What Your Data Didn't Tell You the First Time Around: Advanced Analytic Approaches to Longitudinal Analyses

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Swartout, A. G., Swartout, K. M. & White, J. W. (2011). What your data didn't tell you the first time around: Advanced analytic approaches to longitudinal analyses. *Violence Against Women, 17(3),* 309-321. DOI: 10.1177/1077801211398230.

Abstract:

The present article describes the gap that exists between traditional data analysis techniques and more sophisticated methods that tend to be used more commonly among researchers outside of the study of violence against women. We briefly characterize growth models and person-centered analyses and describe the growing body of work in violence research that has applied these methods. Through an example from our own application of one of these techniques—latent class growth analysis—we highlight the ways that violence against women researchers may benefit from applying these more sophisticated methods to their own data, both past and present.

Article:

In the last few years more advanced analytic strategies have become available for primary and secondary analyses of longitudinal data on violence against women (VAW). These analyses offer interesting ways to examine existing data and also offer new frameworks with which to approach pending projects. This is both exciting and scary. The prospect of reanalyzing our data and realizing how much we did not know the first time around is a bit intimidating. Whether we are excited or intimidated, though, methodological advances are occurring, and it is our responsibility as researchers to learn about them and apply them to our work. Recently these methods have come into more widespread use, with statistical packages such as Mplus (Muthén & Muthén, 2008), SAS, and SPSS making them more accessible than ever.

There has been an increasing call to collect rich, longitudinal datasets on numerous topics of interest to VAW researchers, affording us the opportunities to examine both the predictors and outcomes of various negative life events. When researchers go to the effort to collect longitudinal data, they certainly want to analyze them with the best and most sophisticated methods available to make the most of their hard work. When new analyses are developed, it is important to reexamine old research questions, pose new ones, and reanalyze the relevant data accordingly. Such efforts may reaffirm, contradict, or enhance initial conclusions. This process is especially important when the more advanced data analysis strategies represent potential paradigm shifts in how we view samples or the phenomena under investigation.

Unfortunately, because of space constraints, we cannot describe all of the new and exciting analytic innovations that have become available and are relevant to VAW researchers. Fortunately, however, several other researchers have addressed these issues in more detail (see Macy, 2008, for a more comprehensive review or Singer & Willet, 2003 for detailed approaches). We want to use the present article to advocate for the use of one particular family of analyses—growth mixture models (GMM)—as well as to highlight one approach in particular—latent class growth analysis (LCGA). As these analyses represent the intersection of growth modeling and person-centered models, we briefly discuss both of these approaches before moving on to talk about growth mixture modeling and LCGA. We then describe the unique nature of growth mixture modeling, noting how VAW researchers in particular may find this analytic approach useful. This is followed by a brief description of the small yet important body of work that is currently being conducted using this approach in the study of VAW. Finally, as an example of the way that VAW researchers may consider applying these techniques to their own work, we explain the way in which this analysis has helped us reconceptualize some of our own data as well as some of the phenomena we study. We will offer an example illustrating the application of these methods in our own work (Swartout, Swartout, & White, 2010). We conclude by noting the controversy of these methods and encouraging VAW researchers to consider applying them to both their existing data and in future work.

ADVANCES IN LONGITUDINAL DATA ANALYSIS

Growth Models

Growth models have many names—latent growth models, latent growth curves, hierarchical linear models, multilevel models, and mixture models are among the most common. This differing terminology stems in part from the fact that growth modeling can be approached using either a structural equation modeling (SEM) or hierarchical linear modeling (HLM) framework. Although a vast majority of questions and data generated by VAW researchers can be analyzed using either framework, for sake of brevity we limit our description and examples to the SEM approach. SEM, also known as covariance structure analysis (CSA), was developed through the multivariate regression and path analytic tradition. Researchers who use SEM are able to holistically test their intricate theories and interpretations concerning relations between numerous variables of interest (Bollen, 1989; Singer & Willett, 2003). In its early stages, the utility of SEM was restricted to the analysis of cross-sectional data.

