Identifying Change Trajectories Using Latent Variable Growth Modeling:

A Primer

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Dedication

This thesis is dedicated to Dr. Frazier, Dr. Syed, and my parents, Zvi and Amy Frankfurt.

Abstract

Many issues of interest to counseling psychologists involve questions regarding how individuals change over time. Typically, these analyses examine average levels of change over time in a sample. However, statistical methods known as latent variable growth modeling (LVGM; Muthen, 2004) allow researchers to more fully understand individual differences in change trajectories and may lead to fundamentally different understanding of change over time. The purpose of this paper is to provide a lay person's guide to LVGM in an effort to increase the use of these methods by counseling psychology researchers. In this paper, we discuss the differing conceptual frameworks from which conventional modeling techniques and LVGM techniques are drawn: variable-centered and person-centered frameworks, respectively. We next illustrate the assumptions and limitations of conventional analytic techniques and contrast these to the assumptions and limitations of LVGM. We then discuss three specific types of LVGM (latent class growth analysis, latent growth mixture modeling, and dual trajectory modeling), and provide a detailed example of latent class growth analysis using data from a longitudinal study of distress in recent sexual assault survivors. We conclude with suggestions for other areas of counseling psychology research that may benefit from the use of LVGM methods.

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Chapter 1: Introduction

Many issues of interest to counseling psychologists involve questions regarding how individuals change over time. Typically these analyses examine average levels of change over time in a sample. However, statistical methods known as latent variable growth modeling (LVGM; Muthen, 2004) allow researchers to more fully understand individual differences in change trajectories. These techniques can lead to a fundamentally different understanding of how people change over time. For example, in the trauma literature, it had been assumed that most people follow a similar pattern of recovery from trauma characterized by initial distress that abates over time. However, the use of LGVM has revealed that, in fact, very few people follow this average trajectory (e.g., Bonnano, 2004). The purpose of this paper is to provide a lay person's guide to LVGM in an effort to increase the use of these methods by counseling psychology researchers in other domains in which change over time is assessed. To date, only one study published in the *Journal of Counseling Psychology* has used LVGM (i.e., latent class growth analysis; Duchesne, Ratelle, Larose, & Guay, 2007). Because trauma psychology is one domain in which these techniques have been used to great merit, and because the domain of trauma is very relevant to counseling psychologists (Bonanno, Westphal, & Mancini, 2011), we will use this area of research to illustrate the techniques.

In this paper, we first discuss the differing conceptual frameworks from which conventional modeling techniques and LVGM techniques are drawn: variable-centered and person-centered frameworks, respectively. We next illustrate the assumptions and limitations of conventional analytic techniques and contrast these to the assumptions and limitations of LVGM. We then provide a detailed example of three specific types of LVGM - latent class growth analysis (LCGA), latent growth mixture modeling (LGMM), and dual trajectory modeling (DTM) - using data from a longitudinal study of distress in recent sexual assault survivors. We conclude with suggestions for other areas of counseling psychology research that might benefit from the use of LVGM methods.

Conceptual Frameworks: Variable-Centered vs. Person-Centered Approaches

Researchers can ask two fundamental questions using both variable-centered and person-centered methods with a longitudinal dataset: How do individuals change over time? What variables predict patterns of change over time? The similarities, however, end there.

Variable-centered techniques (e.g., ANOVA, multi-level modeling) analyze means or average levels of constructs or scores. The use of these techniques allows researchers to assess changes in psychological phenomena in a sample (e.g., how depression scores change over time on average). Variable-centered techniques are the oldest and most commonly employed methods for assessing change in counseling psychology research. However, it is quite likely that not all individuals change in the same way or at the same rate. These individual differences in patterns of change over time are not captured in methods that only assess aggregate or group-level change (see Figure 1 for illustration of individual variability around a mean). Instead, unique responses are considered measurement error or noise. Individual data that diverge greatly from the mean are generally not considered to be meaningful, but instead are treated as outliers (Laurenceau, Hayes, & Feldman, 2007; von Eye, Bogat, & Rhodes, 2006). For example, an analysis of average levels of change may indicate no movement over time within a group when in fact half of the group improved and half deteriorated.

Person-centered techniques, in contrast, can identify unique subpopulations within samples that have different change trajectories. In other words, person-centered techniques incorporate individual variability into the analyses, rather than treating it as error. One person-centered approach is cluster analysis which groups people with similar patterns of relationships in constructs together rather than identifying average relationships among variables in samples (Hair & Black, 2000). For example, cluster analysis has been used to identify groups of female child sexual assault survivors using MMPI-2 code-types and subtypes (Elhai, Klotz Flitters, Gold, & Sellers, 2001). Previous research, using variable-centered approaches, had found that female survivors of child sexual assault most often displayed a specific pattern of MMPI/MMPI-2 responses that suggested distrusting, hostile, and resentful attitudes toward the world and social withdrawal. However, this body of literature was inconsistent and inconclusive. Cluster analysis identified five distinct clusters of individuals, thus suggesting heterogeneous responses to sexual abuse within survivors. This finding stands in contradiction to the assumption of variable-centered methods that participants follow the average trajectory. Because survivors of child sexual assault do not respond homogenously, estimating the mean, or group average, is inappropriate. However, person-centered approaches, such as cluster analysis and LVGM, allow for multiple and different trajectories of responding across individuals and are robust to violations of the assumption of homogeneity in a population.

LVGM is conceptually related to cluster analysis; however, whereas cluster analysis models similarity among people using cross-sectional data, LVGM analyzes similarity among people over time using longitudinal data. LVGM is able to capture this similarity between individuals by using a combination of categorical and continuous latent variables to capture both within-person change over time (e.g., continuous latent variables such as slope) and between-person similarity (e.g., categorical latent variable such as cluster or "class" membership). The conceptual foundation of LVGM assumes that populations may be composed of many distinct unobserved (latent) groups of people (Muthen, 2004; Nagin & Odgers, 2010). Latent class growth analysis and growth mixture modeling differ importantly in the way that unseen groups are conceptualized theoretically: latent growth mixture modeling assumes that a population is made up of *mixtures* of distributions from separate subpopulations of people; latent class growth analysis is agnostic as to the population distribution of groups, and just presumes to create a taxonomy of response patterns.

