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Implications of latent trajectory models for the study of developmental psychopathology

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Abstract
The field of developmental psychopathology is faced with a dual challenge. On the one hand, we must build interdisciplinary theoretical models that adequately reflect the complexity of normal and abnormal human development over time. On the other hand, to remain a viable empirical science, we must rigorously evaluate these theories using statistical methods that fully capture this complexity. The degree to which our statistical models fail to correspond to our theoretical models undermines our ability to validly test developmental theory. The broad class of random coefficient trajectory (or growth curve) models allow us to test our theories in ways not previously possible. Despite these advantages, there remain certain limits with regard to the types of questions these models can currently evaluate. We explore these issues through the pursuit of three goals. First, we provide an overview of a variety of trajectory models that can be used for rigorously testing many hypotheses in developmental psychopathology. Second, we highlight what types of research questions are well tested using these methods and what types of questions currently are not. Third, we describe areas for future statistical development and encourage the ongoing interchange between developmental theory and quantitative methodology.

One of the most interesting aspects of working in the field of developmental psychopathology is the never ending cycle of moving from complex developmental theory to rigorous experimental design to comprehensive statistical analysis and back to developmental theory. As a field, we are faced with the challenge of gaining a theoretically and empirically based understanding about the complexities of the world around us, particularly as they relate to the processes of typical and atypical development. Given these complexities, we require correspondingly complex theoretical models. Indeed, Sameroff (2000) concluded, "My own view is that the appropriate model for understanding developmental psychopathology is one that matches the complexity of human behavior" (p. 300). We agree.

However, here lies a challenge. We require a theoretical model that matches the complexity of human behavior, yet we simultaneously require that we subject our theories to rigorous empirical evaluation with the ever-present chance that our theory might be falsified. This is what makes us an empirical science: our theoretically derived suppositions may be empirically rejected at any time (Platt, 1966; Popper, 1963). The challenge we face is that we must carefully balance the complexity of our theoretical models with the requisite complexity demanded by the empirical evaluation of our theory. We must be absolutely certain that the way in which we *think* we are empirically evaluating our research question is the

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way in which we actually *are* evaluating the question. That is, the statistical model must maximally correspond to the theoretical model, and the degree to which these diverge correspondingly threatens the validity of the empirically based inferences we can draw back to theory (Cattell, 1988; Curran, 2000; Shadish, Cook, & Campbell, 2002).

The challenge of balancing theoretical complexity with appropriate methods of empirical falsification is ubiquitous to all areas of basic and applied science. However, in some ways this is particularly salient in the field of developmental psychopathology. The reason is that, by definition, we work in a truly interdisciplinary field of study (Cicchetti & Dawson, 2002). Indeed, strong lines of theory can be traced to psychology, sociology, anthropology, animal learning, public health, and medicine, to name just a few (Cicchetti, 1990). Simple theories can often be empirically evaluated in simple ways. However, if as a field we demand complex theories to capture complex developmental processes, we must then be prepared for the associated challenges that arise when subjecting these theories to empirical tests of falsification. As Einstein is purported to have said, "Our theories should be as simple as possible, but no simpler."

We must then address the following set of challenges. First, the developmental processes associated with the emergence of psychopathology are complex, and we thus require equally complex theoretical models. Second, we are at heart an empirically driven science, and to remain so we must subject our theories to empirical evaluation in such a way as to create a real threat of falsification. Third, in order to empirically evaluate our theories in a thoughtful and valid way, we must be fully cognizant of precisely how our statistical models correspond to our theoretical models; discrepancies between theory and statistics significantly undermine our ability to make valid empirically based inferences back to theory. We believe that one of the most salient dangers in this sequence of scientific progress is that in our role as researchers we often want to pose more complex theoretical questions than we are able to validate in empirical tests. As a result, our statistical model may not adequately correspond well to our theoretical model. To address this threat, we must be as cognizant of the structure and boundaries of our statistical models as we are of the structure and boundaries of our theoretical models. This is the topic on which we focus our paper.

Overview

The core premise of our paper is that for developmental psychopathology to continue to grow and thrive as an empirical science, we must strive to empirically evaluate our theoretically derived research hypotheses in a rigorous and valid manner. Although the field of developmental psychopathology is characterized by a variety of intellectual perspectives and theoretical orientations, a concept that is shared by many theoretical models is an interest in *developmental trajectories*. Our goal is to consider how a broad class of random coefficient trajectory (or growth curve) models may be used to inform substantive questions about individual differences in developmental trajectories over time. We begin with a review of a number of different types of trajectory models and delineate several implications associated with these models as they pertain to the study of developmental psychopathology. We then summarize several fundamental ideas that, although frequently espoused by developmental psychopathologists, are not easily tested using current trajectory models. We conclude by considering the benefits associated with a greater integration between theory and methods development.

Developmental Trajectories

The primary focus of our paper is on the empirical estimation of developmental trajectories. Although there are many possible ways to define a trajectory, we begin with the basic premise that a trajectory is a continuous and individual-specific underlying process that gave rise to an observed set of repeated measures over time for a particular individual. For example, although we may have observed four repeated measures of antisocial behavior for a particular child, we may theoretically believe that these observations were generated by some unobserved underlying trajectory of antisociality that is unique to this child. It is this unobserved (or "latent") trajectory that is of key theoretical interest. However, because the trajectory was not directly observed (and, implicitly, is *unobservable*), we must empirically infer its existence as a function of the set of repeated measures that we did observe. These trajectories may take the form of individual intercepts, linear slopes, curvatures, asymptotes, or many other types of values. However, the core belief is that these individual parameters help us to accurately and parsimoniously summarize a larger set of observed data in a way that is maximally consistent with developmental theory. The trajectory model can be heuristically divided into two components: the "within-person" (or intraindividual) model and the "between-person" (or interindividual) model.[1]

The Within-Person Trajectory Model

We will start by thinking about the within-person model in which we consider the developmental trajectory separately for each case in the sample. This model is based on the premise that a set of repeated measures for a given construct are functionally related to the passage of time. This can formally be expressed as

$$y_{it} = f(\lambda_t) + \varepsilon_{it}, \tag{1}$$

where y_{it} is measure y for individual i at time t; λ_t is the value of time at $t = 1, 2, \ldots, T$, where T is the total number of repeated observations; $f(\lambda_t)$ reflects the functional relation between time and the outcome of interest; and ε_{it} is the residual for individual i at time t. In other words, Equation 1 is simply a general way of stating that an observed value for a given measure for a particular person at a specific time point is some function of the passage of time plus an individual- and time-specific residual (i.e., the part of the observed measure that is not predicted by the function of time).

The functions that reflect the nature of the relation between our observed measure and the passage of time are denoted $f(\lambda_t)$ to be maximally general. Given this generality, we can choose from a broad selection of possible functions that are best suited for a given theoretical question or empirical data set at hand. A common initial trajectory function to consider is linear such that

$$y_{it} = \alpha_i + \beta_i\lambda_t + \varepsilon_{it}, \tag{2}$$

where y_{it} and ε_{it} are defined as above, $\lambda_t = 0, 1, \ldots, T - 1$ reflects equally spaced linear change (where T is equal to the total number of time points observed),[2] α_i is the intercept of the underlying trajectory for individual i, and β_i is the linear slope of the underlying trajectory for individual i. We are thus saying that the repeated observations of our dependent measure is (at least in part) linearly related to time.

What is particularly important to note here is that the intercept and linear slope terms are both indexed with a subscript i to reflect that these values are unique to each individual in the sample. Statistically, this implies that the observed measure of variable y for individual i at time t is due to the underlying trajectory parameters for individual i plus some individual- and time-specific residual. Theoretically, this implies that each individual child is characterized by his or her *own, unique linear trajectory* that best reproduces the characteristics of their observed data over time. This is a tremendous advantage over many more traditional analytical methods in which a single parameter estimate represents the relation between two repeated measures pooled over all subjects in the sample (e.g., autoregressive cross-lagged regression models). The ability to empirically estimate an individual-specific

1. We refer to this distinction as *heuristic* because the within-person and between-person models are actually estimated simultaneously when fitted to empirical data.

2. By starting the coding of time with the value of zero, this allows for the intercept to be interpreted as the model implied value of y at the initial assessment period. However, there are several other options for coding time that provide alternative interpretations of the intercept (Biesanz, Deeb–Sossa, Aubrecht, Bollen, & Curran, 2003).

developmental trajectory of some hypothesized construct over time corresponds remarkably well with many theoretical perspectives of stability and change in developmental processes.

This linear trajectory is our first and most basic attempt to empirically estimate individual trajectories based upon our observed repeated measures over time. For example, say that we were interested in estimating individual trajectories of reading ability over 4 years of school. Because we cannot directly observe these developmental trajectories, we use four repeated measures on some standard reading test to estimate the existence of this underlying trajectory. This is highlighted in Figure 1, in which four repeated measures of reading recognition for a single child are plotted over time (see Curran & Hussong, 2002, for further details about this data). Here we have fit a single regression line to the repeated observations for a single individual (Figure 1a) and for five individuals (Figure 1b). We now have an explicit empirical estimate of the developmental trajectory of reading ability for each individual child that is consistent with many theories of cognitive development.

The linear trajectory model implies that a one-unit change in time is associated with a β-unit change in the outcome, and the magnitude of this relation is constant over all points in time (i.e., there is β-unit change in y between times 1 and 2, and β-unit change in y between times 2 and 3, etc.). Although this may be a reasonable function to summarize the characteristics of an observed outcome over time, there may be either theoretical or empirical reasons to believe that the repeated measures are related to time in some *nonlinear* fashion where a change in y is not equal between equally spaced assessments. The possible presence of nonlinear trajectories is particularly salient in many theories of development. The linear trajectory is a member of the polynomial family of functions. Other members of this polynomial family include the well-known quadratic and cubic functions. We can also consider these higher order polynomial members to define the individual trajectory as long as a sufficient number of repeated observations have been obtained to mathematically identify the function (Duncan, Duncan, Strycker, Li, & Alpert, 1999).

For example, we might choose to evaluate the fit of a quadratic trajectory that is defined as

$$y_{it} = \alpha_i + \beta_{Li}\lambda_t + \beta_{Qi}\lambda_t^2 + \varepsilon_{it}, \qquad (3)$$

where α_i remains the intercept of the trajectory, β_{Li} is the linear component of the trajectory, and β_{Qi} is the quadratic component of trajectory. Just as with the linear model, each of the three trajectory parameters takes on values unique to each individual. However, whereas the linear model implied *constant* change in y between equally spaced time assessments, the quadratic model implies *differential* change in y between equally spaced time assessments. The amount of change in y depends upon precisely *where* in time change is considered. That is, there might be large changes in the repeated measures early in development, but the magnitude of these changes become increasingly smaller with continued development. Given sufficient numbers of repeated observations to allow for proper model identification, we could add a cubic, quartic, or higher order polynomial, each of which would add another powered function of time and one more trajectory parameter that would be unique to each individual.

