CHILD DEVELOPMENT PERSPECTIVES

The Challenge of Modeling Co-Developmental Processes over Time

Patrick J. Curran[1] and Gregory R. Hancock[2]

[1]University of North Carolina at Chapel Hill and [2]University of Maryland

ABSTRACT—***One of the most vexing challenges facing developmental researchers today is the statistical modeling of two or more behaviors as they unfold jointly over time. Although quantitative methodologists have studied these issues for more than half a century, no widely agreed-upon principled strategy exists to empirically analyze codevelopmental processes. Indeed, the plethora of available options makes selecting a specific analytic approach both confusing and overwhelming. In this article, we argue that a key step in adjudicating among alternative modeling strategies is to embrace the concept of within- and between-person components of change over time. First, we define the disaggregation of effects in grouped data, and then we extend these concepts to repeated measures. Then we review several available modeling strategies that capture these effects to varying degrees and raise three issues that can help to guide practice.***

KEYWORDS—*contextual effects; growth modeling; longitudinal data analysis; reciprocal effects; within- and between-person effects*

Few challenges in the behavioral sciences are as daunting as studying the development of children over time. From a methodological perspective, virtually every difficulty seems to arise in the longitudinal study of the child, including missing data, causal inference, nonindependence, population heterogeneity, and nonnormality, to name just a few. Despite advances in methods and statistical analysis, one last untamed frontier remains: the principled modeling of multiple constructs as they codevelop over time. A review of articles in the past 18 months of *Child Development Perspectives* clearly highlights that the developmental sciences need these analytic methods now more than ever.

For example, Owens, Eisenlohr-Moul, and Prinstein (2020) examined developmental processes that place adolescent girls at risk for self-harm and suicide that jointly incorporate within-person fluctuations in menstrual cycles with between-person risk factors in suicidal thoughts and behaviors. Niedzwiecka (2020) identified a need for novel studies to understand more fully the development of infant eye contact and gaze with elevated arousal, emotions, and motivation. Peng and Kievit (2020) reviewed the reciprocal relations between cognitive abilities and academic achievement, concluding that high-quality schooling may trigger bidirectionality between these constructs. We found many other examples, including an exploration of the development of executive function skills, the identification of mechanisms underlying political engagement in youth, the developmental origin of reputational concerns in children, and efforts to link values theory and adolescent motivation to behave aggressively.

There is clearly much interest in the empirical modeling of codevelopmental processes, yet it remains unclear as to how this is best accomplished in practice. Part of the difficulty of addressing questions of codevelopment is that it moves us into a domain with which our discipline is historically not well versed, that of the disaggregation of multiple levels of effects as they arise in longitudinal data. To ease us into this world, which might seem unfamiliar, we first consider these effects in grouped data, which require introducing the critical statistical concept of "*for a...*"

"FOR A..."

Have you ever been out on a walk, spotted a nearby animal, and thought, "Wow, that is huge—*for a* chipmunk"? Or perhaps you saw a crayon drawing on a colleague's office wall and remarked, "That's a great drawing of a giraffe—*for a* 6-year-old." Or you were watching the news and thought, "She makes a really low salary—*for a* CEO." In each of these examples, an individual

Correspondence concerning this article should be addressed to Patrick Curran, Department of Psychology and Neuroscience, University of North Carolina, Chapel Hill, NC, 27599-3270; e-mail curran@unc.edu.

DOI: 10.1111/cdep.12401

characteristic (chipmunk size, artistic prowess, earning potential) is defined in part with respect to (or *contextualized by*) what is typical for the group in which it resides. This conceptualization allows us to distinguish *between-group* effects (typically, chipmunks are smaller than cows but bigger than mice) from *within-group* effects (that is a *really* big chipmunk).

Disaggregation of within- and between-group effects is a standard component of any study of hierarchically nested data structures and well-developed analytic methods are routinely used in practice (e.g., Raudenbush & Bryk, 2002). Yet this concept of disaggregation becomes markedly more vexing when studying children longitudinally. Whereas hierarchical data typically consist of individuals nested within discrete groups (e.g., siblings within families, students within classrooms), longitudinal data have a hierarchical structure arising from repeated observations nested within individuals (e.g., Bryk & Raudenbush, 1987). The child becomes the *group* and the contextual effect is reflected in a child's time-linked assessment relative to typical assessments *for that individual* (Hoffman, 2015).

To make things more concrete, imagine that a set of repeated assessments indicates that, on average, Greg is characterized by lower levels of anxiety than Patrick. This traitlike difference between Greg and Patrick is a *between-person* effect and prompts us to think of Patrick as a more anxious person. However, say that the same repeated assessments indicate that the typically less-anxious Greg has specific days on which he is more anxious *than he usually is*; that is, he is more anxious *for a* Greg day. This time-specific elevation of anxiety for Greg is a *within-person* effect. Indeed, on any given day, Greg and Patrick may have precisely the same level of anxiety, but this might be *higher* than what is typical for Greg yet *lower* than what is typical for Patrick. As such, the very meaning of a daily measure of anxiety is defined in part by what is typical for each person.

The proper theoretical and empirical disaggregation of between-person and within-person effects lies at the crux of the challenges researchers face when studying codevelopmental processes. It has long been recognized that most theoretical models of change posit within-person relations, whereas most traditional statistical models of change capture between-person relations (e.g., Curran & Bauer, 2011). Furthermore, methodological interest in these issues as they relate to the codevelopment of behaviors over time has surged recently (e.g., Bainter & Howard, 2016; Berry & Willoughby, 2017; Curran, Howard, Bainter, Lane, & McGinley, 2014; Curran, Lee, Howard, Lane, & MacCallum, 2012; Hamaker, Kuiper, & Grasman, 2015; Usami, Murayama, & Hamaker, 2019; Zyphur, Allison, et al., 2019; Zyphur, Voelkle, et al., 2019). This literature is vast, contributing significantly to the analysis of longitudinal data. Yet at the same time, this body of work arises from an array of scientific subdisciplines, each of which is characterized by a unique nomenclature and historical approach to statistical modeling (our own work included). These factors often combine to leave an applied researcher overwhelmed by the number of potential options and with no clear path to select analytic designs best suited to test the hypotheses at hand.

