13. Modeling leadership-related change with a growth curve approach

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A variety of leadership and followership theories are dynamic in the sense that they imply change in the focal variables over time. In particular, one thinks of leadership theories that involve the learning and development of leadership skills and behaviors (e.g., Day, Fleenor, Atwater, Sturm, & McKee, 2014), but they also include theories about processes such as the assimilation/adaptation that occurs as a result of workplace socialization or the development of leader–member exchange relationships and trust. Indeed, recent considerations of leadership and followership from a dynamic perspective are yielding new insights.

For example, Day and Sin's (2011) theoretically based empirical study focuses on changes in ratings of perceived leadership effectiveness at four points in time as study participants took part in term-long action learning projects focused on team-building and the development of leadership. Among other results, Day and Sin demonstrated between-participant variability in ratings of perceived leadership effectiveness at the study start, indicating that first-year university students differ significantly in this leadership quality. In addition, they found differences in the shape of the individual change trajectories for leadership effectiveness over the course of the project. Specifically, the majority of the sample showed a drop in leadership effectiveness ratings from the initial measurement time, which then plateaued or showed a very slight upturn, while a smaller group showed a linear, increasing trend in ratings of leadership effectiveness across the four measurement times. This suggests differential benefits from the leadership development initiative, with one group benefiting and (at least in the short run) the other group either not benefiting or possibly even showing negative effects.

In addition, Day and Sin (2011) found several important contingent relationships. One of them was that study participants who more strongly identified as a leader at a specific point in time also tended to have higher leadership effectiveness ratings at that time. They also found that different forms of goal orientation differentially related to initial ratings of leadership effectiveness and/or the pattern of change in effectiveness over time.

Another example of a dynamic study related to leadership and followership is Jokisaari and Nurmi's (2009) study of changes in role clarity, work mastery, and job satisfaction as a function of perceived supervisor support, using measurements collected from organizational newcomers on four occasions over about a year-and-a-half. In general, levels of perceived supervisor support for these newcomers tended to decline over time, in keeping with previous works on the "honeymoon" period of high positive evaluations that often characterizes the start of interpersonal relationships, and is typically followed by a return to more realistic levels (Fichman & Levinthal, 1991). Another interesting finding from this study was that newcomers who experienced a steeper decline over time in their perceptions of supervisor support also had steeper declines in their levels of role clarity and job satisfaction, as well as lower salary increases. Longitudinal studies such as the two just described are particularly helpful in understanding the direction and pattern of change (if any) of leadership- and followership-related variables and the rates at which processes such as leader development and follower socialization occur.

To test theories of change typically requires the collection of longitudinal data consisting of three or more repeated measurements on the focal units of analysis over a time span (e.g., hours, days, weeks, months, years, etc.) that is appropriate for the research question being addressed. The data collection can be done either in a field or a laboratory context (e.g., see Rietzschel, Wisse, and Rus on laboratory studies, Chapter 3 in the current volume). And, the repeated observations may be of persons, dyads, groups, or any other type of entity. Once the data have been collected, then a suitable analytic method must be applied. There are a variety of available choices for the analysis of longitudinal data. The current chapter deals with a general approach that may be useful in many circumstances – growth curve modeling (GCM). The models are also sometimes referred to as latent curve models (e.g., McArdle & Nesselroade, 2014) or latent growth curve models. In general, such growth models are used to "estimate between-person differences in within-person change" (Curran, Obeidat, & Losardo, 2010, p. 122). This highly flexible technique can be implemented using either a multilevel modeling (MLM)/random coefficients regression framework or a structural equation modeling (SEM) framework.

This chapter provides a conceptual description of the underlying logic of growth curve modeling, an overview of multilevel and SEM approaches to specifying growth models, some tips for data collection and analysis strategy, and a discussion of considerations and limitations related to the use of the technique.

OVERVIEW OF GROWTH CURVE MODELING

General Considerations for Modeling Change

To begin, it might be helpful to first consider in the abstract the features a useful method for analysing change should have. Suppose that you wished to model a process of leadership-related change or development over time, what characteristics of your data should you be able to demonstrate or test with an ideal analytic method? It seems that most fundamentally the analysis should allow us to separate meaningful change in leadership-related variables (in either a positive or negative direction) from random fluctuation. That is, we would wish to determine whether the observed variability that appears in the data is consistent and meaningful (i.e., implies systematic change), or does it represent something more banal such as unreliability in our measurement instrument or small and inconsistent changes due to nuisance factors such as fatigue, mood, and so on?

Next, we would want to be able to characterize the pattern of changes that occur. For example, for a particular developmental process, do we see a general increase or decrease in the level of some relevant variable, such as increased self-efficacy for leadership following a training program or developmental experience (e.g., Hannah, Avolio, Walumba, & Chan, 2012; Lester, Hannah, Harms, Vogelgesang, & Avolio, 2011), or a decreased focus on an individual-level leader self-identity accompanied by an increase in relational or collective identity as leaders gain expertise in their role (e.g., Lord & Hall, 2005)? If positive or negative change is present, its rate might stay consistent over time, so that the pattern could be described as following a linear trajectory. Alternatively, there might be a non-linear pattern of change, such as a pattern of acceleration in which change occurs at a faster rate as time progresses, or a deceleration or plateauing effect in which the rate of change is initially high and then slows down. Such patterns are often referred to in the literature as growth trajectories (Singer & Willet, 2003), and can be described by parameters that capture the average direction and rate of change in the sample.

Beyond this, the analytic approach should allow us to determine whether change or growth occurs rather uniformly in the sample as a whole, or whether there is individual variability in the pattern or rate of change. For example, because of a variety of experiential, personality and ability-based factors, we might expect that some persons could quickly acquire critical leadership skills while for others the process might take longer (e.g., Day & Dragoni, 2015). Thus, an ideal analytic approach would allow us to quantify the extent to which there is significant variability across leaders in the rate and pattern of change. Relatedly, this approach should also allow us to determine whether all persons are starting at the same, or different, initial levels of leadership skill or performance, and what implications this has, if any, for the pattern and rate of change. For example, we might want to investigate whether persons receiving a leadership intervention start at very different skill levels, and whether, as a result, they benefit differentially from the intervention, with some advancing rapidly and others struggling or plateaued, depending upon their starting skill level.

Finally, once the pattern of change has been described, it would be advantageous to have some means to predict various aspects of that pattern via other independent variables. (The GCM literature often refers to such predictors as "covariates.") For example, suppose we want to know whether males and females start out at the same level of leadership performance, and whether they develop at the same rate, as studied in a sample of military cadets described in Lord, Hall, and Halpin (2010). In the example just given, gender is what the growth curve literature (e.g., Singer & Willet, 2003) refers to as a time-invariant variable. That is, its value does not change over time, and we could model its effects directly onto growth curve parameters such as the intercept and slope coefficients that describe the pattern of change. The goal orientation effects found in Day and Sin (2011) are also examples of the effects of time-invariant variables.

We might also want to determine the effects of time-varying variables that can change value from one measurement occasion to another, such as whether a leader's current level of mood or self-efficacy influences his or her performance at a specific point in time. For example, Day and Sin (2011) found that the level of a participant's leader identity at a particular point in time was associated with his or her rated leader effectiveness at that particular point in time. Thus, time-varying variables are modeled as directly influencing the value of the dependent variable at a specific point in time, and would normally be variables that we expect to vary within-person – either randomly or systematically – over the timespan of the study.