More recent advances in SEM, however, have adapted the traditional CSA design to test hypotheses concerning both individual and group changes across time. This was accomplished by mapping the multilevel regressional approach to examining change across time onto the SEM model (Singer & Willett, 2003).[1] Manifest repeated measures serve as indicators within a confirmatory factor model with a mean structure; the factors of this model are continuous latent variables that represent parameters of individual change across time (Bauer & Curran, 2003a; Singer & Willett, 2003). Although researchers often use observed variables as indicators, the SEM framework allows the use of latent variables constructed from multiple repeated measures at each time point as indicators of their latent parameters, allowing researchers to decrease the measurement error as well as more accurately model complex phenomena over time (Macy, 2008; MacCallum & Austin, 2000). Time-invariant and time-variant covariates can be modeled to predict these latent trajectory parameters.[2]

These latent growth models carry a list of important assumptions. First, individuals' trajectories across time are assumed to be the same shape. Second, because trajectories are fully informed by the latent parameters from the confirmatory factor model, the manifest repeated-measures data must be completely described by means and covariances. This leads to the assumption that the data are distributed multivariate normally (Raudenbush, 2001). Finally, covariates are assumed to have a uniform effect across parameter values; in other words, covariates will have similar effects for individuals with high and low intercepts (Bauer & Curran, 2003a). One or more of these assumptions may prove problematic to VAW researchers. For example, most data on victimization and perpetration frequency are nonnormal—that is, they are highly skewed, with a high incidence of zeros. One can use different estimation and transformation techniques to account for this nonnormality.[3] However, this nonnormality may result from underlying heterogeneity or distinct subgroups within the data. If researchers have a theoretical reason to suspect that this is the case, they may consider using a person-centered approach.

Person-Centered Analyses

Person-centered analyses are easier to understand if preceded by a short description of variable-centered analyses. Variable-centered analyses, based on the general linear model, are common in the violence literature. This group of analyses includes regression and correlation as well as the factor analytic, growth modeling, and multilevel modeling approaches, parts of which were detailed in the previous section. Variable-centered analyses rely on group means and covariances with the assumption that the sample is drawn from a homogeneous population. In reality, there may be different *types* of people within a given population that are not accounted for by variable-centered analyses (Cairns & Rodkin, 1998). Person-centered analyses—such as cluster analysis, finite mixture modeling, and latent class analysis (LCA)—group individuals into categories using a set of variables deemed relevant by the researcher. In a well-fitting model, members of each category are assumed to be similar to in-group members and dissimilar to members of other categories in terms of the relevant variables (Muthén & Muthén, 2000). The person-centered approach has been widely used in the alcohol literature with the assumption that there is heterogeneity within the population in terms of alcohol use and dependence (Bucholz, Heath, Reich, & Hesselbrock, 1996; Muthén & Muthén, 2000).

Recent research on VAW has used an applied version of LCA known as latent profile analysis to suggest that there is heterogeneity among victims of sexual assault (Macy, Nurius, & Norris, 2007a, 2007b). LCA allows a researcher to estimate unobserved groups of cases (or categories of people) within their data using a set of observed categorical variables (Muthén & Muthén, 2000). This classification is based on individual probabilities of giving a certain set of responses; in a heterogeneous sample, peoples' probabilities coalesce into latent categories.

Growth Mixture Models

The conventional growth model can actually be thought of as a special case of a GMM where only one latent class is modeled (Bauer & Curran, 2003a). GMMs (Muthén, 2004; Muthén & Asparouhov, 2009; Muthén & Shedden, 1999), where more than one latent class is estimated, allow researchers to discover latent heterogeneity within their observed longitudinal data. The rationale for these analyses stems from the person-centered assumption that there are qualitatively different subgroups within some populations. Longitudinally speaking, these latent subgroups each display separate trends, or trajectories, of scores or behaviors across time. GMM is positioned to handle highly skewed and categorical data (Feldman, Masyn, & Conger, 2009), which is often a characteristic of data collected on VAW. Instead of estimating parameters for a whole sample, researchers use a theoretical basis to model subgroups or *classes* within their data. This process results in several normally distributed latent classes comprised of differing proportions of the overall sample and mean structures.[4] Researchers are also provided with model fit statistics (similar to those found in SEM) that signify how well each latent class structure fits the observed data.