Assumptions of variable-centered vs. person-centered approaches.

The assumptions of variable-centered models (e.g., ANOVA) are often not met in longitudinal data common to counseling psychology: (1) score variance must be equal across time, and correlations among scores must be equal across time points (e.g., the correlation between t1 and t2 scores must be equal to the correlation between t1 and t3 scores [i.e., sphericity]), (2) scores on the dependent variable within the population are normally distributed and the mean is an adequate representation of the data (i.e., the data are not skewed); (3) the data collection points are equally spaced and (4) there are no missing data (Fitzmaurice, Laird, & Ware, 2004; Weinfurt, 2000).

LVGM, and the assumptions underlying these techniques, can better match the types of datasets common to the naturalistic field settings of most counseling studies than most variable-centered techniques (e.g., MLM; see Kahn, 2011, for discussion of assumptions of MLM). Similar to MLM, LVGM does not necessitate consistent variability in the dependent variable scores over time; in fact, LVGM assumes unequal variance because the goal is to model latent subpopulations with different distributions (Muthen, 2004). LVGM is robust to and able to model non-normal distributions. LVGM models use maximum likelihood to estimate missing data and group membership is derived from the data, and not assigned *a priori;* thus, LVGM is more robust to participant drop-out and missing data common to longitudinal studies. These techniques are robust and flexible to longitudinal datasets as they actually exist.

The differences between variable- vs. person-centered data analytic approaches reflect more than arcane statistical debates. For example, LVGM has been used to examine post-trauma outcomes and has fundamentally changed our conception of typical responses to trauma from a primarily “recovery” model (i.e., initial distress that decreases linearly over time) to a more nuanced depiction of four prototypical trajectories (Bonanno, 2012). Whereas average-level analyses typically identify a recovery trajectory, LVGM techniques have shown that the “resilience” trajectory tends to be the most common. The “chronic distress” pattern, presumed to be fairly common after PTEs, has been found to be rare. Interestingly, studies that have found these four distinct prototypical trajectories have used samples exposed to different types of potentially traumatic events including breast cancer (Lam, et al., 2010) and traumatic injury (deRoon-Cassini et al., 2010). However, one recent study found two trajectories akin to “recovery” and “resilience” (Armour, et al., 2011). More studies using LVGM (e.g., LCGA and LGMM) need to be conducted to further elucidate the prototypical outcomes after different types of traumas.

Chapter 2

Conducting Latent Variable Growth Models

As we have shown, the use of person-centered modeling techniques, and specifically latent variable growth modeling, can more accurately capture individuals’ experiences over time. We next describe LVGM (e.g., LCGA, LGMM, dual trajectory modeling) in more detail. We discuss what these methods are and when and why to use them. We then provide a step-by-step guide for conducting LCGA, the type of LVGM that has been frequently used by trauma researchers (e.g., Bonanno et al., 2008, Dickstein et al., 2010) and may be most relevant to counseling psychologists, using data from a longitudinal study of response to sexual assault. The reported analyses were run using Mplus, a latent variable software package; alternatively, these models may be run using a SAS-based procedure, called Proc Traj (see Nagin, 2005, for discussion). Examples of LCGA syntax for Mplus software is provided in an online supplement. Additional considerations for model testing (i.e., growth factors, model selection, handling missing data, and predicting class membership using covariates) will also be discussed. Because this paper is meant to be a lay persons’ guide to LVGM, the mathematical explanations are kept to a minimum; instead, we will focus on setting up, testing, and interpreting the results of the analyses (see Nagin & Tremblay, 2001, Muthen, 2004; Nagin, 2005) for more technical information.

Overview of LVGM

LVGM uses a combination of continuous and categorical latent variables to capture individuals' trajectories and classify people into subgroups. The continuous latent variables in LVGM are equivalent to the building blocks (e.g., intercept and slope) in typical regression equations. The innovation of LVGM is the introduction of the person-centered latent categorical grouping variable that classifies each individual in the sample into one of *k*-number of classes, using information about their intra-individual pattern of responding over time. In this way, the LVGM allows researchers to plot individual growth trajectories, and then look for similarities among people in the sample in their patterns of responding. Using maximum likelihood estimation, classes are probabilistically estimated with latent categorical variables that group people together who exhibit similar starting points and patterns of change over time (i.e., similar intercepts and slopes).

LCGA, also known as group-based trajectory modeling, is a type of LVGM that approximates unknown latent groups across individual's trajectories LCGA fixes within-class variability around each group's starting value (intercept) and trajectory (slope) to zero; individuals within the group are assumed to start the same way (zero variance around the intercept) and exhibit the same course over time (zero variance around the slope). LCGA calculates point estimates of each individual's probable class membership into each of *k*-number classes, essentially categorizing the sample into groups that differ by starting point and pattern of change over time. Thus, the focus of the analysis is on between-class differences in these growth factors (intercepts and slopes).

The assumption of no variability within classes may not fit most data, as even unique subpopulations are continuously distributed throughout a population (Nagin, 1999). In contrast, LGMM relaxes this assumption, and estimates within-class variance around the growth parameters, such that individuals within classes are assumed to vary in their starting points and change over time. Because LGMM estimates within class standard deviations, researchers have another metric by which to determine goodness of model fit across sub-populations. Covariates can predict growth factors (e.g., intercept and slope) *in addition* to an individual's class membership. LGMM are much more complicated and complex models to run and LCGA may be employed for both practical and conceptual reasons.

