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Mediation Models for Longitudinal Data in Developmental Research

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Mediation models are used to describe the mechanism(s) by which one variable influences another. These models can be useful in developmental research to explicate the relationship between variables, developmental processes, or combinations of variables and processes. In this article we describe aspects of mediation effects specific to developmental research. We focus on three central issues in longitudinal mediation models: the theory of change for variables in the model, the role of time in the model, and the types of indirect effects in the model. We use these themes as we describe three different models for examining mediation in longitudinal data.

In this article we address aspects and applications of mediation analysis that are likely to be of particular interest to developmental scientists. We explore the interface between mediation models and developmental science, with an emphasis on models specifically designed for application with longitudinal data. These models can be used to address questions such as: What contextual, personality, or developmental factors initiate or influence a developmental process? How does a developmental process link a cause to future behavior? How do some processes mutually influence one another?

Speaking generally, mediation models are useful in describing the way in which one variable (generically, X) has an effect on another variable (Y) through its influence on some intermediate variable (M). Mediation models can be employed by researchers seeking to explicate causal relationships and in particular by developmentalists seeking to explain the ways in which contextual factors or developmental processes have effects on subsequent developmental processes.

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(As with any causal model, statistical results from a mediation model are not sufficient to make a case for causality. Theory and evidence in addition to the statistical results are required to make such a case. See Lindenberger and Pötter, 1998, for further cautions regarding the use of mediation models in developmental research.) The conceptual model underlying most applications of mediation analysis is expressed in the following equations:

$$\begin{aligned} M &= \beta_{0m} + \beta_{xm}X + \varepsilon_m \\ Y &= \beta_{0y} + \beta_{xy}X + \beta_{my}M + \varepsilon_y \end{aligned} \tag{1}$$

where M is predicted by X, and Y is predicted by X and M. Mediation is represented in the model as the indirect effect of X on Y, which is usually operationalized as the product of the β_{xm} and β_{my} coefficients. Often the indirect effect ($\beta_{xm} \times \beta_{my}$) is interpreted in conjunction with the magnitude of the direct effect β_{xy}. If the direct effect is no longer statistically significant after adding the mediator to the model, full mediation is said to occur, and if the direct effect is reduced relative to the direct effect without the mediator in the model but is still significant, partial mediation is indicated. Here we focus on $\beta_{xm} \times \beta_{my}$ regardless of the size or statistical significance of β_{xy}.

USE OF MEDIATION MODELS IN DEVELOPMENTAL RESEARCH

Mediation models in developmental research are typically used to describe the way a cause, usually a contextual factor, has its effect on the outcome, usually some aspect of development. For example, Spinrad and colleagues (2007) used mediation analysis to show that children's effortful control mediates the relation between supportive parenting and various child developmental outcomes such as externalizing behavior and social competence. Dodge and colleagues (2003) used mediation analysis to show that social information processing is one of the mechanisms by which social rejection has an impact on aggressive behavior. Finally, researchers from the National Institute for Child Health and Development's Study of Early Childcare (NICHD ECCRN: 2003) found evidence that attention processes serve as mediators between the family environment and school readiness. Other examples are readily found.

IMPORTANCE OF LONGITUDINAL DATA

There are two important reasons that longitudinal data are to be preferred for the testing of mediation hypotheses in developmental research. The first of these reasons relates to the quality of the results from a mediation model using cross-sectional data and in fact applies to testing mediation in any field. There are a number of fundamental problems with the application of traditional mediation models to cross-sectional data. Three such problems are described by Gollob and Reichardt (1987). First, the causal relationships implied by the paths in the mediation model take time to unfold. However, the use of cross-sectional data implies that the effects are instantaneous. Clearly such an assumption is problematic on logical grounds. Second, it is well known that conclusions based on a causal model that omits a key predictor can be seriously in error, yet a model based on cross-sectional data leaves out several key predictors—namely the variables measured at previous times. When previous levels of the variables are not controlled for, the paths in the mediation model may be over- or underestimated relative to their true values. Third, effects unfold over time, and we would not expect the magnitude of a causal effect to remain the same for all possible intervals. The application of the mediation model to cross-sectional data assumes not only that the causes are instantaneous, but also that the magnitude of the effect is not dependent on the length of time that elapses between the measurements of the variables. Cole and Maxwell (2003; Maxwell & Cole, 2007) elaborate on the pitfalls of using cross-sectional data to model mediation, showing that severe bias is probable in this situation.

The second reason that longitudinal data are to be preferred when testing mediation in developmental research relates more specifically to the interests of developmental researchers. Development is most often conceived of as occurring within individuals. Many have advocated an emphasis within developmental studies on intraindividual variation and individual differences in that intraindividual variation (see, e.g., Nesselroade, 1991). As we subsequently describe, traditional mediation models (even those that utilize longitudinal data) focus on interindividual differences. However, we present two mediation models that allow the user to explicitly include intraindividual variation as a part of a mediation process.

