CHAPTER NINE

Structural Equation Modeling of Mediation and Moderation With Contextual Factors

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Researchers often grapple with the idea that an observed relationship may be part of a more complex chain of effects. These complex relationships are described in terms such as indirect influences, distal vs. proximal causes, intermediate outcomes, and ultimate causes; all of which share the concept of *mediation*. Similarly, researchers must often consider that an observed relationship may be part of a more complex, qualified system. These relationships are described using concepts such as interactions, subgroup differences, and shocks; all of which share the concept of *moderation*. Generally speaking, a mediator can be thought of as the carrier or transporter of information along the causal chain of effects. A moderator, on the other hand, is the changer of a relationship in a system.

In this chapter, we explore both empirical and theoretical considerations in modeling mediation and moderation using structural equation modeling. Our primary focus is on how to model contextual factors that are measured as continuous latent variables, highlighting the power of SEM to represent and test these types of influence (see Little, Card, Slegers, & Ledford, chap. 6, this volume, for a discussion of moderating contextual factors that are measured as categorical variables).

MEDIATION

Contextual factors can be conceptualized as mediated influences where the contextual information is deemed to be a distal causal influence. For example, early prenatal conditions can influence cortical development, which in turn can influence later intellective functioning (see Widaman, chap. 17, this volume). Contextual factors can also be conceptualized as the mediating influence where the contextual information is deemed to carry the distal causal associations. For example, children's temperament characteristics may influence the overall classroom environment, which in turn may influence the quality of learning or school well-being of the children.

Throughout our discussion of mediation, we use the standard convention of referring to the exogenous causal influence as $\boldsymbol{X}$. The endogenous causal influence, or mediator, is referred to as $\boldsymbol{M}$, and the dependent variable or outcome is referred to as $\boldsymbol{Y}$.

Empirical Conditions for Mediation

Baron and Kenny's (1986) influential paper on mediation analyses stated three necessary but not sufficient conditions that must be met in order to claim that mediation is occurring (but see Kenny, Kashy, & Bolger, 1998; MacKinnon, Lockwood, Hoffman, West, & Sheets, 2002).

1. *$\boldsymbol{X}$ is significantly related to $\boldsymbol{M}$.*
2. *$\boldsymbol{M}$ is significantly related to $\boldsymbol{Y}$.*
3. *The relationship of $\boldsymbol{X}$ to $\boldsymbol{Y}$ diminishes when $\boldsymbol{M}$ is in the model.*

In other words, each of the three constructs must show evidence of a nonzero monotonic association with each other, and the relationship of $\boldsymbol{X}$ to $\boldsymbol{Y}$ must decrease substantially upon adding $\boldsymbol{M}$ as a predictor of $\boldsymbol{Y}$ (for a review and comparison of methods of testing mediation, see MacKinnon et al., 2002).[1] The

[1] Typically, these associations are adequately captured as linear relationships. Although it is beyond the scope of the current discussion, nonlinear modeling can also be employed for testing nonlinear mediation.

regression weight of $\boldsymbol{Y}$ regressed on $\boldsymbol{X}$ is sometimes denoted c. A key feature of a mediation analysis is the nature of the correlational structure among the set of three variables. For example, if the $\boldsymbol{X}$-to-$\boldsymbol{M}$ link (denoted a) corresponds to a .8 correlation and the $\boldsymbol{M}$-to-$\boldsymbol{Y}$ link (denoted b) also corresponds to a .8 correlation, the implied correlation between $\boldsymbol{X}$ and $\boldsymbol{Y}$ is .64 (i.e., in standardized metric: $.8 \times .8$), assuming the relationship of $\boldsymbol{X}$ to $\boldsymbol{Y}$ controlling for $\boldsymbol{M}$ is zero. When this correlational structure is observed in the data, a mediation analysis will provide support for mediation (in this case, full mediation, see the following). If the observed correlation is larger than that implied by the product of the two pathways (a and b) then a direct positive effect of $\boldsymbol{X}$ to $\boldsymbol{Y}$ (denoted c') may be needed, depending on the magnitude of the deviation from the model implied correlation. On the other hand, if the observed correlation is smaller than the correlation implied by the product of the two pathways (a and b) then a direct negative value of c' may be needed, depending on the magnitude of the deviation from the model implied correlation, and *suppression* is in evidence. In other words, the empirical need for a direct pathway from $\boldsymbol{X}$ to $\boldsymbol{Y}$ is driven by the magnitude and direction of the deviation of the observed from the implied correlation between $\boldsymbol{X}$ and $\boldsymbol{Y}$ when the c' path is not represented in the model. Table 1 depicts three idealized correlation patterns that would be consistent with full mediation, partial mediation, and partial suppression. Although these variations on the kinds of mediation that can emerge in a mediation analysis are intuitively appealing, they do not necessarily do justice to a more complete understanding of mediation effects. Briefly we describe the concepts as typically found in the current literature, but then turn to a discussion of why these distinctions are unsatisfying descriptors.

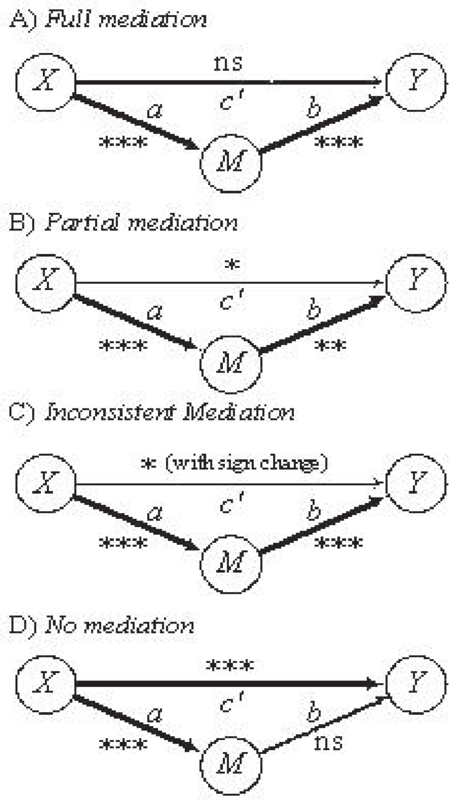
If the relationship between construct $\boldsymbol{X}$ and construct $\boldsymbol{Y}$ is *fully mediated*, then all of the significant variance of that relationship will be accounted for by the direct effect from construct $\boldsymbol{M}$ to construct $\boldsymbol{Y}$ (b). That is, the influence