An interesting alternative trajectory function that corresponds well with a number of theoretical models of development but is not often used in many developmental research settings is the *piecewise linear model* (Raudenbush & Bryk, 2002; Seltzer & Svartberg, 1998). Here, two or more linear functions are joined at some transition point and can thus be used to approximate a nonlinear function. More formally, the repeated dependent measures are expressed as

$$y_{it} = \alpha_i + \beta_{\mathrm{PRE}_i}\lambda_{\mathrm{PRE}_t} + \beta_{\mathrm{POST}_i}\lambda_{\mathrm{POST}_t} + \varepsilon_{it}, \quad (4)$$

where β_{PRE_i} and β_{POST_i} the individual-specific pretransition and posttransition linear components of the overall trajectory, respectively. Now not only do we have an empirical estimate of a developmental trajectory for a given

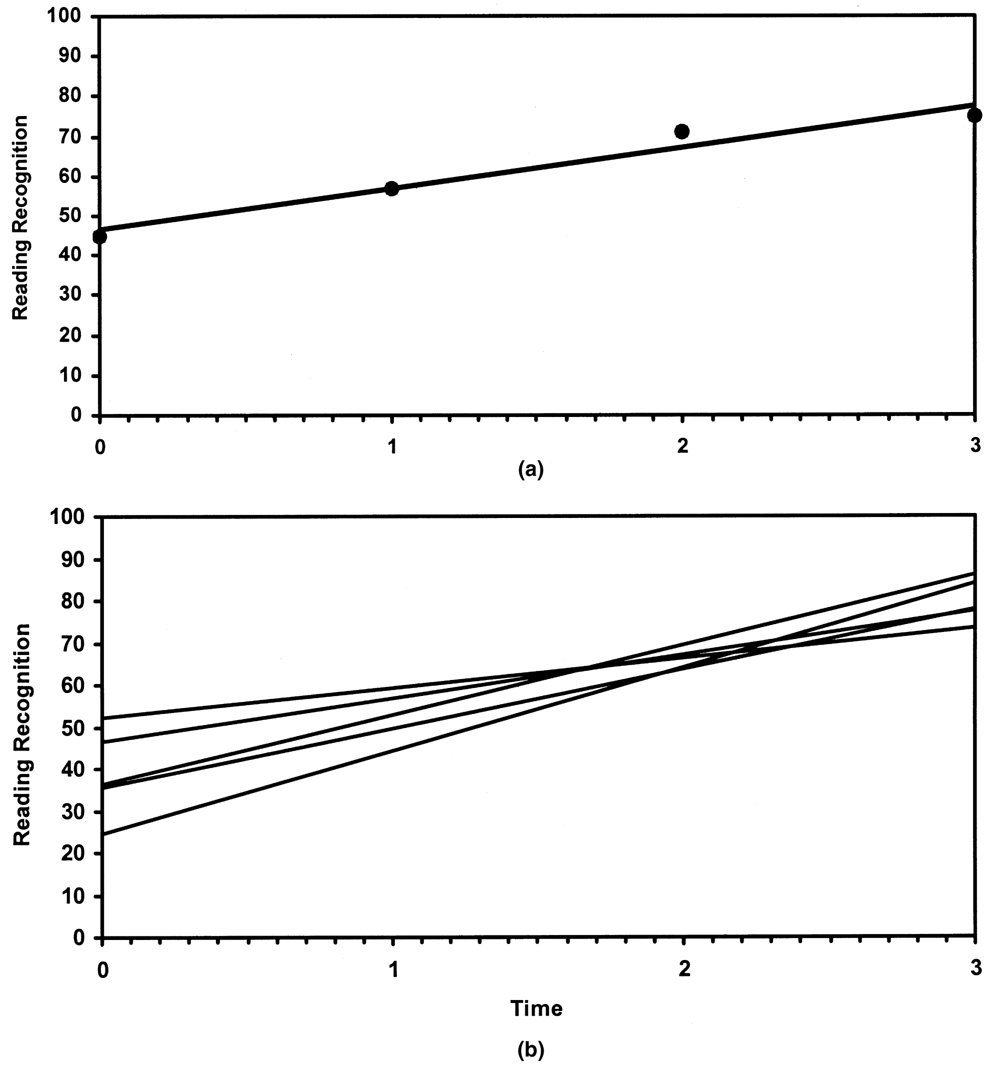

Figure 1. The linear trajectory fit to four repeated measures of reading recognition for (a) a single individual and (b) five individuals.

child, but we also are simultaneously incorporating information about some theoretically important *transition point*. For example, say that three repeated measures were obtained on a sample of children during elementary school, and three more repeated measures were obtained on the same sample of children in middle school. A linear trajectory could be fitted to the three measures during elementary school, a second linear trajectory could be fitted to the three measures during middle school, and the two trajectories would be joined at the point of transition to middle school. The piecewise strategy maps quite nicely onto many theoretical models concerning *deflections* in developmental trajectories resulting from a salient transition event and allows for a powerful empirical test of these unobserved processes.

One important aspect of all of the polynomial functions (including the piecewise linear function) is that the trajectory is considered to be *unbounded* with respect to time. That is, the linear, quadratic, and cubic models all

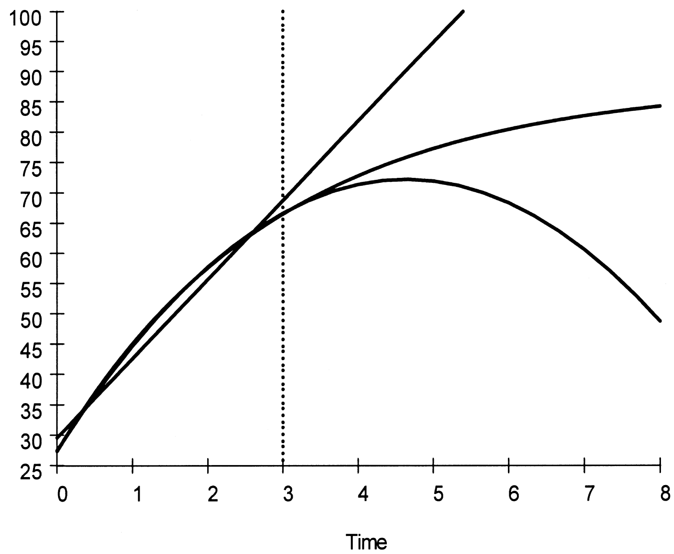

Figure 2. Linear (top line), exponential (middle line), and quadratic (bottom line) trajectories fitted to hypothetical reading ability data in which the first four time points are observed and the following five time points are extrapolated.

tend toward plus or minus infinity. For example, Figure 2 presents a linear, quadratic, and exponential trajectory (the latter will be discussed in a moment) fitted to nine repeated measures of a hypothetical construct *y*. The first four assessments were observed, and the next five are extrapolated. If *y* represented reading ability in children, it is clear that neither the linear nor the quadratic model are appropriate over the full age range shown here. The linear model implies that the children will forever improve in reading, and the quadratic model implies that the children will attain some peak in reading ability and then systematically decrease over time. Again, such a polynomial model may be appropriate as an estimate of the process within a specific span of time. However, in many cases we may not theoretically believe that our measure *y* tends toward infinity, although a linear or quadratic model might be sufficient to characterize the dependent measure within our window of observation.

An alternative trajectory that is bounded with respect to time and thus does not tend towards positive or negative infinity is the exponential function. One common form of this trajectory can be expressed as

$$y_{it} = \alpha_i + \beta_i(1 - e^{-\gamma_i \lambda_t}) + \varepsilon_{it}, \qquad (5)$$

where β_i represents the *total* amount of change at the final observation relative to the initial level and γ_i is the exponential *rate* of change in *y* over time. This trajectory is also presented in Figure 2, where it is contrasted with the linear and quadratic trajectories discussed earlier. As can be seen, the trajectory increases over time, but the rate of increase slows as time progresses. More importantly, an asymptote is reached at which point the trajectory stabilizes and no longer changes. This type of trajectory may be much better suited to modeling some types of behaviors over time compared to the polynomial trajectories, which eventually will again turn toward plus or minus infinity as time increases.[3]

The linear, piecewise linear, quadratic, and exponential trajectories define known functional forms that relate the repeated measures to the passage of time. That is, a specific functional form is defined and then fit to the

3. An important difference between the exponential trajectory and the various members of the polynomial family is that the polynomial trajectories are in the *linear parameters* whereas the exponential is not.

observed data. In some situations these trajectory functions might be excessively restrictive or might not optimally capture the pattern of change that was either hypothesized or observed in the data over time. An alternative approach is to estimate the functional form directly from the data. This approach was first proposed by Meredith and Tisak (1990) and further elaborated by Aber and McArdle (1991), who described this approach as "stretching" and "shrinking" the passage of time. In this approach, the metric of time is not set a priori to define a particular parametric function, but one or more of the values of time are estimated based on the characteristics of the empirical data. This allows for the fitting of a "shape" factor that optimally reproduces the pattern of change over time. Although this is a highly flexible approach, there are several potential associated limitations associated with this model. For example, given that the optimal growth function is fit to the characteristics of a particular data set, it may be difficult to replicate the resulting function in a second sample. Further, because the function is fit to the data within the observation window, it may be challenging to extrapolate the function beyond the observed assessment window. Finally, there remains the possibility that these fitted functions may "overfit" the data and take on functional forms that are a result of idiosyncratic characteristics of the data. Despite these potential limitations, this type of model can be used productively in many different settings (see Aber & McArdle, 1991, and Curran & Hussong, 2002, in press, for further discussion).

Summary

The within-person trajectory model is a key starting point when considering individual differences in developmental trajectories over time. There are a variety of methods for parameterizing these trajectories ranging from fixing known functions of time a priori to estimating the optimal function based on the characteristics of the empirical data. This method for empirically estimating individual developmental trajectories corresponds closely with several important tenets in developmental psychology including allowance for individual trajectories over time, simultaneous consideration of stability and change, and the existence of continuous underlying developmental processes. It is important to note, however, that although we have allowed each individual child to be characterized by its own individual-specific trajectory, each trajectory is wholly independent of any other child in the sample. However, in developmental psychopathology, a key interest is in understanding the development of an *individual* as it relates to the development of *other individuals*. To stay consistent with developmental theory, it is imperative that we explore methods for estimating trajectories for each child and are also able to draw inferences about the *collection* of individual trajectories in our sample. Random coefficient trajectory (growth curve) models are extremely well suited to this task through the use of the *between-person* trajectory model.

The Between-Person Trajectory Model

The within-person model allows us to define a developmental trajectory for each child in the sample. Given that each individual is characterized by his or her own trajectory parameters, whatever that functional form might be, the next step is to examine the means and variances of these parameters *across* individuals. This is accomplished through the between-person model. To express these means and variances in statistical terms, we treat the within-person model parameters as random variables and write equations for the parameters themselves. For example, for a linear within-person model (Equation 2), the individual intercepts and individual slopes can be expressed as

$$\alpha_i = \mu_\alpha + \zeta_{\alpha_i}, \tag{6}$$

$$\beta_i = \mu_\beta + \zeta_{\beta_i}, \tag{7}$$

where μ_α and μ_β are the mean intercept and mean slope pooling over all individuals in the sample and ζ_{α_i} and ζ_{β_i} are the deviations of each individual from the group means. In other words, Equations 6 and 7 simply reflect that an intercept (or slope) for a particular individual is an additive combination of the mean of *all* of the intercepts in the sample plus the deviation of the individual's intercept from this group mean.

Much important information lies in the deviations of each individual from the group means. For example, the variance of these individual deviations are denoted ψ_α for the intercepts, ψ_β for the linear slopes, and $\psi_{\alpha\beta}$ for the covariance between the intercepts and slopes. We can think of these variances in precisely the same way as we do when thinking about any observed variable. That is, larger values of ψ_α and ψ_β reflect greater individual variability in the trajectory parameters (subjects differ from one another in their individual trajectory parameters). In contrast, smaller values reflect less variability in the trajectory parameters (subjects are similar to one another in their individual trajectory parameters), and a variance of zero reflects that all subjects follow precisely the same trajectory. Because of this, these variance estimates are commonly referred to as the *random-effects* part of the model; similarly, the mean estimates are commonly referred to as the *fixed-effects* part of the model.

Equations 6 and 7 are expressed for a linear trajectory, and these would expand accordingly for more complex trajectories (e.g., there would be three equations used to express the intercept, linear slope, and curvilinear slope for a quadratic trajectory, etc.). Thus, whatever the particular functional form of the trajectory, the corresponding mean and variance components allow for a parsimonious summary of the general *course* of a given behavior over time (e.g., Willett, 1988). That is, the fixed effects reflect the mean starting point and mean rate of change pooling over the entire sample, and the random effects reflect whether there is evidence of individual variability around these mean estimates. Now our goal is to compute optimal sample estimates of these fixed and random effects based on the characteristics of our empirical data.