Many researchers are also interested in questions of comorbidity and counseling psychologists often look to multiple indicators of functioning and well-being. A data-driven technique for analyzing patterns of responding across multiple phenomena has been developed, known as dual trajectory modeling or parallel process modeling (Nagin & Tremblay, 2001; Nagin, 2005). Dual trajectory modeling poses an alternative to relying on visual inspection of graphs, or post-hoc analysis of class membership along multiple outcomes. Researchers interested in running LGMMs or dual trajectory models are referred to Muthen (2004), Nagin (2005), or Nagin & Odgers (2010) for more in-depth discussion.

Although a growing number of studies have employed LVGM techniques, few have used LGMM or dual trajectory modeling. This is may be due to the computational challenges posed by running these significantly more complex models. Some researchers may intend to use LGMM to capitalize on its greater complexity, but need to use LCGA for estimation purposes (e.g., Dickstein, Suvak, Litz, & Adler, 2010). However, because of a lack of consistent reporting of data analytic plans or model testing in the published literature, it is sometimes unclear whether the researchers have used LCGA or LGMM.

Whereas the superiority of LCGA vs. LGMM has been debated, these techniques derive from different theoretical conceptualizations of individual differences, and can be employed to answer different questions or meet different ends. For instance, LCGA is good for identifying qualitatively different groups based on their trajectories. Some research questions concern classification or diagnostic issues, and not variability within classes; because of this, LCGA is useful for performing diagnostic analyses on a sample. Second, because LCGA fixes within-class variance to zero, these models have fewer parameters to estimate and may be computed faster and reach convergence more often. Additionally, LCGA results may be more easily interpreted than LGMM because the models are less complex and more transparent. Third, a *k*-number of class LCGA solution can be referenced when running LGMM and to help assess whether within-class variance is meaningful or additional classes would be useful. Because LGMM estimates variability around each group trajectory, more parsimonious models requiring fewer classes may be fit using LGMM than LCGA (Nagin, 2005). LGMM may not be useful or may not run when there is insufficient variability in the sample or around the growth factors to estimate (Feldman, Masyn, & Conger, 2009). LCGA may be chosen practically because LGMM does not produce interpretable results, as discussed below, and thus is a good starting point for model testing. Finally, whether truly distinct unobserved subpopulations exist within a population is a theoretical, as much as statistical question. If hypotheses and prior literature suggest actually distinct latent populations exist—LGMM may be a better conceptual choice. However, Nagin & Odgers (2010) caution that few theories in psychology posit truly distinct subpopulations among phenomena. The implications of this distinction, and indications of when to use LGMM vs. LCGA, will be discussed throughout the article.

Three important considerations must guide the use and interpretation of LVGMs. First, variance within a given population needs to be theoretically expected or established by prior empirical studies to prevent samples from being disaggregated non-parsimoniously or injudiciously (von Eye & Bergman, 2003). Second, the disaggregated final model may still fit only part of the sample. This possibility can be modeled using latent growth mixture modeling (LGMM), which as mentioned, models the variance around each subpopulation's mean. Larger variances for some subpopulations would suggest that a given disaggregated model fits better for some of the sample than for others. Alternately, this possibility can be examined by exploring how the groups differ along meaningful differences not specified in the model (e.g., theoretically chosen predictors of behaviors or secondary outcomes; Nagin & Odgers, 2010). The third, and most serious, vulnerability of LVGM is the possibility of finding support for a misspecified model. Because LVGM allows patterns and trajectories to emerge statistically from the data, careful attention must be paid to the theoretical justification for model construction and selection and compelling models need to be replicated across appropriate populations and situations. Of course, correct model specification is important for all modeling techniques (Tomarken & Waller, 2005), but idiosyncratic data patterns and groups are particularly vulnerable to reification in LVGM.

Additional Considerations for Model Testing

Growth factors.

Growth factors are the building blocks of LVGM, and of structural equation modeling in general, and define the structure of the model. In a simple one-class linear model there are two growth factors: the average beginning point for the individual trajectories (*intercept)* and the average rate of change over time (*slope).* It is also possible to specify models with higher-order growth factors, such as quadratic and cubic growth. When modeling quadratic growth the model includes three growth factors: intercept, linear slope, and quadratic slope. The intercept still represents the average initial value in the sample. The linear slope, however, changes meaning when there are higher-order growth terms (e.g., quadratic, cubic) in the model. In such models, the linear slope corresponds to the instantaneous rates of change at the point of intercept (e.g., whether increasing, decreasing, or no change from the intercept). It conveys the direction of the change and the initial rate of change through its sign and magnitude, respectively. For example, a negative linear term indicates that the quadratic function will have a trough (initial decrease followed by an increase) whereas a positive linear term is indicative of a peak (initial increase followed by a decrease). Higher absolute magnitudes of the linear term indicate more rapid initial change followed by a tapering off, whereas values closer to zero indicate acceleration (negative sign) or deceleration (positive sign) over time. In contrast, the quadratic slope term serves as the indicator of the rate of change over time, much like the linear slope term in linear models. Higher absolute magnitudes of the quadratic term indicate greater curvature in the change over time. Note that the sign of the quadratic term will always be the opposite of the sign of the linear term, as a parabolic function is defined by having different directions of growth at the beginning and end of the function. Similar logic extends to models with higher order growth terms beyond quadratic (see Singer & Willet, 2003).

Similar to variable-centered models, in single-class LVGM models there is a single set of growth terms that describes the entire sample. In LVGM models that have more than one class (*k* number of classes), there will be *k* sets of growth terms in the model. In other words, a three class linear model will contain a set of growth terms for each class, resulting in six growth terms (intercept and slope for each). A three class quadratic model will contain nine growth terms (intercept, linear slope, and quadratic slope for each). These growth terms can vary across classes, although it is possible that the classes will differ on one growth term (e.g., intercept) and not the other (e.g., slope). In LVGM, growth parameters are captured by the continuous latent variables that are fit to the sample. When using LGMM, researchers specify the relationships between growth factors and variance and covariance matrices; this means that researchers must specify whether or not to fix or free the variance of each growth parameter in each class.

Model selection.