In our opinion, the field neither fully understands nor broadly agrees on how an empirical researcher should most effectively evaluate increasingly complex theoretical questions involving within- and between-person change processes over time. These issues are particularly salient when studying the codevelopment of behavior over time. (Given space constraints, we cannot present a comprehensive evaluation of these issues here; see recent work by Curran et al., 2012, 2016; Hamaker et al., 2015; Usami et al., 2019; Zyphur, Allison, et al., 2019; Zyphur, Voelkle, et al., 2019, for discussions of this topic.) Instead, our goals are more modest: We briefly describe traditional and more recent analytical methods that researchers can use, note potential advantages and disadvantages of each approach, and conclude with three broad principles to aid in selecting the optimal statistical model for a given research question.

TRADITIONAL MODELS FOR CODEVELOPMENTAL PROCESSES

Quantitative methodologists have long engaged in heated debates about how to most effectively model change over time (e.g., Cronbach & Furby, 1970; Lord, 1963; Rogosa, 1980). Despite the many apparent differences among competing modeling strategies, all these analytic methods are focused on explicating a particular model structure that optimally reproduces the summary means, variances, and covariances observed in a given sample. The core issues can be distilled down to what might be called a whiteboard problem.

Imagine that we all have precisely the same sample data and the same measured variables, and these variables are represented as rectangles drawn on a whiteboard. These rectangles remain fixed in space, yet we each walk up to the board and draw our own combination of circles (latent variables) and arrows (structural and nonstructural relations) to represent what we believe is the underlying theoretical process that gave rise to those data. Each of us might have subtly or even starkly different ways in which we connect the same set of measures. Much of the confusion stems from the fact that we are often forced to choose one whiteboard model over others based on ambiguous or subjective criteria. Although we do not claim here to solve this challenge, we offer guidance distilled from closely considering within- and between-person effects and how these arise in a given hypothesized developmental process.

We briefly review some of the most relevant model structures that, while not an exhaustive list, represent some of the key tools available. Each is one example of a whiteboard model and each captures somewhat different aspects of the observed data. We use an exemplar model of a hypothetical relation between childhood aggression and peer rejection over five repeated assessments, although any codevelopmental processes over any number of time points could be considered. Furthermore,

although we show exemplar models with linear growth over time, these models can be extended to include nonlinear trajectories, unequally spaced assessments, missing data, nonnormal data, and other complex design features (see, e.g., Bollen & Curran, 2006; Grimm, Ram, & Estabrook, 2016; Hoffman, 2015).

The Autoregressive Cross-Lagged Panel Model

The autoregressive cross-lagged (ARCL) panel model has by far the longest history in analyzing repeated measures and has been a workhorse in the social sciences for decades (e.g., Anderson, 1960; Joreskog, 1979; Wiley & Wiley, 1970). It is centered on what is sometimes called *residual change*, in which a later measure of a construct is regressed on its own prior value (the *autoregressive* component) as well as on the prior value of some other construct (the *cross-lagged* component). The goal is to use the earlier construct (e.g., aggression) to predict a later second construct (e.g., peer rejection) above and beyond the prior level of the second construct (see Figure 1). Advantages include the ARCL panel model taking the form of a standard path model, ease of estimation and model evaluation, and direct tests of mediation. However, several distinct disadvantages that are particularly salient in the developmental sciences include the inability to estimate smooth trajectories of change over time, the carving up of a set of repeated assessments into relations between two time points, and the unavoidable confounding of within- and between-person effects (Hamaker et al., 2015). Given these and many other limitations, alternative models have been sought.

The Time-Varying Covariate Growth Model

Whereas the ARCL model conceptualizes earlier measures of a construct as partial causes of later measures, the time-varying covariate (TVC) growth model posits that the set of repeated measures arose from an underlying, latent, continuous growth process (Bollen & Curran, 2006; McArdle, 2009; McArdle & Epstein, 1987; Meredith & Tisak, 1990). The observed repeated measures are of interest to the extent to which they may be used to infer the existence of unobserved growth, and this in turn allows for a closer alignment of theoretical and statistical models of change in the developmental sciences (Curran & Willoughby, 2003). It is a natural extension of the growth model for one construct to include the time-varying influences of some covariate to incorporate the impact of one construct on another over time (see Figure 2). The TVC growth model has many advantages, including the estimation of continuous growth functions and the pure separation of the within-person relation between the primary outcome and the TVC. Disadvantages include the omission of a growth process for the TVC itself (thus rendering the model incapable of representing codevelopment), the restriction of examining only unidirectional effects, and the omission of the between-person component of change for the TVC.

