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ANALYSIS OF LONGITUDINAL DATA: The Integration of Theoretical Model, Temporal Design, and Statistical Model

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■ **Abstract** This article argues that ideal longitudinal research is characterized by the seamless integration of three elements: (*a*) a well-articulated theoretical model of change observed using (*b*) a temporal design that affords a clear and detailed view of the process, with the resulting data analyzed by means of (*c*) a statistical model that is an operationalization of the theoretical model. Two general varieties of theoretical models are considered: models in which the time-related change of primary interest is continuous, and those in which it is characterized by movement between discrete states. In addition, two general types of temporal designs are considered: the longitudinal panel design and the intensive longitudinal design. For each general category of theoretical models, some of the analytic possibilities available for longitudinal panel designs and for intensive longitudinal designs are discussed. The article concludes with brief discussions of two issues particularly relevant to longitudinal research—missing data and measurement—and a few words about exploratory research.

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INTRODUCTION AND OVERVIEW

This is an exciting time in analysis of longitudinal data. Interest in this topic has grown steadily since the watershed Harris volume (1963) and has been reflected in other books such as Collins & Horn (1991), Collins & Sayer (2001), Gottman (1995), Nagin (2005), Nesselroade & Baltes (1979), Singer & Willett (2003a), and von Eye (1990a,b), as well as in countless journal articles. Computing resources are becoming increasingly powerful, and readily available specialized software enables scientists to apply new and highly sophisticated statistical analyses in their work. Some rich longitudinal data sets have been archived and are available to the scientific public for statistical analysis. Further, creative use of new technology, such as handheld computers and other devices, is making collection of longitudinal data characterized by more frequent and intense measurement increasingly feasible (e.g., Shiffman & Stone 2006, Walls & Schafer 2006).

As more longitudinal studies have been undertaken, and the length and intensity of longitudinal studies have increased, a fundamental tension has emerged between what Molenaar (2004) has termed "attention to interindividual variation," that is, variation between individuals, and "attention to intraindividual variation," that is, variation within individuals. Approaches focusing on interindividual variation emphasize establishment of general developmental principles that apply to all individuals. In contrast, approaches focusing on intraindividual variation emphasize understanding change within the individual, with establishment of general principles a secondary goal. This article takes the perspective that growth is a phenomenon that occurs within the individual, and therefore intraindividual variability is a primary interest in statistical modeling of longitudinal data. The importance of modeling intraindividual variability has emerged forcefully in longitudinal research (e.g., Nesselroade 1991, Rogosa et al. 1982, Rogosa & Willett 1985) and has been the impetus behind the development of many of the statistical procedures discussed here. At the same time, in science we are always engaged in inductive reasoning and so attempting to abstract general principles about interindividual variability in intraindividual change is the ultimate goal (Curran & Wirth 2004).

The main purpose of this article is not to provide an exhaustive review of analytic approaches for longitudinal data; such a review could take up this entire volume! This article also will not cover the important topic of causal inference in longitudinal data, which was discussed at length in Raudenbush (2000). Instead, the aim is to suggest a conceptual framework for longitudinal research methods, and to give the reader a flavor for some of the analytic possibilities that are now available to behavioral scientists who are interested in addressing research questions about change in empirical longitudinal data.

A CONCEPTUAL FRAMEWORK FOR LONGITUDINAL RESEARCH

Suppose a social or behavioral scientist conducts statistical analysis of longitudinal data with the objective of addressing a scientific question that involves the test of a theory. This endeavor is successful if the scientific question is correctly and unambiguously answered. Of course, in empirical settings it cannot be known whether the correct answer has been identified, so it is impossible to know whether success has been achieved in any particular instance. Most likely, the best that can be accomplished is an incomplete or partially correct answer. Nevertheless, "correct and unambiguous" is a useful ideal that behavioral scientists would like to approach as closely as they can. It is possible to identify a conceptual framework for evaluating whether longitudinal research is likely to approach the ideal of providing correct and unambiguous answers to research questions.

Longitudinal research is most likely to approach the ideal described above when it is characterized by the seamless integration of three elements: (*a*) a well-articulated theoretical model of change observed using (*b*) a temporal design that affords a clear and detailed view of the process, with the resulting data analyzed by means of (*c*) a statistical model that is an operationalization of the theoretical model. (The integration of these three elements is necessary to ideal longitudinal research but not sufficient.) Let us consider each of these three elements in turn.

Element 1: The Theoretical Model of Change

The theoretical model is a clear and comprehensive statement about the nature of the change phenomenon that is to be observed. There are many aspects of change to be considered; a helpful list is contained in McGrath & Tschan (2004). Below are listed a few aspects of change that serve as examples, and are of particular interest in the present article:

- The general or characteristic shape of change, e.g., linear, quadratic, or an irregular series of ups and downs.
- Whether there is periodicity or a cyclical nature to the change.
- Whether change is primarily a function of calendar time, a function of some other variable that is related to time (e.g., pubertal status), or in some sense is self-regulating or self-exciting.

- What time-invariant and time-varying covariates may predict change.
- Whether the relation between a covariate and the change phenomenon may itself be time varying.
- Whether the process is more or less continuous, characterized by change in level or amount; discrete, characterized by occurrence of events; or contains elements of both kinds of change.
- Whether there is meaningful interindividual variability in change.

Element 2: The Temporal Design Used to Observe the Change Phenomenon

In the natural sciences, the investigator may choose an instrument, such as a microscope, to provide a view of the phenomenon of interest. In the social and behavioral sciences, research design is a similarly important instrument that provides a view of the change phenomenon of interest. As discussed in Shadish et al. (2002), design choices must be made with great care, because some designs will result in a detailed and unobstructed view of the change phenomenon, whereas others will provide an unsatisfying or even misleading view.

