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CHAPTER ELEVEN

Modeling Complex Interactions: Person-Centered and Variable-Centered Approaches

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In recent decades the developmental systems perspective has grown increasingly influential in the behavioral sciences. Richard Lerner (1998) observed that this perspective is actually a metatheory because it emphasizes several themes that are common to many conceptual models of human development, including the ecological theory (Bronfenbrenner & Morris, 1998), probabilistic epigenesis (Gottlieb, Wahlsten, & Lickliter, 1998), life course sociology (Elder, 1998), and the holistic-interactionist paradigm (Magnusson & Stattin, 1998). One such theme is that a developmental system is comprised of multiple levels (e.g., biological, psychological, sociological, and cultural) that are "inextricably fused" to create a functioning holism. Furthermore, this fusion reflects high levels of interactions both within and between levels of the system (see Gariépy, 1995; Sameroff, 1983; Shanahan, Valsiner, & Gottlieb, 1997). The methodological challenge this perspective presents is the need to capture potentially nonlinear interactions among many variables. It is this challenge that motivates the present work.

In a developmental systems framework, the problem takes several forms, including person-person, context-context, and person-context interactions. Person-person interactions occur among and between, for example, psychological and biological levels of analysis (e.g., Bergman, Magnusson, & El-Khoury, 2003). Person-context interactions refer to the contingent effects of character-

istics of the person and contextual factors, and are especially prominent in models of person–environment fit (e.g., Eccles & Midgley, 1989). Far less frequently considered are context–context interactions, whereby two or more contextual factors have nonadditive effects on behavior (Shanahan & Hofer, 2005). In theory, such interactions are pervasive and detecting and understanding them is central to empirical research on behavioral development.

Many proponents of the systems perspective have relied on traditional linear models to test hypotheses concerning interaction. However, other scholars, notably David Magnusson and Robert Cairns, have asserted that there is a fundamental mismatch between the holism emphasized by contemporary developmental theory and linear models (e.g., Bergman & Magnusson, 1997; Cairns & Rodkin, 1998; Magnusson & Cairns, 1996; Magnusson, 1998; see also Richters, 1997). Specifically, general and generalized linear models (e.g., multiple regression, logistic regression, or structural equation modeling) typically involve the estimation of a main effect for each variable in the model controlling for (or holding constant) the other variables. This atomistic focus on individual variables is inconsistent with the interactionist principle that no variables have “unique” effects divorced from other relevant operating factors. Put simply, such models are “variable-centered,” potentially failing to capture the configurations of factors that jointly explain behavioral processes.

As an alternative, Bergman and Magnusson (1997) advocated the use of “person-centered analyses” that identify key patterns of values across variables, where the person, viewed holistically, is the unit of analysis.¹ Implicit in their argument is that only methods that identify configurations of variables — quite typically, cluster analyses, but also latent class analysis, mixture models and similar techniques — are capable of appreciating the high level of interaction and nonlinear relationships that are likely to characterize developmental systems. These techniques result in the identification of a small set of clusters or classes that then supplant the individual variables as predictors or outcomes in subsequent data analysis. The assumption is that the complex dynamics of the system of variables, including possible nonlinear effects and interactions, have been preserved in the configurations.

Methodologists have countered that the practice of rendering continuous variables into a few discrete categories may actually hinder the identification of true nonlinear and or interactive effects. In a recent review of the methodological literature on this topic, MacCallum, Zhang, Preacher, and Rucker (2002) admonished that the categorization of continuous variables often obscures or attenuates true effects and can even sometimes produce spurious effects. Method-

¹The term *person-centered* emanates from a focus on intraindividual functioning and is perhaps ill chosen, as the operating factors of interest may lie both within the person and their context.

ological studies of categorization have generally focused on relatively simple cases, such as bivariate linear and nonlinear relationships, and the treatment of two-way interactions in regression/ANOVA models (e.g., Cohen, 1983; Humphreys, 1978; Maxwell & Delaney, 1990). Even for complex models involving many variables with potentially nonlinear interactions, however, MacCallum, Zhang, Preacher, and Rucker (2002) state

We have repeatedly encountered the argument that dichotomization is useful so as to allow the testing of interactions . . . In fact, it is straightforward to incorporate and test interactions in regression models, and such an approach would avoid . . . biased measures of effects size and spurious significant effects. Furthermore, regression models can easily incorporate higher way interactions as well as interactions of a form other than linear \times linear . . . (p. 32)