The Bivariate Growth Model

Of all the limitations of the TVC growth model, the most salient may be the omission of a growth process for the TVC itself, which is often not only a lost opportunity to understand more fully the change process at hand but also its possible inconsistency with underlying theory. Fortunately, incorporating a growth structure for the TVC is easily accomplished with a few simple extensions and results in the bivariate growth model (Bollen & Curran, 2006; McArdle, 2009). In this model, growth trajectories in two constructs are modeled simultaneously and the cross-domain relations between the two constructs are evaluated at the level of the continuous trajectories (see Figure 3). This model offers several advantages, including the simultaneous estimation of multiple growth processes and the pure estimation of between-person

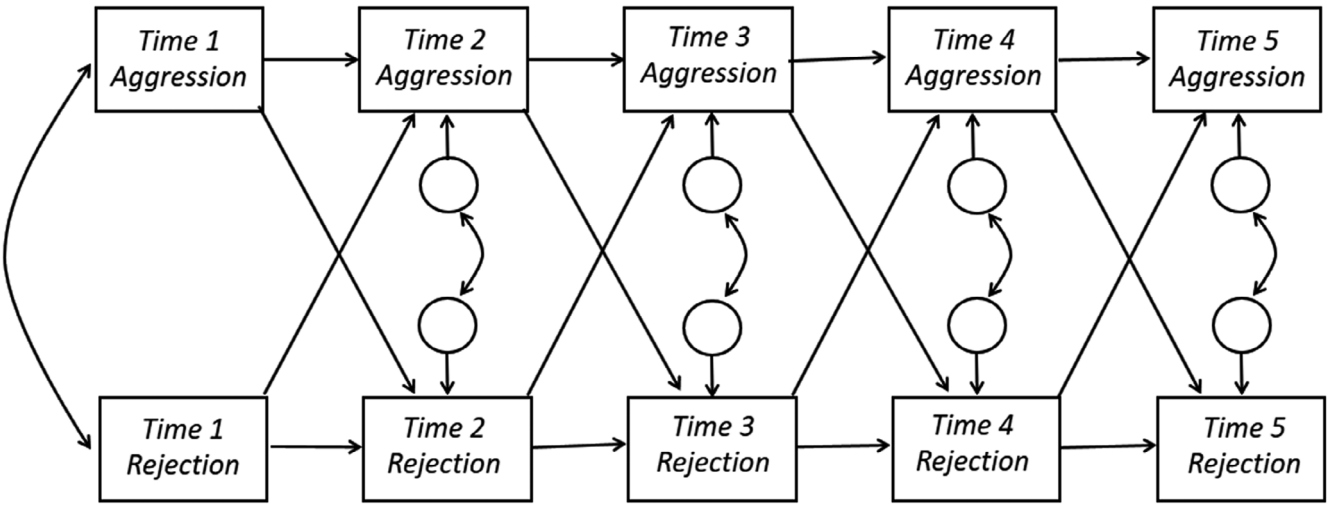

Figure 1. Autoregressive cross-lagged model.
Note. Rectangles are measured variables, circles are residual variances, single-headed arrows are regression coefficients, and double-headed arrows are covariances.

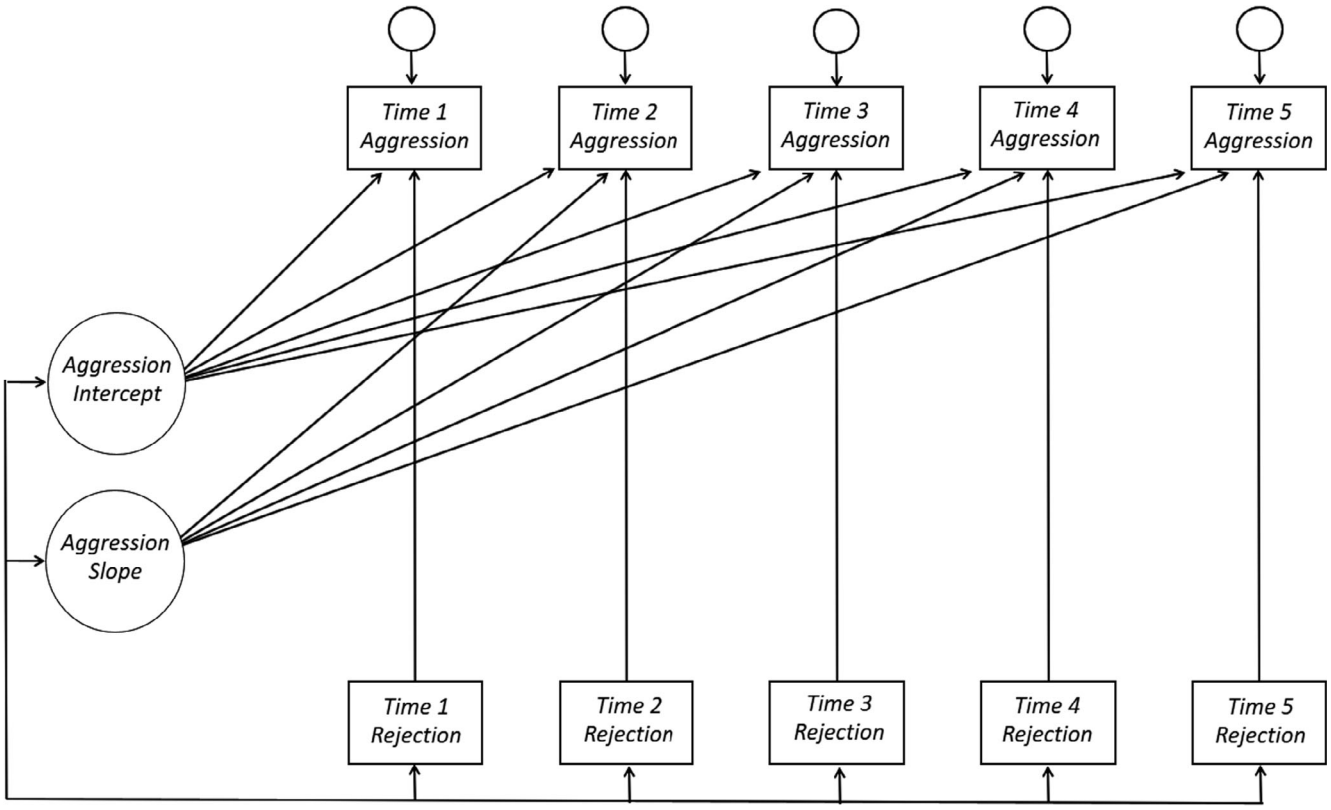

Figure 2. Time-varying covariate growth model.
Note. Rectangles are measured variables, circles are latent variables and residual variances, single-headed arrows are regression coefficients and factor loadings, and all exogenous variables (measured and latent) covary.

effects assessed at the level of the trajectories. However, several disadvantages remain, including the complete omission of the within-person component of change over time and the loss of temporal precedence in which a prior measure of one construct is related to a later measure of another construct.