An often-overlooked aspect of design that can have a substantial impact on the scientist's view of a change phenomenon is the temporal design (Collins & Graham 2002), consisting of the timing, frequency, and spacing of observations in a longitudinal study. Boker & Nesselroade (2002), Cohen (1991), Collins & Graham (1991, 2002), Gollob & Reichardt (1987, 1991), Hertzog & Nesselroade (2003), Kelly & McGrath (1988), McGrath & Tschan (2004), Singer & Willett (2003), and Windle & Davies (1999) all have argued that the most appropriate temporal design is one chosen not primarily on the basis of logistics, but instead on the basis of correspondence with the theoretical model of change. Change that occurs between observations, before a study is begun, or after a study is concluded, is not observed and therefore can at best only be inferred. Thus, for example, if the theoretical model suggests that change is rapid, or characterized by many ups and downs, then more frequent observation may be called for. If periodicity is anticipated, then the exact timing of observation may be an important consideration. If there is a particular period of time during which some important event is anticipated, then more intensive observation may be advisable at that time. (The term "time" as used here is not necessarily intended to mean literal clock time. Important outcomes may be a function of time-related variables such as pubertal development, grade in school, cognitive decline, and so on. In this case, it may make sense to express the temporal design in these terms rather than in terms of calendar time.)

Many investigators planning longitudinal studies consider only temporal designs calling for (*a*) evenly spaced observations (*b*) occurring at the same time for all study participants. However, virtually no contemporary statistical approaches to analysis of longitudinal data make the former requirement and the number that make the latter is dwindling thanks to increases in flexibility and sophistication in statistical modeling. There is little reason to fear that a temporal design informed by the theoretical model of change will complicate later data analysis, and every reason to expect that such a design is likely to provide satisfying answers to important scientific questions.

Collins & Graham (2002) explored the impact of the mismatch of theoretical model of change and temporal design on inferences about characteristics of change and relations between variables over time, and found that under many circumstances the impact can be considerable, resulting, for example, in failure to detect stages in a stage-sequential process, and incorrect conclusions about mediation. Given their findings and the pleas of the above-listed authors, it is surprising to the present author that the behavioral science community appears to give relatively little serious consideration to the impact that temporal design may have on the conclusions drawn in longitudinal research. For example, few peer-review journals routinely request that the choice of temporal design be justified scientifically or that empirical results be considered in the light of temporal design choices. This would appear to be a necessary step for understanding unexpected findings and for explaining the failure of results to replicate across studies with different temporal designs.

Element 3: The Statistical Model of Change

One critical aspect of testing theories about change in human behavior is fitting a model of the change process to empirical data. As is discussed in detail in this article, every approach to statistical analysis of longitudinal data implicitly or explicitly provides an operationalization of some model of the change process. In successful longitudinal research, the operationalization provided by the statistical model corresponds to the theoretical model of change. A mismatch of theoretical and statistical model will result in the addressing of irrelevant or even meaningless scientific questions. On the other hand, a close correspondence between theoretical and statistical model can provide an elegant test of a scientific hypothesis and a penetrating look at longitudinal data. With an unprecedented array of statistical models from which to choose, today's behavioral scientist has an excellent chance of identifying and applying a statistical model well suited to the theoretical model of interest.

Integration of the Three Elements

The seamless integration of theoretical model, temporal design, and statistical model is an ideal that rarely, if ever, is met in social and behavioral research. For some theoretical models of change, particularly those that are very sophisticated, a tailor-made statistical model may not yet be available, forcing the investigator to use a statistical model that is not completely appropriate. In many empirical settings, the degree of correspondence between the statistical model and the theoretical model is limited by the temporal design. To take a simple illustration, if a theoretical model of growth in a continuous outcome is highly complex, involving many peaks and valleys, and the temporal design provides data collected at only two points in time, the only choice of statistical model available to the investigator is linear growth, which clearly does not correspond to the theoretical model. Resource limitations, logistical considerations, and concerns such as the prospect of overburdening study participants frequently may mean that the best temporal design scientists reasonably can use will allow statistical modeling to provide only a rough approximation to a complex and nuanced theoretical model of human development. Nevertheless, this conceptual framework is useful in interpreting the results of longitudinal research. Consideration of the ways in which a particular study approaches or fails to approach the ideal of integration of theoretical model, temporal design, and statistical model may help to identify the strengths and limitations of the study, the generalizability and likely replicability of the conclusions, and directions for future research.

THE PRESENT ARTICLE

To help provide a framework for the present article, two general types of temporal designs are defined for further consideration. These definitions are to an extent arbitrary, and were chosen to allow comparison and contrast of analytic approaches. One is the longitudinal panel design, defined here as a design where there are relatively few occasions of measurement, say eight or fewer, and the observations are separated by at least six months. The second is the intensive longitudinal design, defined here as involving at least 20 occasions of measurement, spaced closely enough in time to provide a detailed look at change in the quantity being observed. The definitions leave a gray area between longitudinal panel and intensive longitudinal designs, in which, depending on the situation, a design may be considered in either category.

In the remainder of this article, two general varieties of theoretical models are considered: models in which the time-related change of primary interest is continuous, and those in which it is characterized by movement between discrete states (e.g., employment and unemployment). For each general category of theoretical models, some of the analytic possibilities available for longitudinal panel designs and for intensive longitudinal designs are discussed. The article concludes with brief discussions of two issues particularly relevant to longitudinal research, namely missing data and measurement, and a few words about exploratory research.