Later, commenting specifically on the use of cluster analysis and related methods to capture complex relationships, MacCallum, Zhang, Preacher, and Rucker (2002) summarize the views of many methodologists, stating that the classifications obtained by such methods “do not provide any insight about variables of interest nor about relationships of those variables to others. Basing analyses and interpretation on such arbitrary groups is probably an oversimplification and potentially misleading (p. 34).” Thus, the methodological literature appears to stand in opposition to the assertions of person-centered theoreticians.²

The current chapter aims to bring some additional clarity and insight to this dialogue between theoreticians and methodologists. Namely, we provide a direct comparison between person-centered and variable-centered approaches to capturing interactive effects in realistically complex data. To our knowledge, this comparison is the first of its kind. Whereas advocates of the person-centered approach have often asserted that configurations and clusters capture nonlinear effects and interactions in a more optimal and interpretable way than traditional linear models, they have neither demonstrated how person-centered methods capture these effects nor have they compared these methods with linear models containing higher order terms. Likewise, advocates of variable-centered approaches for studying nonlinear and/or interactive effects have generally re-

²In contrast, MacCallum, Zhang, Preacher, and Rucker (2002) suggest that clustering may be justified if the aim is to recover qualitatively distinct groups of individuals, but they also note that the existence of such groups can be difficult to establish empirically, a view we share (Bauer & Curran, 2003a, 2004). Here, however, we are concerned only with the use of clusters to recover interactions, leaving aside for the moment the issue of whether the clusters really represent ‘true groups.’

stricted their analyses to patterns of effects among a few variables that can readily be modeled and interpreted with polynomial and product terms. Furthermore, they have primarily considered relatively poor classification methods when studying the detrimental effects of categorization (e.g., median/mean splits or the creation of extreme groups). In this chapter, we use a realistically complex case study to compare person-centered and variable-centered approaches to recovering interactions that involve many variables.

We first introduce the empirical example that will serve as the basis for our case study. We then analyze these data using a traditional variable-centered model, first modeling only main effects, and then modeling the possible interactions that may be present. We follow with an analysis of the same data using a person-centered approach, namely a probabilistic clustering model known as latent profile analysis (LPA). Next, we draw on and extend recent analytical work by Bauer (2005) to provide a direct comparison of the results of the two fitted models. Our conclusions focus on the advantages and disadvantages of each approach as well as important directions for future research.

EMPIRICAL EXAMPLE

The data for the empirical example are artificial, but are loosely based on results presented by Cairns, Cairns, and Neckerman (1989). The focus of the original study was to identify configurations of variables representing social competencies, age and maturation, and socioeconomic status among students in Grade 7 that might differentially predict school dropout by Grade 11. We have simplified matters by basing our example on the results presented for male participants for the four dimensions of the Interpersonal Competence Scale (ICS): aggression, popularity, academic competence, and 'all-American' (reflecting sports, looks, dominance).

Data for the four ICS variables and the dichotomous dropout variable were generated with as much fidelity as possible to the actual characteristics of the data reported by Cairns, Cairns, and Neckerman (1989).³ There were, however, two aspects of the simulated data that differed from the original data. First, we generated data for 2000 cases, whereas only 213 male subjects were originally studied. We chose this sample size to ensure the stability of our results and because we were not interested in studying sampling variability with replicate samples of smaller size. This does not preclude the application of similar mod-

³Details on the data generation are available from the first author upon request. We do not provide this information here for two reasons. First, we wish to keep the level of technical detail to a minimum. Second, we wish to retain a high degree of verisimilitude to real empirical research where the population-generating model is not known.

els with smaller samples. Second, the ICS variables were simulated to be on a standardized scale, whereas the original metric was 1 to 7. Standardization facilitates both variable-centered and person-centered analyses. (In the former case, variables are commonly standardized prior to forming product terms to improve the interpretation of main effects and reduce multicollinearity; see Aiken & West, 1991, and Jaccard, Turrisi, & Wan, 1990. In the latter case, standardization facilitates interpretation of cluster profiles — zero is the grand mean against which cluster means on specific variables can be judged as high or low.)

Throughout the remainder of the chapter we reference the artificially generated ICS data by the same variable labels that were used by Cairns, Cairns, and Neckerman (1989) to enhance the realism and intuitiveness of the results. Consistent with the original study, our analyses focus on the prediction of dropout by the four ICS variables using both variable- and person centered approaches. We caution, however, that the results we report are from the simulated data only and have the sole purpose of providing a realistically complex example for comparing between person-centered and variable-centered approaches. No substantive implications should be drawn from the results presented here, as it is unclear whether the same results would be obtained from the actual data of Cairns and his colleagues.