We might also want to consider models that allow us to determine whether the growth trajectory of one variable relates to the growth trajectory of a second variable. For example, we might investigate whether the initial status and rate of change over time in leadership identity relate to the initial status and rate of change in leadership efficacy? Another example of this type of model, sometimes called a parallel process latent growth curve model (e.g., Wickrama, Lee, Walker O'Neal, & Lorenz, 2016), comes from the Jokisaari and Nurmi (2009) study, in which they showed relationships of the dynamic pattern of change in perceived supervisor support with rates of changes in socialization outcomes and salary increases over time. In addition, recently there has been additional work done on the development of techniques allowing the empirical identification of categories of persons with very different patterns of change in heterogeneous populations. The growth curve modeling approach offers ways to address all of these objectives.

Key Characteristics of Growth Models

Although foundational works were also published earlier, the most recent roots of growth curve modeling include works from the 1980s and 1990s that cut across multiple analytic approaches and scholarly disciplines. The underlying statistical approaches for manifest (i.e., observed or raw) variable longitudinal models of change over time, using maximum likelihood estimation techniques, include latent curve analysis that has most typically been implemented within a structural equation modeling framework (e.g., McArdle, 1988; McArdle & Epstein, 1987; Meredith & Tisak, 1990), random coefficients regression (Laird & Ware, 1982), and multilevel modeling (Bryk & Raudenbush, 1987; Goldstein, 1995). The different growth curve modeling literatures vary in their underlying statistical justifications for the approaches, and may also differ in some aspects such as the extent to which unbalanced or missing data can be accommodated, the variety of estimators available, the fit indices available and the choices for modeling residual terms.

In addition, these somewhat different approaches may influence preferences for certain kinds of software tools. For example, those using the SEM-based approach are likely to prefer structural equation modeling software such as LISREL (Jöreskog & Sörbom, 2015), Mplus (Muthén & Muthén, 1998–2015), EQS (Bentler, 2006) or similar SEM packages. In contrast, those taking a multilevel approach are likely to prefer software such as HLM (Bryk & Raudenbush, 1992) or MLwiN (Goldstein et al., 1988; Rabash, Steele, Browne, & Goldstein, 2016), while those who use a random coefficients approach may employ general purpose statistical packages such as SAS's PROC MIXED (SAS, n.d.) or Stata's "xt" routines such as xtreg and xtmixed (StataCorp, 1996–2016). However, across a very broad range of GCMs (i.e., all linear models and many non-linear models), the different methods of implementing the analysis should yield essentially the same results (e.g., Curran, 2003; Ferrer, Hamagami, & McArdle, 2004). In this chapter, the emphasis will be on the multilevel modeling and the SEM approaches, as they currently seem to be most used in the leadership literature.

Applications of GCM are quite popular in many research areas, including developmental, social, and personality psychology, business and management, and education. In part, this popularity may be because GCMs allow one to start with a simple model describing change over time, and then incorporate additional complexities including covariates, relationships between GCMs, and identification of heterogeneous patterns of change. Our starting point in this chapter, however, will be a very simple growth curve model that has two key variables: an independent variable that reflects time (or some variable related to time, such as age), and repeated measurements of the focal dependent variable at different occasions, for example, repeated measurements of leader self-efficacy or performance. We'll consider some particulars for each of these variables next.

Considerations for the independent time variable

In GCM, even though observations occur at specific points in time and may be indicated with just a few discrete values, time in general is assumed to be a continuous independent variable. As will be described in more detail a bit later, a coded time variable is typically employed in the multilevel approach to GCM, in order to indicate when a particular observation has been made. This is in contrast to some other approaches such as repeated measures ANOVA in which the independent variable indicating time is treated as categorical. The treatment of time as continuous has the advantage of also allowing the analysis of datasets in which not every person is measured at exactly the same time. (Such datasets may have a large number of different observation times, and tend to be better handled with the multilevel approach than the SEM approach.)

For example, imagine that you were studying a large number of supervisors who took part in a day-long leadership training program. The training program needs to be offered at multiple times, spaced out over a four-week time period. Suppose that you wanted to collect repeated measures of a variable such as leadership effectiveness that you believe will change over time as a result of the training, using a self-report survey method and collecting data at the very start of the training program and at three later points in time. However, for practical reasons, you must distribute the post-training surveys at each time period to all of the trainees at once. If the first survey is sent out a week after the last group has received its training, the time that has elapsed since training is +1 week for the last group that was trained, but it is +5 weeks for the first group to receive training. There will be a similar kind of variability in time elapsed for the remaining two measurement periods. The training-related change in leadership effectiveness might well depend upon how much time has elapsed since training (as leadership researchers and practitioners, we hope that it is a positive change, and that it continues to increase over time!) This kind of variability can be accommodated in the growth curve modeling analysis by the coding scheme adopted to indicate the time of measurement.

When data are collected from all persons at exactly the same points in time (or, in some developmental studies, at the same ages), the dataset is said to be "balanced on time" or simply, balanced. This term also applies to those datasets where the original plan was to collect observations from all persons at the same times, but some individuals are missing responses for one or more of these response times, in a pattern that is believed to be missing at random or missing completely at random. Data collections in which people are observed at different points in time, potentially even with no two people sharing the same times of observation, are called unbalanced. In general, the multilevel approach to GCM handles unbalanced datasets more readily than does the SEM approach.

Considerations for the dependent variable

In the models considered in this chapter, the repeated dependent variable is also assumed to be continuous, as well as normally distributed. (However, methods for similar analyses of ordered categorical dependent variable models exist; for example, see Rabe-Hesketh and Skrondal, 2012 as well as syntax examples on the Mplus website at statmodel.com.) It is also important that the dependent variable measure has the same metric or scaling across all measurement occasions, and that the construct underlying the measure maintains the same meaning (Kline, 2016; Singer & Willett, 2003). These latter two requirements are necessary so that any observed change can be attributed to processes occurring over the passage of time, and not simply to changes in the measurement instrument used or changes to what it means to participants as they develop. This is often accomplished by simply using exactly the same instrument for all measurement occasions, but in some circumstances there might be reasons to vary the content of the dependent variable measurement instrument from one time to another. For example, if implicit measures involving word fragments were used as the dependent variable (see Chong, Djurdjevic, and Johnson on implicit measures in Chapter 2 of this volume), the same set of word fragments should not be repeated from one time to the next, in order to avoid familiarity effects. In cases like this, it might be possible to identify equivalent or equated instruments in order to proceed with GCM. Finally, the SEM approach to GCM has the additional option of modeling the dependent variable as a latent factor, thus potentially increasing its reliability and construct validity.

The typical maximum likelihood estimation procedure used in growth curve analysis allows for the accommodation of missing data on the dependent variable side (Curran et al., 2010). This is a very convenient feature, as in practice it can be quite difficult to get a full set of data points from every individual (or other entity) participating in a longitudinal study. However, in order for estimation to be unbiased in the presence of missing data, the missing values should be at least missing at random (i.e., missingness is not contingent upon the level of the dependent variable; see Graham, 2009 or Shafer and Graham, 2002 for a good general overview of modern methods for dealing with missing data).

Parameter estimation in GCMs

Both fixed and random effects are typically estimated in growth models. The fixed effects include an intercept parameter that indicates the mean population level of the dependent variable at the measurement occasion with a time code of "0" (often chosen to be the initial measurement occasion), and one or more additional parameters that describe the mean population pattern of change in the dependent variable over time (for linear models this is often a slope parameter). The key random effects parameters describe the extent of variability across persons in the coefficients that describe individual growth curve trajectories.