CHANGE IN CONTINUOUS VARIABLES

Overview

The most commonly used approach to modeling change in continuous variables is growth curve models. Growth curve models, such as hierarchical linear models

(Raudenbush 2000), fit growth trajectories for individuals and relate characteristics of these individual growth trajectories (e.g., slope) to covariates. The individual growth trajectory can be expressed as

$$Y_{ti} = \beta_{0i} + \beta_{1i}x_{ti} + e_{ti}$$

for a linear model of growth. Y_{ti} represents individual i's outcome score at time t, where $t = 1, \ldots T$; x_{ti} represents the measure of time for individual i; and β_{0i} and β_{1i} represent the intercept and slope, respectively, of linear growth for individual i. This is often referred to as the level-1 equation. The intercept and slope parameters are random effects; in other words, they may vary across individuals, as reflected in the need for the i subscript denoting individual. This leads directly to the level-2 equations:

$$\beta_{0i} = \gamma_{00} + u_{0i}$$

$$\beta_{1i} = \gamma_{10} + u_{1i}.$$

Consider a growth trajectory for individual A with intercept β_{0A} and slope β_{1A}. The level-2 equations state that individual A's intercept β_{0A} can be decomposed into two components: the grand mean of all the β_{0i}'s for all individuals, γ_{00}, and β_{0A}'s deviation from this grand mean, u_{0A}. Likewise, individual A's slope β_{1A} can be decomposed into two components: the grand mean of all the β_{1i}'s for all individuals, γ_{10}, and β_{1A}'s deviation from this grand mean, u_{1A}. Interindividual variability in intercepts is expressed in the variance of the u_{0i}'s, and interindividual variability in slope is expressed in the variance of the u_{1i}'s. It is possible to include predictors in addition to time (or even instead of time; Curran & Willoughby 2003) in the level-1 equation, and to include time-invariant predictors in the level-2 equation. As Curran (2003) showed, the hierarchical approach to growth modeling is in most cases identical to the structural equation model, or latent growth curve, approach developed by authors such as McArdle & Epstein (1987), Meredith & Tisak (1990), Muthén & Shedden (1999) and Willett & Sayer (1994).

Hierarchical linear models have proven to be a very useful general framework for fitting theoretical models of growth curves in continuous variables. In the following sections, growth curve approaches to analysis of data from both longitudinal panel designs and intensive longitudinal designs are discussed. This framework opens up the possibility of fitting some new varieties of theoretical models of change in intensive longitudinal data.

Longitudinal Panel Designs

Much longitudinal research is at the intersection of a theoretical model concerning change in continuous variables and a temporal design that is some version of a longitudinal panel design. Under these circumstances, the theoretical model that is fit in data will usually need to be limited to fairly simple polynomial models of growth. Even with this limitation, such models can be very sophisticated, particularly if several measurement occasions are available. Raudenbush (2000) and McArdle & Nesselroade (2003) provide excellent overviews of growth modeling for longitudinal panel designs. Below are listed a few brief examples of the many kinds of theoretical models that can be fit this way and the corresponding statistical models. For a more thorough treatment of the correspondence between theoretical and statistical growth curve models for continuous change, see Curran & Willoughby (2003).

DISCONTINUITY IN CONTINUOUS CHANGE: PIECEWISE GROWTH MODELS Some theoretical models postulate that there is a discontinuity in continuous change; in other words, there is a distinct change point at which growth accelerates, decelerates, or levels off. This may simply be a change in acceleration, or it may represent a qualitative shift in some underlying process, so that different covariates are expected to predict different phases of the process. In piecewise growth models, the growth curve is divided into segments that are fit simultaneously with separate growth parameters. Cumsille et al. (2000) and Li et al. (2001) demonstrated how to fit piecewise growth curve models in which the change point is known and is the same for all subjects. Cudeck & Klebe (2002) presented an approach to piecewise growth models in which the change point may be unknown and estimated as a random effect. Even when discontinuity in continuous change is not expected, the piecewise approach may offer a straightforward and intuitively appealing alternative for fitting nonlinear models of growth.

STABILITY AND GROWTH: AUTOREGRESSIVE AND HYBRID MODELS The autoregressive model figured prominently in early analyses of longitudinal data (Joreskog 1979). Rather than modeling change within individuals, this approach models stability by using a variable measured at one time to predict itself or another variable at a later time. Bollen & Curran (2004, Curran & Bollen 2001) and McArdle & Hamagami (2001) showed how to incorporate features of both the growth modeling and autoregressive approaches into a single hybrid model. This hybrid model can be used to examine stability and change simultaneously.

PATTERNS OF GROWTH: GROWTH MIXTURE MODELS There are times when the investigator poses the question, what distinct patterns of growth characterize this sample? In other words, are there subgroups of individuals undergoing similar growth? Growth mixture models (Muthén 2001; Muthén & Muthén 2000; Muthén & Shedden 1999; Nagin 1999, 2005; Nagin & Tremblay 2001) identify subgroups corresponding to distinct patterns of growth in longitudinal data and can be used to estimate the prevalence of the patterns and to relate the patterns to covariates. For example, Nagin (1999) identified four prototypical trajectories of physical aggression in a sample of boys across ages 6 to 15. Using the group that never displayed any aggression as a baseline, Nagin found that having low-educated parents and a low IQ increased the risk of being in the groups characterized by chronic aggression and high levels of aggression followed by desistance, but did not increase the risk of being in the low-level aggression group. However, having a teen-aged mother increased the risk of membership in all the aggression groups.