MEDIATION MODELS FOR LONGITUDINAL DATA

Mediation models for longitudinal data have much to offer for improving statistical inference and for allowing the examination of intraindividual variation. However, the choice to use longitudinal data adds considerable complexity to the mediation model. In this section we address three important issues to consider for mediation models using longitudinal data. Two of these issues are common to any longitudinal model but the third is specific to longitudinal mediation models. The first issue relates to what Collins (2006) called the "theory of change." Included under this heading are whether the variables in the model are expected to change, in what ways the variables are expected to change, and what the possible determinants of change may be (see also Ram & Gerstorf, this issue). As we detail in describing the models below, the theory of change should inform the mediation model we choose. The second issue is the important role of time in any model. This applies to choosing the *period*, or time of interest in the life of the participants; choosing the *span* of the study, or length of time that participants will be followed; as well as the *lag*, or the amount of time that will elapse between adjacent measurements. The third issue is one of multiple types of indirect effects possible when using longitudinal data. Contrary to the three-variable mediation models for cross-sectional data in which only one indirect effect is examined, mediation models for longitudinal data often have multiple indirect effects and even different types of indirect effects. It is important to consider whether and how to summarize these multiple indirect effects. Next we examine the aforementioned issues in the context of three mediation models for longitudinal data: a cross-lagged panel model, a latent growth curve model, and a latent difference score model.

Cross-Lagged Panel Model

Cole and Maxwell (2003) present a cross-lagged panel model (CLPM) for longitudinal data, based on a structural equation modeling (SEM) approach that has many advantages over models that use cross-sectional data. The CLPM is a multivariate extension of the univariate simplex model, one of the most commonly used structural models for the analysis of longitudinal data (Jöreskog, 1970, 1979). The CLPM allows time for causes to have their effects, supports stronger inference about the direction of causation in comparison to models using cross-sectional data, and reduces the probable parameter bias that arises when using cross-sectional data. Extensive overviews of the use of this model for mediation analyses are given by Cole and Maxwell (2003) and MacKinnon (2008). Figure 1 depicts such a model. Three constructs—X, M, and Y—are each measured at four times. The CLPM can be used with more or fewer waves of measurement, but at least three are needed to achieve a fully longitudinal mediation model. The constructs X, M, and Y are often latent variables with multiple indicators, although the model can be used with observed variables. Using latent variables has the advantage of addressing the problem of measurement error, thus disattenuating relationships among the constructs. The CLPM for X, M, and Y can be expressed by the following three equations (variables are centered here for simplicity),

$$\begin{aligned}
X_{[t]} &= \beta_{X,[t-1]}X_{[t-1]} + \zeta_{X,[t]} \\
M_{[t]} &= \beta_{M,[t-1]}M_{[t-1]} + \beta_{X,[t-1]}X_{[t-1]} + \zeta_{M,[t]} \\
Y_{[t]} &= \beta_{Y,[t-1]}Y_{[t-1]} + \beta_{M,[t-1]}M_{[t-1]} + \beta_{X,[t-2]}X_{[t-2]} + \zeta_{Y,[t]}
\end{aligned} \tag{2}$$

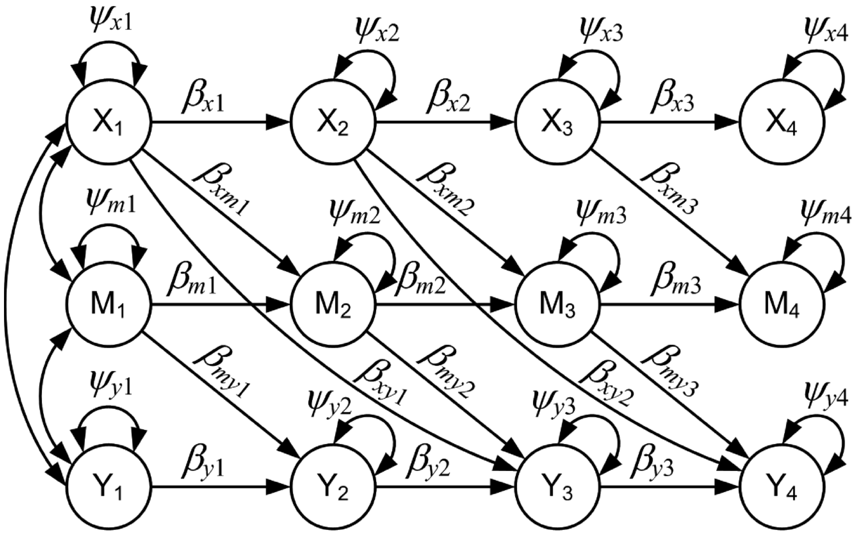

FIGURE 1 A cross-lagged panel mediation model.

where $X_{[t]}$ is the value of X at time t, $\beta_{X,[t-1]}$ expresses the relationship between the construct X at time t and the same construct measured at the previous time $t-1$, and $\zeta_{X,[t]}$ is a random disturbance that is different for each time. Similar interpretations can be given to corresponding terms in the equations for $M_{[t]}$ and $Y_{[t]}$. The CLPM in Figure 1 is restricted in two ways that are specific to the paths of influence in the mediation model. First, the direction of causal flow begins with X, extends to M, and ends with Y. There is nothing about the CLPM that imposes this restriction; it is due only to the fact that we posit a particular path of influence for the mediation model. In fact, Cole and Maxwell (2003) suggest that researchers should test for the presence of the omitted paths in the model. The second restriction on this model is that constructs are affected only by constructs one lag removed with the exception of the Y constructs that are influenced by X measured at time $t-2$. Again, this specification is suited to a particular kind of mediation hypothesis; other paths of influence are certainly possible and may be more appropriate depending on the research context. Choosing the paths to estimate will require a balance between finding the most parsimonious model and ensuring that meaningful paths are not omitted (i.e., constrained to zero).