Although in many other statistical applications we are not especially interested in values of variances, in the GCM context these random effects can be quite interesting because they tell us whether people tend to have the same growth trajectories or not. For example, if most participants in a leadership study have almost the same value of intercept for their individual-level growth trajectories for leadership effectiveness, the variance of the fixed effect intercept parameter will be small, and we might conclude that all participants have begun the study with the same level of effectiveness. However, if intercepts vary widely in value from person to person, the variance associated with the fixed effect intercept parameter will be large, suggesting that there is substantial variability in initial levels of leadership effectiveness. We can similarly look at the estimated variance in slope parameters, to determine whether the rate of change is likely to be constant or varying. For example, although we may have intuitions that some people acquire leadership skills more rapidly than others (i.e., that there is substantial variability in slope coefficients), GCM combined with a thoughtful data collection effort could help us to more precisely determine whether our intuition is correct and if so, more precisely what the actual extent of variability is.

Short Overview of the Multilevel Approach to GCM

The multilevel model analytic approach builds on the idea that repeated measurements of the dependent variable are clustered or nested within a higher-level entity such as a person (e.g., Bryk & Raudenbush, 1987; Rogosa & Willett, 1985). For example, a study might involve ratings of leader effectiveness, collected every three months over a period of a year. Thus, the resulting dataset has four effectiveness ratings (taken at months 1, 4, 7, and 10) for each leader included in the study. As can be inferred from this example, a key difference between the growth curve model and a more general multilevel model is that for GCM datasets the clustered observations at the lower level are ordered with respect to time. This means that time will need to be explicitly treated as a predictor variable in the multilevel GCM data analysis.

The Level 1 model

The most basic multilevel approach takes the form of a two-level model. The lowest level (Level 1) specifies the individual growth model – describing how an individual changes over time – as shown in the example of Equation 13.1. This model describes the value of the dependent variable as depending upon three terms: a constant intercept coefficient, a second coefficient that is multiplied by time, and a residual term. The coefficients on the right-hand side of the model can potentially be different for every person in the dataset. Thus, it captures the shape of the within-individual growth trajectory for any specific person in the dataset. Another way of saying this is that the Level 1 model captures the intra- (within-) individual effects of time on the dependent variable:

$$\text{Level 1: } Y_{ij} = \pi_{0i} + \pi_{1i} Time_{ij} + \varepsilon_{ij} \qquad (13.1)$$

In this model, Y_{ij} is the value of the dependent variable for a given individual (i) at a specific time (j). For example, in a study of change in leader effectiveness over time, Y_{13} would be the leader effectiveness rating for person 1 at the third measurement occasion.

The πs of Equation 13.1 are growth parameters describing change over time at an individual level, and are estimated from the data. They can be thought of as analogous to coefficients in a standard regression model, with π_{0i} representing an intercept term, and π_{1i} representing a slope coefficient that captures the effect of time on the dependent variable. The values of $Time_{ij}$ are supplied by the researcher, to indicate the time at which, for a particular individual, a dependent variable measurement was taken. To help scale the value of the intercept estimate, one of the $Time_{ij}$ values is set at zero. So, for example, if there are four equally spaced measurement occasions, the values of $Time_{ij}$ could be coded as 0, 1, 2, and 3. In this example, we would expect only those values of time to be used, but in datasets that do not have this balanced structure, individuals could vary in their values of $Time_{ij}$.

Finally, ε_{ij} is a residual term that reflects errors of prediction in the individual-level growth trajectory. In other words, at each relevant measurement occasion, there will likely be some difference between the actual, observed value of the dependent variable and the value that is predicted based on the intercept and slope coefficients for that individual. The residuals are assumed to be independent and normally distributed, with a mean of zero. The version of the Level 1 model shown in Equation 13.1 could be used to fit any linear pattern of change, regardless of whether it is slow or rapid, or involves an increase or a decrease in values over time. If desired, additional πs could be included in the model to introduce higher-order terms that allow testing for curvilinear effects, such as a quadratic (squared) effect of time. The effects of additional time-varying predictors could also be incorporated in this model, such as a measure of experienced stress at each point in time. Finally, alternative assumptions about residuals could be incorporated in the model, such as whether they are heteroscedastic over time (i.e., variances are unequal) in various patterns, and/or non-independent.

The Level 2 model

In growth curve analysis, one or more models are also specified at a higher level. While the Level 1 model describes how an individual changes over time, Level 2 models concern potential between-persons differences (i.e., inter-individual differences) in the values of the growth parameters of the Level 1 model. These parameters are typically – at least initially – assumed to randomly vary across individuals. Continuing on with our leadership effectiveness example, we might believe that potentially both the intercept and slope parameters can vary meaningfully between individuals. In other words, the initial value of leadership effectiveness might be relatively low for some individuals, while others have moderate or high initial values of the dependent variable. And some leaders might have a relatively rapid rate of linear change in their effectiveness over time (perhaps as they benefit from developmental training or experiences), while others change slowly or not at all. These ideas are captured in the following two Level 2 models:

$$\pi_{0i} = \gamma_{00} + u_{0i} \tag{13.2a}$$
$$\pi_{1i} = \gamma_{10} + u_{1i} \tag{13.2b}$$

The model in Equation 13.2a describes individual leaders' intercept parameters (π_{0i}) as a function of a latent mean population intercept value (γ_{00}), and (u_{0i}), a term that reflects the deviation of the individual's intercept value from the mean intercept value. Similarly, Equation 13.2b describes an individual slope parameter (π_{1i}) as a function of a latent mean population slope parameter (γ_{10}) and a deviation of the individual slope parameter from the mean slope (u_{1i}). The values of γ_{00} and γ_{10} are estimated as fixed effects, and describe the aggregate pattern of growth or change over time. More complex versions of Level 2 equations can also include additional terms on the right-hand side of the equation representing potential predictors of the values of individual intercepts and slopes. For example, a potential predictor for individual values of the intercept for leader effectiveness is the number of years of supervisory experience that a particular leader has. More specifically, we might expect that there is a positive relationship between years of supervisory experience and leader effectiveness. In this example, supervisory experience functions as a time-invariant predictor, as it has the same value across all measurement times. If this new predictor variable is added to the intercepts equation, it now looks like Equation 13.3 below:

$$\pi_{0i} = \gamma_{00} + \gamma_{01}Experience_i + u_{0i} \tag{13.3}$$

The coefficient for the supervisory experience variable (γ_{01}) can be tested to determine whether it is significantly greater than zero. Similarly, the previous equation for slopes (Equation 13.2b) could also have an added term if we believe that prior supervisory experience not only influences the intercept value but also affects the linear rate of change in leader effectiveness.