HYBRID MODELS FOR CODEVELOPMENTAL PROCESSES

The curious irony of the TVC and the bivariate growth models is that a developmental researcher is forced to choose a model that captures a pure estimate of either the time-specific, within-person component of change (via the TVC growth model) or the individual-specific, between-person component of change (via the bivariate growth model). Many scientists would prefer an approach in which *both* time-specific, within-person effects and individual-specific, between-person effects are captured in a single model. This brings us to two hybrid models of change.[1]

The Autoregressive Latent Trajectory Model

The autoregressive latent trajectory (ALT) model attempts to combine the time-specific parameters of the ARCL model with the continuous trajectories of the latent growth model (Bollen & Curran, 2004; Curran & Bollen, 2001; see Figure 4). The repeated measures simultaneously serve as indicators on the latent growth factors and predictors and outcomes in the ARCL part of the model. The advantages are as expected, namely, the simultaneous integration of time-specific relations among the repeated measures and the underlying continuous trajectories defined for each construct, and the fact that more traditional models are subsets of the more general ALT framework. Among the model's potential disadvantages is one that is key to this discussion: the inability to purely isolate within-person and between-person effects (Curran et al., 2014). That is, the time-linked relations directly affect the underlying growth trajectories and vice versa, an issue that can be viewed as both a limitation (e.g., Voelkle, 2008) and an intended design feature of the model (e.g., Bollen & Curran, 2006).

The Latent Curve Model with Structured Residuals

The latent curve model with structured residuals (LCM-SR) was proposed as a second attempt to obtain both between- and within-person effects in a single model (Curran et al., 2012;

[1]A third hybrid model is the latent change score (LCS) model (McArdle & Hamagami, 2001). This is a powerful method designed to isolate the estimation and prediction of time-adjacent change within and across constructs, with a key advantage of capturing complex nonlinear trajectories over time. Space constraints preclude a detailed examination of the LCS model, but see Grimm, Mazza, and Mazzocco (2016) for a discussion of this approach.