The Structural Equation Based Latent Trajectory Model

Thus far we have distinguished the within-person and between-person models to highlight how the trajectory model maps onto developmental theory. The empirical estimation of the model parameters from sample data actually considers the within and between-person equations *simultaneously*. To retain focus here, we will primarily explore the structural equation model (SEM) approach to trajectory estimation. An alternative method of trajectory estimation is the hierarchical linear model (HLM). The HLM approach was primarily developed in the field of education to allow for the proper analysis of data characterized by nested observations (e.g., children nested within a classroom, classrooms nested within a school, etc.). Bryk and Raudenbush (1987) demonstrated that HLM could be used for growth modeling by considering *time* to be nested within a *child*. It has been shown that under some cases the SEM and HLM trajectory models are equivalent to one another, whereas in other cases they are not (Chou, Bentler, & Pentz, 1998; MacCallum, Kim, Malarkey, & Kiecolt–Glaser, 1997; Willett & Sayer, 1994). Although we are focusing on the SEM trajectory model here, we want to stress that unless otherwise noted, all of our discussions and conclusions also apply to the HLM approach. Willett, Singer, and Martin (1998) present an excellent overview of HLM trajectory analysis in developmental psychopathology.

SEM provides a flexible and powerful framework for estimating the trajectory parameters. The SEM-based trajectory model is sometimes called the *latent trajectory model* (LTM), given the use of multiple-indicator latent factors to represent the random growth functions.[4] The LTM approaches the estimation of individual trajectories from the perspective of a restricted confirmatory factor analysis model. The development of the LTM draws on the seminal work of Tucker (1958) and Rao (1958) and was formalized by Meredith and Tisak (1984, 1990) and expanded on by McArdle (1988, 1989, 1991) among many others. Within the LTM, the repeated mea-

4. We can consider any method for estimating individual trajectories as *latent* given that the trajectories themselves are not directly observed but instead are inferred from the set of repeated measures (see, e.g., Bollen, 2002).

sures of a given construct are used as multiple indicators on one or more latent factors; these factors represent the unobserved trajectories that are believed to have given rise to the observed repeated measures. The passage of time is parameterized through the fixed or freely estimated factor loadings that relate the repeated measures to the underlying factors. Greater details in the theory, estimation, and interpretation of LTMs are presented in Curran (2000), Curran and Hussong (2002, in press), Duncan et al., (1999), MacCallum et al. (1997), McArdle (1988, 1989, 1991), Willett and Sayer (1994), and Willett et al. (1998).

A latent factor is estimated for each component of the specific trajectory function of interest. Thus, for the linear trajectory described in Equations 2, 6, and 7, two latent factors are estimated. The repeated measures of the construct y are linked to the first factor by fixing all of the factor loadings to a value of one; this defines the *intercept* of the trajectory. The repeated measures are also linked to the second factor by fixing the factor loadings to $\lambda_t = 0, 1, \ldots, T - 1$ to represent the linear and equally spaced passage of time.[5] A mean is estimated for each latent factor, and these means reflect the fixed effects of the trajectory (i.e., the mean trajectory for the entire group). A variance is estimated for each latent factor, and these variances reflect the random effects of the trajectory (i.e., the individual differences around the mean values). A covariance is estimated between the latent factors, and this reflects the degree of association between the individual intercepts and slopes. Finally, a residual variance is estimated for each of the repeated observations, and these values reflect the variability in each time-specific measure that is not accounted for by the underlying trajectory factors. A hypothetical unconditional linear LTM for four repeated measures is presented in Figure 3.

The unconditional model reflects the characteristics of the *course* of behavior over time; it describes the mean starting point, the mean rate of change, and the degree of individual variability around these mean values. The model implicitly assumes that the underlying trajectories (i.e., latent factors) *completely govern* the repeated measures over time; that is, any part of the repeated measure of y not explained by the trajectory is considered error (i.e., ε_{it} in Equation 1). Further, these expressions highlight that we can conceptualize the individual intercept and slope estimates as random variables, just as we typically would think about a random variable in more standard types of statistical models (e.g., height, weight, IQ). However, here we do not actually observe the intercepts and slopes; instead we *infer their existence* given the parameterization of the within-person model described above. For the unconditional trajectory model, we are primarily interested in the means and variances of these individual trajectory estimates (i.e., latent factors). However, given that the trajectory estimates are treated as random variables, we can attempt to model or *predict* the trajectory parameters from other information in our sample; this approach is called a conditional trajectory model.

The Conditional Trajectory Model: Time-Invariant Covariates

Recall that Equations 6 and 7 were considered *unconditional* because we have not yet incorporated any exogenous predictor variables of the trajectory parameters. That is, we could express an individual trajectory as a function of the mean of all trajectories plus an individual-specific deviation of the trajectory from the mean. This further implies that the *distribution* of the trajectory parameters are governed by a mean and a variance. Recall that larger variance estimates implied greater individual variability in the trajectory parameters. We can now extend this model to include one or more correlated predictors to try to *explain* this individual variability. That is, we can ask questions about what characteristics of the child or environment are associated with trajectories that start higher versus lower or increase more steeply versus less steeply. This, in turn, broadens the types of theoretical questions that can be empirically evaluated.

For example, say that we were interested in a linear trajectory model of antisocial be-

5. It is quite straightforward to incorporate the unequally spaced passage of time, and this is accomplished by simply fixing the values of time to reflect the differential spacing (e.g., $\lambda_t = 0, 1, 3, 5$, etc.).

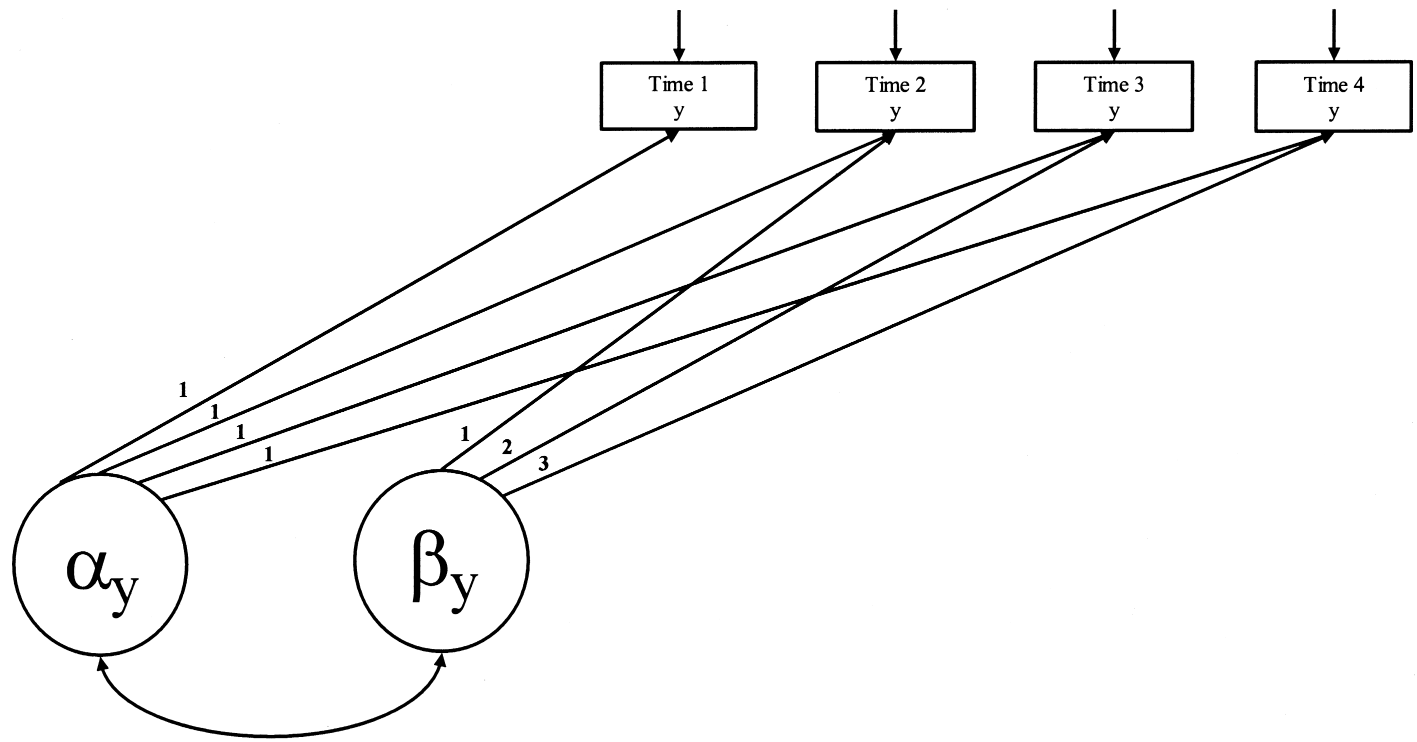

Figure 3. The unconditional linear trajectory model for four repeated measures.

havior over time and we found evidence of significant variability in both intercepts and slopes. Further, our developmental theory predicted that these parameters could be predicted by the gender of the child and by the attention-deficit/hyperactivity disorder (ADHD) symptoms expressed by the child at Time 1. We can thus express our equations for the intercepts and slopes of the antisocial behavior trajectories to be partly influenced by gender and ADHD symptoms at time 1. Specifically, these equations would be

$$\alpha_i = \mu_\alpha + \gamma_{\alpha_1}\text{gender}_i + \gamma_{\alpha_2}\text{ADHD}_i + \zeta_{\alpha_i}, \quad (8)$$

$$\beta_i = \mu_\beta + \gamma_{\beta_1}\text{gender}_i + \gamma_{\beta_2}\text{ADHD}_i + \zeta_{\beta_i}, \quad (9)$$

Equations 8 and 9 can literally be interpreted as a two-predictor regression model. That is, the gamma parameters reflect the relation between child gender and ADHD symptoms in the prediction of the individual intercepts and individual slopes that define the developmental trajectories of antisocial behavior. Further, given the presence of the predictor variables, the means μ_α and μ_β now represent regression intercepts and the variance of the individual deviations now represent residual variation net our set of predictors. This parameterization highlights that we are interested in the relation between the optimal linear combination of our set of predictors and our randomly varying intercepts and slopes. A hypothetical conditional LTM with two correlated predictors is presented in Figure 4.

The conditional model allows for powerful tests of theoretical questions relating to individual differences in the prediction of the individual trajectory parameters. For example, say that we estimated an unconditional trajectory model of antisocial behavior and found both significant fixed and random effects characterizing increasing trajectories of antisocial behavior over time. Further, say that we found a significant and positive regression coefficient predicting both intercepts and slopes of the trajectories as a function of child ADHD symptoms at time 1. The inference here is that children with higher levels of ADHD symptoms at time 1 start significantly higher and increase significantly more steeply in antisocial behavior compared to children characterized by lower ADHD symptoms. This effect can be further probed to gain an even better understanding of the specific characteristics of the trajectories of antisocial behavior across varying levels of ADHD symptoms (see Curran, Bauer, & Willoughby, in press-a, in press-b, for further details). This type of model allows for powerful tests of individual differences in stability and change that vary systematically as a function of one or more individual difference variables, a question of common interest in many areas of developmental psychopathology.

The Conditional Trajectory Model: Time-Varying Covariates (TVCs)

A key implication of the conditional LTM with time-invariant covariates described above is that the set of covariates are assumed to be *independent* of the passage of time. These covariates might be truly time invariant (e.g., biological sex, ethnicity) or they may be potentially time varying, but only one assessment of the construct is of interest (e.g., socioeconomic status of the child at the initial assessment). However, developmental theory might hypothesize that the explanatory variables themselves vary over time and these influences should be explicitly parameterized within the statistical model. Recall from Equation 1 that in the unconditional LTM the repeated observations are completely governed by the underlying trajectories and whatever variability remains in the indicators is treated as error. However, there may be some systematic relation among the residuals *net* the effects of the trajectory function; theoretically, this might reflect some time-specific influence from the child or environment above and beyond the continuous trajectory process. To model these hypothesized influences we can expand Equation 1 to include one or more TVCs.