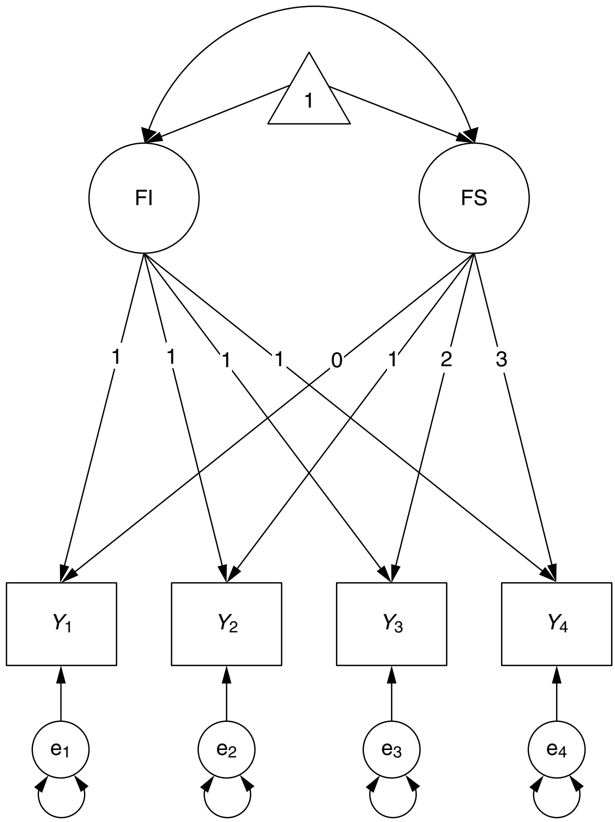
Finally, although they might not at first glance look especially interesting, the values of u_{0i} and u_{1i} from Equations 13.2a and 13.2b can give researchers valuable information about the homogeneity or heterogeneity of the values of the individual growth parameters. These two random effects variables are typically reported on output in the form of two variances and a covariance. The two variances, τ_{00} and τ_{11}, give an estimate of the extent to which there is variability across different individuals in the estimates of the intercept and slope growth parameters, respectively. The estimated values of these two variances can be tested to determine whether they are significantly different from zero. Suppose, for example, that in our study of changes in leadership effectiveness over time, the variance around the intercept is relatively small while the variance around the slope is relatively large. This would suggest that while most individuals were similar in their level of leadership effectiveness at the start of the study, there was substantial variability in the extent (and perhaps direction) of their changes in effectiveness over time.

In addition, the covariance between the individual intercept and slope values, τ_{01}, indicates the extent to which individual intercept and slope values relate to each other, and its estimate can also be tested to determine whether it is significantly different from zero. For example, in our illustration, a positive, non-zero covariance would indicate that leaders with higher initial levels of effectiveness also tend to improve at a faster rate than those with a low initial level of effectiveness, as might be expected if a third variable such as leadership motivation or readiness to learn influenced both one's initial level of leader effectiveness and one's rate of increase in effectiveness. A negative covariance might occur, on the other hand, if leaders at very high initial levels of effectiveness did not have much room to improve further so had low rates of change, while leaders at low initial levels of effectiveness could make easy changes in behavior that rapidly changed their levels of effectiveness.

Finally, note that the separate Level 1 and Level 2 models are sometimes combined into a single equation, by substitution (see, for example, Bryk & Raudenbush, 1992), and the interpretation of output from some analytic programs can be easier if you are familiar with this single equation expression of the GCM. Also, note that for most GCMs taking a multilevel approach, two levels such as have just been described are sufficient. But in some cases, an additional level of nesting is appropriate. For example, one might be looking at changes in followers over time, and those followers might in turn be nested in different work groups. In that case, a three-level model (with work group at the highest level) would be desirable. This type of situation is one where the multilevel modeling approach has an advantage over the SEM approach, as it is possible to specify and estimate such three-level models fairly easily.

Short Overview of the SEM Approach to GCM

As illustrated in the path diagram of Figure 13.1, the structural equation modeling approach to latent growth curve modeling essentially involves a specialized application of factor analysis, using means and covariance analysis (e.g., Meredith & Tisak, 1990; Willett & Sayer, 1994). (See Kline, 2016, Chapter 15, for an introduction to working with means structures in SEM.) In the GCM factor model, one or more common factors that represent change over time are specified, using the repeated measurements of the dependent variable as multiple indicators of the latent factors. Assuming that we are modeling linear growth, two latent factors would be specified: an intercept factor and a slope factor, labeled as "FI" and "FS" respectively in the path diagram of Figure 13.1. Sometimes these are referred to as chronometric factors. The latent means of these factors – illustrated in the path diagram by the paths leading from the triangle above the factors – are estimates of the population mean intercept and slope values that corre-



Note: The rectangles towards the bottom of the figure represent the repeated measurements of the dependent variable *Y* at four different measurement occasions. Towards the top of the figure, the circles labeled "FI" and "FS" are the intercept and slope latent factors respectively. These two latent factors have freely estimated error variances, and are allowed to freely covary. A pattern of fixed factor loadings with values of "1" is used to specify the intercept factor. A pattern of fixed factor loadings with values of 0–3 is used to specify the slope factor. The triangle near the two latent chronometric factors indicates that their means are estimated. Finally, each of the measured dependent variables has a latent residual term, e1–e4.

Figure 13.1 Path diagram depicting an SEM model specifying a linear growth trajectory

spond to the γ_{00} and the γ_{10} in the Level 2 equations of the multilevel model approach that was previously described. In addition, the variances of these factors provide estimates of what were termed τ_{00} and τ_{11} in the multilevel context, and the covariance between the two factors estimates τ_{01}.

The manner in which the factor model for GCMs is specified differs from a standard CFA model in that it tends to have a larger number of fixed factor loadings. These fixed loadings help to define the chronometric factors in a pre-specified manner that describes the desired pattern of change, for example, constant, linearly increasing/decreasing, quadratic, or non-linear change. Depending upon the particular form of growth trajectory that is expected, the values of these fixed loadings will differ somewhat. However, to achieve model identification, at least one loading for each chronometric factor must be fixed to a pre-specified value, rather than freely estimated, and for each factor except the intercept factor, one loading must be fixed to zero (McArdle & Nesselroade, 2014).

For example, suppose you want to fit a linear growth trajectory for balanced data with four measurement occasions, spaced a month apart for all participants in the study. In Figure 13.1, the rectangles along the bottom of the diagram represent the repeated values of the focal dependent variable (e.g., leader effectiveness), labeled as "*Y*," with a subscript to denote the time of measurement. Each of the *Y* variables has a latent residual term (i.e., e_1–e_4). Note that the factor loadings for the intercept factor have all been fixed to a value of "1," as the intercept retains a constant value across all four measurement occasions. In contrast, the factor loadings for the slope factor represent a time multiplier for the value of the slope, analogous to the values of the $Time_{ij}$ variable in the multilevel approach. In the illustration, at the first measurement occasion (t_1), the factor loading is fixed to a value of "0." Because we have equally spaced times of observation for all participants in this example, at Times 2, 3, and 4, respectively, the fixed values of the factor loadings are "1," "2," and "3." With this set of fixed factor loadings (sometimes called basis weights), the intercept factor mean refers to the estimated population mean value of the dependent variable on the Time 1 measurement occasion (i.e., the occasion coded "0"), and the slope factor mean reflects the change in the level of the dependent variable for a one-unit change in time.

Further considerations in coding for time

Depending upon the specifics of one's study, it might be useful to employ alternative weights for the slope factor loadings. For example, continuing with the example introduced in the previous paragraph, suppose that an intervention was made at the second measurement occasion, so that you wanted the estimated intercept value to reflect the mean level of the dependent variable at that point in time. In that case, you might prefer to use values of –1, 0, 1 and 2 for the fixed factor loadings on the slope factor. Alternatively, suppose that you wanted the estimated slope coefficient to be interpretable as the change from Time 1 to Time 4. To do that, you could use proportional values, making the difference between the factor loadings for the first and last measurement occasions equal to one unit, with the loadings for Times 2 and 3 falling proportionally in between, thus you could choose fixed loading values of 0, 1/3, 2/3, and 1. (Although described here in the section on the SEM approach, the same logic can be applied in choosing values for the $Time_{ij}$ variable if the multi-level approach is used.)