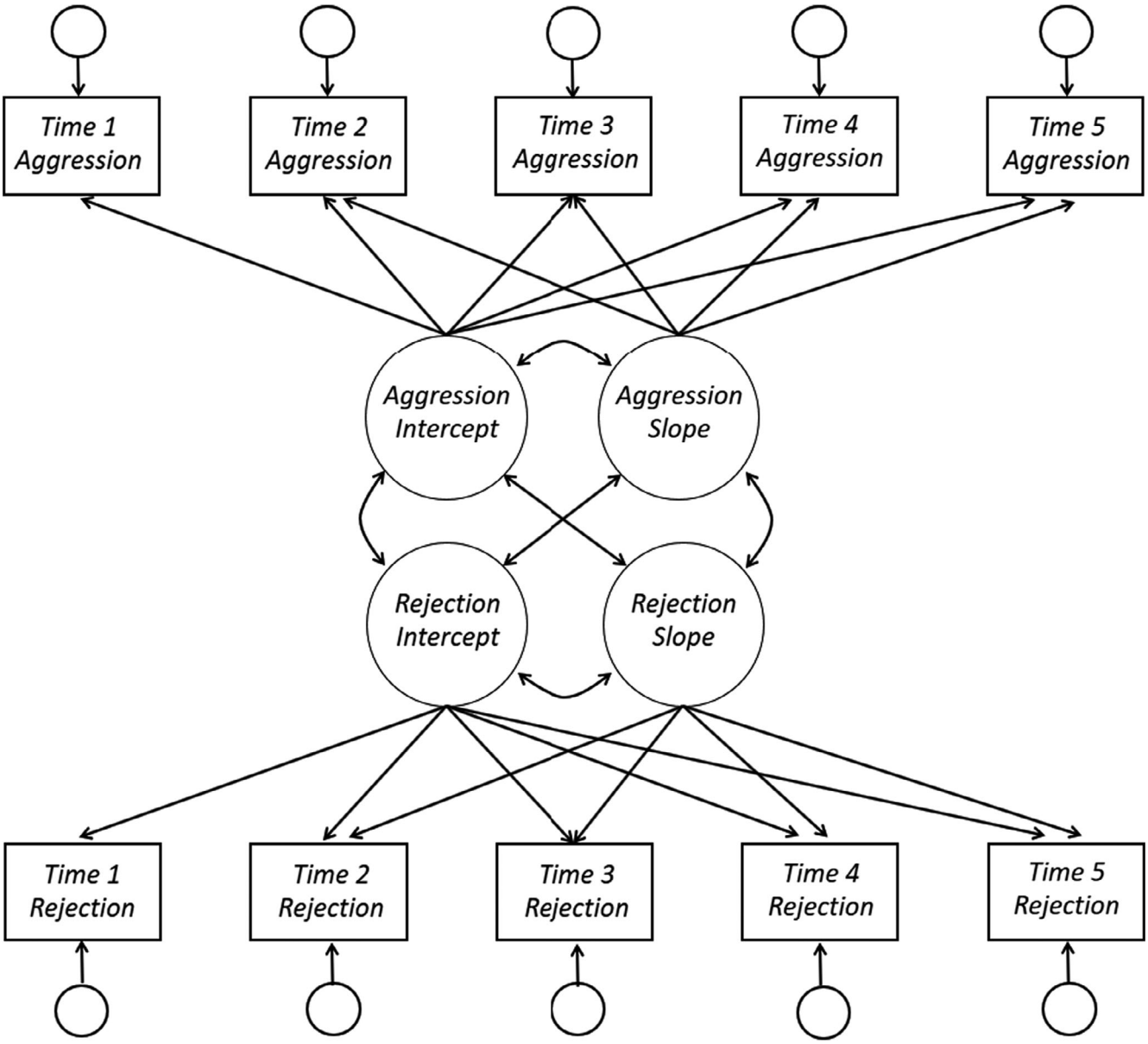

Figure 3. Bivariate growth curve model.
Note. Rectangles are measured variables, circles are latent variables and residual variances, single-headed arrows are factor loadings, and double-headed arrows are covariances.

Curran et al., 2014; see Figure 5). In some ways, this model is quite similar in function and form to the ALT model, but it differs in a subtle and critical way. Whereas the time-linked regressions in the ALT model are estimated at the level of the observed *variables*, these regressions are estimated at the level of the *residuals* of the observed variables in the LCM-SR. This parameterization allows the LCM-SR to isolate the time-linked regression effects from the person-linked growth functions that in turn provide pure estimates of both the within- and between-person components of codevelopmental change over time. As a result, the time-linked regressions do not affect the underlying growth functions (as occurs in the TVC and ALT models), and the means of the growth functions remain unchanged with or without the structure among the residuals. Disadvantages of this model include the current lack of a clear model-building strategy and the increased complexity of the model, which may demand higher numbers of repeated measures to improve estimation.[2]

[2]For information on recently proposed variants of ALT- and LCM-SR-like structures, see Zyphur, Allison et al., 2019, and Zyphur, Voelkle et al., 2019.

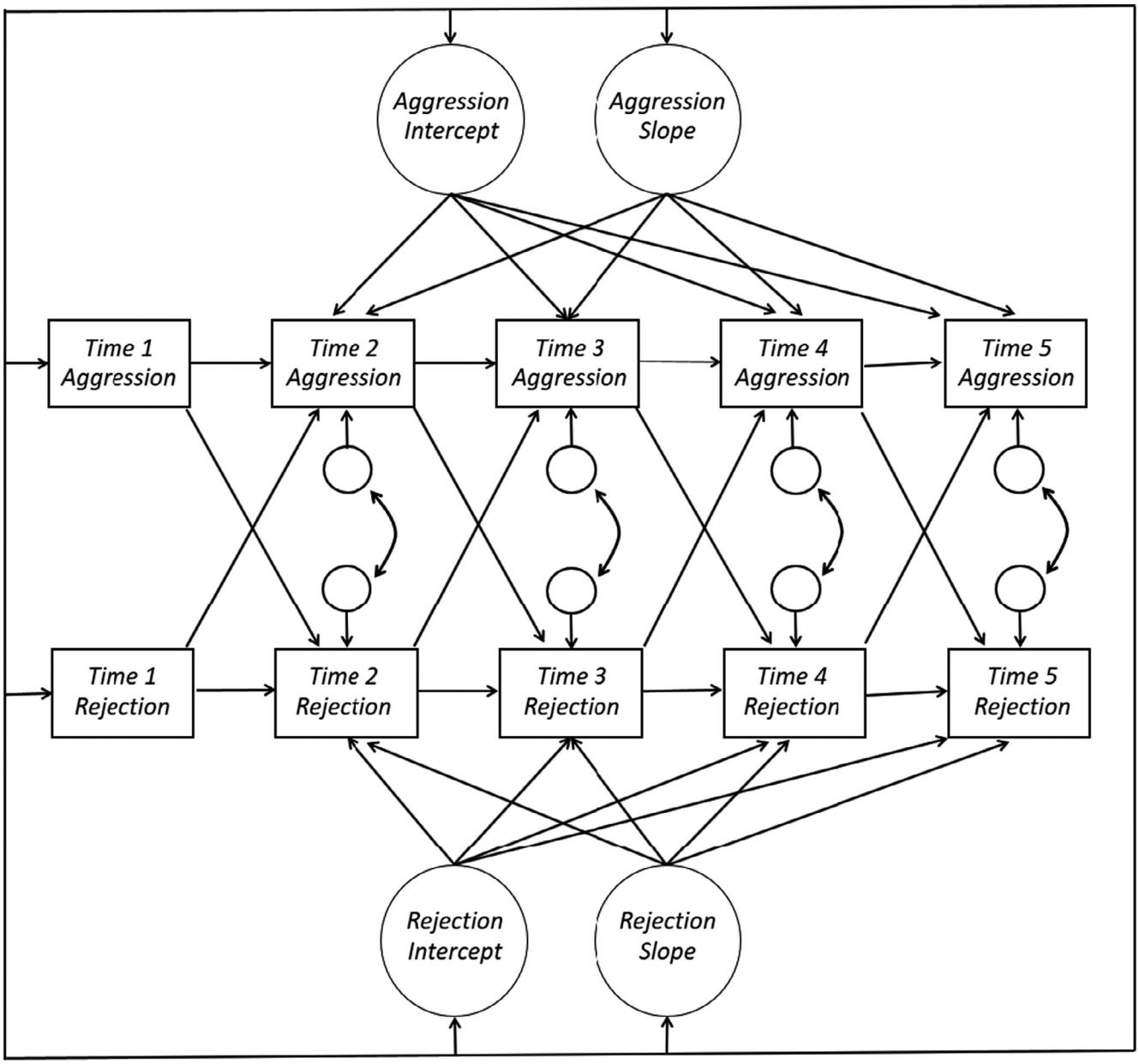

Figure 4. Autoregressive latent trajectory model.
Note. Rectangles are measured variables, circles are latent variables and residual variances, single-headed arrows are regression coefficients and factor loadings, and all exogenous variables (measured and latent) covary.

