Longitudinal Data Analysis

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Abstract

In this essay we review some of the emerging trends in modeling repeated measures data. Three general forms of longitudinal models are discussed: panel model designs, growth curve models, and intensive within-person assessments. Each section discusses design elements that should be considered when using each of these types of longitudinal models, and introduces some emerging trends. In the section on panel designs, continuous time models and planned missing data models are introduced; these ideas will revolutionize the modeling and collection of panel data. In the section on growth curve models, the necessity of separately evaluating mean and covariance model fit is discussed. This section also introduces methods being used to carefully consider the time of measurements in temporal designs. Finally, the budding analysis of intensive within individual observations is considered, including recent work from mathematics that limits the generalizability of interindividual studies to individual outcomes.

INTRODUCTION

Longitudinal data analysis refers to any form of repeated assessments on the same person(s). Three general categories of longitudinal model exist. The first is the panel model where two or more assessment occasions are administered to a sample of persons. The panel model, as we detail later, focuses on the individual differences across a sample of persons (or entities). The types of model that can be fit to multioccasion data include discrete time models, such as the cross-lag panel model, and continuous time models. A second category of longitudinal model is the latent growth curve model, which focuses on intraindividual differences in change across multiple occasions. The third type of model is the intensive within-person assessment approach. These models, which are sometimes called p-technique, dynamic p-technique, or dynamical systems models, focus on within-person changes across a very large number of observations; these models also can be specified as either discrete or continuous time forms. In the following, we delve into the pros and cons of each approach. We then discuss a number of emerging trends

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surrounding design and measurement issues that are associated with these longitudinal models. We close with a discussion of future directions.

Longitudinal models can be analyzed using traditional manifest-variable analyses such as repeated measures ANOVA, ANCOVA, and MANOVA; as cross-lagged regression models, as manifest variable path models, or as latent variable models. We focus on the latent-variable approaches to modeling longitudinal data because of the attendant benefits they have over any manifest variable approach (Bollen, 1989; Little, 2013). The benefits of latent variable approaches include specifying and estimating a measurement model that corrects for measurement error, has relaxed assumptions on the nature of the measured items (e.g., only congenerity is assumed), and allows testing and enforcing factorial invariance. In addition, latent variable models can easily thoroughly assess model fit, powerfully compare competing models, and efficiently test complex statistical hypotheses related to mediation, moderation, and the like (see Little, 2013, for more on these benefits). Latent variable models also can incorporate planned missing data designs as well as efficient recovery of unplanned missing data.

Emerging trends in the area of longitudinal data analyses, therefore, include relying on latent variables, incorporating modern missing data treatments, and advancing the models that can be fit to data (e.g., multilevel structural equation models, continuous time models, and mixture distribution models). Other emerging trends include critical design elements that are often ignored or underutilized. The trends that we highlight are not comprehensive because many areas of longitudinal research are experiencing developments that enhance the rigor and applicability of the techniques (e.g., longitudinal social network modeling, latent transition modeling, integrative data analysis, etc.). We focus on core issues related to the "traditional" longitudinal models that involve latent variables (i.e., constructs represented by multiple indicators).

FOUNDATIONAL RESEARCH

INDIVIDUAL DIFFERENCES PANEL DESIGNS

The foundational longitudinal model is the individual differences panel design. Traditionally, three or more measurement occasions are used. Panel models attempt to model change and predictors of change. Most panel models are fit as discrete time models. The primary characteristic of discrete time models is that they do not explicitly account for the time interval or *lag* between subsequent observations (Voelkle, Oud, Davidov, & Schmidt, 2012). Figure 1 presents a three-wave model for discrete time points with the key parameters labeled (from Little, 2013). This prototypical model shows three