Theory of Change

The CLPM is designed to assess change in interindividual standing on the variables in the model. A key limitation of this model is that it does not address two fundamental components of interest to those who study development: intraindividual change and individual differences in intraindividual change (Nesselroade, 1991). Ignoring cross-lagged regression paths and focusing on autoregressive paths, the CLPM implies that each construct is a function of the level of the same construct at the previous time plus some random disturbance component. The change that is described by this model is change in individual differences. The stability coefficient (e.g., $\beta_{X,[t-1]}$) that depicts change from one time to another describes, roughly speaking, the degree to which there is a reshuffling of individuals' standings on the measured construct. A high stability coefficient means that the change in individual differences was relatively small (i.e., there are minor changes in rank order or the same order is maintained, but the intervals between individuals change). When individuals do show changing levels of the construct being measured, the stability coefficient confounds a number of different types of change. For example, a high stability coefficient may mean, as just stated, that individuals are not changing and therefore individual differences are stable, that individuals are changing to a notable degree but all following a similar trajectory, or that individuals are changing but the magnitude of that change is small relative to the differences among individuals (Hertzog & Nesselroade, 1987, 2003). Finally, the CLPM does not allow the researcher to use development, or change in a construct, as a cause or effect of other variables in the model (Hertzog & Nesselroade, 2003).

Role of Time

The cross-lagged panel model does not explicitly incorporate the effect of the passage of time. It is assumed that observations are ordered in time such that X_2 is measured after X_1, but the length of time that passes is not specified and can range from seconds to decades, depending on the context. The choices of the developmental period and the span of the study are important for the CLPM in that the period must be chosen so that mediation is likely to occur during that time in the participants' lives, and the study must last long enough for the mediation process to have time to unfold. Lag, or the length of intervals between measurement occasions, is important because each autoregressive and cross-lagged effect can be interpreted only with reference to that observed interval. Many authors have pointed out the dangers of poorly choosing these intervals (Cohen, 1991; Cole & Maxwell, 2003; Collins & Graham, 2002; Maxwell & Cole, 2007). Foremost among these pitfalls is the potential to completely miss observing the effect of interest because the interval chosen was either too short for the effect to take place or so long that the impact of one construct on the other had long since faded. In mediation analysis with a panel model, the problem of poorly chosen lags is compounded because at least two (and sometimes several) lagged effects are multiplied together. Because of this potential for misrepresenting longitudinal effects, developmental researchers often face a very difficult dilemma. Although it is imperative that researchers give serious consideration to the choice of lag for a study, often there is no available theoretical or empirical basis for choosing lags. Resources such as a thorough consideration of the time scale of the developmental process under consideration, evidence from previous studies, and evidence from a pilot study may be useful in addressing this dilemma, but we note that no one lag is sufficient to understand a causal relationship and the use of varying lags within or across studies should be considered.

Types of Indirect Effects

In contrast to a mediation model with only three variables, in which only one indirect effect can estimated, the CLPM for longitudinal data may contain many possible indirect effects, depending on the number of waves of measurement. Following Gollob and Reichardt (1991), we can classify these as either time-specific indirect effects or total indirect effects. A time-specific indirect effect is represented by a single path of influence from the predictor, through the mediator(s), to the outcome. In Figure 1 the time-specific indirect effects are the different paths by which X_1 can indirectly influence Y_4. For example, one of the possible time-specific indirect effects of X_1 on Y_4 is represented by the product of the following coefficients: $\beta_{xm1} \times \beta_{my2} \times \beta_{y3}$. We contend that differential mediation occurring at one time but not another should be expected and of substantive interest. Furthermore, a study that captures only one indirect effect should be interpreted as showing an indirect effect that is specific to the observed interval and should not be construed as showing evidence for or against mediation at intervals not included in the study. Finally, this indirect effect will be specific to the ages or developmental stages of the sampled individuals at the time of measurement and also to the context of the study. In some instances it may be wise to examine not just the individual time-specific indirect effects of one variable on another, but the total indirect effect of X on Y inclusive of all time-specific indirect effects. For example, *the total indirect effect* of X_1 on Y_4 in Figure 1 is the sum of three time-specific indirect effects. Specifically, the total indirect effect of X_1 on Y_4 is the sum of the following paths: $X_1 \rightarrow M_2 \rightarrow Y_3 \rightarrow Y_4$; $X_1 \rightarrow M_2 \rightarrow M_3 \rightarrow Y_4$; and $X_1 \rightarrow X_2 \rightarrow M_3 \rightarrow Y_4$. (In defining these effects we are ruling out the possibility of instantaneous effects whereby variables affect other variables measured concurrently.) The point here is that any specific indirect effect in such a model shows only one of many possible paths of influence and the sum of all possible indirect effects more faithfully depicts the degree to which X_1 indirectly influences Y_4.

Recommendations

Due to the fact that the CLPM best captures interindividual change, this model may be most useful when the variables of interest do not exhibit marked intraindividual change over time. Careful thought should be given to the choice of lags and the period of the study. When multiple meaningful specific indirect effects are available, each should be tested. Differential mediation across some spans of time but not others holds the potential for better understanding mediation processes. Finally, we agree with the recommendations of others (Cole & Maxwell, 2003; Gollob & Reichardt, 1991) that reporting the total indirect effect, in conjunction with each of the time-specific indirect effects, is important to capture the entire indirect effect across the span of time studied.