Recall that in the hypothetical example above, we were interested in whether ADHD symptoms measured at time 1 were related to intercepts and slopes of antisocial behavior over time. However, say that our developmental theory predicted that it would be important to examine the relation between anti-

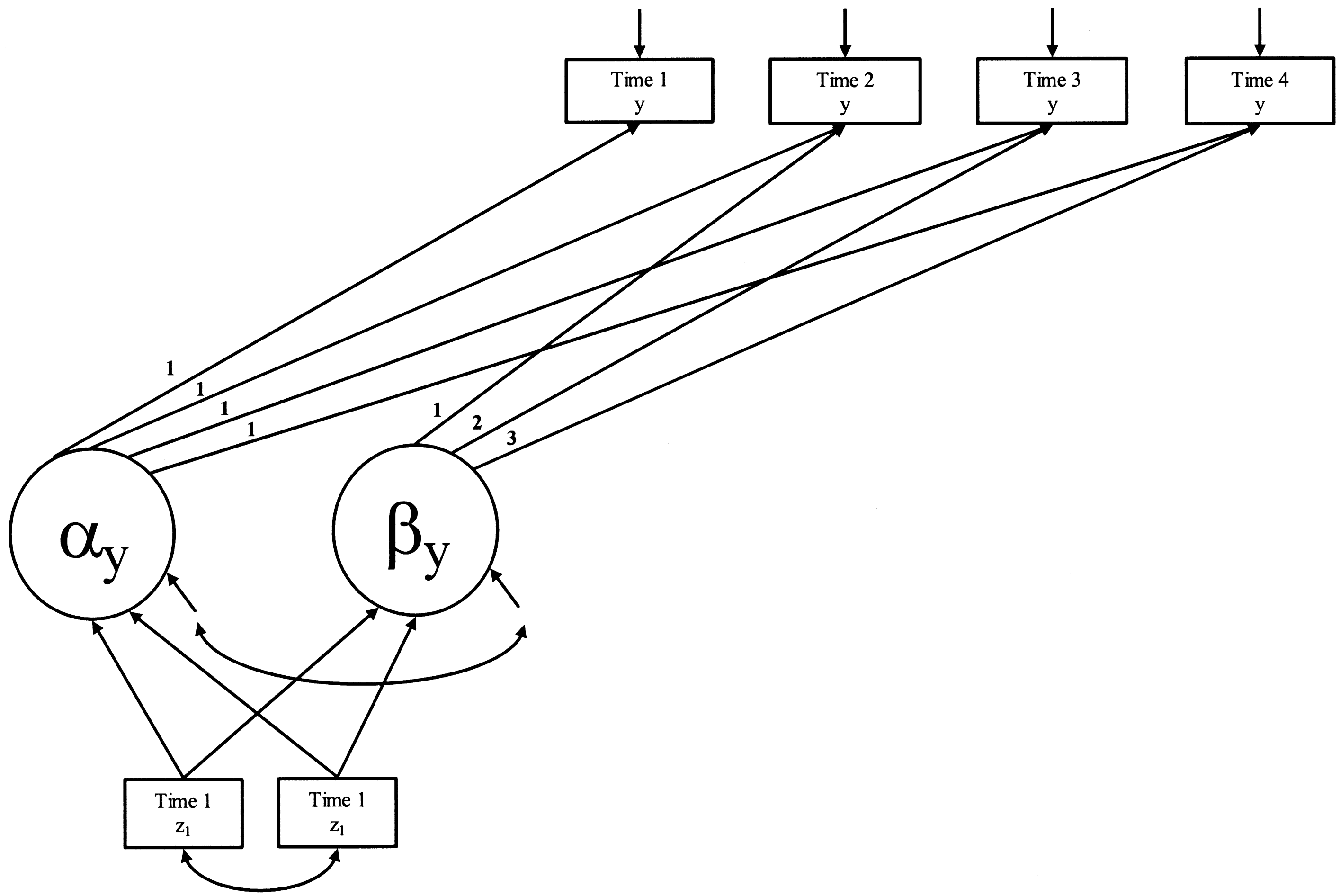

Figure 4. The conditional linear trajectory model with four repeated measures and two correlated predictors of intercept and slope.

social behavior and ADHD symptoms over *all* time points. We can expand our within-person model to allow for this influence from ADHD on antisocial behavior. This model extension is straightforward and can be expressed as

$$y_{it} = (\alpha_i + \beta_i\lambda_t) + (\gamma_t \mathrm{ADHD}_{it}) + \varepsilon_{it}. \quad (10)$$

Note that the first parenthetical term reflects the very same linear trajectory used before. However, in addition to this influence of the underlying trajectory, there is also a *time-specific* contribution of ADHD symptoms for individual i at timepoint t, the magnitude of which is reflected in γ_t. A hypothetical LTM with TVCs is presented in Figure 5.

Although this is a subtle analytic extension of the previous conditional model, the theoretical implications are significant. We are now implying that the observed measure of y for person i at time t is an additive combination of the underlying trajectory function, the time-specific influence of the TVC, and the individual- and time-specific residual. This extension allows us to empirically test an even wider array of developmental hypotheses. Without the inclusion of TVCs, we are implicitly stating that the repeated measures are *entirely due* to the underlying developmental trajectory. However, with the inclusion of the TVCs, we are stating that the repeated measures are due to a *joint* contribution of the underlying trajectory plus some time-specific influence. This additional influence can sometimes be construed as a time-specific "shock" to the system that might originate from the individual or the environmental context (e.g., Curran & Bollen, 2001). This allows for potentially important empirical tests of developmental theory that posits the simultaneous presence of individual trajectories plus time-specific influences.

Interestingly, although we are allowing our predictor variables to vary freely over time (i.e., the TVCs), we are *not* estimating a trajectory model for the TVCs themselves. That is, we allow the TVCs to freely covary with one another, but we are not imposing a *structure* on these repeated measures as a function of time. From a theoretical standpoint, this reflects the fact that we do not hypothesize the existence of an underlying *developmental process* for the covariates. When considering empirical tests of certain theoretical propositions about individual variability in stability and change over time, it may be important to consider developmental processes within *two* constructs over time. This allows for an empirical estimation about how two constructs might "travel together" through time. We can turn to the *multivariate trajectory model* to accomplish this task.

The Multivariate Trajectory Model

To include the repeated measures of our TVCs in the univariate LTM, we expanded the individual trajectory equation to include the time-specific measures of the TVCs (which we can generally denote as construct x). In contrast, we will now simultaneously estimate a trajectory equation for the repeated measures of y and another trajectory equation for the repeated measures of x. This is expressed as

$$y_{it} = \alpha_{y_i} + \beta_{y_i}\lambda_t + \varepsilon_{y_{it}}, \quad (11)$$

$$x_{it} = \alpha_{x_i} + \beta_{x_i}\lambda_t + \varepsilon_{x_{it}}, \quad (12)$$

indicating that we now have an individually varying intercept and slope for our repeated measures of y, but we *also* have an individually varying intercept and slope for our repeated measures of x. This is in contrast to our TVC model in which we incorporated our repeated measures of x as direct time-specific predictors of y, whereas here we are estimating trajectory parameters for both our constructs y and x.

We can write an equation for both sets of trajectory parameters such that

$$\alpha_{y_i} = \mu_{\alpha_y} + \zeta_{\alpha y_i}, \quad (13)$$

$$\beta_{y_i} = \mu_{\beta_y} + \zeta_{\beta y_i}, \quad (14)$$

and

$$\alpha_{x_i} = \mu_{\alpha_x} + \zeta_{\alpha x_i}, \quad (15)$$

$$\beta_{x_i} = \mu_{\beta_x} + \zeta_{\beta x_i}, \quad (16)$$

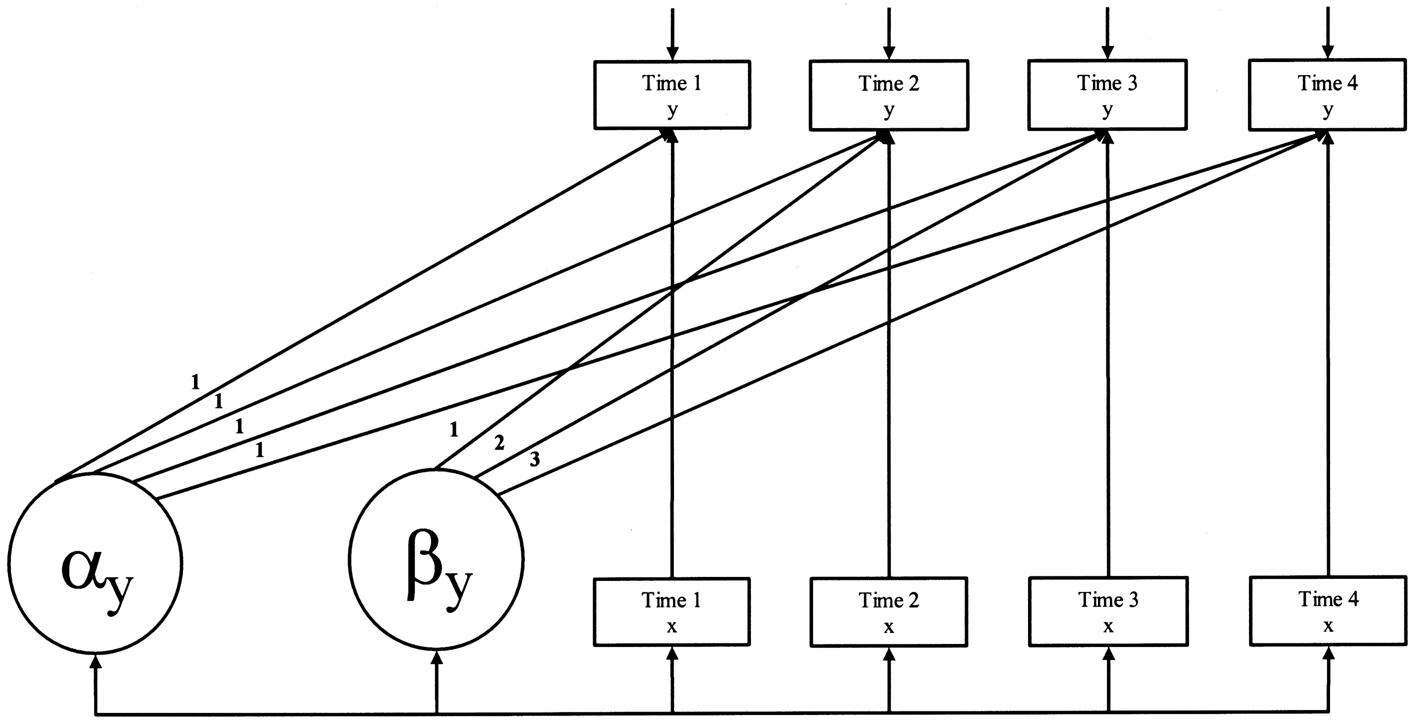

Figure 5. The conditional linear trajectory model with four repeated measures and four time-varying covariates with contemporaneous predictions of the measure *y*.

where each trajectory process is again characterized by a mean intercept and slope and by variances and covariances among the intercepts and slopes both within and across the construct. That is, we can estimate the covariance between the intercepts of the trajectories of construct y with the intercepts of construct x, and we can estimate the covariance between the slopes of the trajectories of construct y and the slopes of construct x. This multivariate LTM is presented in Figure 6. It is not only possible to then regress the set of random trajectories on one or more exogenous predictor variables, but we can also regress the slope of construct y on the intercept of construct x and vice versa. These regressions reflect the prospective relation between the starting point on one construct predicting the rate of change on the other construct. See Aber and McArdle (1991) and McArdle (1989, 1991) for further details on model parameterization and estimation.

The TVC LTM and the fully multivariate LTM test *fundamentally different* theoretical questions about change over time. In the former model we are empirically testing the premise that the repeated observations of one construct are the joint expression of an underlying trajectory process and the time-specific influence of another process; this is highlighted in Figure 5. In contrast, in the latter model we are empirically testing the premise that the two constructs are each governed by a *separate* developmental process and that the two processes are interrelated strictly at the level of the trajectories; this is highlighted in Figure 6. Each of these LTMs provides a powerful test of a particular question put forth by developmental theory. However, neither of these models allows for a *joint* test of the relation between two developmental constructs both at the level of the trajectories and at the level of the time-specific repeated observations; such complex relations may be predicted by developmental theory (e.g., Hussong, Hicks, Levy, & Curran, 2001). To better allow for the testing of these simultaneous developmental influences, we can incorporate aspects of the TVC model with those of the fully multivariate model to create a hybrid model that is sometimes called the *autoregressive latent trajectory* (ALT) model.