TABLE 9.1
Idealized Correlational Structures That Would be Consistent With Full Mediation, Partial Mediation, and Suppression

	1. *Full Mediation*				2. *Partial Mediation*				3. *Suppression*		
	$\boldsymbol{X}$	$\boldsymbol{M}$	$\boldsymbol{Y}$		$\boldsymbol{X}$	$\boldsymbol{M}$	$\boldsymbol{Y}$		$\boldsymbol{X}$	$\boldsymbol{M}$	$\boldsymbol{Y}$
$\boldsymbol{X}$	1.0	.60	.30	$\boldsymbol{X}$	1.0	.60	.50	$\boldsymbol{X}$	1.0	.60	.20
$\boldsymbol{M}$	.80	1.0	.50	$\boldsymbol{M}$	.80	1.0	.50	$\boldsymbol{M}$	.80	1.0	.50
$\boldsymbol{Y}$	.64	.80	1.0	$\boldsymbol{Y}$	.80	.80	1.0	$\boldsymbol{Y}$	.46	.80	1.0

Note. High levels of intercorrelation are depicted below the diagonal and low levels of intercorrelation are depicted above the diagonal.

FIGURE 9.1
Types of mediation.



Note. In these idealized models, the correlations among all three constituents are assumed to be positive in sign and significant. All paths are positive except where noted in Panel C. $*$ indicates relative strengths of associations.

of $\boldsymbol{X}$ on construct $\boldsymbol{Y}$ is adequately captured as an indirect influence through $\boldsymbol{M}$ (see Figure 9.1, Panel A) and the observed association between $\boldsymbol{X}$ and $\boldsymbol{Y}$ is accurately captured by tracing the pathways from $\boldsymbol{Y}$ back to $\boldsymbol{M}$ (b) and from $\boldsymbol{M}$ back to $\boldsymbol{X}$ (a). (See e.g., Loehlin, 1987, for a discussion of Wright's tracing rules; and see Table 9.1)

A *partially mediated* relationship is indicated if the direct effect of the mediator construct, $\boldsymbol{M}$, accounts for a significant amount of variance in $\boldsymbol{Y}$, but c' remains significant. If c' remains significant but differs in sign from the zero-order correlation between $\boldsymbol{X}$ and $\boldsymbol{Y}$, then mediation with suppression is evident (see Figure 9.1, Panel C). In other words, if c' differs in sign from the product of a and b (e.g., one is a positive effect while the other is negative) one interpretation would be that $\boldsymbol{X}$ contains two sources of variance that reflect two opposing channels by which it influences $\boldsymbol{Y}$. Specific interpretations would depend on the signs of the various pathways and the composition of the various constructs. More specifically, one channel would influence $\boldsymbol{Y}$ via the indirect pathway of the mediator, $\boldsymbol{M}$, while the other channel would influence $\boldsymbol{Y}$ in the opposite direction once the influence of $\boldsymbol{M}$ is accounted for in $\boldsymbol{Y}$. In this regard, both c' and b would need to remain significant when they are both in the model (see Figure 9.1, Panel C; and see Table 1). For more information on suppression and its relationship to mediation, consult MacKinnon, Krull, and Lockwood (2000).

Finally, if b is nonsignificant when c' is present in the model, then no mediation is evident (see Figure 9.1, Panel D). Other patterns of associations are also consistent with a lack of mediation. For example, if a is not significant and b is significant, the b pathway would be interpreted as a covariate and not a mediator. Similarly, if a, b, and c' are all nonsignificant then no mediation would be evident.

Some Notes of Caution. Despite the pervasiveness of terms like full and partial mediation, we caution against their use. *Full* and *partial* are essentially informal effect size descriptors. They are intended to capture and communicate the magnitude or importance of a mediation effect, yet they are traditionally defined in terms of statistical significance. In other words, an effect is termed *partial* or *complete* based not only on the strength of the effect, but also on the p-values associated with c and c', and hence on sample size. Traditionally, statistical significance and practical significance are separate concepts, and the latter should not invoke N.

One negative consequence of using p-values to define effect size is that some circumstances are likely to lead to conclusions of full mediation that should more intuitively be considered partial mediation. In other words, there exists the danger of unwittingly exaggerating the size or importance of an effect. For example, given that an indirect effect is statistically significant, the smaller the sample is, the more likely we are to conclude that the total effect of $\boldsymbol{X}$ on $\boldsymbol{Y}$ is fully mediated because the standard error of c' increases as N decreases. In other words, the researcher is rewarded with apparently more extensive mediation the smaller N becomes, but no one would seriously advocate using small samples to achieve large apparent effect sizes. A second negative consequence is that the smaller the total effect (c) is, the more likely one is to demonstrate full mediation; restated, the smaller an effect is, the easier it is to fully mediate it. A consequence of this is that the less reliable one's $\boldsymbol{X}$ and $\boldsymbol{Y}$ variables are, the more likely one is to achieve full mediation. It can be misleading to claim that an inconsequential but statistically significant effect is "fully mediated."

Finally, full mediation can never logically exist in the population because it requires a regression weight to be exactly equal to zero. The probability of this occurring in practice is zero. Finding $c' = 0$ and c' not significantly different from zero are two very different things; with the latter, all the researcher can claim is that there is not enough evidence to reject the hypothesis of full mediation (but given a larger N, we almost certainly would). We recommend instead investigating the statistical significance of the mediation effect and *separately* considering whether or not the effect is practically important or meaningful. What constitutes a practically meaningful effect will vary from context to context, and relies on the scientist's judgment and background knowledge. In what follows, we examine some methods that can be used to establish the statistical significance of a mediation effect.