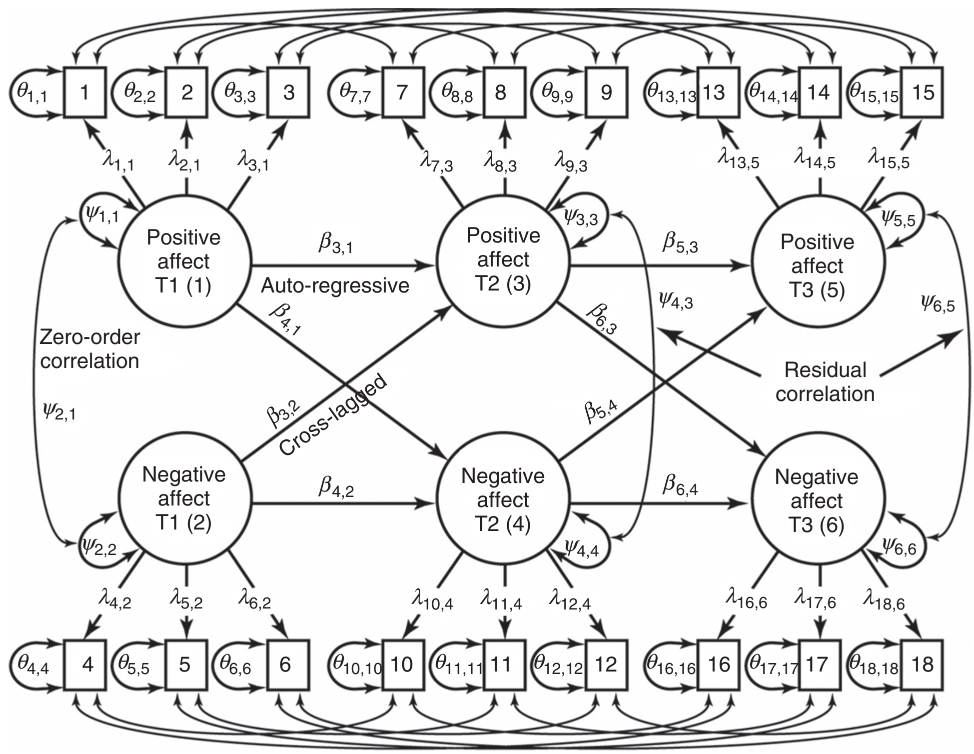

Figure 1 A three-wave cross-lag panel model with parameter labels. *Source*: (from Little, 2013). Little, T. D. (2013). *Longitudinal structural equation modeling*. New York, NY: Guilford.

indicators per construct with strong factorial invariance (factor loadings and intercepts are equal across time) specified. The key parameters of this model are the auto-regressive paths, which estimate the stability or prior levels of a construct, and the cross-lagged paths, which estimate the predictability of the change variance between constructs. Other parameters could be estimated, including additional (higher order) auto-regressive paths and additional cross-lagged paths between Times 1 and 3.

With two-occasion data, difference scores or gain scores are sometimes used to represent change. Gain scores, however, are not sensitive to predictors of change because they are essentially a model for the mean structures and use the individuals' scores to characterize the nature of the distribution round the mean change (Schoemann, Gallagher, & Little, 2015). Residual difference scores, on the other hand, are optimally sensitive to identifying individual difference predictors of the relative changes (Schoemann, Gallagher, & Little, 2015). In this regard, the emerging recommendations are to focus on the residual difference score model to identify predictors of change.

Continuous Time Models

Continuous-time models are emerging as powerful alternatives to the traditional discrete-time cross-lagged panel model. Not explicitly modeling the lag between observations, as is the case with discrete time models, has several impactful consequences. Foremost, the estimated parameters will depend on the selected lag (Gollob & Reichardt, 1987, 1991). Not only does the magnitude of the estimates change with lag but the relative contributions of constructs to an outcome also change depending on lag. Even the sign of parameters (i.e., positive versus negative), statistical inference, and model fit can change depending on lag (Bergstrom, 1990; McCrorie & Chambers, 2006; Oud, 2007). Continuous-time models, which explicitly model the lag between observations, can overcome the overwhelming dependence of results on the lag selected by the researcher (Bergstrom, 1990). Continuous-time models may also provide additional advantages such as the ability to handle unequal lags, even those that differ across individuals.