Questions about the existence of distinctive growth patterns in data may arise simply due to a desire to obtain a descriptive sense of the "natural history" of growth in a data set. Other times questions may arise because it appears that relatively little of the variance in growth parameters can be accounted for by covariates. This suggests that there may be important covariates that have not been measured, or that there may be a complex system of interactions among the measured covariates. Under these circumstances, identifying meaningful patterns of growth and relating these patterns to covariates can be very illuminating. If there is a complex system of interactions among covariates, different covariates may predict growth parameters in different subgroups. Such effects are difficult to discern without identifying the subgroups, especially given that the overall effect of a covariate on a combined sample can be null even if it is a strong predictor in one or more subgroups.

A Variation on Longitudinal Panel Designs: Accelerated Longitudinal Designs

Some interesting developmental research questions involve continuous change unfolding across a period of time that may be years in duration. One alternative to a temporal design that involves observing the process over the entire period of development in a single cohort is an accelerated longitudinal design (Bell 1953, McArdle & Hamagami 2001). In an accelerated longitudinal design, multiple cohorts of different ages are observed longitudinally for a shorter period of time. The cohorts must be overlapping, so that for each cohort, there is at least one age at which at least one of the other cohorts is also observed. Then a statistical approach is used to combine the cohorts and estimate a single growth trajectory, extending from the youngest age observed to the oldest. The accelerated longitudinal design can save a significant amount of time, but it makes the assumption that there is no age-by-cohort interaction affecting development; in other words, it assumes that a single growth trajectory can reasonably represent all the cohorts. Duncan et al. (1996) combined data from four different overlapping age cohorts, each of which was measured at one-year intervals over a three-year period. This enabled them to estimate a growth trajectory for adolescent alcohol use extending from age 12 to age 17. They compared this growth trajectory with one based on a smaller single-cohort sample over the same age range, and found them to be essentially similar, suggesting that the assumption of no age-by-cohort interaction was met. Miyazaki & Raudenbush (2000) showed how to test this assumption empirically and presented a general framework for analysis of data from accelerated longitudinal designs.

Intensive Longitudinal Designs

Standard growth models extend directly to intensive longitudinal data, and are currently one of the most frequently chosen statistical models in this context. One very common implementation of intensive longitudinal designs in psychology is in controlled laboratory studies involving animals. In these studies, it is typical to have a nearly continuous record of important outcome behaviors, such as lever presses to obtain rewards, over several days or weeks. Donny et al. (2004) and Lanza et al. (2004) illustrated how to fit growth models to individual animal data and how to use a growth curve framework to address experimental hypotheses like the ones typically motivating laboratory studies. Growth models also can fit theoretical models of increased complexity. For example, in both animal and human data, intensive longitudinal designs may reveal periodic effects due to time of day, day of the week, weekday versus weekend, and so on. Walls et al. (2006) have provided a detailed exposition of modeling periodicity using a standard growth modeling approach.

FUNCTIONAL DATA ANALYSIS The complexity of the theoretical models that motivate collecting intensive longitudinal data often goes beyond periodicity. Change over time may not be easily characterized by a polynomial. Instead, change may have many irregular ups and downs. There may be time-varying covariates, and some of these time-varying covariates may even have time-varying effects. A time-varying effect occurs when the strength and/or direction of a covariate changes as a function of time. It is even possible for an intervention to operate on an effect. For example, a drug abuse prevention program aimed at adolescents could reduce the influence of peer substance use on adolescent substance use; a therapy intervention aimed at depression could reduce the relation between everyday stressful events and anxiety. Functional data analysis (Fan & Gijbels 1996, Fok & Ramsay 2006, Li et al. 2006) provides a statistical model that is well suited both to these kinds of theoretical models and to intensive longitudinal data. Fok & Ramsay (2006) and Li et al. (2006) have illustrated how to apply functional data analysis in intensive longitudinal data using a growth modeling approach. Li et al. analyzed intensive longitudinal data on affect and urge to smoke collected in a sample of smokers enrolled in a cessation program. They found that urge to smoke was associated with negative affect, and that this relation grew stronger immediately after quitting smoking.

DYNAMICAL SYSTEMS Inspired by the way change and relations between changing variables are represented in engineering, authors such as Boker (Boker & Graham 1998, Boker & Laurenceau 2006, Boker & Nesselroade 2002), who draws on dynamical systems theory, and Ramsay (2006), who draws on process control theory, have offered social and behavioral scientists new ways of thinking about growth. For example, dynamical systems theory includes the idea of intrinsic dynamics, which are features of a system that regulate change in order to maintain equilibrium. Boker & Laurenceau (2006) showed that the familiar autoregressive model can be considered a type of dynamical system that self-regulates. The dynamics of self-regulating systems can be coupled in order to examine how each system can affect regulation of the other, and the effect of external variables on the dynamical system can be examined. Using growth modeling, Boker & Laurenceau (2006) illustrated how to take a dynamical systems approach to model intimacy and disclosure in marriage. They considered each married couple a self-contained dynamical system, and examined how the systems might be coupled. They found that there was symmetric coupling between husband and wife intimacy; in other words, within a marriage, the husband's feelings of intimacy affected his wife's feelings of intimacy, and also the wife's feelings of intimacy affected her husband's. In contrast, they found that disclosure was better represented by asymmetric coupling. This means that the coupling relation went only one way; within a marriage, the husband's disclosure affected his wife's disclosure, but the wife's disclosure did not appear to affect her husband's.

CHANGE CHARACTERIZED BY MOVEMENT BETWEEN DISCRETE STATES

Overview

This section considers theoretical models of change characterized by movement between discrete states. The movement may be, for example, between healthy state to onset of a disease; employment to retirement; passing in and out of various patterns of substance use; and so on. Models involving discrete change have an important place in testing psychological theories based on stage development, which include classic theories in areas such as cognitive (Piaget 1973), moral (Kohlberg 1966), and ego (Erikson 1950) development. A more contemporary example of a stage model is the Gateway Hypothesis of drug use onset (Kandel 2002). Three related statistical models of transitions between discrete states are discussed in this section. For longitudinal panel designs, discrete-time survival analysis and latent transition analysis (LTA) are discussed. For intensive longitudinal designs, point-process models are considered. Each of these is suited to a slightly different, or differently worded, question about movement between states.