RECOMMENDATIONS FOR MOVING FORWARD

Figures 1 through 5 highlight the core of the whiteboard problem we mentioned earlier. Each figure depicts the same rectangles representing the same observed measures, and differs only in the combination of circles and arrows that link the observed measures to one another. Thus, each model represents a different hypothesized structure believed to have given rise to the observed data. As such, no model is right or wrong per se, nor is it useful to argue this way. Rather, these differences make each model better suited for evaluating certain hypotheses and less so for evaluating others. Adopting this contextual perspective, we conclude by discussing three issues researchers might consider in their work. These are neither rigid nor requisite, but are intended to serve as guideposts to help researchers map a route forward.

The Critical Role of Theory

The most important navigational tool we have available is that which guided us here in the first place: theory. Any given model is nothing more than a simplification of a more complex system, and any set of competing models imposes different types of

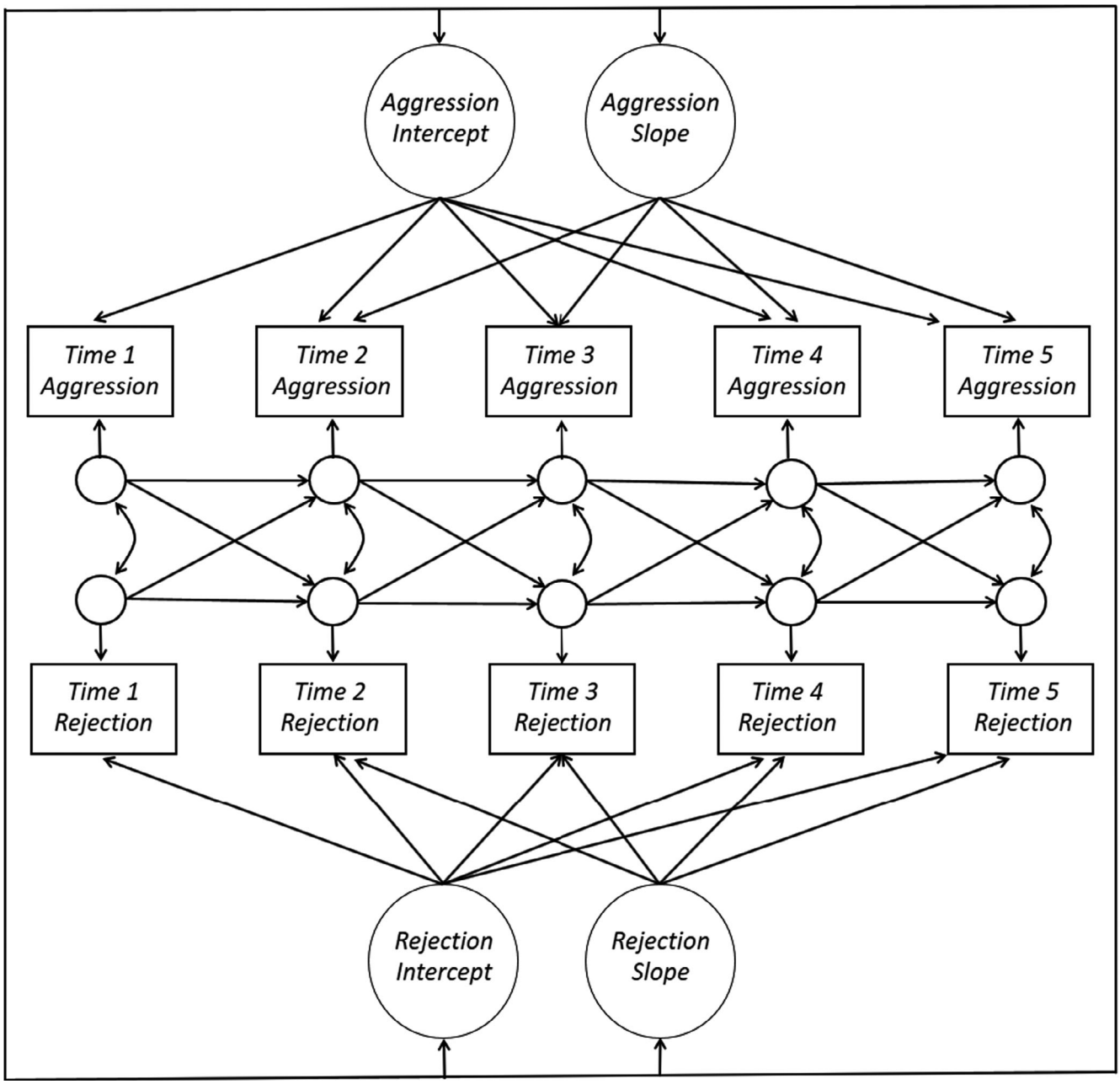

Figure 5. Latent curve model with structured residuals.
Note. Rectangles are measured variables, circles are latent variables and residual variances, single-headed arrows are regression coefficients and factor loadings, and all exogenous latent factors covary.

simplifications on that system. As such, we do not serve science well by selecting a single model for consideration and then working to achieve some acceptable degree of fit to observed data. Instead, we must take a step back and think more carefully about what types of relations are dictated by our theory. Does the theory propose relations solely at the level of within-person processes, solely at the level of between-person trajectories, or at both levels simultaneously? Are we motivated by the prediction of smoothed trajectories, or by inferences about lead-lag relations between two variables over time? These are but a few examples of how theory can, and indeed should, guide model selection.