Figure 2 presents an example of how parameters from a continuous-time model differ from those of the discrete time model. This figure is based on a model using a first-order stochastic differential equation (Oud & Jansen, 2000; Voelkle *et al.*, 2012). The circles at lags of 2 and 6 illustrate the case of two researchers measuring the same construct at differing lags. Both researchers produce three parameter estimates, but these estimates are not directly comparable because each is dependent on the lag at which the observations were collected. The parameter estimates differ in magnitude and, moreover, the conclusions regarding the effect of X on Y would differ—one researcher suggests a positive effect and the other a negative. Continuous-time model parameters are independent of time, but

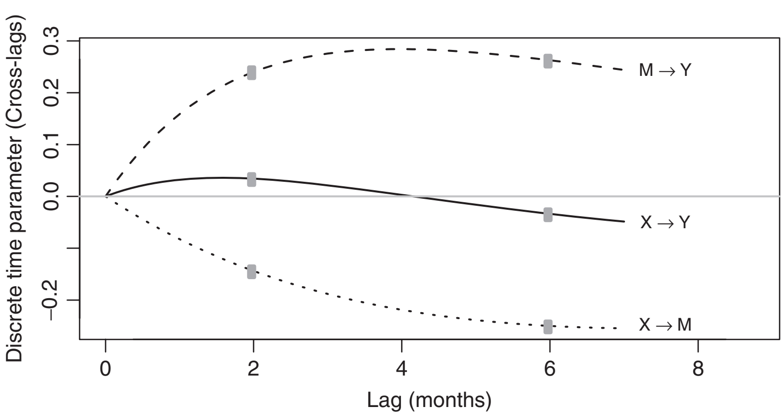

Figure 2 Continuous time estimates of the magnitudes of three effects in a mediation model.

can be used to solve for the expected discrete time parameters for many possible lags. Had both researchers fit a continuous-time model to their data, they could produce the lines in the figure. These lines represent the expected cross-lag effects in a cross-lag panel model; they are calculated from the continuous-time model parameters. In this particular case, a continuous-time model that produces the same fit to the data as the discrete cross-lag panel model was selected using the same number of estimated parameters. Consequently, the continuous-time model does not produce results that differ from the discrete time results; instead, it replicates both sets of results. The discrete time models are similar to a microscope focusing in on the results for a particular lag, while continuous-time models offer the potential of understanding how relations between variables change across a range of lags (Deboeck & Preacher, in press).

Planned Missing Data Designs

Nearly all longitudinal research studies can benefit from the use of planned missing data designs. Various designs are available, including the two-method and the multiform designs. These designs rely on modern techniques for treating missing data, including multiple imputation (MI) and full information maximum likelihood (FIML) estimation. Planned missing data designs have numerous advantages when properly implemented. One key advantage of these designs is that the data are missing completely at random, which means there is no bias in the parameter estimates. Depending on a number of factors, the relative efficiency of these designs can be degraded relative to an equivalent complete case data collection design. The cost to increase the power and to achieve the same relative efficiency is usually offset by the cost savings of using a planned missing element.

The two-method design is an exception to the efficiency/cost balance. It is a design that allows an increase in power relative to the analogous complete case scenario. The two-method design is predicated on the idea that a measure exists that is unbiased but also is expensive to collect (e.g., classroom observations, cortisol assays, Wechsler assessments, clinical assessments, etc.). The design is also predicated on the existence of a cheaper measure of the same construct but this measure is biased (e.g., teacher-report of classroom behavior, self-report of stress, a multiple-choice tool of intellective functioning, self-report of any clinical symptomology). When both measures are given, only a random subsample of participants is given the expensive measure (all participants receive the cheaper measure). The missing values on the expensive measure are imputed using MI (or FIML estimation is used). Then a bifactor SEM model is fit such that the indicators of the cheap and expensive measure load onto the focal construct of interest and a bias factor is specified to extract the bias from the indicators of the cheap measure. The two-method design, thereby, yields maximum validity in the measurement of the focal construct while increasing the size and power of the overall sample. Longitudinal applications of the two-method design can offer further benefits (Garnier-Villarreal, Rhemtulla, & Little, 2014).