Key Considerations in Testing for Mediation. One consideration for finding support for mediation is whether the indirect pathway from $\boldsymbol{X}$ to $\boldsymbol{M}$ to $\boldsymbol{Y}$ $(a \times b)$ is statistically significant (Shrout & Bolger, 2002). All major SEM programs provide estimates of indirect effects and their associated standard errors which are used to determine the significance of the effect by way of the Wald statistic (i.e., an estimate divided by its standard error provides a large-sample Z-value to gauge the statistical significance of the effect). The standard error is given in a number of sources (e.g., Baron & Kenny, 1986; Sobel, 1982) as:

$$se_{a \times b}\sqrt{a^2 se_b^2 + b^2 se_a^2} \qquad (1)$$

The test is conducted by dividing $(a \times b)$ by its standard error and comparing the result to a standard normal distribution. This test is very simple to apply, directly tests the hypothesis of interest, and can be used to form confidence intervals for the population indirect effect. However, it should be used only in large samples because a central assumption underlying its use—that $(a \times b)$ is normally distributed across repeated sampling—is typically violated in practice. However, as N grows larger, the distribution of $(a \times b)$ tends to approximate normality and the normality assumption becomes more tenable.

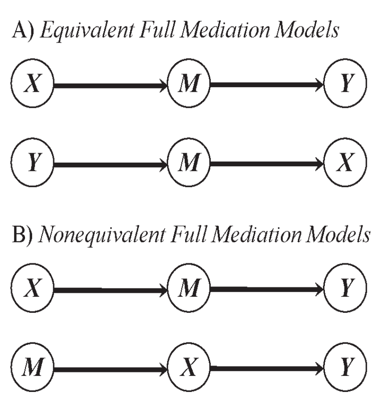
Other methods for determining the significance of the indirect effect include the use of resampling (or bootstrapping) and the *distribution of the product* strategy (MacKinnon et al., 2002; MacKinnon, Lockwood, & Williams, 2004). Resampling is especially useful in small samples, and makes fewer distributional assumptions than the Wald test. Resampling involves repeatedly drawing N cases (with replacement) from the original N cases to form a sampling distribution of $(a \times b)$. This sampling distribution, in turn, is used to form asymmetric confidence intervals without having to assume normality (for descriptions of this method, see Bollen & Stine, 1990; MacKinnon et al., 2004; Preacher & Hayes, 2004; and Shrout & Bolger, 2002). The distribution of the product strategy is a recently proposed method that is similar to the Wald test described earlier, but invokes a more complex sampling distribution than the standard normal distribution. Research on the subject is still in its infancy (MacKinnon, Fritz, Williams & Lockwood, in press), but the method has shown much promise.

Theoretical Considerations in Testing for Mediation

Although the empirical conditions for mediation are straightforward, a number of theoretical issues must also be considered when evaluating the validity of the tested mediation model. In many cases, even though the empirical data are consistent with a mediated relationship, the mediation model has not captured the true indirect pathway. An empirical finding of mediation may support a preferred model, but it does not rule out a wide range of possible alternatives (just a handful of them). These alternative models may be equally consistent with the data, yet may be quite different from the hypothesized mediation model. Because of these equally plausible alternative models, a number of threats to the validity of a mediation analysis must also be considered.

Threat 1: Plausible Equivalent Models: When one is testing for mediation using nonexperimental data with measurements made at the same occasion, any number of interpretive problems can arise (see, e.g., Cole & Maxwell, 2003). Figure 9.2 (Panel A), for example, shows a simple demonstration that a perfect mediated relationship has two statistically

FIGURE 9.2
Alternate mediation models.



equivalent models that could fit the data with c' fixed to zero. In contrast, Panel B of Figure 9.2 shows a set of nonequivalent models that could also be fit to the data. Although the competing models of Panel B can be contrasted statistically, the order of the predictive chains in Panel A must be evaluated on the basis of theory. Without strong theory and good measurement, the order of the predictive chain can be in any combination—although a significant test of mediation may provide support for all of these models equally, it does not provide support for one model over the other.

Threat 2: Unmodeled Variables That Are Correlated With M and $\boldsymbol{Y}$: In experimental work, one can have a situation in which $\boldsymbol{X}$ is manipulated and one then tests the significance of $a \times b$. If b is high prior to the manipulation because of some other source of shared variability ($\boldsymbol{D}$) between $\boldsymbol{M}$ and $\boldsymbol{Y}$, the manipulation of $\boldsymbol{X}$ may lead to a correlational structure that is consistent with mediation, but concluding that mediation has occurred could be invalid (i.e., the true indirect path might be from $\boldsymbol{X}$ to $\boldsymbol{D}$ to $\boldsymbol{Y}$, or there may be no indirect path at all). To remedy this problem in experimental work, one might conduct experiments testing *each* of the putative components of the causal chain (i.e., the manipulation of $\boldsymbol{X}$ is found to cause change in $\boldsymbol{M}$ as well as change in $\boldsymbol{Y}$ that is accounted for by change in $\boldsymbol{M}$; and the manipulation of $\boldsymbol{M}$ causes changes in $\boldsymbol{Y}$) in order to test the relations among $\boldsymbol{X}$, $\boldsymbol{M}$, and $\boldsymbol{Y}$ (Spencer, Zanna, & Fong, 2005). However, in nonexperimental work, it may be difficult or impossible to determine whether a variable, $\boldsymbol{M}$, is a true mediator of the relationship between $\boldsymbol{X}$ and $\boldsymbol{Y}$ or whether it is simply highly correlated with an unmeasured variable, $\boldsymbol{D}$, that has causal influence over $\boldsymbol{M}$ and $\boldsymbol{Y}$. In short, simple tests of mediation models are especially dependent on accurate model specification; when relevant and correlated variables go unmeasured, the results of mediation tests, no matter what level of statistical significance is achieved, may point in the wrong direction.

Threat 3: When Measured Variables Are Proxies for True Causal Variables: In both experimental and nonexperimental work, a key threat to the validity of the mediation analysis is related to the issue of whether the measured variable is the 'true' variable or a proxy of the intended variable. This issue can take a number of forms in that the proxy for the true variable can be located in any of the $\boldsymbol{X}$, $\boldsymbol{M}$, or $\boldsymbol{Y}$ constituents of the causal chain.