Researchers must determine best fitting models, and decide on the most accurate number of classes to represent the latent subpopulations, using both statistical fit indices and theoretical justification (e.g., Muthen, 2004; Nagin & Odgers, 2010). As suggested by Jung and Wickrama (2008), initial model testing should examine the Bayesian (BIC), sample-size adjusted Bayesian (ssBIC), and Akaike (AIC) information criterion indices; entropy values; the parametric bootstrapped likelihood ratio test (BLRT); and proportional class size. All three information criterion indices compare the log likelihood values between a *k*-class model and a *k-1* class model; they are used to compare relative fit across models, but does not index absolute fit per se (Raftery, 1995). The BIC, ssBIC, and AIC differ in the way that parameters are estimated. In simulation studies, the BIC may underestimate model complexity (i.e., suggest fewer classes are needed), while the AIC may overestimate model complexity (i.e., suggest more classes are needed). The ssBIC is calculated similarly, but estimates the number of parameters accounting for sample size. The ssBIC calculates the fit statistic more leniently than the BIC, and will generally not penalize complex models as harshly as the BIC, and will tend to be less than the AIC for samples smaller than 176 (Henson, Reise, & Kim, 2007). The BIC is a commonly reported fit statistic; however, the BLRT has recently been proposed as the preferred indicator of model fit (Nylund, Aspharohouv, & Muthen, 2007). The BLRT tests whether a *k* number of class solution fits significantly better than a *k-1* class solution, essentially testing the parsimoniousness of increasingly complex models. Entropy indexes the classification accuracy of different classes, essentially describing the likelihood that an individual was classified in the correct latent class. Entropy values range from 0 to 1 with higher values indicating better fit. Mplus also provides a table of entropy value broken down by class; if entropy values are lower than expected, the possibility that one class is lowering the entropy (i.e., model fits less well for that class) can be examined. Models with lower information criterion indices, a significant *p* value for BLRT, and higher entropy values are considered better fitting. Finally, models should have at least 1% of the total sample in each class (Jung & Wickrama, 2008).

Additionally, parsimony, theoretical justification, and coherence should be considered in determining final class solutions (Bauer & Curren, 2003a; Muthen, 2004). First, good scientific models need to be parsimonious: Models that require the fewest number of explanatory variables and hypotheses are best (Kuhn, 1977). In the LVGM context, the principle of parsimony suggests that, when deciding between two equally good fitting models, the model with fewer classes should be chosen. Second, good LVGM models need to be grounded in and justifiable by substantive theory (Meehl, 1967). LVGM is a data-driven procedure, and does not test *a priori* null hypotheses; rather, the procedure tests the substantive theoretical hypotheses that the researcher specifies. Because of this, strong theoretical justification for model selection is needed to guard against interpreting and reifying spurious results that may simply be artifacts of a particular dataset (see Bauer & Curran, 2003a, Muthen, 2003, Rindskopf, Bauer & Curran, 2003b, for thorough discussion of this issue). Prior theory should also guide the interpretation and labeling of best-fitting models, in much the same way that theory should guide the naming of factors in factor analysis. Lastly, models should be coherent across multiple outcomes, in that a set of theoretically-related outcomes should logically "hang together." For instance, if LCGA is employed to model the possible trajectories of three outcomes, such as depression, low self-esteem, and general distress, researchers should expect to find similar patterns across the closely related outcomes.

Handling missing data.

In a longitudinal study, dealing with missing values caused by attrition (i.e., drop out) is an important task. Proper handling of missing data is important to retain statistical power and reduce the possibility of biased results caused by missing data patterns (Schlomer, Bauman, & Card, 2010). Traditionally, listwise and pairwise deletions have been used in conventional variable-centered models (e.g., ANOVA). These methods remove a participant's data from the analysis if the responses are not complete. Thus, reduced samples size is an unavoidable problem. Shrunken sample sizes increase the probability of type II error as well as decrease statistical power.

LVGM relies on maximum likelihood with robust standard errors (i.e., MLR) to estimate missing data, a method that is appropriate for data that is missing completely at random and missing at random; MLR is particularly useful for longitudinal study (Schafer & Graham, 2002; Muthen & Muthen, 1998-2010). MLR uses information from the whole dataset to estimate missing values, estimates missing data and runs analyses at the same time which makes this method easy to use, and is generally robust to small sample sizes (Schlomer et al., 2010). See Schlomer et al., (2010) for more information about patterns of missing data and how to test for them.

Predicting Class Membership Using Covariates.

Many previously published studies of post-trauma outcome trajectories using LVGM have reported both conditional (including covariates as predictors of classes and/or trajectories) and unconditional models (without predictors). Considerable debate surrounds the appropriate inclusion of covariates and the interpretability of unconditional and conditional models. Researchers who have developed these techniques suggest running unconditional models (without covariates) as a first step (i.e., Nagin, 2005; Muthen, 2004). Nagin (2005), the developer of LCGA techniques, suggests that the number of classes and trajectory shape must be determined using unconditional models; class membership as determined in the unconditional models are then regressed onto relevant covariates and tested for significance. Alternately, Muthen (2004) suggests that unconditional growth models that exclude theoretically and statistically significant covariates as predictors are misspecified, and as such unconditional models may not be interpretable. Covariates will generally not change the shape of group trajectories, because covariates tend to be time-invariant and the outcome measures tend to be time-varying; however, if running LGMM, covariates impact the classification of individuals into trajectories, model parameter estimates, and model fit (Muthen, 2004, Nagin, 2005).

The developers of LGMM argue that if relevant predictors are not included in model estimation, the model will be misspecified (Muthen, 2003, Muthen, 2004). In this case, the unconditional models would not be interpretable as meaningful representations of outcome trajectories. For instance, previous research has found that, across non-military populations, being female increases one’s risk of post-traumatic stress symptoms in the wake of traumatic exposure (Brewin, Andrews, & Valentine, 2000). If post-trauma outcome trajectories were modeled in a mixed-gender sample and gender was not accounted for, classes may not be accurately specified because an important *a priori* predictor of outcomes was not included. Indeed, the inverse situation must also be noted: If theoretically relevant and important predictors *do not* significantly distinguish between classes, support for the model may be weak (Muthen, 2004).