The multiform designs can come in many different variations. The simplest and most common is the three-form planned missing design. As the name implies, three different forms of a questionnaire protocol are created such that a significant proportion of the items are missing from a given form. The key to this design is to create four different sets of variables, which are referred to as the *X*, *A*, *B*, and *C* blocks or sets, respectively. The *X* block contains key items that are administered to all participants. The *A*, *B*, and *C* blocks are paired into *AB*, *AC*, and *BC* groupings to create the three forms of item sets: *XAB*, *XAC*, and *XBC*. Participants are randomly assigned to a form. The multiform designs provide cost savings and validity enhancements over a corresponding complete case approach.

In terms of cross-section applications of the multiform design, two key design elements much be kept in mind. First, the efficiency of these designs is enhanced by placing items into sets such that the between-set correlations among the items is as high as the item content will allow. For example, a seven-item measure of positive affect would have one item assigned to the *X* block and two items each would be assigned to the *A*, *B*, and *C* blocks, respectively. Placing all items into a single set would have the tendency to reduce the between-set correlation and reduce the efficiency of the design relative to a complete case approach. The cost saving of a shorter protocol can often be used to adjust the sample size to have the same or equivalent power as a complete case approach. A second design trade-off to consider is the gain in validity that is associated with the multiform designs. Because fatigue and burden are reduced, constructs are more validly measured than complete case approaches. In addition, exposure reactivity is reduced, thereby increasing the validity of item responses. In terms of longitudinal applications of these designs, using different forms at different time points provides the greatest validity increases by reducing test-retest effects (Jorgensen *et al.*, 2014).

GROWTH CURVE MODELS

Latent growth curve models are quite ubiquitous as an emerging model for longitudinal data. Its popularity, however, is not without problems. Growth curve models reflect restricted, parsimonious models of the mean–structures information in a longitudinal data set. Although numerous models can be specified and estimated, they all address questions regarding the interindividual differences of intraindividual change (Nesselroade, 1984, 1991). This class of model, however, may not be appropriate for a given research question. Questions regarding predictors of change, for example, are not well examined in the context of growth curve models. When specifying a growth curve model, key considerations include, spacing of measurement occasions, specifying the location of the intercept (centering), and choosing the functional form of the slope construct. Other considerations, include model fit evaluation, residual stationarity, and factorial invariance (Little, 2013; Preacher, Wichman, MacCallum, & Biggs, 2008). Results from fitting a multivariate growth curve model are depicted in Figure 3 and will be used to guide the discussion of these issues (Little, 2013, for sample and constructs details). Here, a measurement model is specified with factorial invariance constraints in place and a linear growth curve is fit to these data.

As mentioned, the timing of measurements is perhaps the most neglected, yet critical element of a longitudinal design. Here, we emphasize that all longitudinal models are only as good as the data collection design will allow. If the design does not adequately reflect the nature of a change processes, the statistical analysis tool will be compromised in its ability to detect and reveal