The ALT Model

Several methodologists have recognized the need to model dynamic systems that involve interrelations among change processes that occur simultaneously at both the random trajectory and the time-specific levels of analysis. Examples of these alternative approaches include the latent state-trait model (Schmitt & Steyer, 1993; Sher & Wood, 1997; Windle, 1997), the state trait error model (Kenny & Zautra, 1995), and the latent difference score model (McArdle, 2001; McArdle & Hamagami, 2001). Here, we focus on the related ALT model, which utilizes the strengths of LTM and traditional autoregressive cross-lagged analyses within the SEM framework to address similar questions (Bollen & Curran, 2002; Curran & Bollen, 2001).

The equations for the ALT model become rather complex and will not be presented here (see Bollen & Curran, 2002, and Curran & Bollen, 2001, for more details). However, an example of an ALT model estimated between two constructs observed over four time periods is presented in Figure 7. Like the fully multivariate LTM, the ALT model estimates latent trajectory factors for two sets of repeated measures. Like the TVC model, the ALT model also estimates time-specific bidirectional relations between each of two constructs at the level of the repeated measure indicators. This simultaneous estimation of relations between the two constructs at the level of the latent trajectories and at the level of the time-specific repeated measures appropriately tests theories for which both processes are important in understanding the relation between the two constructs over time.

For example, Curran and Bollen (2001) used an ALT model to empirically examine the simultaneous influences of underlying developmental trajectories of childhood depressive symptomatology and antisocial behavior in the presence of time-specific bidirectional influences between elevated depression at one time predicting elevated antisocial behavior at

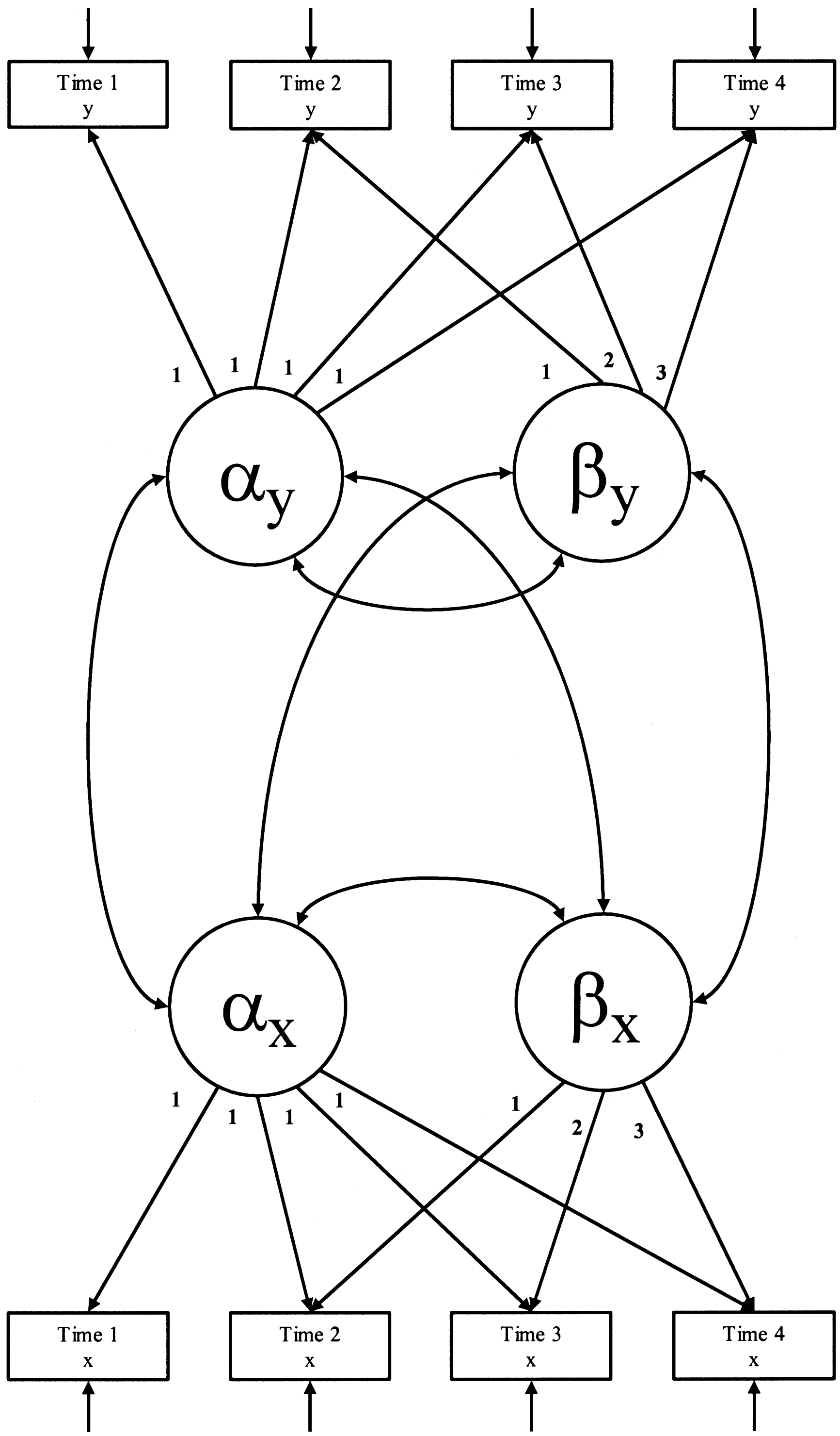

Figure 6. The unconditional multivariate trajectory model with four repeated measures of two constructs *x* and *y* with covariances among all latent trajectory factors.

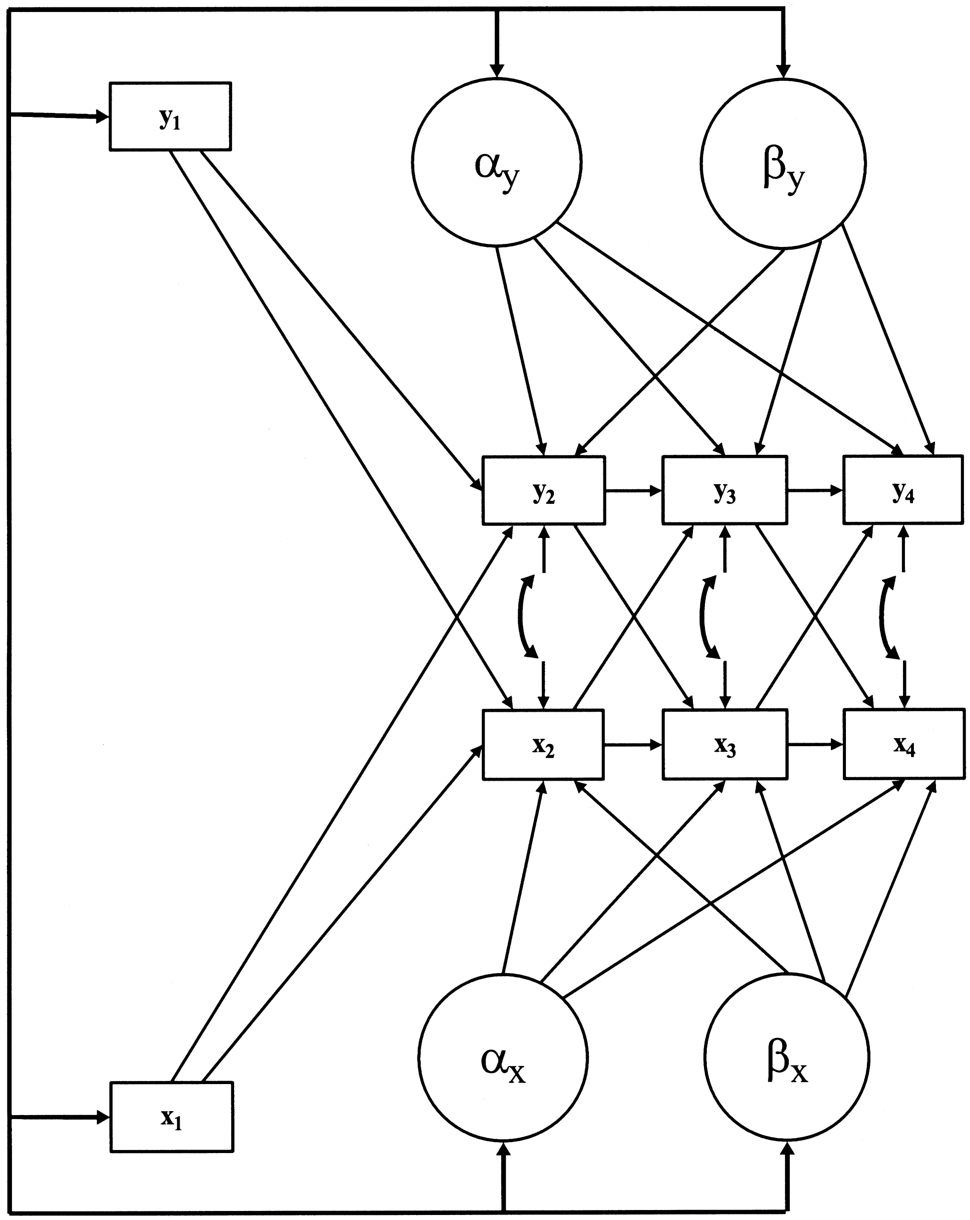

Figure 7. The multivariate autoregressive latent trajectory model with four repeated measures of two constructs *y* and *z* with autoregressive parameters within constructs and cross-lagged parameters across constructs.

another time, and vice versa. Similarly, Hussong et al. (2001) used an ALT modeling approach to test the hypothesis that time-specific elevations in hostility in young adults (above and beyond an individual's average level of hostility) predicted subsequent time-specific elevations in drinking (above and beyond an individual's average level of drinking), and vice versa. This prospective cyclical relation between hostility and drinking behavior was tested over alternating weekends and weekdays (e.g., weekend hostility predicting subsequent weekday drinking, weekday drinking predicting subsequent weekend hostility). These are just two examples of possible uses of the ALT model to incorporating multiple influences on the unfolding of two or more behaviors over time.

One potential advantage of the ALT modeling framework is that several more standard longitudinal models are embedded within the more general ALT parameterization (Bollen & Curran, 2002). For example, by reparameterizing the underlying latent trajectory factors, a standard autoregressive cross-lagged panel model can be estimated. By reparameterizing the autoregressive and cross-lagged structures among the repeated measures, the standard LTM can be estimated. These subsets of models that are embedded within the general ALT framework allow for the testing of various competing models to identify the underlying structure that is most consistent with developmental theory and best reproduces the characteristics of the observed data.

Multiple Group Trajectory Models

All of the models described thus far assume that the subjects have been randomly sampled from a single homogeneous population and any subgroups differences in the trajectory models are strictly related to conditional means. For example, we might find from a conditional time-invariant covariate model that developmental trajectories of antisocial behavior start higher and increase more steeply for males compared to females. Note that these differences in trajectories are at the level of the conditional means of the trajectory components; that is, males are characterized by a higher mean intercept and steeper mean slope, but all other model parameters are forced to be invariant over the two groups. Most importantly, all children are assumed to follow the same functional form of the trajectory and be characterized by the same covariance structure (see, e.g., Curran & Muthén, 1999; McArdle, 1989; Muthén & Curran, 1997). For many types of developmental questions, this is precisely the question in which we are interested. That is, it might be hypothesized that there is some underlying developmental process that is shared by all children but some children vary systematically in the magnitude of the parameters that govern this process as a function of some shared influence (e.g., gender). However, there are other types of theoretical questions in which this type of developmental process is not posited, so we need to consider alternative analytical methods for our empirical tests of theory.