However, LCGA models that test for the significance of predictors of class membership may be inaccurately conceptualized as "conditional," because no part of the measurement model of estimation of trajectory shape is conditional, or dependent, on the covariates. LGMM studies that include covariates predicting both class membership *and* growth parameters may be more accurately described as conditional. For this reason, if relevant predictors are not included in LGMM estimation, the model will be misspecified (Muthen, 2003, Muthen, 2004).

The inclusion of predictors should be justified by theory and previous research (Feldman, et al., 2009); similarly, a well-justified explanation should be provided for the exclusion of relevant covariates predicting class membership and (when appropriate) growth factors (Muthen, 2004). The question of what to do if a theoretically important covariate does *not* significantly predict growth or class membership has been thorny. Subject to debate is whether to include a non-significant covariate as a predictor in a model because it is theoretically justified, and thus the model will be conceptually misspecified without it. In this case, the covariate may be non-significant due to methodological, and not theoretical, reasons. Or, is this evidence that the covariate is actually irrelevant and ought not to be considered? *It depends,* seems to be a reasonable appraisal of consensus among methodologists (Muthen, 2004; Nagin, 2005). Because no hard and fast rules govern the exclusion of predictors, common sense suggests that if covariates are neither theoretically indicated nor significantly improve the model, they ought to be left out.

The appropriate specification of predictors on growth factors and class membership depends on the specific type of LVGM being conducted. Remember the fundamental distinction between LCGA and LGMM. LCGA estimates class membership *only* and thus variables can only predict class membership. In LGMM, covariates can predict intercepts, slopes, and the individual probability of class membership. This distinction is important when interpreting the impact of covariates. In LCGA, covariates predict the likelihood of an individual's membership in a given class compared to a reference class. Only class membership and not growth factors (e.g., intercept, slope) can be regressed on predictors because the variance of these growth factors is fixed to zero. In other words, within classes, there is no variance to predict. When running LCGA, Mplus allows syntax statements specifying covariates to predict growth factors (which are fixed to zero); however, this syntax is nonsensical and will lead to a misspecified model and biased model fit indices. An additional consideration when running LVGM models in Mplus is that missing covariates are not estimated using maximum likelihood procedures; instead, listwise deletion removes cases from the total sample that are missing data on the covariates. Thus, selection of covariates may be further constrained by the completeness of information on each predictor.

Often, information about the ways that a covariate would be expected to impact the intercept (starting point) or slope (change over time) is not known. In such cases, researchers ought to report their decision making process regarding covariate specification transparently in the data analytic plan and results. However, if questions about class-specific predictors are not relevant, LCGA may be a better analytic strategy because model estimation is simpler and clearer.

In LGMM, researchers must tie their interpretation of predictors to precisely how the covariates were specified to impact the model. For instance, if covariates were specified to predict intercepts, conclusions about predictors must be limited to where the classes begin, but not their course over time. Interpreting covariates (in LGMM) when they are allowed to predict both class membership (i.e., between-class variance) and growth factors (i.e., within-class variance) can be difficult: in these LGMMs, covariates are predicting both an individual's class membership and the individual's trajectory relative to a mean class trajectory (Feldman et al., 2009). Indeed, LGMM model specification can be frustratingly flexible: covariates can be specified to influence all the growth parameters, or just some. An additional consideration when choosing covariates is the completeness of the dataset. Because a minimum sample size is necessary to reach convergence, predictors must be mindfully chosen. However, all of these decisions ought to be guided by theory and justified in the reporting of the data analytic plan.

Now that we have described how to set up and run LVGM models in general terms, we will describe now LCGA in more detail. Specifically LCGA will be demonstrated using a longitudinal dataset of phobic anxiety symptoms in a community sample of 171 women seen in a hospital emergency room following a sexual assault. While an N of 171 may seem small, LVGM procedures are not bound by strict guidelines for sample sizes in the same way that conventional variable-centered models tend to be (see Cohen, 1988, for discussion of power analysis for conventional analytic techniques). Procedures for estimating sample size and power using Monte Carlo estimation have been outlined by previous researchers; a discussion of these procedures is beyond the scope of this paper, so interested readers are directed to a few thorough articles on the matter (see Muthen, & Muthen, 2002; Nylund, Asparouhov, & Muthen, 2007). Participants completed questionnaires regarding phobic anxiety symptoms (among other psychological sequelae) at 2 weeks, 2-, 6-, and 12-months post-assault. Participants were instructed to answer all questions regarding distress with regard to their thoughts, feelings, and behaviors in the past week. Additional measures were completed as part of a larger research study on post-sexual assault recovery processes (see e.g., Frazier, 2003; Frazier, Conlon, & Glaser, 2001; Frazier, Mortensen & Steward, 2005). Prior sexual victimization, experienced either as a child or an adult, was included as a covariate. Previous research has demonstrated that prior victimization is a robust predictor of negative outcomes and psychological distress following a sexual assault (Ozer, Best, Lipsey, & Weiss, 2003). This dataset does not meet the assumptions of conventional variable-centered analytic techniques (e.g., had missing data, was non-normally distributed, displayed heteroscedasticity). Analyses were conducted using Mplus 6.0 software (Muthen & Muthen, 1998-2010).

Running LCGA models.

Next, we will describe how to run an LCGA. In our example, LCGA was conducted in three steps: fitting an unconditional single-trajectory class, fitting all theoretically indicated classes with unconditional models, and then testing whether covariates significantly predicted class membership (See online supplemental materials for a check-list and Mplus syntax for each step). This extended example will illustrate the different groups and changes in trajectory course that emerge with each more complex model and the different conclusions that can then be drawn.