Embracing Model Comparison

While it is undoubtedly true that models are not inherently correct or incorrect, some models might be better suited than others to a given question and set of observed data, and thus the effectiveness of the research may be enhanced by using a more

appropriate model. The challenge is reconciling the notion that all models are wrong with the idea that some correspond more closely to the observed data than others. Thus, we recommend that researchers compare and contrast theoretically meaningful competing models in a careful and principled way (e.g., Flora, 2018; Rodgers, 2010). Some models may have such poor fit as to be noncompetitors. For those that achieve an acceptable fit, some will have nested relations that allow formal statistical tests of comparative fit, whereas others will need to be compared using alternative metrics of fit, such as information-based criteria (e.g., Akaike Information Criterion, Bayesian Information Criterion). Finally, researchers must constantly bear in mind that science does not subscribe to a one-and-done philosophy. That is, no single sample or model resolves anything definitively; instead, the empirical results serve as a unique brick in the foundation of cumulative knowledge (Anderson & Maxwell, 2016; Hunter & Schmidt, 1996; Meehl, 1978). Building this base requires a principled and thoughtful balance of both theory and model fit, combined with the appreciation that each model is one representation of reality and that accruing many such representations enhances confidence in our work.

Anticipate Modeling Alternatives in Study Design

The most important and often-overlooked issue to consider when weighing alternative models may be planning new data collection (Shadish, Cook, & Campbell, 2002). Developing a familiarity with the advantages and disadvantages of each modeling approach provides invaluable information when designing a novel study in terms of sampling, measurement, and number and timing of assessments, among many other study features. Gathering data in a particular way can allow a more rigorous comparison of model types than would otherwise be possible, and enhances both the internal and external validity of the resulting inferences.

FINAL THOUGHTS

Because of space constraints, we have not fully explored many important methodological issues, including developmental concepts of dynamics, ergodicity, and idiographic versus nomothetic modes of inquiry (for additional information, see Molenaar, 2004, and Ram & Gerstorf, 2009). However, coming full circle to the "*for a*..." concept that motivated this article, the utility of any given model is by definition contextual: One model might be ideal *for a* given research question and sample data, yet flawed *for a* second question and sample data. Much of the current confusion about selecting one of many possible modeling strategies stems in part from approaching model selection from the perspective of right versus wrong; such discussions are unhelpful. Instead, we advocate considering model selection with joint respect to theory and formal model comparison, and with a constant eye on the future, both in designing the next study and in our continuing quest to build a truly cumulative science.

REFERENCES

Anderson, S. F., & Maxwell, S. E. (2016). There's more than one way to conduct a replication study: Beyond statistical significance. *Psychological Methods*, *21*, 1–12. https://doi.org/10.1037/met0000051

Anderson, T. W. (1960). Some stochastic process models for intelligence test scores. In K. J. Arrow, S. Karlin, & P. Suppes (Eds.), *Mathematical methods in the social sciences* (pp. 205–220). Stanford, CA: Stanford University Press.

Bainter, S. A., & Howard, A. L. (2016). Comparing within-person effects from multivariate longitudinal models. *Developmental Psychology*, *52*, 1955–1968. https://doi.org/10.1037/dev0000215

Berry, D., & Willoughby, M. T. (2017). On the practical interpretability of cross-lagged panel models: Rethinking a developmental workhorse. *Child Development*, *88*, 1186–1206. https://doi.org/10.1111/cdev.12660

Bollen, K. A., & Curran, P. J. (2004). Autoregressive latent trajectory (ALT) models: A synthesis of two traditions. *Sociological Methods and Research*, *32*, 336–383. https://doi.org/10.1177/0049124103260222

Bollen, K. A., & Curran, P. J. (2006). *Latent curve models: A structural equation perspective*, Vol. *467*. Hoboken, NJ: John Wiley & Sons. https://doi.org/10.1002/0471746096

Bryk, A. S., & Raudenbush, S. W. (1987). Application of hierarchical linear models to assessing change. *Psychological Bulletin*, *101*, 147–158. https://doi.org/10.1037/0033-2909.101.1.147

Cronbach, L. J., & Furby, L. (1970). How we should measure "change": Or should we? *Psychological Bulletin*, *74*, 68–80. https://doi.org/10.1037/h0029382

Curran, P. J., & Bauer, D. J. (2011). The disaggregation of within-person and between-person effects in longitudinal models of change. *Annual Review of Psychology*, *62*, 583–619. https://doi.org/10.1146/annurev.psych.093008.100356

Curran, P. J., & Bollen, K. A. (2001). The best of both worlds: Combining autoregressive and latent curve models. In L. M. Collins, & A. G. Sayer (Eds.), *New methods for the analysis of change* (pp. 105–136). Washington, DC: American Psychological Association. https://doi.org/10.1037/10409-004

Curran, P. J., Howard, A. L., Bainter, S., Lane, S. T., & McGinley, J. S. (2014). The separation of between-person and within-person components of individual change over time: A latent curve model with structured residuals. *Journal of Consulting and Clinical Psychology*, *82*, 879–894. https://doi.org/10.1037/a0035297

Curran, P. J., Lee, T. H., Howard, A. L., Lane, S. T., & MacCallum, R. C. (2012). Disaggregating within-person and between-person effects in multilevel and structural equation growth models. In J. R. Harring, & G. R. Hancock (Eds.), *Advances in longitudinal methods in the social and behavioral sciences* (pp. 217–253). Charlotte, NC: Information Age Publishing.

Curran, P. J., & Willoughby, M. T. (2003). Implications of latent trajectory models for the study of developmental psychopathology. *Development and Psychopathology*, *15*, 581–612. https://doi.org/10.1017/S0954579403000300

Flora, D. B. (2018). *Statistical methods for the social and behavioral sciences: A model-based approach*. Thousand Oaks, CA: Sage Publications.