Longitudinal Panel Designs

DISCRETE-TIME SURVIVAL ANALYSIS As discussed above, the standard longitudinal panel design involves relatively long intervals, often months or years, between occasions of measurement. Data collected using this kind of temporal design may reveal during which interval a transition, often called an event, occurred, but beyond this cannot be used to determine when the event took place. For example, consider a standard longitudinal panel study in which adolescents are measured once per year. At each time, the adolescents are asked if they have ever tried smoking. Such data may indicate that an adolescent tried smoking for the first time between the previous observation and the current one, but exactly when in that interval the encounter with tobacco occurred is unknown. Often a research question such as the following is of interest: Given that at time interval t an individual has never tried smoking, what is the probability that the individual will try smoking during a particular subsequent time interval? This question and related questions can be addressed by means of discrete-time survival analysis (e.g., Cox 1972). As the name suggests, survival analysis was originally developed in the biostatistics literature to model time until the occurrence of death and other medical events such as relapse of disease. Today its application in psychology and other areas in the behavioral sciences is growing (Singer & Willett 2003a,b).

Fundamental to survival analysis are two closely related functions, the hazard function and the survival function. Singer & Willett (2003a) presented a survival analysis of data collected yearly on a cohort of special education teachers newly hired in the Michigan public schools. The target event was leaving teaching. Let T_i represent the time interval j when individual i experienced the event; in this case, left teaching. Then the hazard for a particular time interval is

$$h(t_{ij}) = P[T_i = j | T_i \geq j],$$

or in words, the probability that individual i will experience the event during time interval j, given that individual i has not experienced the event during a previous time interval. There is a hazard associated with each time interval. For example, Singer & Willett (2003a) found that given that an individual did not leave during the first year of teaching, the probability was about 11% of leaving during the second year; given that an individual remained for at least six years, the probability was about 6% of leaving during the seventh year.

Closely related is the survival function

$$S(t_{ij}) = P[T_i > j],$$

which is the probability that individual i will not experience the event (will "survive"), conditional on not already having experienced the event in a previous time interval. Often of particular interest is the median lifetime, which is time interval during which the survival function reaches 0.5; in other words, the time interval by which half of the sample has experienced the event. Singer & Willett (2003a) found that sometime during year seven of teaching, 50% of the teachers in their sample had left.

It is possible to introduce time-invariant and time-varying covariates into a survival analysis, in order to address research questions such as whether the hazard function differs across groups or whether elevation in the hazard function corresponds to an elevation or decrease in another variable. For example, if it is of interest to examine whether more experienced teachers are more likely to remain in teaching longer, a covariate representing years of prior experience before beginning the current teaching position can be included. If it is suspected that feelings of burnout may be associated with an increased hazard of quitting, a yearly measure of burnout can be included as a covariate.

CENSORING AND SURVIVAL ANALYSIS As discussed above, the temporal design of a study has an impact on the conclusions that can be drawn from data. This is very evident in censoring, a topic that is of great concern in survival analysis. Suppose a study is evaluating a new approach to psychotherapy for depressed inpatients. It is expected that patients receiving the new psychotherapy will go longer before experiencing a recurrence of depression. In this case, the event of interest is recurrence of depression. Suppose the new therapy is delivered, and then the patients are followed for two years. For each patient, it is recorded when the individual has a first recurrence of depression. Of course, at the end of two years not every patient will have had a recurrence of depression. At the conclusion of the two-year period, all that is known is that some patients have not had a recurrence; it is not known whether these patients will have a recurrence in the future. This is called right-censoring. Right-censoring is present in most survival analyses because rarely is it practical to conduct a study long enough for the event in question to occur for all subjects—and in some cases it is expected that some subjects will not experience a reoccurrence of the event. Somewhat less common, and more problematic, is left-censoring. Left-censoring is present when for some individuals the event in question occurred at some indeterminate time before the start of the study. Censoring is a sort of partially missing data problem. Censored individuals provide some information about the timing of the event, but not the complete information desired. In a sense, they inform about when the event did not occur, but not about exactly when it occurred. Another way to think of this is that if you are interested in modeling how long until an event occurs, it is best to time data collection so that you have a chance to observe the event. Thus, ideally censoring should be kept to a minimum. Survival and hazard models can deal with censoring, and do make use of the partial information censored data provide, but it is wise to give careful consideration to the implications of censoring in the interpretation of any results. For a careful treatment of censoring as well as many other issues related to survival analysis, see Singer & Willet (2003a,b).

LATENT TRANSITION ANALYSIS Another approach for modeling transitions between states in data from longitudinal panel and similar designs is LTA (Langeheine 1994; Lanza et al. 2003, 2005), a version of latent class analysis (LCA). LTA addresses questions concerning prevalence of discrete states and incidence of transitions between states. LTA is suited to situations where there are numerous states, individuals can transition relatively freely among the states, and the states are measured with multiple fallible indicators.

Research questions about discrete change among an array of states are often expressed in terms of transition probabilities. A transition probability is the probability of being in state y at Time 2, conditional on membership in state x at Time 1. Inference about an individual's transitions between states is based upon the individual's state membership as assessed at each observation. When a single variable can reliably indicate state membership and the theoretical model is uncomplicated, it may be possible to model transitions between states using an ordinary contingency table approach. However, more sophistication and flexibility can be found in LTA (Goodman 1974, Langeheine 1994, Lanza et al. 2003).