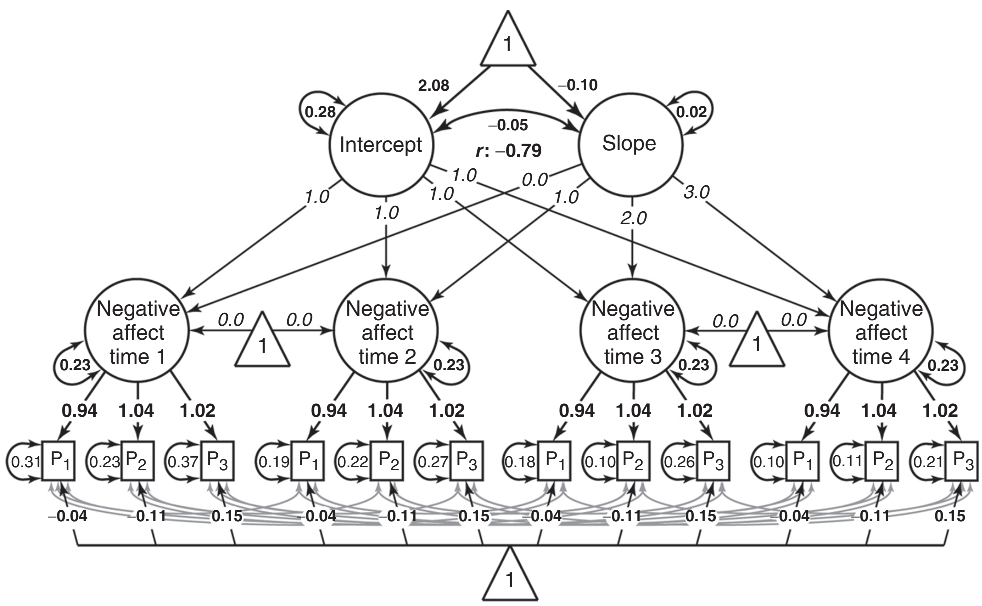

Figure 3 A growth curve model fit across four waves with factorial invariance constraints and effects coded scaling constraints to retain the meaningful metric of the observed indicators. *Source*: (from Little, 2013). Little, T. D. (2013). *Longitudinal structural equation modeling*. New York, NY: Guilford.

any information about change or growth. Too often, data collection intervals are selected on the basis of convenience or tradition rather than any depth of theoretical consideration (Selig, Preacher, & Little, 2012). Pilot work is an essential element of a high-quality longitudinal design because it can reveal the pace with which a construct changes. Such information would allow a more refined measurement design that would allow the statistical models to more readily characterize the magnitude and strength of any change effect under scrutiny.

Another important consideration is model fit evaluation. Complexity arises as growth curve models involve both mean and covariance structures. The misfit in the covariance structures can potentially mask the misfit in the mean structures. To better identify the sources of misfit, Wu and West (2010) highlight the need to test model fit separately for the mean structures versus the covariance structures. They recommended specifying the covariance structures as saturated, which would remove misfit from the covariance structures, to isolate the misfit in the mean structures. In addition, there are two types of mean structures in growth curve models: one for individual change trajectories and the other for average change trajectories (Wu, West, & Taylor, 2009). Wu and West (2013) showed that the traditional fit indices are poor in detecting misfit in the mean structures for individual change trajectories and suggested using some new indices such as concordance correlations and residual plots similar to those used in regression analysis in detecting misspecifications in mean structures.

One key assumption of latent growth curve models is that the construct under scrutiny is factorially invariant across time (i.e., no evidence of differential item functioning) and that the indicators are tau-equivalent (equal loading magnitudes on the construct). Unfortunately, most applications of latent growth curve models are specified to the manifest variable representation of the construct (Figure 3). This simplified growth curve model suffers from the same problems as manifest-variable ANOVA or ANCOVA regarding the tenability of the assumptions. On the other hand, a latent variable approach as reflected in Figure 2 directly assesses the factorial invariance assumption and makes no assumption on the nature of the items representing a construct. Thus, an emerging trend is the use of a rigorous measurement model to undergird the application of latent variable growth curve models. The effects-coded method of scaling and identification (Little, Slegers, & Card, 2006) allows the mean and variance of the growth curve factors to be estimated in the metric of the measurement scale, thereby producing accurate population estimates of the intercept and slope values in a nonarbitrary metric.

A common specification dilemma is whether to constrain the residual variances of the indicators of the latent growth curve constructs to be equal across time (i.e., the stationarity assumption or whether the residual information should be allowed to vary across the measurement time points. The (weak) stationarity assumption, as defined in classical time series analysis, also assumes constant means over time and constant correlations between observations over a given lag. These assumptions are often not tested in structural equation modeling. Fundamentally, the stationarity assumption is an assumption that the process underlying one's data is not changing as it is being measured. If this is the case, changes in the distributional properties within and between observations are not expected to occur. As Little (2013) explains, when a growth curve model is specified using manifest constructs at each time point (as in Figure 3), the stationarity assumption may not be tenable because the residual variances are the sum of the random error and the time-specific variance. When the latent growth curve model is specified using the latent variable approach (as in Figure 2), the time-specific variance of the construct at each time point is separated from the error information. Testing the stationarity of this time specific residual is, thereby, a reasonable and unconfounded test (Figure 4) (Little, 2013).