Note that any of the three different sets of fixed factor loadings just described would result in the same value for the overall fit of the GCM. However, these choices will affect the values of some of the estimated model parameters. More specifically, when different values of the fixed factor loadings are used, the slope mean and variance parameters will not change, and neither will the error variances. However, the intercept mean and variance will change and so will the covariance of the slope and intercept (McArdle & Nesselroade, 2014).

The previous examples of values for fixed factor loadings were for data collected at equally spaced intervals. Yet sometimes there may be good reasons to collect data at unequally spaced intervals. In such situations it may be worth considering whether a set of factor loadings that reflects the unequal spacing might be of use. For example, Boswell, Shipp, Payne, and Culbertson's (2009) study of honeymoon and hangover effects provides a nice illustration of the application of GCM to the study of job satisfaction in the context of work socialization. In their study, they collected data on newcomer job satisfaction at four points in time, specifically: (a) Time 1, the first day on-the-job; (b) Time 2, three months after Time 1; (c) Time 3, six months after Time 1; and (d) Time 4, a year after Time 1. Notice that the time interval between Times 3 and 4 is twice as large as the interval between Times 2 and 3. Importantly, they had an a priori rationale for this data collection schedule, based on both previous socialization research and input from knowledgeable organization members. Although their published results suggest that they likely used a 0, 1, 2, 3 coding for time in their analyses, which indeed may be quite appropriate, they could also have considered values that reflect the unequal time intervals. One such fixed factor loading pattern would be 0, 1, 2, 4. (Astute readers might also notice that one way of interpreting such a loading pattern is that there is a "missing data collection occasion" halfway in between Time 3 and Time 4, for which no person in the sample has data.)

To give another example of this issue that allows some more elaboration of the implications of choice of the fixed factor loading values, consider the following schedule of data collection at four points in time, with unequal intervals: Time 2 data were collected at two weeks following Time 1, Time 3 data were collected at six weeks following Time 1, and Time 4 data were collected at 12 weeks following Time 1. The choice of fixed loadings on the slope factor could accommodate this and reflect the differences in the time intervals between observations. If you used values of 0, 2, 6, and 12 as your fixed loadings, the estimated slope coefficient would reflect the mean population change in the dependent variable for a time unit of one week. Or, you could use values of 0, 1, 3, and 6, in which case the slope coefficient now provides an estimate of the change over a two-week period. Or, you might alternatively prefer to use values of 0, 0.17, 0.50, and 1. This latter coding would make the slope coefficient reflect the mean population change over the time period spanning from Time 1 to Time 4 – a period of three months. Notice that in determining these values, it does not matter whether the actual units of time are minutes, days, months, years, or any other unit. The key idea is to reflect the spacing between measurement intervals.

Specification of curvilinear, non-linear and other alternative growth trajectories

Two factors – specifying a linear growth trajectory – may be sufficient to describe the pattern of change over time in your data. However, it is not unusual for there to be a second- or even higher-order component to the growth trajectory. A curvilinear (i.e., polynomial) growth pattern that includes a quadratic effect can be specified by adding a third chronometric factor, and fixing the loadings from that factor to values equal to the square of the corresponding linear factor value. For example, factor loadings on the quadratic factor for Y_1 to Y_4 would be 0, 1, 4, and 9 (i.e., 0^2, 1^2, 2^2, 3^2), if the linear factor (FL) had loadings of 0, 1, 2, and 3. (A similar approach to specifying a quadratic term can be taken if you are using the multilevel approach, by adding another term to the Level 1 equation, consisting of $\pi_{2i}Time^2_{ij}$. Also, a corresponding additional Level 2 equation could be added if you wish to determine variability around this component.) In addition, you might want to investigate an alternative re-parameterization of the quadratic model developed by Cudeck and Du Toit (2002), which allows for the estimation of the quadratic function's minimum and maximum values, instead of the more familiar slope and quadratic components.

A cubic effect could also be specified following a similar strategy in which the fixed factor loadings are the slope coefficients, taken to a power of three. However, although the quadratic, and sometimes the cubic, models have been used fairly extensively by researchers who want to accommodate deviations from linearity in their models, they often imply an unrealistic pattern of growth if used to predict the value of the dependent variable at time points beyond the final time of observation.

For example, a quadratic function might fit a growth trajectory that rises rather quickly initially but then slows down substantially, but its extension into future time periods might imply that the level of the dependent variable at some point decreases over time, a condition that is probably not true for variables such as leadership identity, effectiveness, and so on. That drawback might make other – non-linear as opposed to polynomial – functions more attractive, even though they may be somewhat more difficult to implement.

Indeed, many processes that at least partly have biological underpinnings – such as learning, or some of the biometric indicators discussed by Dixon, Webb, and Chang in Chapter 7 of this volume – are likely to change in a non-linear manner (e.g., Grimm, Ram, & Hamagami, 2011). Non-linear forms include exponential and logistic functions, as well as other possibilities. If you wish to fit growth trajectories that you believe have a non-linear – rather than a curvilinear – form, you have some reading ahead of you as they will not be covered in detail in this chapter, but the investment of time could be very rewarding! As a starting point, you may want to see Grimm et al. (2011) for an excellent general overview.

Two additional options might be considered when fitting complex growth trajectories. The first of these is the piecewise latent growth model (e.g., Bryk & Raudenbush, 1992). The piecewise model is especially useful when the nature of your sample is such that you might expect an abrupt change in slope at some point in time. Often, such changes can occur when your measurement period spans a transition of some sort. For example, perhaps you have a series of measurements of leadership identity over time from a group of managers. The first several measurement times occur before a promotion, and the remaining measurement times follow the promotion. We might expect a moderately high but flat or only slowly increasing level of leadership identity before the promotion, as these managers have been functioning in their current leader roles for a period of time. Following promotion, there may be a sudden rapid change in leader identity as the managers engage in cycles of identity claiming and granting with new subordinates and peers (e.g., DeRue & Ashford, 2010). This type of model can be fit by having two slope factors, rather than one. Pre-promotion identity measures would load on the first slope factor and post-promotion identity measures would load on the second, with the promotion as the point of inflection for the piecewise growth trajectory. For a published example of the application of this type of model, see Li, Duncan, Duncan, and Hops (2001).

The second alternative model that can be helpful to consider is the fully latent curve model (McArdle, 1988; Meredith & Tisak, 1990). In this model, a subset of the fixed factor loadings is freed so that they can be estimated. The resulting estimates can be compared to the values of fixed loadings that would specify growth curves of specific forms, to indicate the extent of variability from those functional forms. Specifying such models so that they achieve identification has some subtleties, you may wish to consult Ghisletta and McArdle (2001) for an example.

Finally, it should be at least briefly mentioned that one important advantage of the SEM approach to GCM is that it is relatively easy to specify models in which the dependent variable (e.g., leader effectiveness, leader identity, etc.) is latent, rather than measured. The GCMs that have been considered in this chapter so far have had manifest (measured) dependent variables, thus they fall into the category of "first order latent growth curve models." When the dependent variable is latent, the GCM is frequently called a "second-order latent growth curve model" or a "curve of factors model" (McArdle, 1988). In such models, the dependent variables are latent factors with multiple indicators, all measured at the appropriate points in time. An advantage of using latent dependent variables is that reliability is increased because measurement error can be separated from true variance. Greater reliability might improve the ability to model the change and to find statistical significance for covariate relationships. Another advantage of latent dependent variables is that you can directly test the measurement invariance of the dependent variable across time, using a multiple group analysis.