LCA is a latent variable model conceptually similar to factor analysis (McDonald 1985). Generally, factor analysis is based on a covariance matrix; LCA is based on a contingency table. Whereas in factor analysis the latent variable has a continuous distribution, in LCA the distribution of the latent variable is discrete, so that each individual belongs to one and only one latent class. Extensions of latent class theory to LTA (Lanza et al. 2003, 2005) and latent Markov models (Langeheine 1994) provide a way of statistically modeling movement between latent states, including estimating the prevalence of each discrete state and the incidence of transitions between states, adjusted for measurement error. For example, Lanza & Collins (2002) used LTA to model a contingency table that included adolescent girls' self-reports, taken in grade 7 and again in grade 8, of whether they had ever tried several substances. Each latent state in the model represented which substances had been tried at a particular time, e.g., alcohol only, alcohol and cigarettes, etc. Let y designate a cell in the contingency table. Then such an LTA model can be expressed as follows:

$$P(Y = y) = \sum_{a=1}^{S} \sum_{b=1}^{S} \delta_a \tau_{b|a} \rho_{i|a} \rho_{j|a} \rho_{k|a} \rho_{l|a} \rho_{i'|b} \rho_{j'|b} \rho_{k'|b} \rho_{l'|b},$$

where S represents the number of latent states in the model; a and b represent latent state at the first and second occasion, respectively; and i, j, k, and l are observed values of variables (e.g., a response of "no" to the question about ever having tried alcohol). The δ's, τ's, and ρ's are all model parameters to be estimated. δ_a is a parameter representing the probability of membership in latent state a at the first occasion (e.g., probability of membership in the alcohol-only latent state); $\tau_{b|a}$ represents the probability of being in latent state b at the second occasion, conditional on membership in latent state a at the first occasion (e.g., probability of being in the alcohol-and-cigarettes latent state at the second occasion, conditional on membership in the alcohol-only latent state at the first occasion); and the ρ's represent the probability of observed values of variables conditional on latent state (e.g., the probability of a response of "yes" to the question about ever having tried alcohol conditional on membership in the alcohol-plus-cigarettes latent state). The ρ parameters are the conceptual equivalent of factor loadings, in that they express the relation between the observed (self-reports of substance use) and latent (substance-use state) variables.

In order to compare transitions between latent substance-use states for girls who were early pubertal developers with transitions for girls who were on-time or late developers, Lanza & Collins (2002) included indicators of pubertal status in the model described above [to do so requires estimation of some additional parameters; such models are described in detail in Lanza et al. (2003) and in Lanza et al. (2005)]. They found that the earlier developers were much more likely to be in relatively advanced substance-use states in grade 7 and to transition to more advanced substance-use states between grades 7 and 8.

The latent class approach to modeling transitions between discrete states provides several advantages as compared to an ordinary contingency table approach. First, it is straightforward to fit models that specify a kind of change, such as only forward-moving change, or that specify that any particular transition probability is fixed to zero (or any other legitimate parameter value) and to compare the fit of these different models of change in empirical data. Second, this approach provides a way of modeling measurement error, thereby producing a more accurate estimate of the transition probability matrix and other model parameters. Importantly, because this approach models measurement error, it deals in a principled way with observations that do not appear to map directly onto hypothesized states, such as individuals who report having tried cigarettes at one time and then at a later time report never having tried cigarettes. In other words, there is no need to remove such individuals from the sample or to "correct" the data to make it internally consistent (ad hoc practices with no statistical basis that are never recommended but, regrettably, are sometimes used in practice). Third, this approach provides a way of making scientific sense of large, complex contingency tables such as those formed by crosstabulating several discrete variables that have been measured repeatedly. Such contingency tables can easily have hundreds or even thousands of cells; for example, the contingency table analyzed by Lanza & Collins (2002) had 4096 cells.

RECENT DEVELOPMENTS IN LATENT CLASS MODELS FOR LONGITUDINAL DATA The latent class approach to modeling change has been extended in some interesting directions. It is now possible to include continuous covariates in latent class models of longitudinal data (Chung et al. 2005, Dayton & Macready 1988, Humphreys & Janson 2000). For example, Chung et al. (2005) extended the analyses reported in Lanza & Collins (2002) by including a wider range of ages in the sample, and by incorporating not only pubertal development but also age and the interaction of age and pubertal development as covariates. They found that older girls whose puberty was in progress were at particularly increased risk of advancing in their substance use. Another area of extension has been in making use of observed variables at a level of measurement other than nominal. Kim & Böckenholt (2000) developed a latent class model for longitudinal data that can incorporate ordered categorical responses. Dolan et al. (2004) used a normal finite mixture approach to model stage-sequential Piagetian development in children based on a covariance matrix of continuous variables rather than a contingency table of discrete variables.

IMPACT OF TEMPORAL DESIGN ON LTA AND SIMILAR APPROACHES The considerations about censoring discussed above apply here as well. In addition, exactly when the observations in a panel design are collected and how much time is allowed to elapse between observations can have an effect on the results obtained using the statistical analysis methods described above. For example, when the change process is rapid, or when certain states within a process are of short duration, individuals may pass into and out of one or more states between observations. In that case the prevalence of certain states may be underestimated, or the presence of some states may be overlooked altogether (Collins & Graham 2002).

