate to not perform as well as some of its product of coefficient peers (MacKinnon et al., 2002). More specifically, the Sobel equation is relatively weak in terms of statistical power and has a less accurate Type I error rate than some of the other product of coefficient equations.

One of the MacKinnon et al. product of coefficient alternatives performs the best in terms of retaining greater statistical power and the maintenance of an accurate Type I error rate. The MacKinnon et al. (2002) Monte Carlo simulation points to the MacKinnon et al. (1998) distribution of products test as the best direct test for mediation. This equation involves the conversion of each parameter estimate that makes up a potential mediating relationship into a z-score by dividing each unstandardized parameter estimate by its respective standard error and then obtaining the product of the two z-scores that make up the specific indirect effect. Researchers can then look to a product of two random, normal variables table to establish statistical
significance (see Craig, 1936; Meeker, Cornwell, & Aroian, 1981; Springer & Thompson, 1966).

Although the various SEM software packages do not directly estimate the statistical significance of specific indirect effects, all of the information needed to calculate the MacKinnon et al. (1998) distribution of products test is readily accessible in traditional SEM software output. The MacKinnon et al. distribution of products formula is the most accurate product of coefficients equation to test for the existence of a mediator and is easily obtained by media effects researchers interested in this type of relationship.

Example. We would like to provide an example of the MacKinnon et al. (1998) distribution of products formula being employed to directly test for mediation in a structural equation model. We have created a four-variable model stemming from a recent study by Holbert et al. (2002) and that matches the structural framework established in Figure 1. Holbert et al. completed a political communication study using data from the 1996 American National Election Study to assess the relative influence of six different campaign information outlets (e.g., debates, television news, political advertisements) on citizens' issue knowledge and salience concerning the two major party candidates in that election, Clinton and Dole. We wish to isolate and extend one portion of the Holbert et al. study to analyze two potential mediators.

The model will focus on the potential indirect effects of individual-level viewing of the first televised presidential debate of the 1996 general campaign (Variable A) (see Figure 2). Debate viewing is an additive index consisting of exposure and

![Figure 2](Image)

**Figure 2**
The 1996 ANES Four-Variable Mediation Model

Note: Unstandardized parameter estimates (standard errors in parentheses)
attention measures. The two mediators in the model (Variables B and C) are positive issue salience for Clinton and Dole, respectively. Each respondent was asked if he/she could think of anything positive about each of the two major party candidates, and was allowed to provide up to five responses for each candidate. The dependent variable in the model (Variable D) is traditional political participation. This variable is an additive index consisting of dichotomous measures concerning whether the citizen worked for, gave money, displayed a bumper sticker, etc. for one of the major party candidates. We wish to assess in this four-variable model whether viewing the first debate made people retain more positive thoughts of Clinton and/or Dole and whether having more positive thoughts will lead to a greater likelihood of citizens taking part in the campaign. Thus, there are two potential specific indirect effects for debate viewing on political participation in the model which travel through the respective salience variables.

The latent composite model fits the data well as indicated by the following fit statistics: Root Mean Square Error of Approximation = .03, Standardized Root Mean Square Residual = .02 (90% confidence interval: .00 - .11), Comparative Fit Index = .95 (Holbert & Stephenson, 2002). For purposes of model comparison, the $\chi^2 (1, 729) = 1.88, p = .17$. The $z$-score product for the mediation path through Clinton-salience = $(.10/.05) \times (.11/.05) = 4.40$, and the path through Dole-salience has a $z$-score product = $(.01/.05) \times (.15/.06) = 0.50$. Consulting the product of two normally distributed variables table in Craig (1936), we determine the former path to be significant at the $p < .01$ level and the latter to be nonsignificant. Thus, we find in the model that Clinton-salience is a statistically significant partial mediator in the relationship between debate viewing and political participation, while Dole-salience does not play this same role. Not only does debate viewing directly affect political participation, but it also influences greater positive thought-generation about Bill Clinton. Subsequently, positive issue salience of Clinton leads to a greater likelihood of participating in the election process. Mediation answers the questions of "how" and "why" an effect takes place (Baron & Kenny, 1986), and the mediation process outlined above shows how debate viewing influences positive issue salience for the incumbent, Clinton, and how these positive thoughts can influence participatory behaviors. Also, it is important to note that the positive specific indirect effect through Clinton-salience creates a larger total effect (direct + indirect) for debate viewing on the dependent variable. Thus, the direct testing of mediation in this model allows us to more "fully consider" the true role of televised debate viewing in this context.