GMM should be enticing to researchers of VAW because it allows the assumption of a normally distributed sample to be relaxed; it estimates multiple, normally distributed classes within a skewed sample. This is especially useful to VAW researchers because many phenomena in this research area have low base rates or the data are censored at zero (i.e., relatively few participants have engaged in or experienced the behavior in question), resulting in skewed datasets. There are instances, however, when within-class normality cannot be assumed. For these cases, a more simplified case of GMM, LCGA, can be used. In LCGA, unlike GMM, within-class variances are fixed at zero (Feldman et al., 2009; Kreuter & Muthén, 2007; Nagin, 1999; Roeder, Lynch, & Nagin, 1999). The classes that correspond with more severe behaviors or experiences are likely to account for a small number of cases and are unlikely to be normally distributed. LCGA can be used, then, to estimate a model without violating the normality assumption of the more general GMM.

In LCGA, because there is no within-class variability, individual differences are entirely attributed to latent class membership (Muthén & Muthén, 2000); this class structure forms a categorical variable that can then be analyzed as a function of covariates to assess the level to which these variables are generally able to predict latent class membership. In other words, one can use covariates to predict class membership. Finally, when conducting complicated analyses a larger sample size is always preferable. An additional advantage of using LCGA is that it does not require the listwise exclusion of cases containing missing data; all the data can be used just as they were collected. Some participants may have completed only one time point, others may have completed them all, or some number in between. In a LCGA, however, all data are included to provide the most accurate picture of the sample and to make the most of all data.

APPLICATIONS OF THESE METHODS IN VIOLENCE RESEARCH

Despite the applicability of GMM and related techniques to variables of interest in research on VAW, these methods have been sorely underutilized in the field. While a small number of researchers are now applying these techniques to violence research in general (e.g., Ozer, Tschann, Pasch, & Flores, 2004; Schwalbe, Macy, Day, & Fraser, 2008; Swaim & Kelly, 2008), a review of PsycINFO revealed almost no publications using growth modeling or person-centered analyses in the study of sexual assault, domestic violence, or other related areas. Important exceptions are found in the work of Macy and colleagues (2007a, 2007b). These researchers have advocated for the use of GMM (Macy, 2008) and person-centered approaches to the study of VAW (Nurius & Macy, 2008). They have also used a cross-sectional person-centered approach—latent profile analysis—to determine subgroups of sexual assault survivors. Using contextual variables such as the relationship between the victim and perpetrator, women's own victimization histories, and alcohol consumption, they were able to establish differential profiles of victims and their responses to assault.

The value of analyses such as these is that not only do they allow us to more specifically tailor treatment responses to perpetrators or even self-defense training to potential victims but also at a broader level they allow us to garner a more accurate picture of what the phenomena we study truly entail. Variable-centered analyses have told us a great deal about how broad factors interact and have allowed us to examine theoretical implications without having to account for individual difference. The advantage of person-centered approaches is that they can complement the existing findings and generate a more nuanced picture of the patterns of relations between our variables and participants. We argue that to truly move the field forward, researchers in this area need to begin using these approaches in their own data analyses. We would also argue from our own experience that it would behoove VAW researchers to look back at some of their existing data to determine if GMM or related techniques may tell them something new.

AN EXAMPLE FROM OUR OWN RESEARCH

In 2004, White and Smith used a longitudinal dataset to examine men's sexually aggressive behaviors from adolescence through 4 years of college, and also to analyze the effects of negative childhood experiences (including childhood sexual abuse, parental physical abuse, and witnessing domestic violence) on men's sexually aggressive behaviors across time. By examining the overall frequency of sexual aggression at each time point, they were able to determine that there was a decline in the actual rates of sexual perpetration across time. Using hazard rates and survival analyses, they also concluded that early negative experiences influenced later aggressive behaviors: all three types of negative childhood variables were associated with adolescent sexual aggression; adolescent sexual aggression was then associated with sexual perpetration across college. Interestingly, however, when they controlled for sexual aggression in adolescence, there was no significant relation between negative childhood experiences and sexual aggression in either the first or subsequent years of college. This was a bit of an anomaly in their results and is the question that initially interested us in a reanalysis of this dataset.

The data White and Smith (2004) used were drawn from a larger longitudinal dataset collected at a midsized, southeastern, public university over a period of 5 years (data available at http://dx.doi.org/10.3886/ICPSR03212). Three incoming classes of 1st-year men completed surveys about their experiences with various components and predictors of interpersonal violence throughout childhood, adolescence, and college. The first survey was administered on participants' matriculation at the university and asked about their childhood and adolescent experiences (retrospective data); subsequent surveys were administered during the spring semesters of each year of college (longitudinal data). The majority of participants were White, and all were between the ages of 18 and 20 years during the first survey. Sixty-five percent of those who were initially invited (n = 835) completed the first survey, and 22% of the initial sample completed all five surveys (see White & Smith, 2004 for a more detailed description of the sample).