Example

Pardini, Loeber, and Stouthamer-Loeber (2005) used a CLPM to examine the relationships among family conflict, adolescents' affiliation with deviant peers, and adolescents' beliefs about deviant behavior. Each of the three constructs was modeled as a latent variable with multiple indicators and was assessed on an annual basis from the 6th to the 11th grades. Whereas the indirect effect of family conflict on beliefs about deviant behaviors as mediated by affiliation with deviant peers was not directly tested, this research design, in which each construct is measured repeatedly, is well-suited for testing mediation. To address the three issues introduced above, it would be incumbent upon the authors to address how these constructs are expected to change over time and whether intraindividual change is of particular interest. Consideration of the role of time in the study would require examination of: whether the period studied (i.e., Grades 6 – 11) is a time when the mediation process would be expected to occur, whether the 5-year span of the study allows sufficient time for the mediation to occur, and whether the choice of one-year lags was appropriate for detecting the wave-to-wave influence of the constructs on one another.

THE LATENT GROWTH MEDIATION MODEL

Latent growth curve modeling (LGM) is another application of SEM to the analysis of change over time. In longitudinal settings, typically individuals are measured at multiple occasions, and often it is of interest to gauge the average rate at which they change (the slope mean), along with the interindividual variability in that rate (the slope variance). In LGM, intercepts and slopes are represented as latent variables that are allowed to vary across individuals. In the standard linear LGM, estimated parameters include the intercept and slope means, the intercept and slope variances and covariance, and residual variances that may or may not be constrained to equality over repeated measures. Consider a situation with four equally spaced repeated measures of Y, which load on an Intercept factor and a Slope factor. The loadings for the Intercept factor are set equal to 1, and the loadings for the Slope factor are set equal to values of the time variable (t). $Y[t]$ can thus be expressed as a function of the factors on which it loads:

$$Y_{[t]} = Intercept + [t-1]Slope + \zeta_{Y,[t]} \tag{3}$$

and the Intercept and Slope factors, in turn, can be expressed as functions of means and individual deviations away from those means:

$$\begin{aligned} Intercept &= \alpha_i + \zeta_i \\ Slope &= \alpha_s + \zeta_s \end{aligned} \tag{4}$$

Because LGM is an application of SEM, the growth curve model may be included in larger models in a modular fashion, treating Intercept and Slope factors as variables in larger networks of interrelated constructs. There are many extensions and elaborations of LGM for application in specific settings. The interested reader is referred to Bollen and Curran (2006) and Preacher, Wichman, MacCallum, and Briggs (2008; see also Grimm & Ram, this issue).

LGM has intriguing potential for application in mediation analysis. For example, Cheong, MacKinnon, and Khoo (2003) describe a parallel process LGM that introduces latent growth models to the study of mediation. This model is depicted in Figure 2. In this model, individuals participate in an intervention program (X) and subsequently two variables (M and Y) are repeatedly measured over the same span of time. The variances for the intercept of M (ψ_{im}) and the slope of Y (ψ_{sy}) are now residual variances. One of the possible mediation paths, then, extends from X to the intercept for M (i.e., initial status on the mediator) and then to the slope for Y (i.e., change in the outcome variable), although other models with different paths may be reasonable to specify. In this way the parallel process mediation model can address research questions such as whether the impact of the intervention on change in Y is mediated by initial standing on M. MacKinnon (2008) showed how this model can be extended to situations in which there is no intervention and instead there are three parallel growth processes. Many hybrid models are also possible that would incorporate aspects of the CLPM with the LGM mediation model. For example, the model in Figure 2 could be changed so that the mediator is measured repeatedly but modeled in an autoregressive fashion. This would mean that any of the repeatedly measured variables (M_2–M_3) could serve as potential mediators of the relationship between the intervention (X) and initial status or change in the outcome (Y). However, as we note below, care should be taken not to test mediation paths in which a variable affects variables measured at the same or a previous time.