Fortunately, well-developed methods exist that allow for the relaxation and testing of the implied restriction that all subjects are drawn from a single homogenous population, at least under the condition that two or more groups are discrete (e.g., gender, treatment condition, ethnicity) and that the grouping variable has been observed (see Bollen, 1989, pp. 355–369, for details about the multiple group model in general SEM). In the LTM case, a trajectory model is estimated within each of the groups (say, boys and girls), and a series of equality constraints can be imposed and tested to determine the invariance of parameter estimates as a function of group membership. This analytical strategy allows for a variety of powerful tests of developmental hypotheses without the assumption that all subjects were drawn from a single homogeneous population. This multiple group approach can be used to evaluate interactions between trajectory processes and group membership in any of the trajectory models described above, but given space constraints we do not present further details here (see Hussong, Curran, & Chassin, 1998, for an example of a multiple group LTM). Suffice it to say that the set of LTMs described earlier can be extended within the multiple group framework to allow for a broad class of developmental questions to be empirically tested by a statistical model that corresponds well to underlying theoretical models involving comparisons of a priori known groups.

We have thus far explored a variety of well-known variants of the LTM and have attempted to highlight the implications associated with each modeling strategy with respect to empirical tests of developmental theory. We now turn to several issues of theoretical importance within developmental psychopathology and consider how these are manifested within the latent trajectory model.

Measurement Invariance and Homotypic Versus Heterotypic Continuity

There is an extremely important implication associated with all of the LTMs discussed thus far that may play a significant role in many empirical tests of developmental theory. From a statistical standpoint, recall that the within-person trajectory model defined in Equation 1 expressed the observed measure y for individual i at time point t as some function of time plus an individual- and time-specific residual. In other words, the measure of y represents the same construct, *regardless of the individual or time point*. From a theoretical standpoint, this analytical expression directly implies that we are empirically imposing the condition of *homotypic continuity*. Kagan (1971) defined homotypic continuity as "stabilities in the same response modality" and heterotypic continuity as "stabilities between two classes of responses that are manifestly different, but theoretically related" (p. 14). More generally, the distinction between homotypic and heterotypic continuity refers to whether behaviors of interest are manifested differently over time and, if so, whether different sets of behaviors reflect some common process (Caspi & Bem, 1990; Rutter, 1989a).

A simple example of homotypic continuity might be the measured height of a child; the outcome measure is height in inches, and this is a constant and valid measure of the outcome regardless of the developmental status of the child. However, there are many situations in developmental psychopathology in which such constant manifestation may not hold and indeed may even be strongly predicted by theory to *not* hold. For example, if one were to study developmental trajectories of aggression in children from ages 3 to 18, although theory may predict some constant underlying construct of aggression, the observable manifestation of aggressive behavior changes radically across development. Pinching and biting might be an excellent indicator of aggression at ages 3 and 5, but this is likely a less valid indicator at ages 16 and 18, even though theory hypothesizes the presence of the same underlying construct of aggression at both early and later developmental stages. Examples from nearly all other areas of development abound. It is thus critically important to understand from a theoretical standpoint that the entire set of LTMs we have discussed thus far *strictly* impose the statistical manifestation of homotypic continuity.

There are several well-developed methods available to empirically address these measurement issues in greater detail, although these are often complex and are not widely used in developmental research. In both basic and applied developmental research, by far the most common measurement strategy is to create a time-specific scale score for each child. Here, a sum or mean is computed of all of the available items at a given assessment and this scale score is used as the dependent variable. Thus, if 10 items were given to each child assessing different aspects of aggressive behavior, the child-specific and time-specific scale score representing aggression would simply be the sum of these 10 items. Of course, in many areas of developmental research, this is a perfectly valid measurement model. However, to compute and subsequently analyze a sum score in this way, we must be aware that we are imposing several key assumptions. Four of these assumptions are that (a) the individual items used to assess the underlying construct are the same over all assessments, (b) the individual items are related to the underlying construct in the same way over time, (c) the individual items are all equally indicative of the underlying construct over time, and (d) there is no measurement error in the individual items. When explicated in statistical terms, it is clear that the standard use of scale scores in some empirical tests of developmental theory may not always be an optimal modeling strategy.

There is a long and rich history in the classic psychometric literature addressing these issues, and this is broadly referred to as *measurement invariance* (Meredith, 1993). This statistical field focuses on the empirical study of how a set of observed items relates to an underlying theoretical construct over group or over time. (A full overview of measurement invariance is beyond the scope of this manuscript, but see Widaman & Reise, 1997, and Horn & McArdle, 1992, for accessible overviews.) Briefly, measurement invariance draws on the idea that the meaning of a construct is empirically inferred from the interrelationships between observed measures of that construct. In order to meaningfully interpret individual differences in stability and change in a particular construct across time, it is necessary to first establish that the construct *itself* is measured in the same way across time. If it is not, individual differences in stability or change over time are equivocal because *true* change in the construct is inextricably confounded by differential changes in the *measurement* of the construct. This issue is particularly salient in trajectory modeling, given the implicit assumption that our measure y is constant over time and any mean or covariance structure differences are interpreted to reflect true change in the construct and not simply change in the psychometric measurement of the construct over time.

A powerful analytical approach for formally testing measurement invariance over time is through the confirmatory factor analysis model (CFA). Here, the individual observed items are used as multiple indicators of an unobserved latent factor, and a separate factor is estimated for each construct within each assessment period. Meredith (1993) distinguished between three hierarchically ordered forms of factorial invariance (i.e., weak, strong, and strict invariance). The distinction between these types of factorial invariance refers to the specific sets of factor analytic model parameters (i.e., factor loadings, factor variances/covariances, residual variances, means/intercepts) that are assumed to be equivalent across time and/or groups. A series of statistical tests can be imposed to better understand the type of invariance present for a given set of measures. Rather than assuming that an instrument functions equivalently over time, procedures are available to empirically test this proposition (Meredith & Horn, 2001).

Given that the LTM is *itself* a highly restricted CFA model, we can use multiple indicator latent factors to empirically test the invariance of a set of measures over time prior to fitting a trajectory model. Although the idea of second-order trajectory models is not new (McArdle, 1988), these have only begun to garner attention (Chan, 1998; Li, Duncan, Harmer, Acock, & Stoolmiller, 1998; Raudenbush, Rowan, & Kang, 1991; Sayer & Cumsille, 2001). The central idea behind second-order trajectory models is the simultaneous estimation of both a measurement model for the repeated measures and a trajectory model for the latent variables represented in the measurement model. A hypothetical second-order unconditional LTM is presented in Figure 8. Typically, a CFA is first estimated without the underlying trajectory factors and a series of nested model comparisons is made to identify the extent to which the measurement structure is invariant over time. Once established, then the trajectory factors can be added to examine the fixed and random effects of stability and change in the constructs over time (Sayer & Cumsille, 2001).

In sum, there are tremendously important empirical and theoretical implications of using a trajectory model to examine a single construct over time. Great care must be taken to avoid inadvertently interpreting changes over time that are a function of the *measurement* of the construct as opposed to changes over time of the actual construct itself. Summing up individual scores to compute a single manifest score within each time does not necessarily circumvent these issues. The time-specific scale score may simply be obscuring important issues of measurement invariance over time. Much more research is needed to better understand the specific implications of measurement invariance over group and over time in tests of developmental theory.

The Many Metrics of Developmental Time

The basic premise of the within-person trajectory model is that the set of repeated observations for each individual is adequately summarized by some developmental function, that is, $f(\lambda_t)$ from above. As we described earlier, there are a variety of parameterizations of $f(\lambda_t)$ that can be used to characterize different functional forms of change (e.g., linear, quadratic, exponential). However, each formulation implicitly assumes that there is some agreed upon unit of time that adequately characterizes changes in y for all individuals i.

Developmental researchers commonly utilize the *assessment occasion* as the metric of time. For example, if there were three repeated assessments, then the passage of time might be coded 0, 1, and 2 and the resulting trajectory parameters will provide a synopsis of changes in y over the 3-year course of the

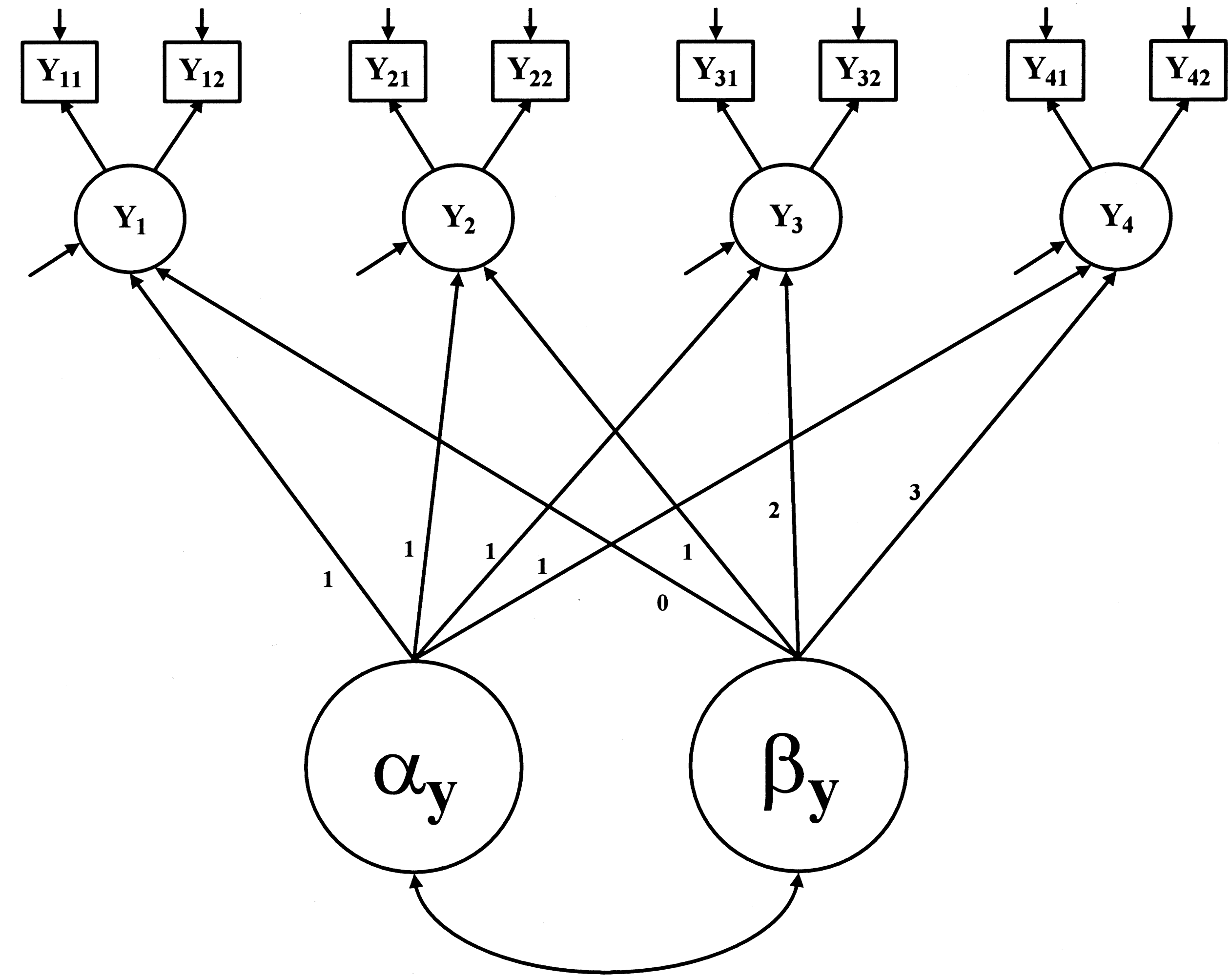

Figure 8. The unconditional second-order linear trajectory model for four repeated measures.

study. If there is age heterogeneity within the assessment period (e.g., children range in age from, say, 11 to 15 at the first assessment), then age is often entered as a covariate in the prediction of the trajectory parameters (see Curran, Stice, & Chassin, 1997, for an application using this approach). However, it has recently been highlighted that there are potential limitations to this analytic strategy, and alternative methods can be used to capitalize upon the available data. Specifically, Mehta and West (2000) proposed routinely using individually varying *chronological age* in place of assessment occasion. In the above example, instead of having every child in the first assessment period receive a score of zero for time, the value of time for each child would reflect his or her chronological age at the first assessment period. Thus, instead of all children receiving the same value of time, there is now much greater variability in time given the assessment of chronological age. There are many additional advantages to this strategy as well (Bryk & Raudenbush, 1987; Mehta & West, 2000; Raudenbush & Bryk, 2002).