A VARIABLE-CENTERED APPROACH

We first fit a logistic regression model to predict dropout (1 = dropped out of school by Grade 11; 0 = otherwise) as a function of the four continuous ICS variables. We begin by describing the logistic regression model in general terms, and then proceed to describe the results obtained by fitting logistic regressions with and without interaction terms to the ICS data.

The Logistic Regression Model

In general, if the probability of occurrence of the outcome (e.g., dropout) for individual i is designated τ_i , then the logistic regression model can be written as

$$\ln\left(\frac{\tau_i}{1-\tau_i}\right) = \alpha + \beta' \mathbf{x}_i \quad (1)$$

where the log of the odds (ratio of the probability of the outcome to its complement), or logit, is assumed to be a linear function of the predictors within the vector \mathbf{x}_i . The intercept of the regression of the logit on \mathbf{x}_i is designated

α and the regression coefficients are contained in the vector β . Exponentiation of these coefficients gives the odds-ratios for the predictors. The predicted probability of the event is then given by

$$\pi_1 = \frac{1}{1 + e^{-(\alpha + \beta' x_i)}} \quad (2)$$

Thus the model assumes that the predictors relate linearly to the logit, but that they are nonlinearly related to the actual probability of the outcome occurring.

Following conventional practice for linear models, interactions are estimated in the logistic regression model through the formation of product terms. For instance, to assess an interaction between x_1 and x_2 , the product term $x_1 \times x_2$ would be added to the model. The significance of a two-variable product term, net the main effects, is taken as evidence of a bilinear interaction between two variables (Cohen, 1978), indicating that the effect of one variable on the log-odds changes linearly with the value of the other. Similar interpretations obtain for still higher order interactions involving three or more variables (e.g., for a three-way interaction, the magnitude of the bilinear interaction between two variables is a linear function of a third variable). Interactions that are not linear in form can potentially be modeled through the creation of linear \times quadratic product terms (e.g., $x_1 \times x_2^2$, although this is rarely done in practice. Given the partialling of lower and higher order terms (e.g., main effects and interactions) that takes place in the estimation of interactions, it is sometimes difficult to interpret the individual coefficients. Plotting the relations implied by the model can aid in this endeavor. The most frequently used approach is to compute and graph 'simple slopes' indicating the effect of one predictor on the criterion at certain selected levels of the moderating variables (see Aiken & West, 1991; Jaccard, Turrissi, & Wan, 1990).

Logistic Regression Modeling Results

The results of the initial logistic regression model, including only the main effects of the four ICS variables, are presented in Panel A of Table 11.1. The estimated odds-ratio for aggression indicated that with each standard deviation increase in aggression the odds of an individual dropping out of school increased by a factor of 1.75. In addition, with each standard deviation increase in academic competence the odds of dropping out decreased 1.72 times (the reciprocal of .58). The effects of the popularity and all-American variables were nonsignificant. Note that the focus of these interpretations is on the unique effect of each variable, not on configurations of values across variables. For this reason, advocates of the person-centered approach have roundly criticized

TABLE 11.1
Results of Logistic Regression Models Excluding and Including Product Interaction Terms (effects that are statistically significant at the .05 level are listed in bold)

Variable	Coefficient(β)	se β	Odds-Ratio ^a
Panel A. Main Effects Model (-2*Log-Likelihood = 1631)			
Intercept	-1.86	.074	
Agg	.56	.067	1.75
Pop	.05	.070	1.06
Acad	-.54	.068	.58
	-.13	.070	.88
Panel B. Interaction Model (-2*Log-Likelihood = 1604)			
Intercept	-1.83	.078	
Agg	-.58	.077	
Pop	-.12	.096	
Acad	-.54	.080	
Amer	-.26	.088	
Agg \times Pop	.06	.092	
Agg \times Acad	-.03	.07	
Agg \times Amer	.11	.088	
Pop \times Acad	.20	.102	
Pop \times Amer	-.20	.074	
Acad \times Amer	.09	.086	
Agg \times Pop \times Acad	-.03	.099	
Agg \times Pop \times Amer	-.09	.064	
Agg \times Acad \times Amer	-.17	.083	
Pop \times Acad \times Amer	-.01	.081	
Agg \times Pop \times Acad \times Amer	-.04	.068	