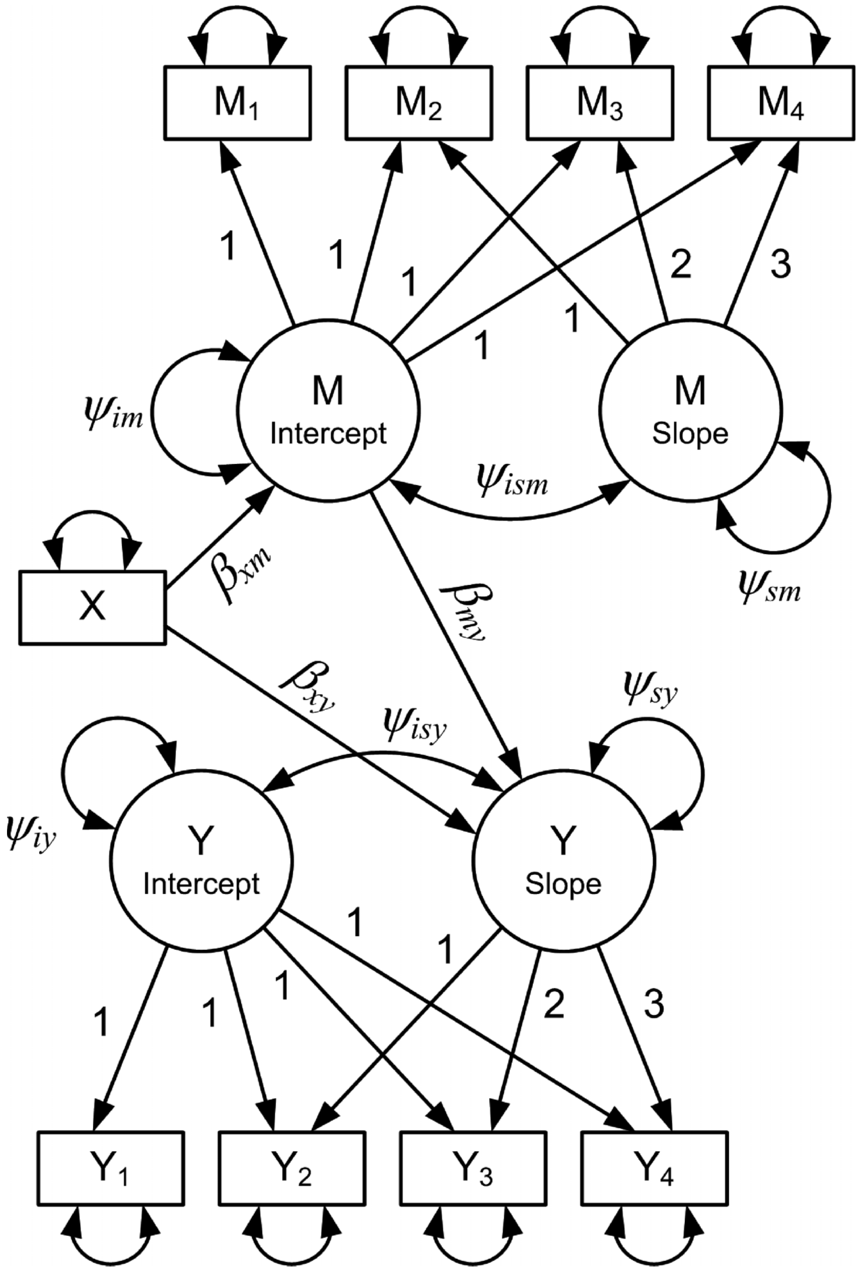

FIGURE 2 A latent growth curve mediation model in which the M and Y are permitted to change over time (mean structure omitted for simplicity).

Theory of Change

The kind of change modeled in a LGM is quite different from that modeled with a CLPM. The focus of the LGM is on inter- and intraindividual change in the level of a variable over time. For example, it is known that there is a systematic increase in vocabulary during early childhood (see, e.g., Pan, Rowe, Singer, & Snow, 2005), but there is considerable variability in initial vocabulary at the beginning of this period and the rate at which vocabulary increases. It would be important in cases like this to use a modeling framework that permits trajectories of change to vary from individual to individual. In choosing the latent growth mediation model, the researcher acknowledges that, for at least one of the variables of interest, individuals are changing in a systematic way on average, and that interindividual variability exists around that average rate of change. Further, not only is the kind of change emphasized in a latent growth mediation model different from that emphasized by the CLPM, but the use of change as a variable that can play a role as an independent, dependent, or mediator variable makes such a model distinct from the CLPM.

Role of Time

Unlike the CLPM, the choice of lags plays less of a role in interpreting the indirect effects. The primary importance of choosing the intervals between measurements is on measuring frequently enough to capture the underlying shape of the trajectory. Choosing the span of the study plays an important role in this model both in the sense it did for the CLPM (i.e., ensuring that there is sufficient time for the mediation process to occur) and in the sense that the span of time chosen for each separate LGM is of critical importance. The issue of choosing lags also reappears in the choice of how much time elapses between the separate LGMs in the full model. Finally, the arbitrary choice of the point at which time = 0 (which in turn determines the interpretation of all parameters relating to the intercept) for each LGM makes any indirect effect that includes one of the intercepts only one of many possible indirect effects for that model. One could change any indirect effect involving an intercept by changing the time chosen to define the intercept.

We note that the previously described problem of using cross-sectional data to model a mediation process that unfolds over time may also be present when using parallel growth processes to model mediation. Care should be taken so that mediation that includes paths that run contrary to the flow of time is not tested. For example, we would not expect that change in M over the measured span of time would influence the initial status of Y, which exists before the change in M had a chance to occur. It may be preferable to use a *sequential process* latent growth mediation model. In such a model, X would be measured repeatedly on some interval t_0 to t_j, M would be measured repeatedly on a sequential interval from t_j to t_k, and Y would be measured on a sequential interval from t_k to t_l ($j < k < l$). In this model, the initial status and change constructs could serve as predictors for any status and change construct measured on a later interval, while avoiding logical problems involving reverse or concurrent causation.

Types of Indirect Effects

When modeling three growth processes or an intervention and two growth processes, there is not an issue of time-specific indirect effects—the variables (i.e., intercepts and slopes for *X*, *M*, and *Y*) involved in the mediation path are measured only once. However, the fact that intercept and slope latent variables can be part of the mediation paths for the latent growth mediation means that there are now three characteristically different types of indirect effects: those involving only intercepts, those involving only slopes, and those that involve intercepts and slopes. Therefore, the idea of combining the different types of indirect effects into a total or summary indirect effect is not useful and could result in considerable confusion. For example, the use of the latent growth mediation model implies that intraindividual change is of primary interest, therefore a significant total indirect effect that is based only on indirect effects including the intercepts would be very misleading.