We first tested one class unconditional linear and quadratic models of phobic anxiety (see online supplemental material for Mplus syntax). Single trajectory models allow the research to ensure that there is significant variability around the growth parameters, which lends additional support to the utility and meaningfulness of running LCGA, and added evidence for the presence of latent sub-populations. We also tested quadratic models because previous LVGM models have tested, and some have found, both linear and curvilinear trajectories of post-trauma change (e.g., deRoon-Cassini et al., 2010; Lam et al., 2010). This single trajectory model illustrates the mean symptom levels across the sample, with missing data estimated using maximum likelihood procedures.

Table 1 provides the fit statistics for all the 10 models tested (e.g., linear and quadratic 1-5 class unconditional models). Let’s look the simplest model and what would be reported in the conventional variable-centered analysis: the single-class linear unconditional model. This is shown in Figure One. The one-class linear models show that, post-sexual assault, women on average report high levels of phobic anxiety that abates over time (see Figure 1). Phobic anxiety at 2 weeks post-assault (intercept) was about two standard deviations above the adult non-inpatient female norms, at levels that suggest clinical “caseness” (Derogatis, 1993). However, significant variance exists around both the intercept and the slope, suggesting that these mean scores may mask a large amount of inter-individual variability, and suggest that many individuals are reporting symptoms that are far different from the “average” respondent. A useful graphing feature of Mplus software is that individual trajectories can be plotted with the latent class trajectories; in this way, individual variability around the trajectory can be visually assessed. Individual trajectories visibly vary around the mean; many more individuals do not follow the average trajectory than do (see Figure 1).

Looking at Table 1, you can see that the best fitting unconditional model is the three class quadratic model because the criterion fit indices (e.g., AIC, BIC, and ssBIC) are all more than 10 points smaller than both the four class linear and three class quadratic models, the BLRT suggests that adding an additional class (over 2 classes) significantly improved the fit, and the entropy is close to 1. The four-class unconditional model does not improve upon the three-class unconditional model because the BLRT value is non-significant, suggesting adding a fourth class does not significantly improve fit and the lower entropy value suggests individuals are not as well classified into classes.

The three trajectories in the best fitting model generally followed the shape and distribution predicted by Bonanno’s (2004) theory of prototypical post-trauma outcomes (see Figure 2 and Table 2). The first class, “chronically phobically anxious,” started with a mean BSI level over three times higher than the “caseness” cut-off, and did not significantly decrease over time. The second class, “recovering,” started with mean BSI levels about 2.5 times higher than the “caseness” threshold, and significantly decreased over time. The third class, “resilient,” started with a mean BSI level above the “caseness” cut-off, and significantly decreased over time. This class did not meet the “caseness” threshold by 6 months post-assault; at 12-months post-assault, this class was about at the normed mean (T-score = 56).

Predicting class membership.

Because prior victimization (childhood sexual victimization and adult sexual victimization) has consistently been demonstrated to be a robust predictor of post-sexual assault outcomes, whether these covariates significantly predicted class membership was tested on the three-class quadratic model. In this example, we are only using two covariates as predictors to illustrate their role in model specification; however, more than two predictors can be included. Because of missing data on the covariates, the conditional models’ sample sizes were somewhat smaller (N=156) than the total sample (N=171).

In our example, the covariates were used to predict an individual’s likelihood of class membership using multinomial logistic regression. Mplus computes these logistic regressions, using covariates as predictors and number of groups as outcome categories, and includes the results in the output. Because the “resilience” class was the most common and theoretically important, it was designated the referent class. Neither child nor adult prior sexual victimization significantly predicted class membership (see Table 3).

Chapter 3

Discussion

In review, the use of appropriate modeling techniques is hugely important to be able to accurately and confidently interpret data and draw conclusions about people's experiences. Our findings suggest that person-centered LVGM techniques, and not the conventional variable-centered techniques, are more appropriate for analyzing individual differences in patterns of change over time. Our dataset, like typical datasets from trauma research, did not meet all of the assumptions of variable-centered techniques (i.e., no sphericity, normal and homoskedastic distribution, and no missing data); the assumptions of LVGM did fit out dataset (e.g., unequal variance on outcome variable, non-normal distribution, and robust to missing data). A fundamental assumption of conventional variable-centered techniques is that the mean, or "average," is representative of the sample. However, in review of the results of LCGA, generally less than 25% of women actually fell into the "average" pattern of phobic anxiety following a sexual assault indicated in the single trajectory model. Instead, a majority of women displayed "resilience" and many more "recovered" within a year of surviving sexual assault. This stands in stark contrast to conventional wisdom that most women are significantly impaired and distressed in the wake of a sexual assault. Unexpectedly, in our sample, prior victimization did not significantly predict being in a less resilient class of responders. Additional research is needed to explore the outcome trajectories and significant predictors of resilience and distress following potentially traumatic events.

Calls for counseling psychologists to incorporate innovative analytic techniques, and particularly person-centered methods, have rang more frequently and clearly than in the past. Laurenceau et al. (2007) have noted that LVGM techniques should be used to study individual differences in responses to counseling interventions, because these techniques allow researchers to interpret atypical patterns of responding. These techniques have been used to study counseling-related topics such as different patterns of responding to family therapy among HIV+ ethnic minorities (Szapocznik, Feaster, Mitrani, Prado, Smith, Robinson-Batista, Schwartz, Mauer, & Robbins, 2004) and different patterns of anxiety over multiple sessions of exposure therapy (Hayes, Hope, Heimberg, 2008), among others. LCGA methods have been suggested to study differences in vulnerability to sexual revictimization, as well as patterns of response to trauma (Macy, 2008; Bonanno, & Mancini, 2012).

This review of the theory, application, and interpretation of LVGM is meant to benefit both researchers and clinicians. For counseling research psychologists, this paper is meant to describe a new, and underused, methodology for analyzing change over time. For clinicians, the substantive point of is that individual differences in longitudinal trajectories exist for many, if not most, psychological phenomena. For instance, even after a sexual assault, which is commonly recognized as a severely traumatizing event, many women are able to maintain functioning. However, it may be that a minority of women experience extremely elevated distress, and thus pull the group mean of psychological distress up from where the median or mode may fall. These questions, and these results, would not be found using a single-trajectory/mean-based analysis.