A Quick Note about Residual Structures

Residual terms (e_1–e_4 in the SEM approach or ε_{ij} in the multilevel approach) represent the variance in the Y_t variables that is not explained by any of the chronometric factors (and any other variables that are modeled as having direct effects on Y at a given time, such as time-varying covariates). An advantage of using an SEM approach to estimating latent growth curves is that the residual terms can be flexibly modeled and tested. The default assumption in the specification of the GCM discussed so far in this chapter has been that the residuals are homoscedastic (i.e., of equal magnitude across time) and independent (i.e., uncorrelated with each other) once the growth component of the model has been properly specified. These assumptions are often unrealistic with longitudinal data. Researchers using the SEM approach may place additional – or relax existing – constraints on the error terms. For example, in most software packages by default the covariances among the residuals are all fixed to zero (i.e., independent/uncorrelated residuals), however, some of these restrictions might be relaxed, allowing adjacent error terms to covary, as would be implied by an autoregressive error structure. The multilevel modeling approach to GCM also allows for the investigation of autoregressive and heterogeneous error structures (e.g., Curran & Bollen, 2001), although not as flexibly as in the SEM approach. As mentioned earlier in the chapter, once the best fit to a functional form has been established, it is important to test alternative error structures. For an introduction to this issue, see Singer and Willett (2003). For further study, Wu, West, and Taylor (2009) have a good – if somewhat technical – discussion of sources of misspecification in GCMs and the variety of fit indices that may be employed to help determine the sources of misfit in one's model.

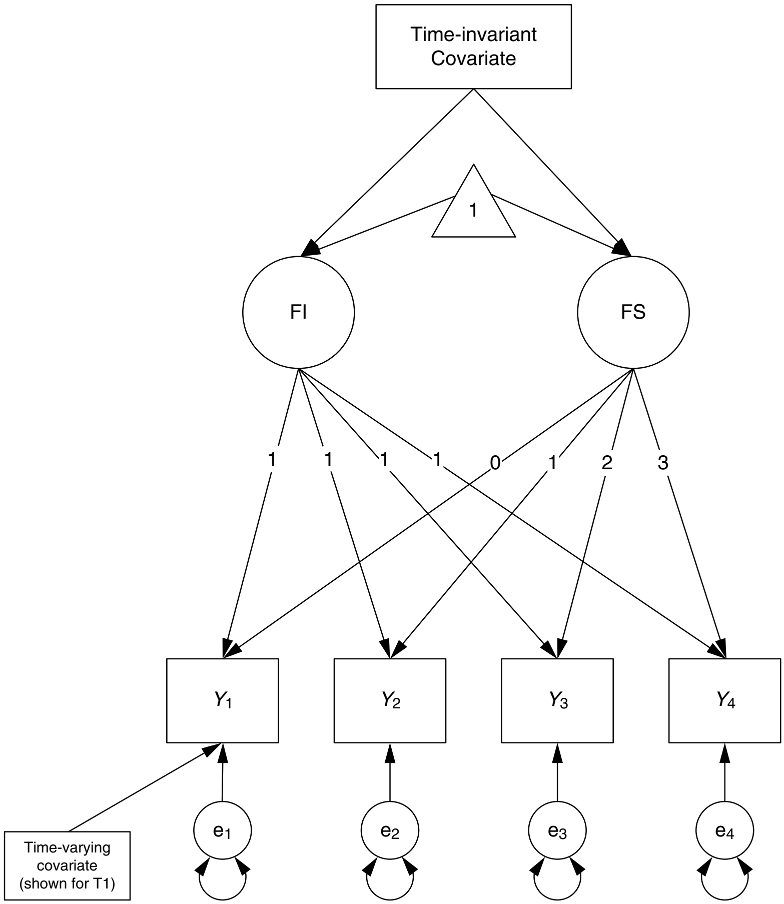
Conditional GCMs: Adding Covariates

As already indicated in the section on the multilevel modeling approach, once the general form of the growth trajectory is successfully modeled, then additional predictor variables can be added to the model. These variables are typically mean-centered before being included in the analysis, to aid in the interpretation of the resulting parameter estimates. Figure 13.2 shows, in path diagram form, a latent growth curve model that includes generic time-invariant and time-varying predictor variables. The effects of time-invariant covariates can be tested for statistical significance to determine whether they influence intercepts and rates of change (i.e., a linear slope, quadratic term, etc.), while time-varying covariates can be tested to determine whether they affect the values of the dependent variable directly. For example, in the Day and Sin (2011) article, leader identity at each measurement occasion was a significant time-varying predictor of ratings of perceived leader effectiveness, while various types of goal orientation predicted intercept and slope values.

PRACTICAL CONSIDERATIONS

Planning the Data Collection

In general, longitudinal data collection involves substantial forethought and planning. Decisions need to be made about the optimal number of participants, as well as about how frequently and for how many occasions data should be collected. In making such decisions, you will likely want to balance requirements based on theory, a knowledge of what previous researchers have done and statistical requirements, with competing considerations of cost and accessibility. The desirable sample size depends upon several factors, including the functional form of the growth curve being estimated (more complex forms will require larger samples) and the number of



Note: A single time-varying covariate effect is also depicted on the dependent variable at Time 1 (typical models would also include time-varying covariates at the remaining measurement times as well).

Figure 13.2 Path diagram for linear growth trajectory with freely estimated time-invariant covariate effects directly on intercept and slope parameters

measurement occasions (to reach a given level of statistical power, you need more persons in the study if the number of measurement occasions is small). In general, maximum likelihood estimators require larger sample sizes, and also the statistical power to detect effects increases with a greater number of persons. Statistical power will be decreased when there are missing data.

For further specifics, you might wish to consult Zhang and Wang (2009) for an example of how to implement a power analysis via SAS macros.

When it comes to the issue of choosing how many measurement occasions to have, a minimum of three is advisable even for relatively simple growth models. Although technically you could fit a linear growth trajectory with only two measurement occasions, having only two measurement periods does not provide the opportunity to disconfirm a linear form, much less compare it to a more complex functional form, as a straight line will fit any two points perfectly. To demonstrate deviations from linearity, you must have at least three measurement occasions. In addition, if you expect to fit a polynomial trajectory (e.g., quadratic, cubic), you should always have at least one more measurement occasion than the highest-powered term in the equation for your functional form. For example, if you are fitting a quadratic form, the highest power would be 2, so you would need an absolute minimum of $2 + 1 = 3$ measurement occasions, and it would be preferable to have *more* than three measurement occasions in order to help disconfirm a quadratic form if it is not the correct one. Also, as the number of measurement occasions is increased, the precision of the estimated growth parameters (e.g., intercept and slope coefficients) increases. Yet, a desire for precision might need to be balanced with practical concerns. For example, too many measurement occasions might lead to participant fatigue and dropout or careless responding, and will certainly increase the costs and effort required.

How to space occasions of measurement depends upon the particular phenomenon you are trying to model. Some processes, such as the development of leader–member exchange relationships might be expected to occur fairly rapidly, and then remain relatively stable over time. The measurement occasions for such processes probably span days or weeks. In contrast, the development of certain leadership skills might take months or years, thus measurement occasions for these variables should be spaced much further apart over time. Other aspects being equal, you also might want to consider whether longer intervals could lead to greater dropout from the study or whether shorter intervals might result in too much carry-over in responding from the previous measurement occasion. Finally, it is critical to be certain that you have designed your data collection procedure to allow you to link responses from the same participant across all measurement occasions.