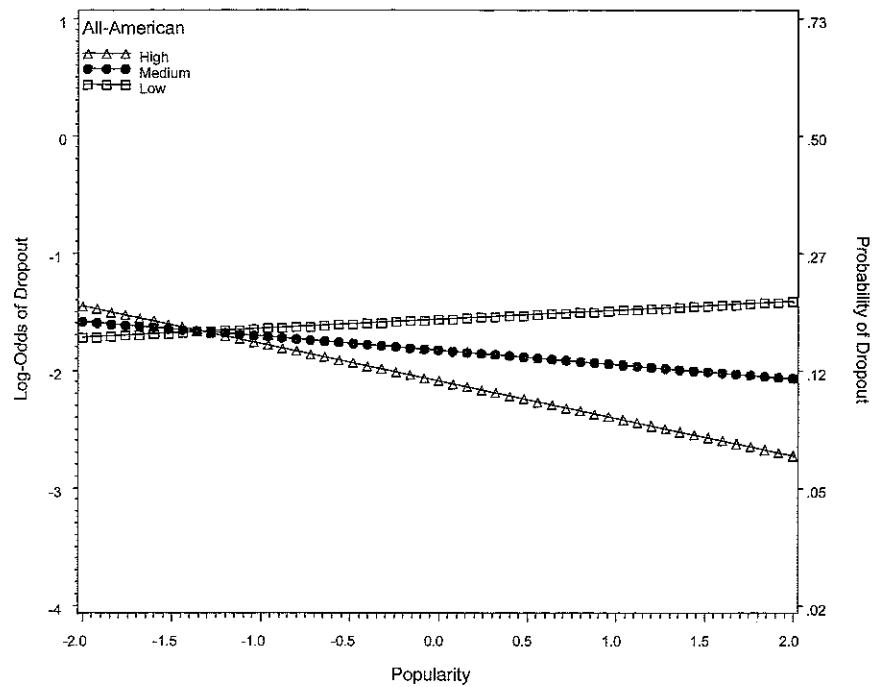
Note. Agg = Aggression; Pop = Popularity;

Acad = Academic Competence; Amer = All-American.

traditional modeling approaches as being insensitive to the hypothesized complexity of developmental systems.

In an effort to address such criticisms, our second logistic regression model included all possible product interactions between the four ICS predictors, including 6 two-way interaction terms, 4 three-way interaction terms, and 1 four-way interaction term. The addition of these terms resulted in a modest improvement in fit relative to the model containing only main effects, $\chi^2(11) = 27, p < .05$. As shown in Panel B of Table 11.1, for this model, statistically significant effects included both the two-way interaction between popularity and all-American and the three-way interaction between aggression, academics, and all-American. In the absence of any further analysis, these interactions are rather difficult to interpret, given the parsing of lower and higher order effects. Following standard practice, however, we computed 'simple slopes' in an effort

FIGURE 11.1
Results of the logistic regression model for popularity.

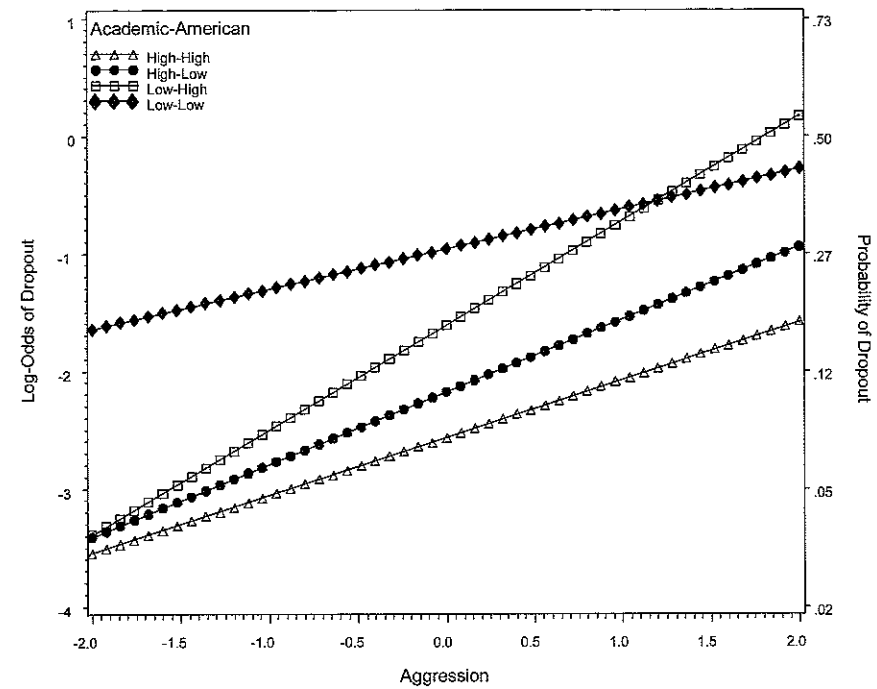


Note. The log-odds and predicted probability of school dropout by the 11th grade as a function of 7th grade popularity at high, medium, and low levels of 7th grade all-American attributes.

to combine these estimates into a coherent picture of how the ICS variables interact to predict dropout.