Recommendations

The use of LGMs for testing mediation is relatively new. This approach appears promising in that it provides a better approach, compared to the CLPM, to examining mediation when one or more of the variables exhibit a meaningful trajectory of change. In this way it could be a useful tool for those studying developmental issues. The latent growth mediation model requires a considerable amount of preparation prior to estimating the mediation aspect of the model. First, careful consideration is required for each of the growth processes modeled. One must consider the appropriate shape of each trajectory (i.e., linear, quadratic, etc.) and the span of time over which each process is measured. Finally, careful consideration must be given to the components of any mediation path. Causal issues become more complex when making the case that change in one variable over some period of time is used to predict change in another variable over some subsequent period of time. Just as in the CLPM, the length of time that elapses between measurements will affect results, so too will the choice of the span of time for each variable as well as the amount of time that elapses between the chosen spans for each of the variables. When the intercepts are included as part of the mediation process, careful consideration must be given to the choice of what point in time will be represented by zero. The magnitude and interpretation of the indirect effect will change when the location of the intercept is changed.

Example

The latent growth mediation model can be useful when change in one of the three variables involved in the mediation process is of particular interest. Such a situation could arise in the study of cognitive processes in older age. There is much evidence to show that certain aspects of fluid intelligence decline in later life (Salthouse, 2004). Some see this decline as being related to a decline in mental activity in later life, the “use it or lose it” hypothesis. A number of interventions have been designed to stave off declining mental performance by engaging older individuals in mental training (see Salthouse, 2006, for a review). It is possible to address the questions of whether and how an intervention may affect cognitive decline through the use of a latent growth mediation model. Such a model could appear as the model in Figure 2 where the intervention is the mental training program, the mediator could be some measure of the amount of mental activity engaged in by the participants, and the outcome could be some measure of mental performance (e.g., a subtest from an intelligence scale). Mental training and mental performance could be measured in parallel or in sequence. As we previously cautioned, measuring the processes in parallel weakens the potential to draw causal conclusions regarding the relationship between the mediator and outcome. However, measuring in sequence requires giving careful consideration to the most meaningful span of time over which to measure the mediator and the outcome. Such a model could be used to address the primary question of the intervention regarding whether the intervention produced less decline in mental performance, and it could further be used to address whether such a result were due to change in mental activity.

MEDIATION IN LATENT DIFFERENCE SCORE MODELS

Latent difference score (LDS) models are similar to LGMs in that change, and individual differences in change, are explicitly represented in the model. There is a growing methodological literature on such models, and they are being used more frequently in substantive applications (e.g., King et al., 2006). A variety of models may be considered latent difference score models. Such models have in common that change, represented by the difference between adjacent observations, is represented in the model as a distinct latent construct. Here we use a relatively simple version of a LDS as described by McArdle and Nesselroade (1994); for further extensions and more elaborate models see McArdle (2001) and Hamagami and McArdle (2007), and see MacKinnon (2008) for a description of how such models may be used to assess mediation.

In the LDS model for one construct, X, the construct is repeatedly measured. The model is structured such that the change between two measurements is represented as a latent variable ΔX. The repeated measures of X are then represented as the latent variables X_1, X_2, and so on. The construct X at time t is described by the following equation as the sum of two components: X at the previous time and change in X.

$$X_{[t]} = X_{[t-1]} + \Delta X_{[t]} \tag{5}$$

The change in X, in turn, is expressed as a function of X at time $t - 1$:

$$\Delta X_{[t]} = \beta_{t-1} X_{[t-1]} \tag{6}$$

The coefficient $\beta_{[t-1]}$ is the effect of the previous level of X on change in X. In this model we do not assume that change will be constant for each lag or that the effect of the previous level of X on change in X will be the same for each lag.

Theory of Change

As with the LGM, the LDS model focuses on intraindividual change and individual differences in that within-individual change. A difference between the LGM and LDS mediation models is that the change modeled by the LDS model spans only a single interval. In a situation in which a trajectory of change is expected to differ from one interval to the next, the LDS may be preferred over the LGM.

Role of Time

As with the two previous models, choice of developmental period and the span of the study are important to ensure that the mediation process is likely to occur during the chosen period and that the span of the study is sufficient for the mediation process to take place. Similar to the CLPM, choice of lag plays an important role in the interpretation of the indirect effects because the meaning of the difference score construct is specific to the chosen interval. Change over one-month intervals will certainly have a different meaning than change over 6-month or yearly intervals.

Types of Indirect Effects

As with the parallel and sequential process LGMs, a multivariate LDS model would make possible the estimation of multiple indirect effects. For example, in a LDS model of X, M, and Y we can model an indirect path from the initial status of X_1 to the initial status of M_2 to the initial status of Y_3, or a path from ΔX_1 to ΔM_2 to ΔY_3, or any combination of the initial status and change constructs. Each of these indirect effects has a distinct substantive interpretation. As with the LGM, we do not recommend combining the different types of indirect effects into a total indirect effect. The meaning of an indirect path containing only initial status constructs will be quite different from the meaning of an indirect path containing only latent difference scores or some mixture of the status and change constructs. Indirect paths containing only status constructs speak to changes in individual standing on the construct, whereas those based wholly or in part on latent difference scores speak to individual standing on change between measurements.

Recommendations

The LDS model may be preferred to the LGM when the focus is on within-individual change, but when that change may be different during different phases of the study. For example, if the effect of *X* or change in *X* on *M* or change in *M* is expected to change across the span of the study, the LDS mediation model may be superior to the LGM approach because the trajectories of change for the constructs in the LGM approach are usually assumed to be equal across the span of time the construct is measured (if growth is linear). In a related manner, the LDS model may be preferred over the LGM when, during the span of the study, some event or developmental milestone occurs such that the trajectory for one or more of the constructs is expected to change.