Structuring the Dataset for Analysis

Depending upon your choice of statistical analysis packages, your dataset will need to be either in one of two different forms, described by Singer

Table 13.1 Illustration of two dataset forms: (a) person-level dataset, one data record per individual; (b) person-period dataset, one data record per measurement occasion per individual

(a) Person-level dataset

Person	Repeated dependent variable			Time-invariant covariate	Time-varying covariate		
	$Efficacy_1$	$Efficacy_2$	$Efficacy_3$	Sex	$NegAff_1$	$NegAff_2$	$NegAff_3$
1	4	5	6	1	2	1	2
2	3	3	4	2	3	3	2
3	3	4	5	2	4	1	3
etc.	...	...	...	...	...	...	...

(b) Person-period dataset

Person	Time	Dependent variable	Time-invariant covariate	Time-varying covariate
		Efficacy	Sex	NegAff
1	1	4	1	2
1	2	5	1	1
1	3	6	1	2
2	1	3	2	3
2	2	3	2	3
2	3	4	2	2
3	1	3	2	4
3	2	4	2	1
3	3	5	2	3
etc.	...	...	...	...

Note: The same values are displayed in each dataset.

and Willett (2003) as either a person-level dataset or a person-period dataset (Table 13.1). As can be seen in the table, the person-level dataset is more similar to the datasets typically used for other types of analysis, in that it has a "wide" or horizontal structure in which each person in the dataset has a single data record. The dependent data measures from the different time points are saved with different variable names. For example, you might name multiple measures of a leadership self-efficacy measure taken at different points in time as "$Efficacy_1$," "$Efficacy_2$," "$Efficacy_3$," and so on, to make clear which measurement occasion each one is associated with. Time-invariant covariates, such as gender or supervisory experience are indicated with a single variable for each. In contrast, time-varying covariates must be saved as multiple variables, in a manner similar to that used for the dependent variable. For example, if you wanted to treat negative affect as a time-varying covariate, you would need to have a set of variables such as "$NegAff_1$," "$NegAff_2$," "$NegAff_3$," and so on. Person-level datasets are more typical when a structural equation modeling approach is used to estimate the GCM.

In contrast, as illustrated in Table 13.1, person-period datasets have multiple data records for each person in the dataset. Because this typically results in a dataset with many lines of data, it is sometimes called a "long form" dataset. Each line of data contains the values for one individual, for one specific measurement occasion. For example, if a balanced study had data collected from 100 persons at four points in time, there would be 400 data records in the dataset. In contrast to the person-level dataset, this data form typically has a variable that explicitly indicates time (e.g., the measurement occasion, age at which measure was taken, etc.).

Ideally, you would check on whether a person-level or person-period dataset is required for your analytic package before entering your data into a dataset, and then input the data accordingly. However, if you end up with your data in the wrong form, it can generally be easily transposed. Most broad purpose data analysis packages such as SPSS, SAS, or Stata have a procedure that allows you to move from one form to the other. Indeed, even if you plan to use a more specialized software package for the GCM analyses, it is often easier to use a more general analysis package such as one of those mentioned above for those data tasks that need to take place before estimating the GCMs, such as screening for outliers, creating scale scores from survey items, and assessing reliability.

Preliminary Data Steps

Among the preliminary analysis steps to undertake, you should try to get a sense of the shapes of individual growth trajectories to see if the function (linear, curvilinear, non-linear, etc.) that you intend to fit is even plausible for your data. One way in which this is often done is to produce graphic displays of the individual data points, nested within individuals. An example of this is shown in Figure 13.3, which displays the pattern of data points for six different individuals who all have measurements taken at five points in time. The variability in patterns of the data points over time for different individuals shown in this figure is fairly typical. Suppose one wanted to fit a linear growth trajectory to these data. Although none of the figures shows a strictly linear pattern of change, this form would not be dismissed out of hand as several of the plots have a somewhat linear form, and all appear to show a general positive (upward) trend. A variation on this type of individual plot adds a fitted

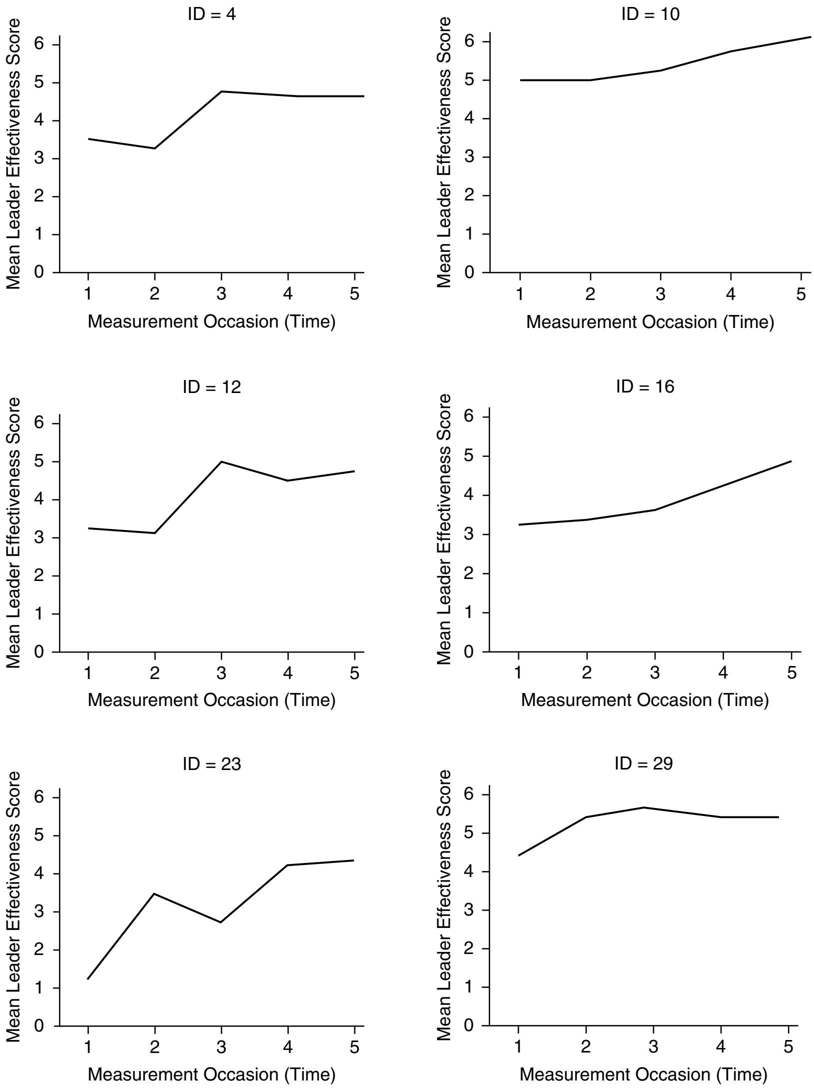
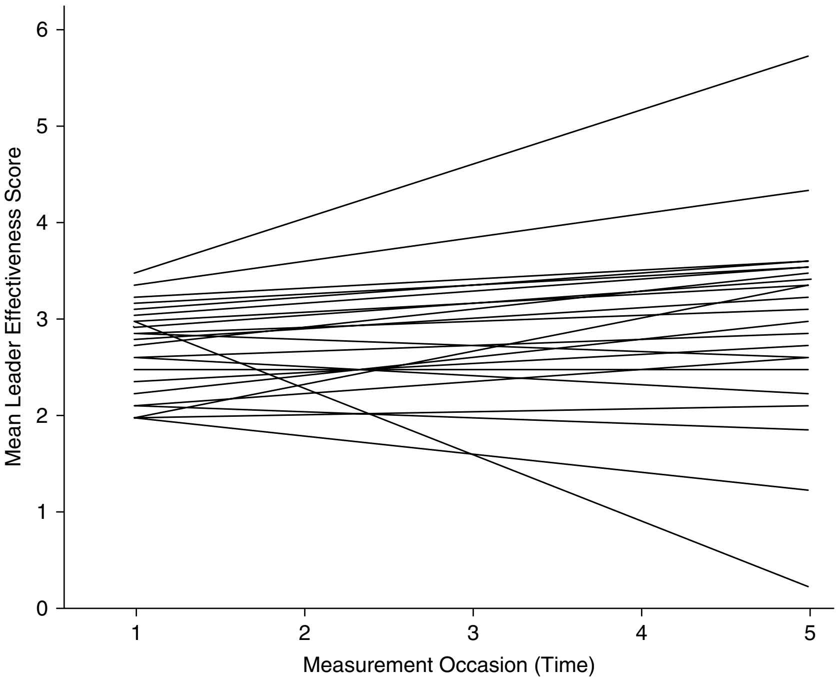