Proxy Causal Variables. Among exogenous variables, an unmeasured true cause may be highly correlated with the measured/manipulated variable. In this case, $\boldsymbol{X'}$ is a proxy for the true distal cause, $\boldsymbol{X}$. In school-based studies, for example, free and reduced lunch status is used as a proxy for SES. If one tests a model of whether the effect of SES on academic outcomes is mediated by parental involvement, using a proxy measure may provide support for the hypothesized model. In this case, it may appear as if the effect of the ‘false cause’ is mediated by $\boldsymbol{M}$ when, in fact, the measured $\boldsymbol{X'}$ is not the true causal effect on $\boldsymbol{M}$. Similarly, consider an experiment in which one manipulates $\boldsymbol{X'}$ but believes they have manipulated $\boldsymbol{X}$. If $\boldsymbol{X'}$ has a substantial causal effect on $\boldsymbol{M}$ and $\boldsymbol{Y}$, and its effect on $\boldsymbol{Y}$ is mediated by $\boldsymbol{M}$, then one might incorrectly conclude that $\boldsymbol{M}$ mediates the $\boldsymbol{X}$ effect on $\boldsymbol{Y}$.

A similar situation can occur when there are more links in the causal chain, such as when $\boldsymbol{X}_1$ causes $\boldsymbol{X}_2$ which in turn affects $\boldsymbol{Y}$ through mediator $\boldsymbol{M}$, and the researcher measures only $\boldsymbol{X}_1$. Ignoring more distal causes is not a specification error *per se*, but ignoring a more proximal cause would be a specification error. Another variation on the unmeasured variable problem occurs when $\boldsymbol{X}_1$ and $\boldsymbol{X}_2$ are highly correlated because both are caused by $\boldsymbol{D}$, and the researcher measures $\boldsymbol{X}_1$ or $\boldsymbol{X}_2$, when $\boldsymbol{D}$ is the ‘true’ cause.

Proxy Mediator Variables. A second type of proxy problem occurs when the presumed mediator variable is a proxy variable, $\boldsymbol{M'}$, for the ‘true’ mediator, $\boldsymbol{M}$. This scenario is important because the probability of measuring a proxy variable can be substantial, such as when a related concept is more appropriate (e.g., ethnicity vs. SES), when the true mediator cannot be easily measured (e.g., SES), or when a specific variable is measured when a more construct-level measure is more appropriate (e.g., free-reduced lunch status vs. SES). If the presumed mediator variable is a ‘proxy’ or even a mere strong correlate of the true mediator variable, which is unmeasured (or simply not specified in the model), then mediation analyses can ‘work’ when they should not. This kind of problem increases to the extent that the variables in the mediation analyses are conceptually close to one another. That is, proxy variables can be quite problematic when analyzing mediation models involving constructs with precise theoretical distinctions and where variables in the actual analysis have enough measurement and conceptual overlap to act as proxies for the true cause.

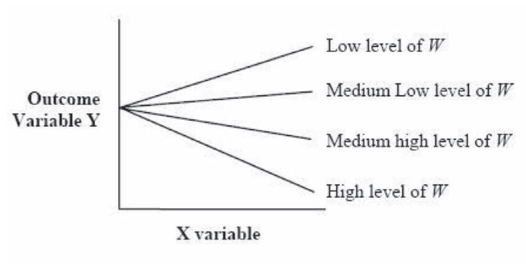
Proxy Dependent Variables. Finally, one may measure a proxy variable for $\boldsymbol{Y}$ (i.e., the measured dependent variable is only correlated with the true outcome variable). In many cases, dependent variables are not the conceptual variables themselves, but are conceptualized as proxy measures (e.g., choice behavior as a proxy for a preference, discrimination as a proxy for prejudice, grades as a proxy for school performance, test scores as a proxy for aptitudes, etc.). But in some cases highly correlated proxy variables (e.g., self-esteem for anxiety or depression) can lead to significant but misleading indirect effects. Similarly, if $\boldsymbol{Y}_1$ causes $\boldsymbol{Y}_2$, but only $\boldsymbol{Y}_2$ is measured as the outcome variable, one would draw an invalid conclusion about the actual causal chain.

Threat 4: Differential Reliability of Measurement: This source of potential error is empirical in nature. If the constructs are measured with differential levels of reliability then the 'true' relationships will be differentially attenuated such that one would not be able to conduct a valid test of mediation (Judd & Kenny, 1981). When new measures that are not honed, focused, and validated are used, unreliability may bias the true mediation process. Lack of measurement development is especially a problem when a construct has a high level of meaning in one group, but not another, for example, racial identity for majority and minority groups (e.g., White identity is much weaker, less meaningful, and has a lower reliability and internal consistency than Latino and Black identity). In such cases, the low reliability of measures—for one group but not the other—may cause mediation to masquerade as between-group moderation. As mentioned above, the latent-variable SEM approach to testing mediation mitigates the problem of differential reliability and allows one to test, and thereby ensure, that the constructs are measured equivalently across the groups (see Little, Card, Slegers, & Ledford, chap.6, this volume).

MODERATION

Thus far we have focused on the technical and theoretical issues associated with mediation analyses. As mentioned in the introduction, however, researchers may also be interested in questions related to moderation, or the changing of a relationship as a function of some moderating influence. When the moderating influence is measured in a continuous manner, this influence is generally modeled by creating a new variable that is the product of the variable that is being moderated $(\boldsymbol{X})$ and the variable that is moderating $(\boldsymbol{W})$. This interaction term $(\boldsymbol{XW})$ is then entered into the regression equation after the linear main effects on the outcome $(\boldsymbol{Y})$ of the moderating $(\boldsymbol{W})$ and moderated variables $(\boldsymbol{X})$ are estimated. If the effect of $\boldsymbol{XW}$ is significant, then the effect of $\boldsymbol{X}$ on $\boldsymbol{Y}$ is dependent upon the levels of $\boldsymbol{W}$. Aiken and West (1991) describe simple procedures for taking the estimated regression weights from the full equations and plotting a number of implied regressions in order to provide a visualization of the moderated effect. Such plots might look like the one depicted in Figure 9.3.