DATA EXAMPLE

Of the three models described in this article, the LDS mediation model is the only one for which an empirical example has not previously been published. Therefore we illustrate this model with an empirical example. The example we used posits maternal sensitivity (*SENS*) as a mediator of the relationship between maternal depressive symptoms (*MD*) and children's problem behavior (*CPB*). There is much evidence that children whose mothers are depressed show higher levels of problem behavior (e.g., Leve, Kim, & Pears, 2005). But this association alone does not explain how the presence of depressive symptoms in the mother has its impact on the behavior of the child. It is possible that the problem behaviors may result from shared genetic influence that results in problems for mother and child, or that there is some other unobserved factor present in the life of the family that jointly affects parent and child. Here we examine a third possibility, that a mother's depressive symptoms affect her level of sensitivity toward her child, and it is this diminished sensitivity that leads to subsequent problem behavior in the child.

Sample

The data for this example are drawn from the National Institute for Child Health and Development's Study of Early Childcare (NICHD ECCRN, 1993). We use data from mothers' reported levels of depressive symptoms from the Center for Epidemiological Studies Depression measure completed when the children were 6 and 15 months of age (CES-D; Radloff, 1977); observed maternal sensitivity was coded by trained observers from a videotaped structured interaction when children were 15 and 24 months of age (NICHD ECCRN, 1999); and mothers' ratings of children's behavior problems from the Child Behavior Checklist (CBCL; Achenbach, 1992) were completed when children were 24 and 36 months of age. For ease of presentation, we label the times of observation as Time 1 (child age 6 months), Time 2 (child age 15 months), Time 3 (child age 24 months), and Time 4 (child age 36 months).

Instruments

The CES-D (Radloff, 1977) is a widely used instrument that measures depressive symptoms. The CES-D contains 20 items and is usually reported as a total score. To model the information from the CES-D as a single construct, we used the 20 items to form parcels by randomly assigning items to one of three parcels (Little, Cunningham, Shahar, & Widaman, 2002). This procedure assumes that the items are exchangeable and that all items contribute information about a single depressive symptoms construct. The maternal sensitivity construct is based on three 4-point global ratings from trained observers of a mother–child structured interaction (NICHD ECCRN, 1999). Indicators for the maternal sensitivity constructs are the three global ratings from the observed mother-child interaction: (1) mother's sensitivity to nondistress, (2) mother's intrusiveness (reverse-scored), and (3) mother's positive regard for the child. These ratings have been used in previous research to form a sensitivity construct (NICHD ECCRN, 1999). A global child problem behavior construct was formed by using four of the syndrome scores from the CBCL: (1) Anxiety/Depression, (2) Withdrawal, (3) Aggressive behavior, and (4) Destructive behavior.

Model

Figure 3 shows the LDS model for the data example. For simplicity we included each construct measured at only two times, thus resulting in a total of nine latent variables. Including multiple measurements of each construct over time would allow for the test of differential mediation across different spans of time. The constructs MD_1, $SENS_2$, and CPB_3, respectively, represent the status of maternal depressive symptoms at Time 1, the status of maternal sensitivity at Time 2, and the status of child problem behavior at Time 3. The constructs $\Delta MD_{1–2}$, $\Delta SEN_{2–3}$, and $\Delta CPB_{3–4}$, respectively, represent change in depressive symptoms between Time 1 and Time 2, change in sensitively from Time 2 to

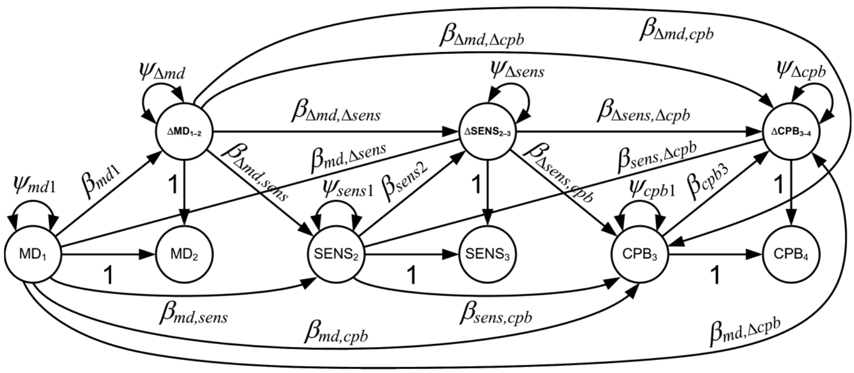

FIGURE 3 A latent difference score (LDS) model for maternal depressive symptoms, maternal sensitivity, and child problem behavior.

Time 3, and change in child problem behavior from Time 3 to Time 4. When reviewing the three issues we earlier introduced, we note that in some ways this is an example of a LDS mediation model rather than an exemplar because the use of secondary data precludes the thorough consideration of issues such as the choice of the period, span, and lag for the study. However, regarding the theory of change, using a LDS approach allows us to focus on change in each of these constructs rather than in level alone. Thus we are suggesting that a change in one of these constructs (e.g., a mother's level of sensitivity) may be equally or more important than maternal sensitivity per se. Again, because this is a secondary analysis of an existing data set, we must assume that the chosen period is a reasonable time to observe mediation and that the times at which each construct is measured (e.g., maternal depressive symptoms at 6 and 15 months) is meaningful. It is potentially problematic that the assessments are spaced many months apart and that the lags vary across the study. However, we can give a clear appraisal of the meanings of the different types of indirect effects present in the results.