We first consider the two-way interaction between popularity and all-American. Figure 11.1 plots simple slopes showing the effects of popularity on the log-odds and predicted probability of dropout at high, medium, and low levels of all-American (set at one standard deviation above the mean, the mean, and one standard deviation below the mean, respectively), holding aggression and academic competence at the mean. Figure 11.1 clarifies the assumptions of the model: First, that the log-odds of dropout are linearly related to popularity and, second, that the effect of popularity changes linearly with the level of all-American (i.e., that there is a bilinear interaction effect). The latter assumption is reflected in the symmetry of the regression lines for high and low all-American relative to the line plotted at the mean of all-American.

FIGURE 11.2
Results of the logistic regression model for aggression.



Note. The log-odds and predicted probability of school dropout by the 11th grade as a function of 7th grade aggression for specific combinations of high and low levels of 7th grade academic competence and all-American attributes.

To facilitate interpretation of these results, the scale on the right side of the figure translates the predicted log-odds into predicted probabilities of dropout via the nonlinear relation in Equation 2. As can be seen, the interaction indicates that popularity can reduce the risk of dropout, but only if paired with medium to high levels of all-American. That is, adolescents who are popular with peers and also good looking, confident, and athletic are less likely to drop out than those who are unpopular with peers. In contrast, for adolescents who do not possess these all-American attributes, popularity has little effect on the probability of dropout.

We now turn to the interpretation of the three-way interaction between aggression, academic and all-American. Figure 11.2 plots the effect of aggression on both the log-odds and predicted probability of dropout at high and low levels of academic and all-American, defined as one standard deviation above

and below the mean, respectively, holding popularity constant at the mean. These values are plotted on the same scale as Figure 11.1, making immediately apparent the larger magnitude of the effects displayed in Figure 11.2. The strong main effect of aggression is clearly visible: higher levels of aggression are associated with higher levels of dropout, regardless of which values of academic and all-American are exhibited. Academic competence and all-American attributes serve as protective factors in this relationship: Youth who are aggressive but also high on these other two scales show a less pronounced probability of dropout than youth who are low in one or both of the academic and all-American scales. There is also an interesting crossover between the lines for low-low and low-high values of academics and all-American. For low to moderate levels of aggression, we see that being low in both academic competence and all-American attributes places an adolescent at greatest risk for dropout. However, for particularly aggressive youth, this trend reverses: For those who are low in academics, being high in all-American attributes actually *increases* the risk of dropping out.

Overall, Figures 11.1 and 11.2 indicate that all-American, which was not a significant main effect predictor in the first analysis, actually plays a complex interactive role with the other ICS variables in predicting dropout. Moreover, using a variable-centered model, we were able to consider how specific configurations of variables influenced the probability of dropout through the plotting of simple slopes for significant interactions. These results are consistent with the contention, prominent among methodologists, that variable-centered models can recover complex interactive patterns through the use of product terms. Furthermore, this approach has the advantage that the continuous nature of the data is preserved.

The results also provide support for the critics of the variable-centered approach, who maintain that the parsing of lower and higher order effects make holistic interpretations of the results difficult: Even with the plotting of simple slopes, each interaction must be considered separately. We now turn to a person-centered analysis of the same data as an alternative way to capture the relations between configurations of ICS variables and school dropout.

A PERSON-CENTERED APPROACH

As previously noted, the person-centered approach involves the identification of key configurations of values across a set of operating factors. In practice, these patterns are often identified through heuristic cluster analytic techniques, including partitioning algorithms like k -means and hierarchical or agglomerative clustering algorithms. Alternatively, finite mixture models like latent profile

analysis and latent class analysis provide model-based approaches to pattern detection. Model-based clustering methods are distinguished from heuristic clustering algorithms in that they involve an explicit underlying statistical model. Due to the probabilistic basis of the models, a sample need not be partitioned into disjoint sets, but rather clusters may be overlapping and individuals can have non-zero probabilities of belonging to several clusters (i.e., cluster membership is 'fuzzy'). Given these important advantages of a model-based approach, we next conducted a latent profile analysis of the ICS data. As before, we begin with a general description of the model and then proceed to discuss the results obtained by conducting a LPA with the ICS data.