Grimm, K. J., Mazza, G. L., & Mazzocco, M. M. (2016). Advances in methods for assessing longitudinal change. *Educational Psychologist*, *51*, 342–353. https://doi.org/10.1080/00461520.2016.1208569

Grimm, K. J., Ram, N., & Estabrook, R. (2016). *Growth modeling: Structural equation and multilevel modeling approaches*. New York, NY: Guilford Press.

Hamaker, E. L., Kuiper, R. M., & Grasman, R. P. (2015). A critique of the cross-lagged panel model. *Psychological Methods*, *20*, 102–116. https://doi.org/10.1037/a0038889

Hoffman, L. (2015). *Longitudinal analysis: Modeling within-person fluctuation and change*. New York, NY: Routledge. https://doi.org/10.4324/9781315744094

Hunter, J. E., & Schmidt, F. L. (1996). Cumulative research knowledge and social policy formulation: The critical role of meta-analysis. *Psychology, Public Policy, and Law*, *2*, 324–347. https://doi.org/10.1037/1076-8971.2.2.324

Joreskog, K. G. (1979). Statistical models and methods for analysis of longitudinal data. In K. G. Joreskog, & D. Sorbom (Eds.), *Advances in factor analysis and structural equation models* (pp. 285–352). Cambridge, MA: Abt Books.

Lord, F. M. (1963). Elementary models for measuring change. In C. Harris (Ed.), *Problems in measuring change* (pp. 21–38). Madison, WI: University of Wisconsin Press.

McArdle, J. J. (2009). Latent variable modeling of differences and changes with longitudinal data. *Annual Review of Psychology*, *60*, 577–605. https://doi.org/10.1146/annurev.psych.60.110707.163612

McArdle, J. J., & Epstein, D. (1987). Latent growth curves within developmental structural equation models. *Child Development*, *58*, 110–133. https://doi.org/10.2307/1130295

McArdle, J. J., & Hamagami, F. (2001). Latent difference score structural models for linear dynamic analyses with incomplete longitudinal data. In L. M. Collins, & A. G. Sayer (Eds.), *Decade of behavior. New methods for the analysis of change* (pp. 139–175). Washington, DC: American Psychological Association. https://doi.org/10.1037/10409-005

Meehl, P. E. (1978). Theoretical risks and tabular asterisks: Sir Karl, Sir Ronald, and the slow process of soft psychology. *Journal of Consulting and Clinical Psychology*, *46*, 806–834. https://doi.org/10.1037/0022-006X.46.4.806

Meredith, W., & Tisak, J. (1990). Latent curve analysis. *Psychometrika*, *55*, 107–122. https://doi.org/10.1007/BF02294746

Molenaar, P. C. (2004). A manifesto on psychology as idiographic science: Bringing the person back into scientific psychology, this time forever. *Measurement*, *2*, 201–218. https://doi.org/10.1207/s15366359mea0204_1

Niedzwiecka, A. (2020). Look me in the eyes: Mechanisms underlying the eye contact effect. *Child Development Perspectives*, *14*, 78–82. https://doi.org/10.1111/cdep.12361

Owens, S. A., Eisenlohr-Moul, T. A., & Prinstein, M. J. (2020). Understanding when and why some adolescent girls attempt suicide: An emerging framework integrating menstrual cycle fluctuations in risk. *Child Development Perspectives*, *14*, 116–123. https://doi.org/10.1111/cdep.12367

Peng, P., & Kievit, R. A. (2020). The development of academic achievement and cognitive abilities: A bidirectional perspective. *Child Development Perspectives*, *14*, 15–20. https://doi.org/10.1111/cdep.12352

Ram, N., & Gerstorf, D. (2009). Time-structured and net intraindividual variability: Tools for examining the development of dynamic characteristics and processes. *Psychology and Aging*, *24*, 778–791. https://doi.org/10.1037/a0017915

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods*, Vol. *1*. Thousand Oaks, CA: Sage Publications.

Rodgers, J. L. (2010). The epistemology of mathematical and statistical modeling: A quiet methodological revolution. *American Psychologist*, *65*, 1–12. https://doi.org/10.1037/a0018326

Rogosa, D. (1980). A critique of cross-lagged correlation. *Psychological Bulletin*, *88*, 245–258. https://doi.org/10.1037/0033-2909.88.2.245

Shadish, W. R., Cook, T. D., & Campbell, D. T. (2002). *Experimental and quasi-experimental designs for generalized causal inference*. Boston, MA: Houghton Mifflin.

Usami, S., Murayama, K., & Hamaker, E. L. (2019). A unified framework of longitudinal models to examine reciprocal relations. *Psychological Methods*, *24*, 637–657. https://doi.org/10.1037/met0000210

Voelkle, M. C. (2008). Reconsidering the use of autoregressive latent trajectory (ALT) models. *Multivariate Behavioral Research*, *43*, 564–591. https://doi.org/10.1080/00273170802490665

Wiley, D. E., & Wiley, J. A. (1970). The estimation of measurement error in panel data. *American Sociological Review*, *35*, 112–117. https://doi.org/10.2307/2093858

Zyphur, M. J., Allison, P. D., Tay, L., Voelkle, M. C., Preacher, K. J., Zhang, Z., . . . Diener, E. D. (2019). From data to causes I: Building a general cross-lagged panel model (GCLM). *Organizational Research Methods*, *23*, 651–687. https://doi.org/10.1177/1094428119847278

Zyphur, M. J., Voelkle, M. C., Tay, L., Allison, P. D., Preacher, K. J., Zhang, Z., . . . Diener, E. D. (2019). From data to causes II: Comparing approaches to panel data analysis. *Organizational Research Methods*, *23*, 688–716. https://doi.org/10.1177/1094428119847280