We used the M*plus* version 5.1 (Muthén & Muthén, 2007) software package to estimate the parameters of the LDS model. (Complete script is available at www.quantpsy.org.) M*plus* allows users to define any function of parameters (e.g., $\beta_{md,sens} \times \beta_{sens,cpb}$) as a model parameter and in addition provides bias-corrected bootstrap confidence intervals for such parameters. Some cases had missing data, so we used the full-information maximum likelihood estimator. Confidence intervals are based on 5,000 bootstrap resamples. See Preacher and Hayes (2008) for more information regarding the advantages of bootstrapping in mediation models.

RESULTS

We estimated all possible indirect effects in the LDS model. Table 1 shows the eight possible indirect effects, the function of model parameters used to quantify each indirect effect, and the associated 95% bias-corrected bootstrap confidence intervals. There is evidence supporting the presence of four of these indirect effects. First, the relationship between maternal depressive symptoms at Time 1 and child problem behavior at Time 3 is mediated by maternal sensitivity at Time 2 ($MD_1 \rightarrow SENS_2 \rightarrow CPB_3$). Because this indirect path involves only initial status constructs, it can be interpreted in a manner very similar to an indirect effect from a CLPM with the distinction that this model also controls for change in the previous predictors. The relationship between level of depressive symptoms at Time 1 and change in behavior problems between Time 3 and Time 4 is mediated by change in maternal sensitivity between Time 2 and Time 3 ($MD_1 \rightarrow \Delta SEN_{2–3} \rightarrow \Delta CPB_{3–4}$). This indirect effect suggests that a mother's level of depressive symptoms when the child is 6 months of age has an impact on her change in sensitivity, and that change in sensitivity in turn predicts change in the development of problem behavior in the child. Change in maternal sensitivity between Time 2 and Time 3 mediates the relationship between the level of maternal depressive symptoms at Time 1 and the level of behavior problems at Time 3 ($MD_1 \rightarrow \Delta SEN_{2–3} \rightarrow CPB_3$). Finally, the relationship between change in depressive symptoms between Time 1 and Time 2 and the level of child behavior problems at Time 3 is mediated by the level of maternal sensitivity at Time 2 ($\Delta MD_{1–2} \rightarrow SENS_2 \rightarrow CPB_3$). So mothers who become more depressed during the 9-month period between Time 1 and Time 2 are less sensitive to their children, and that decreased sensitivity predicts higher levels of problem behavior for the children.

TABLE 1
Confidence Intervals for Indirect Effects from the Latent Difference Score Model

Indirect Effect	*Parameters*	*95% Confidence Interval*
$MD_1 \rightarrow SENS_2 \rightarrow CPB_3$	$\beta_{md,sens} \times \beta_{sens,cpb}$	0.29, 0.83[a]
$MD_1 \rightarrow SENS_2 \rightarrow \Delta CPB_{3–4}$	$\beta_{md,sens} \times \beta_{sens,\Delta cpb}$	–0.13, 0.11
$MD_1 \rightarrow \Delta SEN_{2–3} \rightarrow \Delta CPB_{3–4}$	$\beta_{md,\Delta sens} \times \beta_{\Delta sens,\Delta cpb}$	0.01, 0.23[a]
$MD_1 \rightarrow \Delta SEN_{2–3} \rightarrow CPB_3$	$\beta_{md,\Delta sens} \times \beta_{\Delta sens,cpb}$	0.03, 0.36[a]
$\Delta MD_{1–2} \rightarrow \Delta SEN_{2–3} \rightarrow \Delta CPB_{3–4}$	$\beta_{\Delta md,\Delta sens} \times \beta_{\Delta sens,\Delta cpb}$	–0.02, 0.13
$\Delta MD_{1–2} \rightarrow \Delta SEN_{2–3} \rightarrow CPB_3$	$\beta_{\Delta md,\Delta sens} \times \beta_{\Delta sens,cpb}$	–0.04, 0.20
$\Delta MD_{1–2} \rightarrow SENS_2 \rightarrow CPB_3$	$\beta_{\Delta md,sens} \times \beta_{sens,cpb}$	0.08, 0.56[a]
$\Delta MD_{1–2} \rightarrow SENS_2 \rightarrow \Delta CPB_{3–4}$	$\beta_{\Delta md,sens} \times \beta_{sens,\Delta cpb}$	–0.08, 0.06

Note. [a]Bias-corrected bootstrap confidence intervals that exclude 0.

CONCLUSION

We believe that mediation models can be used profitably to test hypotheses about the mechanisms by which contextual factors or developmental processes affect developmental change. By using more traditional, cross-sectional methods, researchers risk committing a logical fallacy by modeling developmental processes as if they occur instantaneously. Moreover, mediation models specifically designed for longitudinal data maintain the all-important consistency between theory and method. Developmental research often concerns change that occurs within individuals, so it is important to use methods that not only consider the longitudinal nature of the data, but also maintain the distinction between intra- and interindividual change (see also Hoffman & Stawski, this issue).

On the other hand, we also believe that the use of mediation models to address developmental research questions brings with it many complexities that far exceed those of the traditional three-variable mediation models for cross-sectional data. Careful consideration must be given to aspects such as the theory of change for the variables in the model, the critical role of time in planning the study and interpreting results, and the variety of possible indirect effects that are a part of each model.

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