The Latent Profile Analysis Model

Latent profile analysis (LPA) was developed by Gibson (1959) as a continuous variable analog to traditional latent class analysis for binary variables. LPA can also be motivated from classical test theory. According to classical test theory, the observed scores for each individual are assumed to reflect both 'true scores' on the characteristics of interest as well as random error due to imperfections of measurement or momentary disturbances. Individuals are defined as representing a homogeneous cluster or *latent class* if they share a common set of true scores. The model for the observed scores can then be written as

$$\mathbf{x}_i = \boldsymbol{\xi}_k + \boldsymbol{\delta}_i \quad (3)$$

where \mathbf{x}_i is the vector of observed scores for individual i , $\boldsymbol{\xi}_k$ is the vector of latent true scores characterizing *all* individuals within latent class k , and $\boldsymbol{\delta}_i$ is the vector of errors or disturbances. These random errors are assumed to be uncorrelated across both variables and persons, and to be normally distributed with expected values of zero. Under these assumptions, within each class, \mathbf{x}_i is multivariate normally distributed with class mean vector equal to $\boldsymbol{\xi}_k$ and class covariance matrix equal to $\boldsymbol{\Delta}_k$, a diagonal matrix of within-class error variances for $\boldsymbol{\delta}_i$. The probability density function (PDF) for class k can then be designated $\phi_k(\mathbf{x}_i; \boldsymbol{\xi}_k, \boldsymbol{\Delta}_k)$.

When individuals from many classes are mixed together in the population, then the aggregate density function for the population can be described as a weighted sum or mixture of the within-class PDFs:

$$f(\mathbf{x}_i) = \sum_{k=1}^K \pi_k \phi_k(\mathbf{x}_i; \boldsymbol{\xi}_k, \boldsymbol{\Delta}_k) \quad (4)$$

where K is the total number of classes in the model and π_k is probability that

an individual case would be drawn at random from class k , also interpretable as the proportion of cases in the population belonging to class k .

Most methods of estimation for LPA, such as maximum likelihood, do not allow the number of classes K to be estimated directly from data.⁴ In practice, the investigator instead fits a sequence of models with increasingly more classes until some stopping criterion is reached. The most common such criterion is to select the model with the minimum Bayesian Information Criterion (BIC), a measure that balances the ability of the model to reproduce the data against the parsimony of the model. Many other fit criteria exist, and the number of classes they suggest will not always be consistent with one another, given that they were developed with different rationales (McLachlan & Peel, 2000). Ideally, the choice of measure should be informed by studying its performance with simulated data of known structure and whether or not the measure was developed for a rationale that matches the investigator's goals. Other than model fit, the decision to adopt a given number of classes is often also based on theoretical considerations, such as whether or not a newly added class seems to contribute sufficiently unique information to warrant an increase in the complexity of the model.

An important additional consideration in estimating latent profile models, and other clustering models, is that the results can be sensitive to the initial values that are used to start the maximum likelihood fitting function. Many local optima may exist that represent inferior solutions and do not accurately recover the parameters that are being estimated. Using multiple sets of starting values is thus advisable to avoid accepting and interpreting such a solution (McLachlan & Peel, 2000). Fortunately, most software available for fitting these models (e.g., Latent Gold, *Mplus*) now provide randomized start value routines. Convergence problems can also be encountered. Such problems most frequently arise when the variance-covariance matrices of the latent classes (Δ_k) are allowed to differ. If the within-class variances become very small, tending toward zero, this will produce a singularity in the likelihood surface (a spike to infinity) and the model will fail to converge. Setting the class covariance matrices to be equal (e.g. $\Delta_k = \Delta$) avoids this problem. Such constraints have the additional appeal of producing a more parsimonious model, yet they may not always be appropriate for the data. Finally, another common source of convergence problems is when one class collapses during the iteration process, that is, the class membership drops to zero. The use of alternative starting values may help to avoid this problem as well.

⁴Some Bayesian approaches to fitting LPA and mixture models do allow the number of classes to be estimated (e.g., Stutz & Cheeseman, 1996). However, these approaches are (at present) less common than maximum likelihood.