Some hybrid models that attempt to combine elements of a panel model and a latent growth curve model have been introduced in the literature,

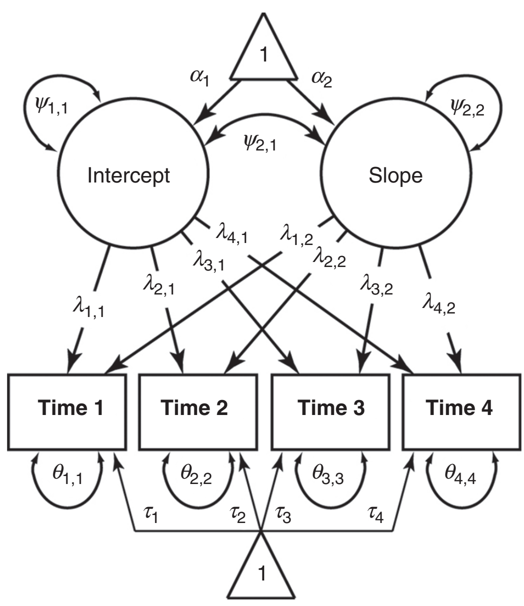

Figure 4 A simple growth curve model with parameter labels. Note. The parameters denoted with the Greek letter lambda are fixed to specific values to provide the basis loadings that are used to define the meaning of the two factors. *Source*: (from Little, 2013). Little, T. D. (2013). *Longitudinal structural equation modeling*. New York, NY: Guilford.

but these designs have been highly questioned in their utility; thus, their application is trending down (Little, 2013). The primary problem with such models is that they attempt to fit a model for the mean structures, which uses the variance–covariance information to estimate variability in the mean–structure parameters (the growth curve model). When the covariance–structures information is simultaneously used to estimate stability and change relationships among the measured constructs the mean–structures information appears to become biased. That is, in some cases the mean–structures model simultaneously competes for information that the panel model needs to accurately reflect the parameters of that model. This issue is complicated by the fact that the latent parameters labeled "intercept" and "slope" are not in fact latent intercepts and slopes, but rather a combination of parameters including the autoregressive effect (Hamaker, 2005), and do not lend themselves to the interpretations expected.

In summary, considerable future research is still needed to provide clearer guidance on using a latent growth curve model for addressing a longitudinal research question. Future directions included improvements in model specification guidelines and model fit evaluation.

CUTTING-EDGE RESEARCH

TIMING OF MEASUREMENTS AND TEMPORAL DESIGN

An emerging trend is the treatment of measurement intervals and how time can be represented in various longitudinal models. For example, Selig *et al*. (2012) recently introduced the lag as moderator model to capture the fact that measurement intervals often vary at the level of the individual and this variance in interval can have implications for understanding the nature of a longitudinal association. Very simply, the lag as moderator model is applicable when the interval between measurement occasions is not precisely the same for all individuals. Quite often, a stated goal of, say, 6 months is made. The actual intervals, however, can vary by days, weeks, and sometimes months given all the logistical issues in capturing an exact 6-month interval between measurement occasions. The differences in lag can be coded and included as a measured predictor in a longitudinal model in order to assess the degree that variability in interval lag influences the estimated strength of an association between any two variables in a longitudinal model. The newly coded lag variable is simply included as part of an interaction term to examine the moderation of an association by the lag in measurements (for details, see Selig *et al*., 2012; similar information is available in continuous time models, Deboeck & Preacher, in press).

Lag information can also be used to refine the estimates of growth in a growth curve modeling framework. The software package, Mplus, for example, has "*t*" scores, which function as definition variables do. Here, the time lag around a target data collection date can be added or subtracted from the target date for each individual. This score, which represents, the true time interval for a given person is assigned to a given basis weight loading. This assigned value allows the true variance in the interval of measurement to be the fixed value for each person. Because the fixed value of the basis weight changes for each individual, the true change in the scores is estimated more accurately.

Often, the interval of measurement for each person is not controlled by the investigator. This selective influence needs to be considered when the effect of lag is interpreted. For example, the lag in measurement could be related to a factor such as income in that more affluent persons participate later than less affluent persons, particularly when monetary incentives for each measurement occasion are provided. Or, the lag in measurement could reflect conscientiousness of the participant wherein very conscientious persons participate earlier than scheduled than lower conscientious persons. If measurement lag is more happenstance and related more to the researcher and less to the participant's discretion, the more likely measurement lag would be unconfounded with an alternative interpretation. To the degree possible, reasons for the deviation from the target lag can be coded and used as potential time-varying covariates.