Recommendations

Total indirect effects. Once again, the Sobel (1982) product of coefficients equation is used by SEM software packages to estimate the total indirect effect of an independent variable on some dependent variable in the structural model. There is solid evidence that the Sobel estimates perform well for moderate to large effect sizes
with samples of 200 or larger (MacKinnon et al., 2002). We encourage media effects scholars to pay greater attention to the indirect effects contained in their models. Estimating and evaluating the Sobel estimates for total indirect effects is a reasonable first step in recognizing the importance of moving beyond the use of SEM for the singular purpose of analyzing direct effects. We would argue that media effects scholars only take on the additional step of employing an alternative product of coefficients equation (e.g., MacKinnon et al.'s, 1998, distribution of products) for estimating total indirect effects if they expect small effects sizes in their models or are working with a sample size below 200.

Specific indirect effects. If researchers are hypothesizing and testing for the existence of a specific indirect effect, then it is important to use the equation that provides the most accurate reading of that potential mediating relationship. The MacKinnon et al. (1998) distribution of products equation based on the creation of a pair of z-scores for the parameter estimates that make up the specific indirect effect is the best option available to media effects scholars. Given that the study of mediation is essential to the media effects discipline, it is important to begin to employ this product of coefficients equation in future research.

Discussion

The importance of mediation to the study of media effects has been stressed by many scholars (e.g., Mcguire, 1986; McLeod & Reeves, 1980). It could be argued that mediation is one of the defining relationships for some of the more important subfields in the discipline (e.g., political communication, health communication). However, a recent critical assessment of the use of SEM in communication reveals that very few scholars decompose the effects that stem from their structural equation models, much less formally test for mediation via a product of coefficients examination of specific indirect effects (e.g., Holbert & Stephenson, 2002). SEM affords media effects researchers the opportunity to assess multiple potential mediators in their models, but most have not used this multivariate technique to step beyond a discussion of direct effects. Thus, the use of SEM in mass communication research does not match well with the theories that drive the discipline.

We recommend media scholars use MacKinnon et al.'s (1998) distribution of products equation for the direct testing for potential mediation. This product of coefficients equation performs best in terms of retaining statistical power and providing an accurate Type I error rate (MacKinnon et al., 2002). Structural equation modeling experts have long understood that it is essential for a product of coefficients equation to be used to directly test for mediation in structural equation models due to the fact that structural models will most often contain multiple potential mediators for most independent-outcome variable relationships (Bentler, 1995; Jöreskog & Sörbom, 1996). Many mass communication theories point to a central role for mediation and the field's models often contain multiple potential mediators (e.g.,
McLeod, Sotiropic, & Holbert, 1998; Scheufele, 2000; Scheufele & Shah, 2000). Therefore, we should be able to hypothesize, isolate, and directly test for these types of relationships in our structural equation models.

With this stated, it is important to close with a discussion of the role of measurement error in the study of mediation. Kenny et al. (1998) state, “if the mediator is measured with less than perfect reliability, then the effects are likely to be biased” (p. 262). Holbert and Stephenson (2002) note that communication researchers employ three different techniques for the creation of a structural equation model (i.e., observable variable, latent composite, and hybrid), with the observable variable-only model type being dominant. Each of these techniques creates a unique set of relationships between what can be observed (i.e., observable variables), the measurement error associated with those observations, and that which we are most interested in but can not directly measure (i.e., latent variables). Stephenson and Holbert (2003b) find in a recent monte carlo simulation that each model type produces distinct parameter estimates for the same model using the same data, with the estimates generated by the observable variable technique performing poorly relative to the two latent variable model types (e.g., latent composite and hybrid). This result was due in large part to how observable variable models allow for measurement error to directly and adversely influence path coefficients. If measurement error is not properly accounted for in a structural equation model, then the path estimates that make up a specific indirect effect will likely be attenuated.