Once the number of classes is decided and estimates for the parameters of the model have been obtained, probabilities of class membership for the sample can be computed. Specifically, the probability that individual i belongs to latent class k given their observed scores \mathbf{x}_i can be calculated as

$$p_{ik} = \frac{\hat{\pi}_k \phi_k(\mathbf{x}_i; \hat{\xi}_k, \hat{\Delta}_k)}{\sum_{k=1}^K \hat{\pi}_k \phi_k(\mathbf{x}_i; \hat{\xi}_k, \hat{\Delta}_k)} \quad (5)$$

Unlike clustering algorithms that assign cases to one and only one cluster, the *posterior probabilities* obtained from Equation 5 range between zero and one. For example, in a 2-class LPA, an individual might have a .8 probability of belonging to the first latent class and a .2 probability of belonging to the second latent class. These probabilities gauge uncertainty in assigning individuals to specific classes.

Let us now turn to the results of conducting LPA with the ICS data.

Results Obtained by Latent Profile Analysis

The LPA model we fit to the simulated ICS data actually differed slightly from the model described earlier in that the dichotomous dropout variable was also included (see L. K. Muthén & Muthén, 1998, Appendix 8, for analytic details).⁵ Thus the resulting latent classes were defined by both mean differences on the ICS variables and different predicted probabilities of school dropout. This simultaneous analysis is preferable to first conducting the LPA exclusively on the ICS variables and then subsequently predicting dropout by class using a logistic regression model. Such a two-stage analysis would require that the class probabilities be taken into account to prevent classification errors from biasing the results. Modeling the probability of dropout directly in the LPA takes account of this uncertainty in class assignments.

Our first task was to select the precise LPA model to use with the data. We began by estimating models with one through six classes both with and without invariance constraints on the within-class variances. Each model was estimated from 100 random starts to help avoid suboptimal (local) solutions and convergence problems. A comparison of the BIC values obtained from these different models is provided in Table 11.2. The two bolded entries in Table 11.2 reflect the best fitting models, according to the BIC. Although the 4-class model with homogeneity of variance constraints had the minimum BIC,

⁵All LPA models were fit in *Mplus* 3.1 (L. K. Muthén & Muthén, 1998). The data and program files are available at Quant.KU.edu

TABLE 11.2
Bayes' Information Criterion (BIC) Values for LPA Models Fit to the ICS Data

Classes	Structure Imposed on Within-Class Variances	
	Homogeneous Δ_k	Heterogenous Δ_k
1	24723.32	24723.32
2	23919.74	23931.06
3	23372.54	23407.61
4	23272.77	23353.27
5	23303.54	23405.80
6	23340.36	23462.56

comparison of the class means between this and the next-best 5-class model with the same constraints suggested that the 5-class model was theoretically more interesting. The estimated class means for the ICS variables from the 5-class model are presented in the profile plot in Figure 11.3. In the 4-class model, the fourth and fifth classes were collapsed into a single group; however, the differentiation of the fourth and fifth class is substantively important. Although both of these classes show high levels of aggression, average popularity and average all-American, the fifth class is distinguished by very low levels of academic competence, whereas the fourth class is average academically. Given our interest in school drop out, we viewed this difference as sufficiently important to warrant selecting the five class model. Thus, we interpret only the results of the 5-class model from this point onward.

As can be seen, the most common configuration of values is represented by latent class C2, comprising 56% of the sample. Individuals with a high probability of belonging to this class are effectively at the average (grand mean) on all of the ICS variables and have a dropout rate of 12.0%. Latent class C1 is the next most common pattern, comprising 23% of the sample, and is characterized by below average aggression and high popularity, academic competence, and all-American ratings. As one might expect, C1 also has the lowest estimated rate of dropout of all the classes, at only 1.3%.

Classes C3, C4, and C5 are particularly interesting given that they all share high levels of aggression, one of the variables of key interest in the original study. They are the least frequent data patterns, at 6.6%, 9.2%, and 5.2%, of the sample, respectively, but they have the highest dropout rates. These rates are not uniform, however, suggesting that for aggressive youth other social competencies play an important role in moderating the likelihood of dropout. The actual pattern of findings is unexpected. Latent class C3 would appear to be most at risk, with high aggression, low popularity, and a low all-American score, but in fact the estimated dropout rate for this class is only 19.2%. In

comparison, latent class C4, high in aggression but average on the other variables, has a dropout rate of 56.0%. Latent class C5, with high aggression and low academics, is the configuration with the highest dropout rate at 70.4%.