FIGURE 9.3
Hypothetical plot of a moderate relationship between X and Y as a function of a moderator (W).



As with mediation analysis, a number of technical and theoretical issues arise when testing for moderation. A key theoretical issue is conceptualizing which variable is the moderator $(\boldsymbol{W})$ and which is the focal predictor $(\boldsymbol{X})$. Mathematically, the product term $(\boldsymbol{XW})$ used to represent an interaction does not distinguish which variable is which—it simply provides empirical evidence that the nonlinear combination (product) of the two variables accounts for a unique amount of variability in the outcome variable $(\boldsymbol{Y})$ above and beyond the linear main effects of the two variables $(\boldsymbol{X}$ and $\boldsymbol{W})$. For example, in standard ordinary least squares regression, the product of two variables can be used to represent the interactive effect, as seen in Equation 2:

$$\boldsymbol{Y} = b_0 + b_1\boldsymbol{X} + b_2\boldsymbol{W} + b_3\boldsymbol{XW} + e \tag{2}$$

where $\boldsymbol{Y}$ is the outcome variable of interest, e is the assumed error term, $\boldsymbol{X}$ and $\boldsymbol{W}$ are the first-order predictor variables, and $\boldsymbol{XW}$ is the newly formed multiplicative term. Such a regression equation specifies that the slope of the line relating $\boldsymbol{X}$ to $\boldsymbol{Y}$ changes at different levels of $\boldsymbol{W}$. In an equivalent way, however, this equation specifies that the slope of the line relating $\boldsymbol{W}$ to $\boldsymbol{Y}$ changes at different levels of $\boldsymbol{X}$ (see Saunders, 1956). Similar to product terms, powered variables (i.e., natural polynomials such as $\boldsymbol{X}^2$, $\boldsymbol{X}^3$, $\boldsymbol{X}^4$, etc.) can be used to represent other nonlinear functions such as quadratic, cubic, or quartic relationships between $\boldsymbol{X}$ and $\boldsymbol{Y}$.

Under typical conditions, the product and powered terms will be highly correlated with the first-order predictor variables from which they are derived. The resulting collinearity of the product or powered term compromises the stability and interpretation of some regression coefficients. A high degree of collinearity indicates that within the predictor set, one or more of the variables are highly linearly related to other predictors. Under these conditions, even minor fluctuations in the sample, such as those related to measurement and sampling error, can have major impacts on the regression weights and their standard errors. In other words, the collinearity of the powered and product terms with the first-order predictor variables is often problematic because it can create instability in the values for the estimated regression weights, leading to 'bouncing beta weights.'

Ideally, an interaction term will be uncorrelated with (orthogonal to) its first-order effect terms. For example, orthogonal contrast codes are commonly used when there are a small number of categories needed to represent the levels of the variables involved. However, with continuous variable interaction terms, the orthogonality property is harder to achieve. Several authors (i.e., Aiken & West, 1991; Cohen, 1978; Cronbach, 1987) have shown that if the first-order variables are mean centered (i.e., transformed from a raw-score scaling to a deviation-score scaling by subtracting the variable mean from all observations), the resulting product term will be minimally correlated or uncorrelated with the first-order variables if the variables are more or less bivariate normal.

Even though the significance of the partial regression coefficient of an interaction term does not differ depending on whether or not the constituent predictors are mean centered (see Kromrey & Foster-Johnson, 1998 for a convincing demonstration; see also Little, Bovaird, & Widaman, 2006), mean centering the predictor variables prior to creating interaction or product terms has two distinct advantages. First, mean centering alleviates problems of collinearity among the predictor variables that results from the 'nonessential' collinearity among the main effects and their interaction term when one simply forms the product of the variables (as well as powered terms such as $\boldsymbol{X}^2$ or $\boldsymbol{X}^4$; see Marquardt, 1980). This reduction in collinearity reduces or eliminates the associated instability of regression estimates and standard errors when collinearity is not removed (i.e., the 'bouncing beta weight' problem).

The second characteristic of mean centering concerns the interpretability of the estimates. The regression coefficient for a mean centered predictor may be more *practically* meaningful than the same coefficient for the same predictor with an arbitrary zero point (i.e., interpreting the relative size of change in $\boldsymbol{Y}$ for a one-unit change in $\boldsymbol{X}$ at a given level of $\boldsymbol{W}$ may be easier if the zero point of $\boldsymbol{W}$ is the average value of $\boldsymbol{W}$ rather than an arbitrary and nonmeaningful scale value). Plotting the predicted relationship between $\boldsymbol{X}$ and $\boldsymbol{Y}$ over a range of plausible $\boldsymbol{W}$-values can then be done, which would also increase interpretability of the interaction (e.g., Aiken & West, 1991; Cohen, Cohen, West, & Aiken, 2003; Mossholder, Kemery, & Bedeian, 1990).

Under most circumstances, mean centering is an adequate solution to the collinearity problem using multiplicative terms. At times, however, the resulting product or powered term will still have some degree of correlation with its first-order constituent variables, resulting in partial regression coefficients that may still show some modest instability (e.g., when bivariate normality is substantially violated). To remedy this lack of complete orthogonality when performing mean centering, a simple two-step regression technique called *residual centering* is available that ensures full orthogonality between a product term and its first-order effects (Lance, 1988). As with mean centering, this technique is also generalizable to powered terms.

Residual centering is an alternative approach to mean centering that also serves to eliminate nonessential multicollinearity in regression analyses. Residual centering (see Lance, 1988) is a two-stage ordinary least squares (OLS) procedure in which a product term or powered term is regressed onto its respective first-order constituent terms. The residual of this regression is then saved and subsequently used to represent the interaction or powered effect. The reliable variance of this new orthogonalized interaction term contains the unique variance that fully represents the interaction effect, independent of the first-order effect variance. Similarly, the reliable variance of a residual-centered powered term contains the unique variance accounted for by the curvature component of a nonlinear relationship, independent of the linear components.