There are, of course, many other potential measures of time that might be considered as well. For example, in some theoretical applications, chronological age may not be the ideal metric of time, but time might be better represented by, say, academic grade or mental age (e.g., if studying academic achievement). Similarly, treatment effects may be best conceived of as changing as a function of the number of sessions attended, or reading ability may develop as a function of the number of days of instruction. Finally, the metric of time might be the progression through puberty as measured by the Tanner stages of development. The important point to appreciate here is that researchers have choices regarding how the metric of time is best conceptualized for their phenomenon of interest. In the end, the wave of assessment might very well be the ideal metric of time; however, other metrics should be closely considered as well.

Extending the above point, it is also important to consider whether *multiple* metrics of developmental time may simultaneously impact changes in their phenomenon of interest. In addition to parameterizing trajectory models as a function of chronological age, researchers may be interested in the unique effects associated with normative developmental transitions and/or events (e.g., school transitions, puberty, divorce). For example, researchers who study adolescents may be interested in evaluating whether pubertal status makes unique contributions above and beyond chronological age to changes in a given set of behaviors over time. To this end, the effect of pubertal status could be incorporated as a TVC within a trajectory model with the passage of time defined as chronological age. Moreover, the simultaneous inclusion of chronological age and pubertal status allows for the explicit testing of the interaction between these two measures that would provide empirical insight into the role of pubertal *timing* for a particular outcome. Thoughtful attention to which metric of time optimally characterizes changes in a given construct over time represents an untapped opportunity in the use of trajectory models and provides a powerful framework for rigorously testing developmental questions.

Regardless of the metric of time that is chosen, care must be taken when drawing strong inferences about the presence of *underlying mechanisms* when using current LTMs in developmental research. The reason is that, although LTMs provide powerful tests of the individual and group characteristics of developmental trajectories over time, these models may not necessarily inform *why* these trajectories exist. Indeed, nearly 80 years ago Pearl (1924) applied early trajectory models to the study of human growth and noted that "a particular sort of equation . . . can give but little if any insight into the operation of the biological factors which underlie this growth" (p. 253). He believed that simply because a curve fit the sample data, it does not necessarily mean that the curve will help in the understanding of the causes and regulatory factors of growth.

In the study of developmental psychopathology, we might apply an unconditional trajectory model to a sample of adolescents and find compelling evidence for both fixed and random effects in developmental trajectories of drug use over time. We can thus make rather strong conclusions about the developmental course of drug use in our sample over time. However, what this model implies is that the passage of time is a causal agent; that is, growing older *causes* the adolescent to use more substances. Of course, from a developmental perspective we do not believe that the passage of time is necessarily causally related to drug use. Instead, the passage of time is an observable marker for all of the other developmental phenomenon that are occurring in the bodies and lives of these adolescents. This is consistent with previous characterizations of chronological age as an ambiguous variable in developmental research (Rutter, 1989b; Wohlwill, 1970, 1973). Researchers must be vigilant to distinctions between strategies that are used to describe *intraindividual* change, to predict *interindividual* variations in change, and to characterize the *functional processes* that give rise to change.

Nomothetic Versus Idiographic Approaches to Development

Another interesting implication associated with the trajectory model relates to nomothetic and idiographic views of development. Recall from equations 6 and 7 that the basic premise of the between-person trajectory model for simple linear change is that we can describe a mean developmental change with reference to fixed effects (i.e., μ_α, μ_β), as well as the variability in this mean trajectory with reference to random effects (as reflected in ζ_{α_i} and ζ_{β_i}). As noted above, more complicated forms of change can be estimated through alternative parameterizations of the model. However, regardless of the parameterization, fixed effects estimates provide insight into the mean rate of change over time and the random effects provide insight into individual variability around this mean trajectory, whatever the form of the trajectory might be.

The provision of both a mean rate of change and individual variations in this rate of change can be thought to correspond loosely to the long-held distinction between nomothetic and idiographic perspectives of development (Allport, 1937; Lamiell, 1998). Whereas a nomothetic approach refers to the study of general laws, an idiographic approach refers to the study of individual and unique laws. Developmentalists have frequently suggested that adopting a nomothetic perspective has the potential to undermine a full understanding of the individual differences associated with ontogeny and, as a result, have promoted a greater reliance on an idiographic perspective (Cairns, 1986; Richters, 1997). Stated differently, a criticism of "traditional" (i.e., nomothetic) approaches is that they implicitly assume that participants are drawn from a homogenous population and that data from different individuals can be treated as interchangeable. However, to the extent that this assumption does not hold, important individual differences are potentially obscured in favor of general, aggregate findings that may not characterize any individual well. The distinction between nomothetic and idiographic research perspectives is consistent with the more recent distinction made between variable-centered and person-centered approaches to data analysis (Bergman & Magnusson, 1997). Traditional statistical models have been referred to as variable-centered approaches that correspond to a nomothetic research perspective. In contrast, person-centered approaches are said to correspond to an idiographic research perspective.

In terms of the trajectory models described above, a loose analogy can be drawn between the fixed effects parameters and a nomothetic tradition of thinking and the random effects parameters and an idiographic tradition of thinking. Specifically, consistent with a nomothetic tradition of conceptualizing development, fixed effects parameters provide insight into the mean rate of change over time, irrespective of individual differences. In contrast, random effects parameters provide insight into individual variations from this mean rate of change over time. In this light, trajectory models might be viewed as residing at an intersection between variable-centered and person-centered analysis. The within-person model is very much a person-centered manifestation of development and the between-person model is very much a variable-centered manifestation. A key strength of the latent trajectory model is its ability to accommodate both nomothetic and idiographic traditions of thinking and to establish them as complementary rather than contradictory strategies.

Deconstructing Continuous Trajectories Into Their Component Parts

A final implication of trajectory models for testing developmental theory that we would like to explore is the tension between estimating continuous trajectories and the deconstruction of these trajectories into their component parts. This can be thought of as distinguishing between *trajectory parameters* and *trajectory types*. More specifically, we theoretically construe developmental trajectories from a continuous and holistic perspective. That is, a developmental trajectory is *jointly* defined as a function of the intercept and the slope; this is what we highlighted in Figure 1 (by definition, the overall trajectory is an additive combination of the individual intercept and the individual slope). It is these individual intercepts and slopes that then become the dependent variables of interest.

However, note that in the conditional latent trajectory models described earlier, the component parts that jointly define the developmental trajectory (i.e., the intercepts and the slopes) are predicted *separately* from one another. This is highlighted in Equations 8 and 9 and in Figure 4. More specifically, gender and ADHD symptoms predict individual intercepts without regard to slope (Equation 8) and individual slopes without regard to intercept (Equation 9). Although a perfectly reasonable aspect of the analytical model (that is, this raises no problems statistically), this deconstruction of trajectories might have significant implications with regard to testing developmental hypotheses and drawing subsequent inferences back to theory.

To reiterate, gender and ADHD predict intercepts *regardless of slope* and slopes *regardless of intercept*. What does this imply? Consider two hypothetical children, one of whom reports no antisocial behaviors at time 1 and one who reports seven antisocial behaviors at time 1. Now imagine that both report precisely the same *rate* of increase in antisocial behavior over time; hypothetically, say each child increases by one antisocial act per year. Of course, in this case the two children have different individual intercept scores (0 for the first vs. 7 for the second child), yet the individual values of slope for these two children are *exactly equal* (a slope of 1.0 for *both* children). Thus, in the LTM these two children differ with respect to intercepts but are treated as identical with respect to slopes. This is what we mean by *deconstructing trajectories*; the overall individual trajectories are clearly different for the two children, yet the slope component of these overall trajectories is equal for the two children. This issue may have tremendous implications when thinking about many constructs in studies of developmental psychopathology.

One way to address this issue in conditional trajectory models is to test and plot the model implied trajectories in all conditional models. We describe these methods in detail for SEM (Curran et al., in press-a) and HLM (Curran et al., in press-b) trajectory models. Using these techniques, the separate prediction of intercepts and slopes are rejoined by plotting the simultaneous effects of the exogenous measure on the trajectory components. This results in what we called a *simple trajectory*, which is a continuous trajectory that is implied across varying levels of the exogenous predictors. We believe that these testing and plotting methods significantly overcome the potential limitations of deconstructing trajectories in standard conditional trajectory models.

However, a problem with the deconstruction still remains when using the trajectories themselves as predictors. Specifically, it is analytically possible to use the trajectory factors as exogenous predictors of some later outcome measure (see, e.g., Muthén & Curran, 1997, Figure 3). Although statistically feasible, this represents a vexing problem for many applications in developmental psychopathology. Specifically, using trajectory parameters as predictors tests whether there is a significant prediction of the outcome variable from the slopes, above and beyond the effects of intercepts, and whether there is a significant prediction of the outcome variable from the intercepts, above and beyond slopes. Thus, not only is the continuous trajectory being deconstructed into its component parts, but the effect of each component part is assessed *net* all other component parts. This same problem holds when considering developmental trajectories as mediators between some proximal predictor and distal outcome (e.g., trajectories as mediators of a treatment intervention program in the prediction of some outcome behavior). Both analytical and theoretical work is needed to better understand these issues prior to using these models in many developmental research settings.

Current Limitations of Trajectory Models When Testing Developmental Theory

Thus far we have considered implications of currently available trajectory models as they pertain to various theoretical concepts in developmental psychopathology. Key implications included measurement invariance, metrics of time, nomothetic and idiographic conceptualizations of development, and the deconstruction of continuous trajectories. When these implications are understood and the assumptions are adequately met, LTMs provide a truly powerful and exciting method for rigorously testing many theories in developmental psychopathology. However, we conclude our paper by briefly considering several important theoretical concepts that are frequently espoused by developmental psychopathologists but are currently difficult, if not impossible, to empirically evaluate using existing trajectory modeling techniques. By exploring these issues we hope to both highlight potential limitations in using these methods for testing certain types of theoretical questions and to advocate for the ongoing integration of advances in statistical methods and developmental theory to overcome these limitations in the future.

Individual development and measurement invariance revisited

As we discussed earlier, an implicit assumption imposed when estimating trajectory models with scale scores is that the measurement of the dependent variable is constant across individuals and across time. We encouraged the greater utilization of tests of measurement invariance to empirically evaluate this assumption. However, it is noteworthy that tests of measurement invariance *themselves* make assumptions. Most importantly for research in developmental psychology, testing for measurement invariance of a construct across time implies that if changes are evident, they will be evident for the entire sample. That is, the data for all individuals are aggregated and tests are based on group-level changes in the covariation among indicators of a given construct across time.

Molenaar et al. recently suggested that inferences made from testing for measurement invariance across an entire sample of individuals do not necessary generalize to individuals (Molenaar, Huizenga, & Nesselroade, in press). In general, Molenaar and colleagues raise questions about the use of traditional measurement invariance techniques, which are based on interindividual change, to inform questions regarding potential changes in the organization of behavior at the individual level, which corresponds to intraindividual change. In other words, traditional measurement invariance techniques may make an unrealistic assumption that changes (or lack thereof) in the factor structure of a measure over time must occur for the entire sample. This would not be well suited to situations where behavioral consolidation/integration occurs for unknown subgroups of the larger sample along varying time frames. Future theoretical and statistical work is needed to better understand these interesting and provocative ideas about measurement and change.

Modeling coactions

There is a long history of relying on world hypotheses and root metaphors to help organize thinking in developmental psychology (Reese & Overton, 1970). Mechanistic and organismic perspectives, in particular, have provided a framework for clarifying what development is and how it is best studied (Sameroff, 1995). Overton (1991, p. 265) provided a concise definition of each perspective.

An organismic definition states that development refers to changes in the form or organization of any system, with these changes being directed toward defined endstates or goals. A mechanistic definition states that development refers to changes that are a function (i.e., are caused by) antecedent variables (e.g., environmental factors, biological factors).