The lag in measurement can become a key design element for a given study. Here, the lag for a measurement interval would be randomly assigned, which would allow the investigator to code lag as mentioned earlier and use lag to examine the potential moderation of an effect between any two variables in a longitudinal model.

Intensive within Person Modeling. A final emerging trend is in the area of intensive modeling of a given individual. Although such modeling approaches have a long history (Cattell, 1952), their recent emergence has been spurred by both methodological advances and theoretical refinements that are concerned with dynamic growth and change. Originally discussed under the rubric of p-technique factor analysis and dynamic p-technique, these models are multivariate time-series techniques that utilized latent variable modeling techniques as applied to a person's or set of persons' intensive repeated measurements. These models are also covered under the general rubric of state-space modeling, and applying differential equation models (i.e., continuous time models) is also expanding (e.g., Boker, Leibenluft, Deboeck, Virk, & Postolache, 2008, Deboeck, 2011; Deboeck & Bergeman, 2013).

A key motivation behind the advances in intensive per person models is the issue of ergodic generalizability (Molenaar, 2004; Molenaar & Campbell, 2009). Ergodic theory, an area of mathematics, focuses on the degree to which relationships among variables that are identified in the population generalize to the level of the person. The conditions in which such generalizability is warranted are extremely limited. Population parameter estimates derived from a sample of persons will generalize to a given person in the population when persons in the population are homogeneous and when the modeled process is time invariant (i.e., stability of the process can be assumed). If the population has known or unknown heterogeneity in it, or if the change process is not time or age universal, then identified relationship will not generalize to a given person. The results of such analyses are not uninformative, but they do possess limited generalizability for practitioners and providers who must use knowledge to make person-level decisions.

Intensive per person modeling has evolved as a way to build models that characterize a given individual. When a set of individuals are examined in an intensive per person approach, the ideographic results of model can be compared across individuals to test (quite powerfully) which parameters of a model are invariant across persons and which are unique to one or some subset of the persons. The balance between a fully ideographic and fully nomothetic universe of generalizability can be achieved through a shift in focus: collect more data on fewer persons and using the modeling procedures described here will allow both nomothetic generalization as well as provide an estimate of the frequency and nature of ideographic exceptions. Big sample issues of invariance, model fit/evaluation, power, and the like are in play when intensive per person data are modeled. The application of some of these issues, however, can shift. For example, Nesselroade and colleagues have introduced the idea of the ideographic filter. Here, the "measurement model" for a given person is allowed to vary to capture the ideographic characteristics of a given person. Invariance is then tested and examined as expectations about the associations among the constructs that are estimated for each person.

KEY ISSUES FOR FUTURE RESEARCH

Although big data and machine learning are emerging as trends in the analysis of the massive amounts of data that are now easily generated by technologically enhanced data collection protocols, the models and design issues that we have highlighted here are still quite relevant for advancing our understanding of longitudinal processes. The emerging trends highlighted in each category are still in need of further refinement and guidance. For example, most of the models that we highlighted currently rely on maximum likelihood estimation of the model parameters. Advances in Bayesian estimation procedures will likely add even greater precision and power for these models. Researchers whose research domain has matured to a level of complex theorization will benefit from the advances in the measurement, design, and analysis procedures we have highlighted here. The prospective and original data collection efforts of tomorrow's longitudinal studies will contain a confluence of the ideas we have highlighted here. The findings from big data explorations that are becoming popular will need to have further testing and refinement from future studies. Bringing sophistication to the prospective original research of the future will yield results that maximize generalizability at the level of persons, subgroups, and time.

Each model we described can also be estimated in the context of hierarchically nested data structures or a mixture distribution framework to identify unobserved heterogeneity. Future directions here include developing software and measurement tools to assess critical characteristics at all levels of a hierarchically nested data structure and include more levels in the analysis model. The statistical and mathematical theory is developed—unfortunately, the software tools that fit such models have lagged behind but they are evolving. For example, the mixture distribution tools that are available will continue to be refined to give better guidance on how many groups to extract and how the parameters of such models can be interpreted.

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