Figure 13.3 Plot of data over time by individual, showing varied patterns of individual growth or change

(linear) regression line to the data points in each plot, rather than simply connecting adjacent values.

Figure 13.4 shows another way in which this issue can be explored. It depicts a "spaghetti plot" in which all (or for large datasets, a sizeable sample



Note: Alternative versions of such plots may simply connect values of observations or may fit non-linear functions to each individual's data points.

Figure 13.4 Spaghetti plot showing fitted linear regression lines for multiple individuals on the same axes

chosen at random) of the individual growth trajectories are displayed using the same set of axes. Again, there can be variations on this type of figure in whether different trajectories are fitted to the individual lines, or whether raw data points are simply connected. In addition to graphic displays, you can also simply estimate linear regression models for each individual's data (using time as a predictor variable) and inspect the resulting coefficients, to get a sense of the range of intercept and slope values that would result from fitting a linear function. For more detail on producing and interpreting plots and other preliminary analysis procedures, see Singer and Willett (2003).

Assessment of Model Fit and Parameter Estimates

Interpretation of the results from the estimation of GCMs involves both an assessment of the adequacy of model fit, and significance tests of specific estimated parameters. The initial focus should be on fitting the growth trajectory, without including any of the intended covariates in the model. In the multilevel approach, the assessment of overall model fit has tended to emphasize comparisons of alternative models. SEM approaches typically also involve comparisons of alternative models, but in addition tend to consult a larger number of model fit indices, including the likelihood ratio test statistic (LRT, also commonly called the chi-square goodness of fit statistic), the RMSEA, CFI and TLI. Comparisons of nested models can be made with the LRT, and non-nested models can be compared with the AIC or BIC. An initial step in data analysis is often to fit two simple models for comparison purposes. These allow assessing: (1) whether there is sufficient variance to justify a multilevel analysis and (2) whether there is evidence for any form of growth or change. Singer and Willett (2003, Chapter 4) term these the unconditional means model and the unconditional growth model.

The unconditional means model is extremely simple. It does not involve a time predictor at all, but merely partitions the total variance in the dependent variable into two portions – variability associated with differences across time points within a person, and variability associated with differences in mean levels across individuals. If variance at either of these levels is zero or very close to zero, it does not make sense to try to predict the outcome at that level. The unconditional growth model is slightly more complex – it does include a linear time predictor in the Level 1 model, but the Level 2 models do not have any additional predictors (i.e., they are simply in the form of Equations 13.2a and 13.2b). If the linear slope parameter is not statistically significant, it may mean that (on average) there is no change over time in the dependent variable, or that the change takes a complex non-linear form such as an oscillator. A comparison of results from these two models, along with results from any more complex forms of growth trajectory (such as polynomial forms) that are deemed plausible can lead to a determination of the best fitting functional form. This should be followed by some tests of alternative models to determine whether the error structure is properly specified. Estimations of models involving covariate effects should only be attempted after these preliminary models are satisfactorily specified. There is considerably more detail that should be attended to in this process, but it is beyond the scope of this overview chapter. If you plan to use GCM, you should read further in Singer and Willett (2003) or one of the other many excellent sources on the topic (see mention of some of these in the final section of this chapter).

CONSIDERATIONS, LIMITATIONS, AND CONCLUDING REMARKS

The goal of this chapter has been to make at least a mention of many aspects of growth curve modeling and to encourage you to apply it to your own leadership research interests. However, if you want to become proficient in this technique, you should devote some additional time to more study of the finer details of the technique. There are many excellent books with very readable descriptions, and in many cases, they provide sample syntax for various statistical packages. For example, the Singer and Willett (2003) book cited in this chapter also has a companion website with many examples that include both multilevel and SEM approaches. Other helpful books for newcomers include Duncan, Duncan, and Strycker (2006), and Wickrama et al. (2016). Persons specifically interested in the multilevel modeling approach would do well to refresh their acquaintance with relevant sections of Bryk and Raudenbush (1992). It is also helpful to carefully read other research studies that have applied GCM to see how their authors formulated their research questions and then went about addressing them analytically.

Although many of the methodological and statistical issues have received emphasis in this chapter, it is critical to remember that a key ingredient for a top-quality GCM study is a thorough grounding in theory. Even if there are some exploratory aspects to your empirical investigation, your ability to interpret results depends upon your understanding not only of the analytic technique but how those results fit in with a body of literature. For example, the Day and Sin (2011) study described at the start of this chapter was firmly grounded in theories of leadership development. And, an important idea underlying the Jokisaari and Nurmi (2009) study that was described is Fichman and Levinthal's (1991) idea of the honeymoon in interpersonal relationships. Theory may also inform decisions about how frequently measurements should be made and how many might be necessary to address your research issue.

This chapter described both the multilevel and the SEM approaches to GCM. For many applications, either would be a reasonable choice, and which one is chosen might simply be based on researcher preferences and familiarity with a particular software. However, as has been discussed by various authors, including Lindenberger and Ghisletta (2004), there may be factors that make one approach preferable to the other. For example, the multilevel approach better handles datasets with unbalanced data and also those where there are a large number of patterns of missing data. The SEM approach offers a wider variety of fit indices, some of which are sensitive to sources of misfit that cannot be specifically identified with the multilevel approach (e.g., Wu et al., 2009). The SEM approach is also preferred if you want to use latent dependent variables, and when you want to look at relationships between trajectories for two different sets of dependent variables.

Finally, there are a number of techniques that were not covered in this overview chapter, but that might be interesting directions for further learning. Wickrama et al. (2016) provide illustrations and guidance on a wide variety of growth curve models. In addition, when the sample contains different groups with known membership for whom it is believed the growth trajectories might differ, multiple group growth curve modeling using an SEM approach provides a fairly straightforward extension of single group models. This type of technique would allow testing for differences in leadership development trajectories for men versus women, or for groups receiving different leadership interventions. When group membership is not known in advance, but it is expected that there might be heterogeneity in growth trajectories, latent growth curve mixture modeling can be used to identify different patterns of change over time – the chapter by Pastor and Gagné (2013) on mean and covariance structure mixture modeling provides a very readable illustration of a linear growth mixture model. The Day and Sin (2011) article also provides an illustration of a similar approach, described in detail in Nagin's (2005) book.

In sum, GCM provides a flexible and useful tool for furthering our understanding of dynamic processes and relationships in the domains of leadership and followership. Finding an appropriate source of longitudinal data and learning to properly use GCM takes some investment in time and effort to achieve, but the results are likely to advance our understanding of dynamic leadership and followership processes.

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