A fundamental distinction between these perspectives is the role that individuals play in contributing to their own development. Specifically, a mechanistic tradition embodies the notion that individuals are "at rest, only becoming active under the influence of outside forces" (Sameroff, 1995, p. 661). In contrast, an organismic tradition embodies the notion that individuals are "in a continuous transition from one state to another in unceasing succession. No outside source of motivation is necessary because activity is a given in the definition of life" (Sameroff, 1995, p. 662). This distinction has also been characterized in terms of closed versus open systems models of development (Richters, 1997).

Developmental psychopathology is most clearly aligned with an organismic perspective of development. Consistent with this perspective, developmental psychopathology is said to endorse a relational (Gottlieb & Halpern, 2002) or transactional (Sameroff, 1995) view of causality. From this perspective, ontogeny is said to result from the "coaction" of different (e.g., genetic, neural, behavioral and environmental) influences across developmental time (Gottlieb & Halpern, 2002).[6] Thus, for example, the emergence of new behaviors (i.e., novelty) is said to result from the bidirectional (transactional) relationship among and between endogenous and exogenous influences over time.

Although theoretically appealing, perhaps *the* major challenge for developmental psychopathology is consideration of how one goes about actually empirically testing coactions. It is one thing to posit that novel behavior emerges from the coaction between different levels of influence, but it is quite another to subject this proposition to a rigorous test of empirical falsification. However, an underlying theme of our paper is that empirical evaluations of propositions of this sort are critically important if developmental psychopathology is to continue to thrive as a discipline. It is our impression that the idea of a coaction necessarily involves some insight into how two constructs relate to each other across developmental time. To that end, our earlier discussion of multivariate trajectory models and related techniques (e.g., ALT model) is relevant. Specifically, the ability to test coactions would appear to necessitate the simultaneous modeling of intraindividual changes between two (or more) constructs across developmental time. However, although this is necessary, it is not sufficient.

Recall that we characterized the estimation of developmental trajectories as a statistical procedure to more parsimoniously summarize a large amount of observed data in a way that is maximally consistent with developmental theory. By extension, multivariate trajectory models summarize repeated measures data for two or more constructs over time, as well as providing an understanding of whether individual variations on one construct are systematically related to individual variations on some other construct. However, nowhere in the analytical models that we have discussed is there a place to model the emergence of *new* behavior. That is, none of the parameters in trajectory models directly correspond to the idea of coactions or the emergence of novelty. At best, coactions may be *inferred* from developmental trajectory models, but they cannot be definitively *tested*. In this respect, despite the many benefits associated with modeling developmental trajectories, these methods are still consistent with a "closed system" strategy of inquiry (Richters, 1997).

Multifinality and equifinality

We opened our paper by noting the importance of the concept of *developmental trajectories* among many areas of study in develop-

6. The term coact, rather than interact, is used because the latter term has a specific meaning in the statistical literature that is distinct from its intended meaning among developmentalists.

mental psychopathology. A closely related concept to developmental trajectories is that of *developmental pathways*. Indeed, the terms *pathways* and *trajectories* are often used synonymously with one another, sometimes even in the same sentence. Although these terms are often used interchangeably, we consider developmental pathways and developmental trajectories to be distinct concepts. Specifically, we think of developmental trajectories as referring to *empirical* estimates of changes in an observable construct over time. In contrast, we think of developmental pathways as referring to a more general interest in the *theoretical* processes related to changes in one or more constructs over time. For example, in terms of the study of conduct problems, our use of the term developmental trajectories refers to the application of random coefficient trajectory (growth curve) models to make inferences regarding changes in a specific behavioral construct over time. In contrast, our use of the term developmental pathways refers to a broader set of theories and hypotheses involving not only changes in an identically measured set of behaviors over time but also issues such as the differential manifestation of conduct problems over time, the developmental processes or mechanisms that give rise to these changes, and the short- and long-term sequelae stemming from these changes.

By differentiating the concepts of developmental trajectory and developmental pathway, we intend to draw the distinction between specific hypotheses that can be empirically evaluated from broader theoretical models that are not necessarily directly testable but instead are informed by integrated theory and prior research. That is, whereas we have statistical models that directly test questions about the developmental trajectory of a given behavioral construct over a specific span of time, we do not (and, arguably, *cannot*) have statistical models that directly empirically test developmental pathways. We raise the potential differentiation of trajectories from pathways because we believe this distinction directly relates to the important developmental concepts of *equifinality* and *multifinality*.

Equifinality has been defined as "(*a*) developing organisms that have different early 'initial' conditions can reach the same endpoint and (*b*) organisms that share the same initial condition can reach the same endpoint by different routes or paths" (Gottlieb, Wahlsten, & Lickliter, 1998, p. 236). In contrast, multifinality states that individuals with similar early experiences can experience different outcomes (Cicchetti & Rogosch, 1996). In the spirit of our distinction drawn above, we conceptualize equifinality and multifinality as referring to developmental pathways and not to developmental trajectories. That is, we do not necessarily believe that the results of any empirical study that utilizes trajectory models unambiguously informs questions of equifinality and multifinality.

There are both strengths and weaknesses associated with linking the ideas of equifinality and multifinality to developmental pathways and not to developmental trajectories. One key strength is to make explicit the idea that not all developmental theories are currently empirically testable. This does not trouble us in the slightest given that our major thesis here is not to suggest that the only useful developmental ideas are those that neatly correspond with available statistical techniques. Such a position is not only naive but also contradicts the philosophy of science in which research is viewed as an ongoing process of discovery using any and all available methods and developing new methods to foster future discovery (e.g., Cattell, 1988). Moreover, we believe that familiarity with developmental concepts that are often abstracted from other disciplines (e.g., embryology) serves an important function of challenging both basic and applied researchers to think about their phenomenon of interest in new ways.

Yet herein lies a potential danger. It is reasonable to appeal to the concepts of equifinality and multifinality to help augment a theoretical model with the results of a number of specific empirical findings. Moreover, it is reasonable to appeal to the concepts of equifinality and multifinality to help conceptualize a research area from a different perspective and to potentially generate new, testable hypotheses in the process; indeed, this is a cornerstone of developmental psychopathology. However, we believe that it is *not* reasonable to appeal to these concepts in order to explain away a set of specific results that may not be consistent with some expected theoretical processes. This latter possibility helps highlight the danger of having theoretical concepts that are not empirically testable. These might be inadvertently applied indiscriminately and without strong justification. Indeed, we are hard pressed to imagine the results of any single study that could not be explained alternatively by invoking the concepts of equifinality and multifinality. However, the temptation to do this not only undermines the utility of these concepts but also undermines the motivational goals of the field.

Our main point here is that we must be constantly vigilant that we do not inadvertently pose a theoretically derived hypothesis that we cannot empirically evaluate using existing analytical methodologies. This is not to say that we have to "dumb down" our theoretical propositions, nor do we have to walk away from an empirical evaluation of a theoretically salient question. Instead, we must simply be cognizant of the aspect of our theoretical question that is being empirically evaluated, the aspect may not be, and the implications of the degree of correspondence between our theoretical and statistical models.

The symbiotic relation between theory and statistics

Throughout our discussion we have implied that in order for developmental psychopathology to continue to flourish as an empirically based scientific discipline, greater efforts are needed to empirically test complex theory. Statistical methodology has thus far been presented mostly in the role of serving theory. However, it would be inaccurate to suggest that theory must always precede method. Rather, we agree with Wohlwill (1991), who suggested that the relationship between theory and method is best conceptualized as a symbiotic one. Just as theory makes claims that can be empirically evaluated via statistical methods, it is also the case that an improved understanding of statistical methods challenges one to clarify theory. When so many options are available for statistically modeling individual differences in stability and change over time, the responsibility is thrust back onto theory to identify precisely what *type* of developmental process is hypothesized. However, this assumes that the hypothesized developmental process can be validly empirically tested using an existing statistical model. When such a situation does not hold, it is critically important that developmental theorists and quantitative methodologists work collaboratively so that new analytical techniques can continue to be developed. Indeed, developmental theory can serve as a catalyst for the creation of entirely new analytic methods. To highlight this symbiotic process, we will briefly consider the recent bidirectional influences between theory and statistics in the process of development and application of growth mixture models.

Earlier we described how multiple group LTMs could be used to examine interactions between discrete group membership and developmental processes over time. A required condition to use these models, however, is that group membership be directly observed (e.g., child gender, treatment condition). However, several recent theoretical models of developmental psychopathology have posited that distinct subgroups exist, but the grouping variable has *not* been directly observed. A salient example is Moffitt's theory of adolescent limited and life course persistent delinquency (Moffitt, 1993). Drawing on a complex theoretical model, Moffitt (1993) hypothesizes that many children follow one of these two trajectory "types" or "classes" in terms of the development of delinquent and antisocial behavior. However, individual class membership is not observed and must be inferred from the data. At the time of her seminal work (Moffitt, 1993), few statistical methods were even remotely well suited to empirically evaluate these hypotheses in a systematic and rigorous way.

Based in part on the increased theorizing about the presence of unobserved trajectory classes, a number of quantitative methodologists began working on ways to better test these ideas empirically. Drawing upon many years of prior statistical work (see Bauer & Curran, in press-a, for a review), an entirely new set of analytic methods was developed, sometimes referred to as growth mixture models (GMMs). No single person is responsible for the development of GMMs, but the combined efforts of people such as Arminger, Stein, and Wittenberg (1999), Jedidi, Jagpal, and DeSarbo (1997), Muthén (2001), Nagin (1999), Yung (1997), and many others have resulted in a powerful set of methodologies that are potentially well suited for testing the question of heterogeneous trajectory classes when class membership was not observed. Many of these statistical developments directly resulted from quantitative methodologists working in conjunction with developmental theorists with the joint goal of overcoming the limits of current statistical methods for testing advanced developmental theories. For example, in a description of one type of GMM, Nagin (1999, p. 140) noted "The group-based modeling strategy is prototypal in design and provides a methodological complement to theories that predict prototypal developmental etiologies and trajectories within the population . . . " Thus, developmental theory facilitated new methodological developments, and this new set of analytic techniques allows for the testing of developmental hypotheses in a way not previously possible.

However, these new developments now require closer analytical scrutiny in order to better understand the potential limitations for their use in research applications. For example, Bauer and Curran (in press-a, in press-b) recently demonstrated that multivariate nonnormality, model misspecification, and nonlinear relations among constructs will often lead to the identification of multiple classes in a sample when, in actuality, only one class truly exists in the population. From a statistical standpoint, these findings are without problem; that is, the statistical models are performing precisely as designed (as was first described by Pearson, 1894). However, from a theoretical point of view, these findings have potentially significant implications when testing developmental theories. For example, the clear extraction of multiple trajectory classes might indeed be reflective of the true structure of the population, or it might simply be attempting to model a complex nonnormal distribution of the repeated measures. New statistical methods are now needed to attempt to differentiate these two conditions and thus further strengthen our ability to test complex questions in developmental psychopathology using these new and powerful analytical methods (Bauer & Curran, in press-c).

Conclusion

We stand at an exciting crossroads between developmental theory and quantitative methodology. We look in one direction and see comprehensive and multifaceted theoretical models that describe developmental processes at a level of complexity and abstraction that begins to reflect the complexity of human development itself. We look in the other direction and see remarkable advances in quantitative methods that were not available even a few years ago that can now be applied to existing data using existing software. Given this current intersection, there is an ever present danger that we may hypothesize relations that exceed the boundaries of existing statistical methods, which raises the dangerous possibility that we are empirically evaluating a question that is different from the question that was posed. The motivating goal of our paper has been to delineate the boundaries associated with the use of trajectory models as they apply to the study of developmental psychopathology. We have attempted to identify currently existing trajectory models, explore the implications of these models for testing developmental theory, and identify several key theoretical issues that we feel cannot be empirically tested using existing methods. In closing, we note Cicchetti and Cohen's (1995, p. 14) charge: " . . . future investigations must strive to attain enhanced fidelity between the elegance and complexity of our theoretical models and the measurement and data-analytic strategies employed in our studies." We hope that we have contributed in some small way to allow our field to better meet this important challenge.

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