Intensive Longitudinal Designs: Point-Process Models

As compared to longitudinal panel designs, intensive longitudinal designs provide information that can be used to place events in time more precisely. For example, experience sampling methods (Csikszentmihalyi & Larson 1987, Shiffman et al. 2002) involve much smaller intervals between measures than those of longitudinal panel designs. Another approach involves less frequent measurement, but includes carefully and methodically elicited recall of occurrence and dates of important past events occurring since the last measurement occasion, or sometimes even over the individual's lifetime (e.g., Kandel et al. 1997). When the timing of events of interest can be determined with a high degree of precision, a continuous-time approach may be used. A well-known example is continuous-time survival analysis (Singer & Willett 2003a). Like discrete-time survival analysis, continuous-time survival analysis is used to estimate survival and hazard functions. However, unlike discrete-time survival analysis, the continuous-time approach assumes a nearly continuous record of when the events take place. Most continuous-time survival analysis approaches can be considered a special case of the more general point-process model.

The point-process model (Cox & Lewis 1966, Cressie 1991, Diggle 1983, Lewis 1972, Rathbun et al. 2006) can be used to address questions about the frequency and timing of a single discrete event or a series of discrete events. Originally developed for use in fields such as biostatistics, ecology, and geography, point-process models are just beginning to find their way into the social and behavioral sciences. The input data for a point-process analysis is a record of each time a particular discrete event occurred over some period. Thus, point-process analyses work best with intensive longitudinal and similar temporal designs involving frequent and closely spaced measurement. For example, Rathbun et al. (2006) described a series of point-process analyses aimed at modeling smoking behavior. Data on smoking and related variables, such as emotional state at the time each cigarette was smoked, were collected nearly in continuous time, using immediate self-reports entered in handheld computers (Shiffman et al. 2002).

Fundamental to point-process models is the intensity function

$$\lambda(t) = \lim_{\delta \to 0} \frac{E\{N[t, t+\delta]\}}{\delta}.$$

In this equation, $[t, t+\delta]$ represents a time interval beginning at time t and enduring for length δ. The numerator of the right-hand side of this equation is the expected (mean) number of events N occurring during this time interval. As the length of the interval δ approaches zero, the intensity function $\lambda(t)$ becomes the instantaneous rate of event occurrence at time t. In other words, a high intensity means more occurrences of the event, on average, per unit time. Note the close similarity between the intensity function and the hazard function. In fact, the hazard function for continuous-time survival models is a special case of the intensity function for point-process models.

Point-process models can readily be used to study periodicity, such as effects attributable to month of the year, day of the week, hour of the day, etc. Rathbun et al. (2006) illustrated this by investigating how time of day and day of the week affect rates of cigarette smoking. The results yield a detailed picture of the natural history of smoking behavior. For example, they showed that during the week, peak smoking rates occurred shortly after 5 PM and again around 8:30 PM, whereas on the weekends there were no discernable peaks at those times. Point-process models can incorporate random (in other words, individual subject–level) effects, and also time-varying covariates. By adding random effects and time-varying covariates to their model, Rathbun et al. were able to show that although negative affect did not appear to be related to smoking, there was a strong relation between restlessness and smoking.

As Rathbun et al. (2006) demonstrated, point-process models open up some interesting possibilities for modeling change. A multivariate approach can be taken to examine the relations between two or more types of point processes, such as cigarette smoking and alcohol consumption. Self-exciting processes, in which the occurrence of an event itself increases the probability of another occurrence of the same event, can be modeled. Chain-smoking may be a self-exciting process if having one cigarette itself increases the probability of having another one. Another possible model of change is called a stress-release point process, in which the event becomes more likely to occur when another variable reaches a certain threshold level. For example, when nicotine in the blood falls below a certain level, the probability that cigarette smoking will occur increases. Once the event occurs, blood nicotine increases above the threshold for a time, and then gradually drops to a level low enough to trigger the next episode of cigarette smoking.

MISSING DATA

Unplanned missing data in longitudinal research can occur because a participant fails to respond to one or more questions in a questionnaire or interview, or because a participant is unavailable to the research study at one or more occasions of measurement. Scientists engaged in longitudinal research deal with unplanned missing data constantly; in fact, it is difficult to imagine a longitudinal study without at least some unplanned missing data. For this reason, how to handle missing data is an important question facing anyone who wishes to analyze longitudinal data.

For years investigators have used ad hoc procedures for dealing with missing data, such as eliminating individuals with missing data from analysis ("casewise deletion") or substituting the sample mean for missing observations ("mean substitution"). Such procedures may be convenient, but they have no basis in statistical theory. There are two potential consequences of using ad hoc procedures to deal with unplanned missingness. One is a greater-than-necessary loss of statistical power, particularly in association with casewise deletion, which involves discarding data for any subject whose data are incomplete. The other consequence is bias in results, which can occur if the cause of missingness is related to variables of scientific interest.

A much better option is to use modern missing data procedures (Schafer 1997, Schafer & Graham 2002), such as multiple imputation and maximum likelihood, which are based in statistical theory. When the assumptions underlying these procedures are met, they restore much statistical power and eliminate bias due to missing data; even when the underlying assumptions are not met, modern missing data procedures are an improvement over ad hoc methods (Collins et al. 2001). This is particularly so if variables that are highly correlated with those subject to missingness are included in the analysis. Frequently in longitudinal studies, previous or later measures of a variable may serve this role well. Collins et al. (2001) and Graham (2003) discuss why and how to implement this missing data strategy.

Most longitudinal research projects set aside resources to devote to tracking down individuals who are absent for a data-collection session. Assuming that these resources are finite and are insufficient to obtain data from all the dropouts, one can imagine two different ways of spending them: on obtaining data from as many of the dropouts as possible, or on obtaining a smaller, but representative, sample of dropouts. Graham & Donaldson (1993) showed that the latter is the better approach, and demonstrated how such a sample can be tremendously useful for making the most of modern missing data procedures in longitudinal research.