The primary longitudinal analysis that White and Smith (2004) used was survival analysis. As they describe it, survival analysis indicates the likelihood of engaging in a certain behavior (in this case, sexual perpetration) during a specific time period, given that the behavior has not already occurred. Thus, in this analysis, pairs of time points are analyzed together (e.g., adolescence with 1st year of college; 1st year of college with 2nd year of college). This technique is most useful for comparing paired time points; unfortunately it neither truly addresses the longitudinal nature of the data, nor does it allow researchers to examine patterns in the data across time. In addition, although White and Smith did report that their comparisons showed no significant differences between the participants who dropped out of the study before time point five and those who completed all time points on key variables, it is important to remember that only 22% of the initial sample completed all five time points. Fortunately, GMMs allow the use of all available data.

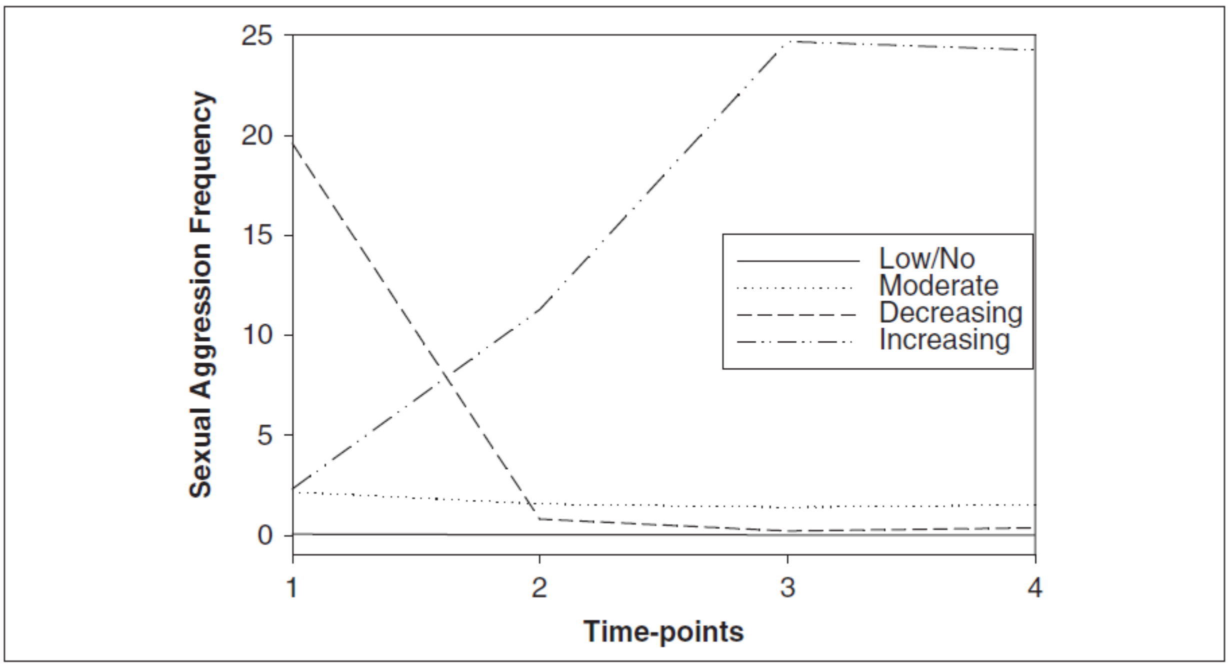
White and Smith's (2004) analysis left some questions unaddressed, including the lack of an adequate interpretation of why the childhood variables only predicted adolescent sexual aggression, as well as whether the analytic approach used could address all the relations between these variables. Although negative childhood experiences were found to be predictive of adolescent sexual aggression, they did not predict sexual aggression across college. The application of GMM, specifically LCGA, allows us to describe the relations between early childhood risk factors and subsequent sexual aggression more fully and take greater advantage of the entire longitudinal dataset. What we found both surprised and intrigued us.