Residual centering has a number of inherent advantages for regression analyses. First, the regression coefficients for orthogonalized product or powered terms are stable. That is, the regression coefficients and standard errors of the first-order variables remain unchanged when the higher order term is entered. Second, the significance of the product or powered term is unbiased by the orthogonalizing process. Third, unlike mean centering, orthogonalizing via residual centering ensures full independence between the product or powered term and its constituent main effect terms (Lance, 1988; Little et al., 2006).

Both mean centering and residual centering are beneficial for testing interactions in regression models; however, estimating interaction effects within regression models is still problematic. A key concern is the effect of measurement error on the power to detect such effects. Because OLS regression assumes that variables are measured perfectly reliably (i.e., without error), violating this assumption will lead to bias in the parameter estimates (Busemeyer & Jones, 1983). Measurement error is problematic for all variables in a regression analysis, but it is particularly troublesome for an interactive or nonlinear term because the unreliabilities of the constituent variables are compounded in the interactive or higher order term. A related concern is the differentiation of multiplicative and nonlinear effects under such conditions of low power (for more complete discussions, see Cortina, 1993; Ganzach, 1997; Kromrey & Foster-Johnson, 1998; Lubinski & Humphreys, 1990; MacCallum & Mar, 1995).

Structural equation modeling (SEM) represents an important advance in the study of multiplicative or nonlinear effects because of its ability to properly address the presence of measurement error within a statistical model. In SEM, the proportion of variance common to multiple indicators of a given construct is estimated, and the structural relations among these latent constructs may then be modeled, disattenuated for measurement error. Numerous authors have described techniques to represent latent variable interactions within the context of SEM (see Algina & Moulder, 2001; Jaccard & Wan, 1995; Jöreskog & Yang, 1996; Ping, 1996a, 1996b; Schumacker & Marcoulides, 1998; Wall & Amemiya, 2001). Most of these approaches are based on the Kenny and Judd (1984) product-indicator model and require complex nonlinear constraints.

As described in Little et al. (in press), Bollen (1995, 1996, 1998), and Bollen and Paxton (1998) presented a two-stage least squares (2SLS) approach that does not require the nonlinear constraints but has been found to be less effective than other methods (Moulder & Algina, 2002; Schermelleh-Engel, Klein, & Moosbrugger, 1998). Klein and Moosbrugger (2000) proposed a latent moderated structural model approach (LMS) utilizing finite mixtures of normal distributions which was further refined by Klein and Muthén (2002) as a quasi-maximum likelihood (QML) approach. The LMS/QML approach was found to perform well under conditions where first-order indicators are normally distributed (Marsh, Wen, & Hau, 2004). Finally, Marsh et al. (2004) proposed an unconstrained product-indicator approach that also performed well, even when underlying distributional assumptions are not met.

Most SEM software programs can implement the nonlinear constraints that are necessary to model latent variable interactions based on the Kenny and Judd (1984) product-indicator method. The less-effective 2SLS approach is available through PRELIS, the pre-processor for LISREL (Jöreskog & Sörbom, 1996), while the LMS/QML approach was made available in Mplus starting with version 3 (Muthén & Asparouhov, 2003; Muthén & Muthén, 2006). Although these programs make latent variable interactions more accessible, researchers must either use these two software programs or implement complex nonlinear constraints.

Little et al. (2006) recently proposed a straightforward method that can be used across any SEM platform. Their method is also based in principle on the product-indicator approach but uses the orthogonalizing procedures described earlier to create product indicators that are uncorrelated with the indicators of the main-effect constructs. In our view, the orthogonalizing technique (a) is less technically demanding than alternative methods of including interactive and powered terms in latent variable models based on nonlinear constraints, (b) can be implemented in any SEM software platform, and (c) provides reasonable estimates that are comparable to other existing procedures including the LMS/QML approach of Mplus (see Little et al., 2006, for a comparison). Other advantages of the orthogonalizing technique include: (a) main effect parameter estimates are unaffected when the interaction latent construct is entered into the model, (b) model fit is not degraded once the interaction latent construct is entered into the model, and (c) the orthogonalizing technique is readily generalizable for creating powered latent variables to represent quadratic, cubic, or higher order nonlinear relationships.

Although the steps and procedures are detailed in Little et al. (2006), we briefly outline the steps and technical issues related to implementing the orthogonalized latent variable interaction construct. Like other procedures that utilize the product-indicator approach, the orthogonalizing technique begins with the formation of all possible products of the corresponding indicators of the two constructs involved in the interaction. Assuming the moderated construct has three indicators ($\boldsymbol{X}_1,\ \boldsymbol{X}_2,\ \boldsymbol{X}_3$) and the moderating construct has three indicators ($\boldsymbol{W}_1,\ \boldsymbol{W}_2,\ \boldsymbol{W}_3$), one would calculate nine total product variables ($\boldsymbol{X}_1\boldsymbol{W}_1,\ \boldsymbol{X}_1\boldsymbol{W}_2,\ \boldsymbol{X}_1\boldsymbol{W}_3,\ \boldsymbol{X}_2\boldsymbol{W}_1,\ \boldsymbol{X}_2\boldsymbol{W}_2,\ \boldsymbol{X}_2\boldsymbol{W}_3,\ \boldsymbol{X}_3\boldsymbol{W}_1,\ \boldsymbol{X}_3\boldsymbol{W}_2,\ \boldsymbol{X}_3\boldsymbol{W}_3$. In the next step, each of the product indicators would be regressed onto the set of indicators representing the indicators of the main-effect constructs in order to remove any of the main-effect information contained in any of the indicators of the constructs:

$$\boldsymbol{X}_1\boldsymbol{W}_1 = b_0 + b_1\boldsymbol{X}_1 + b_2\boldsymbol{X}_2 + b_3\boldsymbol{X}_3 + b_4\boldsymbol{W}_1 + b_5\boldsymbol{W}_2 + b_6\boldsymbol{W}_3 + e_{x1w1}. \quad (3)$$