In the previous paragraphs, the term "unplanned" missing data was used to refer to data loss that is out of the investigator's control. Missing data may also be planned when an investigator chooses to collect partial data using a carefully controlled missing data design. Reasons for choosing to use a planned missing data design include economy and a desire to reduce the response burden on study participants. For more about planned missing data designs in longitudinal research, see Graham et al. (2001).

MEASUREMENT CONSIDERATIONS IN LONGITUDINAL RESEARCH

Psychology has a long tradition of measurement theory, with early roots in intelligence testing, employment testing, and factor analysis (Lord & Novick 1968). Most traditional measurement theories, such as classical test theory, are aimed primarily at developing measures sensitive to interindividual variability, and essentially ignore intraindividual variability. For example, the traditional definition of reliability, the proportion of observed score variance that is made up of true score variance, is defined entirely in terms of interindividual variability. It follows that measurement instruments evaluated by methods that focus on interindividual variability may or may not be adequate measures of intraindividual change.

A few measurement approaches have been aimed at variables measured longitudinally. Willett (1989) demonstrated how to use growth curve models to assess the longitudinal reliability of an instrument. He showed convincingly that obtaining additional observations in time can greatly improve the reliability with which a growth curve is measured. Collins & Cliff (1990) extended the Guttman scale to longitudinal data, and showed that it could be used as a basis for developing and evaluating measures for certain kinds of intraindividual change processes. Embretson (1991) showed how to use latent trait theory to develop measures of intraindividual change. An exciting feature of this approach is that it addresses a knotty problem in lifespan research, namely how to develop and equate different measures of the same construct for administration at different points across the life course.

Open questions remain in the theory and practice of measurement of intraindividual change. Coombs (1964, p. 5) wrote, "a measurement or scaling model is a theory of behavior, admittedly on a miniature level, but nevertheless theory . . . ." This suggests that any measurement theory aimed at intraindividual growth processes must start with a theoretical model of change. It follows that it is unlikely that a single approach to measurement can be adequate for development of instruments across the entire panoply of growth processes. As statistical models are invented for fitting theoretical models that specify increasingly complex change, corresponding measurement methods are needed. Such models are critical for reliable and valid measurement of growth processes, and ultimately for testing important hypotheses about intraindividual change.

A FEW WORDS ABOUT EXPLORATORY RESEARCH

This article has emphasized situations where there is a clear theoretical model guiding research. But many studies, of necessity, are not guided by theory. Some studies are breaking new ground in areas where theory is incomplete or even nonexistent. Sometimes the original theory guiding a study has been soundly refuted by the empirical data collected to test it, leaving the investigators to conduct secondary analyses with the hope of beginning to build a new theory. Where theory cannot inform choice of temporal design and statistical model, these choices must be made in a more exploratory manner.

Where there is little theory to guide choices, it may be wise for investigators to do their best to keep options open. For example, consider the choice of number and spacing of observations in a temporal design. If there are too many occasions of measurement spaced too close together, it is always possible to base analyses on a subset of measurement occasions or to aggregate (e.g., sum) occasions that are close together. However, if there are too few occasions or they are spaced too far apart, there may be little the investigator can do to recover information about what happened between observations. Thus, erring on the side of more, and more frequent, observation may be prudent.

In cases where secondary analyses are being performed on existing data in order to build a theory, it may be helpful to interpret the results in the light of the temporal design used to collect the data. This interpretation could involve considering what kinds of change processes the temporal design might reasonably have been able to reveal and what kinds the temporal design would tend to hide from view. For example, consider a secondary analysis based on a three-wave longitudinal panel study, with yearly data collection. A linear model of growth might simultaneously be an excellent representation of the empirical data and a poor representation of the underlying growth process. There may be considerable curvilinearity, even repeated peaks and valleys, in the growth process, but the temporal design obscures these features of growth, preventing them from being observed.

Exploratory studies and secondary data analyses will always have a place in social and behavioral research. The argument here is not that such studies and analyses should be avoided. Rather, the argument is that even when theory is absent, the impact of the relation between temporal design and statistical model is an important consideration in longitudinal research. Careful thought about these matters can be tremendously helpful in interpreting empirical results and building theories to be tested in future studies.

SUMMARY AND CONCLUSIONS

This article has argued that ideal longitudinal research is characterized by the seamless integration of a well-articulated theoretical model of change, an appropriate temporal design, and a statistical model that is an operationalization of the theoretical model. Although no research study is perfect, it is useful to articulate an ideal as a standard for evaluation. Using the ideal as a conceptual framework, this article has surveyed a number of familiar and less familiar approaches to analyzing longitudinal data.

Of the three elements discussed here, the theoretical model is perhaps under the most direct control of the investigator. A clear and detailed theoretical model is a necessary foundation for all longitudinal research. This model then provides the basis for choosing a temporal design. In many cases, the temporal design is not completely under the control of the investigator, due to resource limitations and other considerations. Nevertheless, an articulation of the ideal temporal design will provide a useful perspective when difficult tradeoffs have to be made and compromises reached with respect to the design that is chosen for implementation. The most appropriate statistical model is as close to a direct operationalization of the theoretical model as possible, subject to the limitations imposed by the temporal design. Even when the ideal of seamless integration of the three elements is met, unplanned missing data and measurement reliability and validity are important issues that can have a major impact.

We are entering a new era of longitudinal data analysis. Increasingly elegant statistical models and new technology supporting more intensive longitudinal data collection are enabling data analysis and design to catch up with sophisticated and nuanced psychological theories of human development and change. It will be interesting to see what the next decade brings!

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