The findings described below are for illustrative purposes only. Our goal is to provide an example of how the application of these alternative analytic techniques may be useful to VAW researchers not only in their future research but also for reanalysis of existing data. We realize that inquisitive researchers will want to evaluate the specific methods and procedures underlying this example. The scope of this special issue does not allow for such a discussion. For an expanded review of the data collection, methods, and variables used in this project, see White and Smith (2004). See Swartout et al. (2010) for an in-depth description and discussion of the analytic strategies, model specification, and model comparisons involved in this reanalysis.

For this reanalysis, Swartout et al. (2010) used the same measures of sexual perpetration frequency and negative childhood experiences that White and Smith (2004) used for all analyses. Men completed the Sexual Experiences Survey (Koss, Gidycz, & Wisniewski, 1987) at all five points of data collection. The measures of childhood victimization were also based on measures used by Koss et al. (1987) and were collected only at the first time point. Childhood sexual victimization was assessed by asking about experiences perpetrated by adults or similarly aged peers before the age of 14; questions assessed parental physical abuse and witnessing domestic violence by asking about recurrent experiences with these two phenomena in their households of origin (see White & Smith, 2004 for a more complete description of the variables used). Data corresponding to the total number of sexually aggressive acts men reported perpetrating at each time point (i.e., frequency) were fit to the latent class growth model; negative childhood experiences were used as predictors of latent class membership (but did not help determine the class structure).

When analyzing sexual perpetration in the past, we as researchers have assumed that we were dealing with one skewed distribution of men, most committing little to no sexual aggression and a sizeable minority engaging in more aggressive acts. The application of LCGA has changed this approach. Using Mplus (Muthén & Muthén, 2008), a statistical program particularly suited to constructing and analyzing mixed models, we applied this framework to our sample. We found that we were actually dealing with quite a heterogeneous group of men, based on their patterns of perpetration across time. Our analyses showed that there were four distinct groups of men5: those who engaged in little to no sexual aggression across time (*Low/No*; comprised of 71.5% of our sample); those who were moderately sexually aggressive both in adolescence and throughout college (*Moderate*; 21.2%); those who were only moderately sexually aggressive in adolescence but became highly sexually aggressive in college (*Increasing*; 3.1%); and those who were highly sexually aggressive in adolescence but who decreased in aggression across college (*Decreasing*, 4.2%; see Figure 1). This information alone is more than we could have learned from the analyses used by White and Smith (2004). Whereas they were able to determine that sexual aggression decreased over time, as well as that a small group of men were perpetrating more and more over time (based on relative risk analyses), they did not have the means to determine if there were qualitatively different groups of men in the sample. LCGA showed us that not only was a small group of men perpetrating at a high level across college (*Increasing*), but also that this small group of men was actually different from the small group of men who were perpetrating at a high level during adolescence (*Decreasing*).

Figure 1: Mean frequency of sexual assault at each time point



The picture became even more nuanced when we included the negative childhood predictor variables used in White and Smith's analyses. Recall that White and Smith found that negative childhood experiences were predictive of sexual aggression during adolescence, but when controlling for adolescent aggression, these childhood variables were not predictive of aggression across college. By including these childhood variables as predictors of class membership in the LCGA, we were able to see that the childhood variables were predictive of membership in only the *Decreasing* trajectory—the young men who were the most aggressive during adolescence. As can be seen in Figure 1, the *Decreasing* class has a very high average frequency of sexual aggression in adolescence, looks similar to the *Moderate* trajectory by year 1, and looks most similar to the *Low/No* trajectory by later in college. Thus, it appears that the group for which childhood variables are significant predictors is the group that decreases their aggression most dramatically from adolescence to college. Using LCGA with the childhood predictors, then, we can make a more educated hypothesis about why White and Smith found such an anomaly in their use of negative childhood experiences to predict sexual aggression across time. It is likely that the reason the childhood variables did not predict sexual aggression throughout college in White and Smith's analyses was that the group of men for whom those variables were most predictive in adolescence was no longer as likely to be engaging in sexual aggression when they reached college. A different latent class of young men was engaging in most of the sexual perpetration committed in college (see the difference in trajectories of *Increasing* and *Decreasing* in Figure 1).