As of February 2012, only one study using LVGM (i.e., LCGA) has been published in the *Journal of Counseling Psychology* (Duchesne, et al., 2007. Duchesne and colleagues examined the high attrition rate from college science programs by looking at trajectories of coping and adjustment and the impact of supportive relationships on science-program tenure. A two class model (high positive emotional and academic adjustment, and declining adjustment) best fit the sample; positive parental relationships (but not teacher relationships) were significantly associated with displaying high adjustment. Future recommendations for this line of research include exploring individual differences among well-adjusted students and characteristics of positive parental supportive relationships (Duchesne, et al., 2007).

Counseling psychologists are generally interested in the development of mental health and well-being over time (Gelso & Fritz, 2001). Although these methods were illustrated here using data from a study on psychological functioning post-sexual assault, many areas of research relevant to counseling outcomes would benefit from the application of these methods. For instance, treatment outcome studies that analyze individual's responses to therapy could benefit from these methods. LVGM could help uncover which people respond to certain treatments and, using predictors, *why* some people seem to respond. Because there may be differential gains after therapy at follow-ups, LVGM can help sort out who maintains their therapeutic gains post-treatment and who does not.

Counseling psychologists should not lag behind the developments in neighboring fields of psychology, wherein these techniques are being fruitfully applied (e.g., developmental psychology, addition research; Nagin & Odgers, 2010). Innovations in counseling psychology research help ensure the relevance, effectiveness, and timeliness of our field. More information about the different pathways people may follow, and predicting these pathways, may improve the effectiveness of counseling. Perhaps, in the future, treatments can be tailored to individuals based on the projected course of symptoms or disorders. Studying individual’s well-being over-time, using person-centered longitudinal methods, may ultimately change, for the better, the treatment and care that people receive.

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Table One

Model Fit Indices of 1-5 class linear and quadratic unconditional LCGA models

	Unconditional	
	Linear	Quadratic
1 class	1076.702	1075.023
AIC	1095.552	1097.014
BIC	1076.553	1074.850
ssBIC		
2 class	998.895	990.915
AIC	1027.170	1025.473
BIC	998.672	990.642
ssBIC	.701	.729
entropy	.0000	.0000
BLRT p-value		
3 class	974.869	964.628
AIC	1012.569	1011.753
BIC	974.571	964.257
ssBIC	.712	.737
entropy	.0000	.0000
BLRT p-value		
4 class	974.923	963.241
AIC	1022.048	1022.933
BIC	974.552	962.771
ssBIC	.672	.658
entropy	.2000	.5000
BLRT p-value		
5 class	971.153	961.284
AIC	1027.703	1033.542
BIC	970.708	960.714
ssBIC	.622	.655
entropy	.0952	.1579
BLRT p-value		

Table Two

Model Results: 3 class quadratic unconditional phobic anxiety LCGA model

Class 1:		
N=19 (11%)		
Intercept	Slope	Quadratic
Mean: 3.402	Mean: -.191	Mean: .014
S.E.: .198	S.E.: .187	S.E.: .015
P-value: .000	*P*-value: .307	*P*-value: .359
Class 2		
N=77 (45%)		
Intercept	Slope	Quadratic
Mean: 1.073	Mean: -.157	Mean: .009
S.E.: .109	S.E.: .052	S.E.: .004
P-value: .000	*P*-value: .003	*P*-value: .027
Class 3:		
N=75 (44%)		
Intercept	Slope	Quadratic
Mean: 2.626	Mean: -.260	Mean: .014
S.E.: .148	S.E.: .071	S.E.: .006
P-value: .000	*P*-value: .000	*P*-value: .021

\

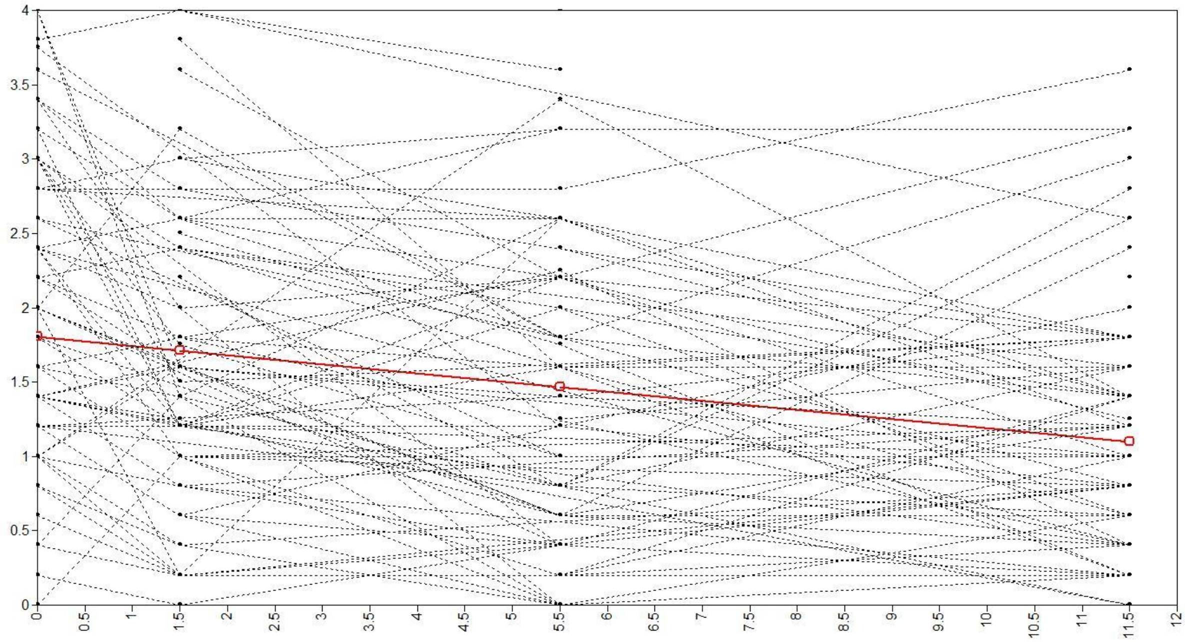

Figure 1. Individual trajectories and estimated mean of phobic anxiety scores.