For each regression, the residuals of the prediction (e.g., e_{x1w1} from equation 3) would be saved as a new variable in the dataset (e.g., $\boldsymbol{o\_X}_1\boldsymbol{W}_1$, where $\boldsymbol{o\_}$ denotes the fact that this variable has been orthogonalized with respect to the set of main-effect indicators). The nine new orthogonalized indicators would then be brought into the SEM model to serve as indicators for a latent interaction construct. Each of the nine indicators would be allowed to load on the latent interaction construct which, thereby, would be defined as the common variance among the nine orthogonalized indicators. For the interaction effect to be estimated in an unbiased manner, however, specific residuals are expected to correlate. For example, in the case of nine orthogonalized indicators, there are 18 combinations of residuals among the nine indicators that need to be allowed to correlate. Specifically, each pair of orthogonalized product indicators that share a common indicator in their composition should be allowed to correlate. For example, $\boldsymbol{o\_X}_1\boldsymbol{W}_1$ should be allowed to correlate with each product indicator that shares $\boldsymbol{X}_1$ and each product indicator that shares $\boldsymbol{W}_1$. That is, because $\boldsymbol{o\_X}_1\boldsymbol{W}_1$ contains unique variance associated with $\boldsymbol{X}_1$, one would expect correlated residuals with $\boldsymbol{o\_X}_1\boldsymbol{W}_2$ and $\boldsymbol{o\_X}_1\boldsymbol{W}_3$. Similarly, because $\boldsymbol{o\_X}_1\boldsymbol{W}_1$ contains unique variance associated with $\boldsymbol{W}_1$, one would expect correlated residuals with $\boldsymbol{o\_X}_2\boldsymbol{W}_1$ and $\boldsymbol{o\_X}_3\boldsymbol{W}_1$). The product indicators would not be correlated with the corresponding main effect indicators because the linear information associated with these main effect indicators has been removed via the orthogonalizing steps.

When this latent interaction term is included in the model, the focus is solely on the significance of the estimated effect of this latent interaction construct onto the outcome construct. As mentioned, because the latent interaction construct is orthogonal to the main effect constructs, the estimates for the latent main effects would be unchanged between the model in which the interaction construct is present and when it is not included in the model (see Little et al., 2006; see also Marsh et al., 2004; Marsh, Wen, Hau, Little, Bovaird, Widaman, in press).

COMBINING MODERATION AND MEDIATION

It is not uncommon for hypotheses about moderation and mediation relationships to occur in the same context. Models in which interaction effects are hypothesized to be mediated or indirect effects are hypothesized to be moderated are appearing with increasing frequency. When an interaction effect is mediated by $\boldsymbol{M}$, the effect is termed *mediated moderation* (Baron & Kenny, 1986). When an indirect effect is moderated by at least one moderator variable, the effect is termed *moderated mediation* (James & Brett, 1984; Lance, 1988; Muller, Judd, & Yzerbyt, 2005).

Mediated moderation

It is often of interest to ascertain how a moderation effect is transmitted to a dependent variable. A theoretical precedent for investigating such effects can be found in Hyman (1955), who termed moderation *specification* and mediation *interpretation*: "... specification may almost always be considered a prelude to interpretation, rather than an analytic operation which is sufficient in itself" (p. 311). Indeed, Kraemer, Wilson, Fairburn, and Agras (2002) recommend that moderation be automatically considered in any mediation analysis. Echoing Hyman (1955), Baron and Kenny (1986) described an intuitive method for assessing *mediated moderation* (a term they coined) that involves first showing an interaction effect of $\boldsymbol{X}$ and $\boldsymbol{W}$ on $\boldsymbol{Y}$, then introducing a mediator of that interaction effect. Wegener and Fabrigar (2000) characterize mediated moderation as occurring "when a moderator interacts with an IV to affect a DV, but the moderator has its effect via some mediating variable" (p. 437). Morgan-Lopez and MacKinnon (2006) note that mediated moderation models "involve the interaction effect between two predictor variables on a mediator which, in turn, affects an outcome." Mediated moderation, according to Muller et al. (2005), "can happen only when moderation occurs: The magnitude of the overall treatment effect on the outcome depends on the moderator (p. 853)."

Under such circumstances, the same procedures used to assess simple mediation may be applied to key regression weights in the model (Lance, 1988; Morgan-Lopez, 2003; Morgan-Lopez, Castro, Chassin, & MacKinnon, 2003; Morgan-Lopez & MacKinnon, 2006). The hypothesis is simply that the product of the regression weights linking $\boldsymbol{XW}$ to $\boldsymbol{M}$ and $\boldsymbol{M}$ to $\boldsymbol{Y}$ is too large relative to its standard error to be considered due to chance. Morgan-Lopez and MacKinnon (2006) recommend probing significant effects, but doing so implies that the researcher has ceased thinking of the effect as mediated moderation and has instead adopted a moderated mediation hypothesis (see following). We suggest instead that, because the mediated moderation effect as defined above *is not* conditional on $\boldsymbol{W}$, no probing is necessary (it is the interaction effect that is hypothesized to be mediated, and this effect is considered constant across all $\boldsymbol{X}$ and $\boldsymbol{W}$ unless higher order terms are added to the model), although it may be of interest to plot and probe the interactive effects of $\boldsymbol{X}$ and $\boldsymbol{W}$ on $\boldsymbol{M}$ and $\boldsymbol{Y}$ separately by computing simple slopes (Aiken & West, 1991) or by using the Johnson-Neyman technique (Bauer & Curran, 2005; Preacher, Curran, Bauer, in press).

Moderated Mediation

If the moderator is a discrete variable, one might combine the mediation analyses described here with multiple-group approaches (see Little et al., chap. 6, this volume). If the moderator is a continuous variable, one might create an interaction term to reflect how a is moderated by $\boldsymbol{W}$ (i.e., create an $\boldsymbol{X}$ by $\boldsymbol{W}$ latent interaction variable that would predict $\boldsymbol{M}$) and/or a second interaction term to reflect how b is moderated by $\boldsymbol{W}$ or another moderator $\boldsymbol{Z}$ (Lance, 1988). Lance (1988) and Preacher, Rucker, and Hayes (in press) have outlined frameworks for assessing indirect effects that are conditional on the value of at least one moderator. We briefly describe their approaches.