It is important that mass communication scholars understand and properly account for measurement error in their structural equation models by moving toward greater use of latent variable models. Stephenson and Holbert (2003b) argue and provide empirical evidence for the superiority of latent variable models. We wish to reiterate this point with special attention to the study of mediation. As outlined above, a direct test of mediation requires obtaining the product of two path estimates. Thus, attenuation can be especially harsh in biasing an estimate of mediation because the combined measurement error of each variable influences the product term that determines whether this type of relationship exists. In fact, the error associated with the potential mediator will influence both path estimates leading to even greater attenuation in the product of parameters that make up a specific indirect effect (Hoyle & Kenny, 1999). We encourage future research to recognize the importance of measurement error in the direct testing of mediation and urge the use of latent variable modeling techniques to best account for the role of the error associated with one’s observations.

Notes

1 The conditional effects approach to media influence concerns the existence of moderators as well as mediators (see Baron & Kenny, 1986, for distinction). The testing of nonlinear relationships via SEM has been the source of much recent debate (e.g., Blom & Christoffersson, 2001; Yang-Wallertin, 2001; Yang-Wallertin, Schmidt, & Bamberg, 2001). Researchers have
often raised concerns with the special circumstances surrounding interaction effects (e.g., Evans, 1991; McClelland & Judd, 1993), but this has been a particularly problematic issue for latent-variable SEM analyses (e.g., Schumaker & Marcoulides, 1998). Several important strides have been made in establishing more formal tests of nonlinear relationships with this multivariate tool (e.g., Schumaker, 2002). However, we are segregating our present mass communication-related discussion of mediation from that of moderation, with the latter being addressed more formally in another work (e.g., Stephenson & Holbert, 2003a).

Multiple mediators in a structural equation model may form nonrecursive relationships with one another (i.e., reciprocal causation or correlated disturbances). Nonrecursive models should always be treated with caution (e.g., Teel, Bearden, & Sharma, 1986), and this pertains to the study of mediation in particular. For example, the existence of reciprocal paths between mediators creates additional specific indirect paths between an independent variable and a dependent variable. These paths need to be assessed along with the traditional two-step mediation paths that are the focus of most social scientific research.

We are deeply indebted to and heavily reliant upon MacKinnon et al. (2002) and their summary of the various tests of mediation in this section of our essay. We wanted to make this essay as accessible as possible to the widest mass communication audience, so we made a decision to not provide the specific equations for each test of mediation. Instead, we attempt to provide a broad overview of three mediation equation categories. Those who would like to see all of the mediation equations in full should refer to MacKinnon et al. (2002).

MacKinnon et al. (2002) discuss how each of these equations vary only in their accounting of the product of the variances for the parameter estimates in the estimation the standard error term. The Sobel (1982) estimate does not account for the product term, whereas the Goodman (1960) equation subtracts the term and Aroian (1944) adds the product. This product term is quite small and the three equations have been shown to produce quite similar standard error estimates (MacKinnon, Warsi, & Dwyer, 1995).

Variables B and C do not have an indirect effect on Variable D because there are no intervening variables between the former pair and the latter variable in this example.

Dillard (2002) argues for greater clarity and simplicity in the construction and testing of structural equation models. Researchers often create structural equation models that are needlessly complex relative to the theories being tested in their models. Dillard’s comments mirror those of Boster (2002) concerning the general state of design and analysis in the discipline as a whole. Boster states the discipline needs greater sophistication, not more complexity.

It is important to note that the MacKinnon et al. (1998) direct test for mediation is applicable to all estimation procedures offered through the various SEM software packages (e.g., TSLS, ULS, GLS), as well as OLS regression path analysis.

Observable variable models do not contain latent variables. However, they do create a unique relationship between measurement error and the estimation of path coefficients relative to either the latent composite or hybrid model types.

References


Dillard, J. P. (2002). Structural equation modeling and the virtues of simplicity. In M. Pfau (Chair), *Structural equation modeling in mass communication*. Symposium conducted at the annual meeting of the National Communication Association, New Orleans, Louisiana.