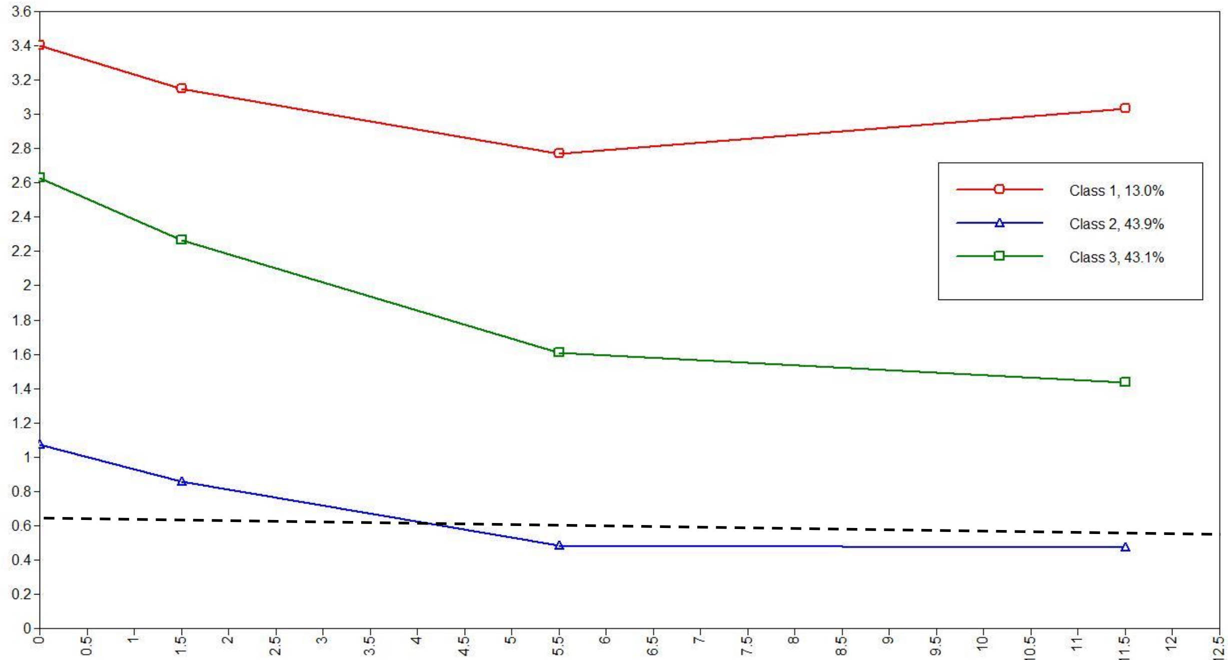

Figure 2. 3-class quadratic model of phobic anxiety.

Appendix A

Checklist for running LCGA:

1. Test for presence/type of missing data
2. Run unconditional 1-class latent growth curve model
3. Run unconditional models testing all theoretically proposed number of classes
4. Test if covariates significantly predict trajectories
    a. If running latent class growth analysis, covariates predict *only class membership*
    b. If running latent growth mixture models, covariates predict class membership *and* growth parameters

Appendix B

Syntax for Step One and Step Two: Unconditional Latent Class Growth Analysis Model

INPUT INSTRUCTIONS

Title: LCGA one class phobic anxiety *Names the model; not necessary syntax*
Data: file is 'small_id_phobanx_child_adult_priorvic.csv'; *Save the input and the data in the same folder*
Variable: names are id phobanx1 phobanx2 phobanx3 phobanx4 CSA ASA;
usevar = phobanx1-phobanx4;
missing = all(999);
CLASSES = c(1); *To test additional classes (e.g., 2-5 class models) increase this numerical input*
SAVEDATA: FILE IS phobanx_1lin_output;
save=cprobabilities; *Creates a datafile with class membership. See Mplus Guidebook for additional information.*
Analysis: type = MIXTURE missing;
STARTS = 100 10;
STITERATIONS = 10;
PROCESSORS = 2 (STARTS); *Specifies computation to run on dual processors, a time saver*
Model: %OVERALL%
i s| phobanx1@0 phobanx2@1.5 phobanx3@5.5 phobanx4@11.5; *Measurement model*
i-s@0; *Holds variance of the intercept and slope at 0; unique to latent class growth analysis*
Output: sampstat standardized tech1 TECH11 TECH14;
PLOT: SERIES = phobanx1-phobanx4 (s);
TYPE = PLOT3;

Syntax for Step Three: Testing Predictors of Class Membership in LCGA Model

INPUT INSTRUCTIONS

Title: LCGA 4 class phobic anxiety conditional model
Data: file is 'small_id_phobanx_child_adult_priorvic.csv';
Variable: names are id phobanx1 phobanx2 phobanx3 phobanx4 CSA ASA;
usevar = phobanx1-phobanx4 CSA ASA;
missing = all(999);
CLASSES = c(4);

SAVEDATA: FILE IS phobanx_4quad_x1x2_output;
save=cprobabilities;
Analysis: type = MIXTURE missing;
STARTS = 500 50;
STITERATIONS = 20;
LRTSTARTS = 2 1 50 25;
PROCESSORS = 2 (STARTS);
Model: %OVERALL%
i s q| phobanx1@0 phobanx2@1.5 phobanx3@5.5 phobanx4@11.5; *"q" = quadratic term*
i-s@0;
q@0; *Holds variance of quadratic term at zero*
c#1 ON CSA ASA; *Specifies the multinomial logistic regression of childhood and adult victimization on class membership, while comparing class one to class two, three, and four*
c#2 ON CSA ASA;
c#3 ON CSA ASA;
Output: sampstat standardized tech1 tech11 tech14;
PLOT: SERIES = phobanx1-phobanx4 (s);
TYPE = PLOT3;