A BRIEF CAVEAT CONCERNING GMM INTERPRETATION

As Bauer and Curran (2003a, 2003b, 2004) point out, there is a possible alternative explanation for the fit of a GMM to longitudinal data. Bauer and Curran argue that a well-fitting GMM may not necessarily indicate population heterogeneity; fit may simply be a function of a nonnormally distributed sample drawn from a homogeneous population. The difficulty is that the process for testing these two interpretations is identical, meaning that the available model fit statistics are unable to discriminate between the two interpretations. Although the analyses are the same, the two interpretations of GMM fit are vastly different and may lead researchers to false conclusions concerning the heterogeneity of their population of interest as well as spurious relations between supposed class membership and covariates.

In his response to Bauer and Curran (2003a), Muthén (2003) proposes tests for skewness and kurtosis that he claims will differentiate model fit because of a nonnormally distributed sample versus population heterogeneity. Researchers should be aware, however, that this test—that has since been integrated into the Mplus software—is not available for analyses involving missing data, which is commonplace with datasets on VAW. There is not yet a statistical solution to this important theoretical distinction; therefore, some applied researchers can only assume that the fit of their GMM is due to latent heterogeneity. Although this can be seen as a self-fulfilling prophecy, Muthén (2003) argues that researchers should take substantive theory, auxiliary information, and practical usefulness into account when interpreting GMMs just as we would with correlational and factor analytic designs. These concerns also underscore the importance of replications.

CONCLUSION

Despite the limitation described in the previous section, as we stated earlier it is important to make use of innovative analysis techniques, especially in terms of longitudinal data. These techniques offer the potential for complete paradigm shifts in how we approach the phenomena in which we are interested. For example, in this case, we used LCGA to reconceptualize the study of sexual perpetration. This analysis suggests that we are not dealing with one homogeneous group of perpetrators, or even two separate groups of men (perpetrators and nonperpetrators). Using LCGA we see that there is a genuine heterogeneity in sexual assault perpetrators and that their behaviors, in particular a trajectory of behaviors, can be differentially predicted by variables that we have traditionally associated with sexual perpetration in general (e.g., negative childhood experiences). This knowledge enhances our ability to theorize about sexual perpetration. These new analyses allow us to understand sexual perpetration from both a developmental and longitudinal perspective, encouraging us to think in a more sophisticated way about the patterns of behavior.

This knowledge also opens the door to new questions about other variables that further distinguish between these groups. For example, an important question emerges from our current findings about the group of men that we have labeled *Increasing*. Childhood experiences do not predict that specific trajectory membership, yet according to the patterns described here, the men who comprise this group turn out to be the most frequent perpetrators across college. Focusing on predictors of this group of men may offer insights into prevention and intervention strategies that we have not been able to conceptualize before. Analyses such as these may be able to help us develop more focused interventions, hopefully leading to better prevention of sexual assault on college campuses. Although we have described just one example of the way in which new analytical approaches can be used to reexamine questions to highlight more fully the richness of our longitudinal data, we would encourage VAW researchers to begin to think outside the box and to apply these new analytic techniques to their own datasets. We were intimidated initially, but by learning as much as we could about alternative methodological and analytical techniques we have been able to make better use of our data. We are moving forward with additional analyses of sexual and physical perpetration, and extending our efforts to more fully understand sexual and physical victimization across time. We urge researchers in the area of VAW to make more use of these emerging analytic approaches, especially when analyzing longitudinal data.

DECLARATION OF CONFLICTING INTERESTS

The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

FUNDING

The authors disclosed that they received the following support for their research and/or authorship of this article: This research was made possible by funding from the National Institute of Mental Health (R01MH45083) and the National Institute of Justice (98WTVX0010).

NOTES

[1] Singer and Willett (2003) provide detailed and easily understandable descriptions and examples of the multilevel model of change (chapter 3) as well as modeling change using CSA (chapter 8).

[2] Covariates can also be modeled to predict specific indicators of a measurement model, although this is rarely seen in application.

[3] Although outside of the scope of this article, researchers who would like to learn more about modeling nonnormally distributed outcomes should consult Long (1997) or Hilbe (2007) for in-depth reviews and suggestions.

[4] Class membership is rarely exact; individuals are not usually categorized solely into one latent class. Each individual is assigned a probability of belonging to each possible latent class, known as *posterior probabilities*. Each individual's posterior probabilities add up to 1. These metrics are used, in part, to determine how well class structures fit observed data.

[5]According to all of the fit statistics provided by the analysis, the four-class model fit the data significantly better than the 1-3 class models. See Swartout et al. (2010) for model specifications, comparisons, and fit.

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