Lance (1988) describes a strategy for assessing moderated mediation that involves using residual centering. In Lance's approach, the product of mediator $\boldsymbol{M}$ and moderator $\boldsymbol{W}$ is computed and regressed on its constituent terms, yielding residuals $\boldsymbol{o\_MW}$. These residuals in turn may be included in a standard mediation model: $\boldsymbol{X} \rightarrow \boldsymbol{o\_MW} \rightarrow \boldsymbol{Y}$, and mediation may be assessed by any of a number of traditional methods described here and elsewhere. Lance's approach is limited to the situation in which b is moderated by some variable $\boldsymbol{W}$, but it would be straightforward to extend the method to other models. Lance's approach may be applied in SEM with latent mediators by computing products of residual centered variables and using them as indicators of a latent mediator. However, it is unclear how the moderation effect can be further explored or clarified by means of simple slopes analysis.

Preacher et al. (in press) describe five archetypal models of moderated mediation to establish a framework for discussing *conditional indirect effects*, defined as the magnitude of an indirect effect conditional on (or at a hypothetical value of) at least one moderator. These models are illustrated in schematic form in Figure 9.4 (Lance's [1988] model corresponds to the model in Panel C). These models provide a starting point for discussing moderated mediation, and by no means do they exhaust the range of models that could describe moderated mediation processes. In each of the models depicted in Figure 9.4, a mediation effect is potentially being moderated by $\boldsymbol{W}$ and/or $\boldsymbol{Z}$. If the conditional indirect effect varies significantly as a function of the moderator(s), then moderated mediation is said to occur.

For example, say a researcher hypothesizes that the number and severity of children's internalizing problems affect self-esteem indirectly through physical and verbal victimization by peers, but that this indirect effect depends on peer rejection (for similar hypotheses see Hodges, Malone, & Perry, 1997; Hodges & Perry, 1999). If this turns out to be the case, then the indirect effect of internalizing on self-esteem through victimization is moderated by peer rejection. This hypothesis resembles Preacher et al.'s (in press) Model 2. The relevant regression equations are:

$$\begin{aligned}\boldsymbol{Victimization} &= a_0 + a_1(\boldsymbol{Internalizing}) + a_2(\boldsymbol{Rejection}) \\ &\quad + a_3(\boldsymbol{Internalizing} \times \boldsymbol{Rejection}) + e_V. \end{aligned} \tag{4}$$

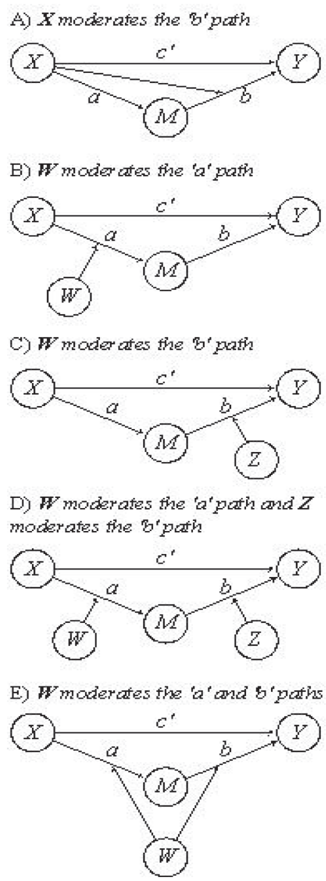
$$\begin{aligned}\boldsymbol{Self\text{-}Esteem} &= b_0 + b_1(\boldsymbol{Victimization}) + c'_1(\boldsymbol{Internalizing}) \\ &\quad + c'_2(\boldsymbol{Rejection}) + c'_3(\boldsymbol{Internalizing} \times \boldsymbol{Rejection}) + e_S. \end{aligned} \tag{5}$$

In this model, the conditional indirect effect of internalizing on self-esteem can be quantified as $(a_1 + a_3(\boldsymbol{R})) \times b_1$, where $\boldsymbol{R}$ represents a conditional value of peer rejection. Preacher et al. provide normal-theory standard errors and resampling approaches for testing the significance of such effects, as well as software to conduct these analyses.[2] Of potentially greater value and utility to the applied researcher, the method can be adapted to reveal the range of values of the moderator(s) for which the indirect effect of $\boldsymbol{X}$ on $\boldsymbol{Y}$ is statistically significant (the *region of significance*). Although their method was developed for the case in which all variables are measured rather than latent,

[2] An SPSS macro is available at http://www.quantpsy.org/ for use with measured variables.

the method can be straightforwardly extended for use in SEM with latent variables. Point estimates and standard errors for conditional indirect effects at any value of the moderator may be computed using parameter estimates and asymptotic variances and covariances available from most SEM software. Alternatively, resampling may be used in SEM if AMOS or Mplus is used to estimate model parameters. All of the issues we discussed earlier with respect to simple

FIGURE 9.4
Five types of moderated mediation.



mediation—regarding proxy variables, unmodeled variables, equivalent models, and unreliab-ility—are at least as important in assessing moderated mediation as for assessing simple mediation. Also worth emphasizing is that the methods described by Preacher et al. are intended to address *statistical* significance rather than *practical* significance. In applied settings, both are important.

CONCLUSIONS

Hypotheses about mediation and moderation are commonly offered up by developmentalists, particularly those who are keenly interested in the influence of contextual variables on key developmental outcomes. In comparison to standard regression approaches, such complex extensions of these concepts of mediation and moderation are readily analyzable in the context of SEM analyses. Moreover, the basic tests of mediation and moderation in SEM are handled in a way that provides strong empirical evidence for or against a mediation or moderation hypothesis, particularly because effects are corrected for measurement error. With the added ability to directly estimate indirect relationships (as opposed to inferring them from a series of sequentially estimated regressions) and make direct statistical tests of the significance of any of the pathways modeled, SEM approaches to testing such complex hypotheses are very powerful. We hope that researchers will now find these approaches to be readily accessible. To aid in this accessibility, LISREL and Mplus scripts for testing mediation and moderation are available on the support Web page for this volume at Quant.KU.edu.

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