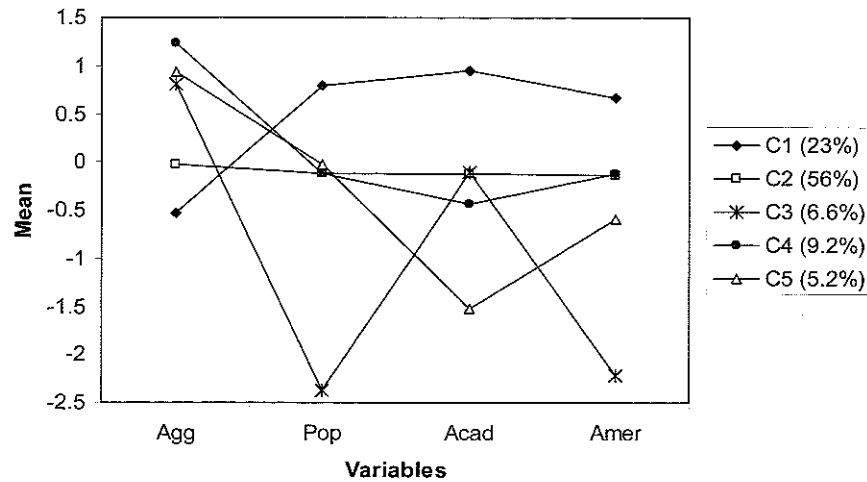
These results are substantively interesting and far simpler to interpret than the results obtained earlier from the logistic regression model. However, two key questions remain unsettled. First, do the configurations represented by the latent classes capture interactive relations between the ICS variables? The dropout rate of configurations with high aggression differs with their levels on other ICS variables like academics and all-American, but this might simply reflect the accumulation of independent main effects across these variables rather than a true interaction. Second, even if the latent classes do capture interactions between the ICS variables in the prediction of school dropout, at what cost is this achieved? Many methodologists would no doubt question whether rendering continuous variation on the ICS variables into a few discrete latent classes does more harm than good. Whereas the logistic regression model produced the smooth predicted probability curves in Figures 11.1 and 11.2 for various configurations of values on the ICS variables, on its surface, the LPA appears only to provide five predicted probabilities, one for each latent class, discarding much information on individual differences. Drawing on analytic developments made by Bauer (2005), however, we show that the results obtained from the LPA can be used to generate curves similar to those presented in Figures 11.1 and 11.2 and these curves will allow us to answer both of the two questions raised above. In addition, these new curves will permit us to compare more directly between the predictions of the logistic regression model and the latent profile analysis.

TRANSLATING THE RESULTS OF THE PERSON-CENTERED APPROACH

The most literal interpretation of LPA is that there are K classes of individuals mixed together in the population, within which individuals are identical with respect to their true scores, but that there is some error variation around those true scores. Due to this error variation, sampled individuals cannot be assigned with perfect precision to their respective classes, hence the need for probabilistic measures of class membership. The difficulty of this interpretation is that it assumes the presence of discrete groups and this assumption can be difficult to justify on the basis of the available evidence (see Bauer & Curran, 2003a, 2003b, 2004). In the absence of such groups, LPA may appear to represent a gross simplification of the data.

FIGURE 11.3

Plot of the means of the five classes identified in a latent profile analysis.



Note. (Agg = Aggression, Pop = Popularity, Acad = Academic Competence, Amer = All-American). The class labels and percent of the sample predicted to belong to each class are indicated in the legend.

An alternative (and more easily defended) interpretation of LPA begins with two key concessions. First, the distribution of true scores may not be discrete (i.e., it may be continuous). Second, the latent classes may not directly represent true groups within the population (i.e., the population may consist of individuals that differ only quantitatively and not qualitatively). Given these caveats, it may seem puzzling why one would use a model involving discrete latent classes at all. LPA can still be justified, however, by the argument that the estimated latent classes represent discrete points on a potentially continuous but unknown multivariate distribution (an interpretation that even Gibson, 1959, considered; see also Nagin, 1999, Nagin & Land, 1993). We can then conceptualize these points as being similar to landmarks on a map from which we can triangulate the position of any new location. In the LPA, this triangulation is accomplished through consideration of the posterior probabilities of class membership, which, to continue the analogy, can be thought of as distances from the known landmarks. For instance, if a sampled individual had modest posterior probabilities of belonging to both latent class C1 and latent class C2, then we would guess that the individual's dropout probability would be midway between the dropout probabilities estimated for C1 and C2 but would probably not be close to the probabilities estimated for C3, C4, or C5.

More formally, extending analytic developments made in Bauer (2005), we can estimate the probability of an event given a particular set of values on the continuous predictors \mathbf{x}_i to be

$$\tau_i = \sum_{k=1}^K p_{ik} \tau_k \quad (6)$$

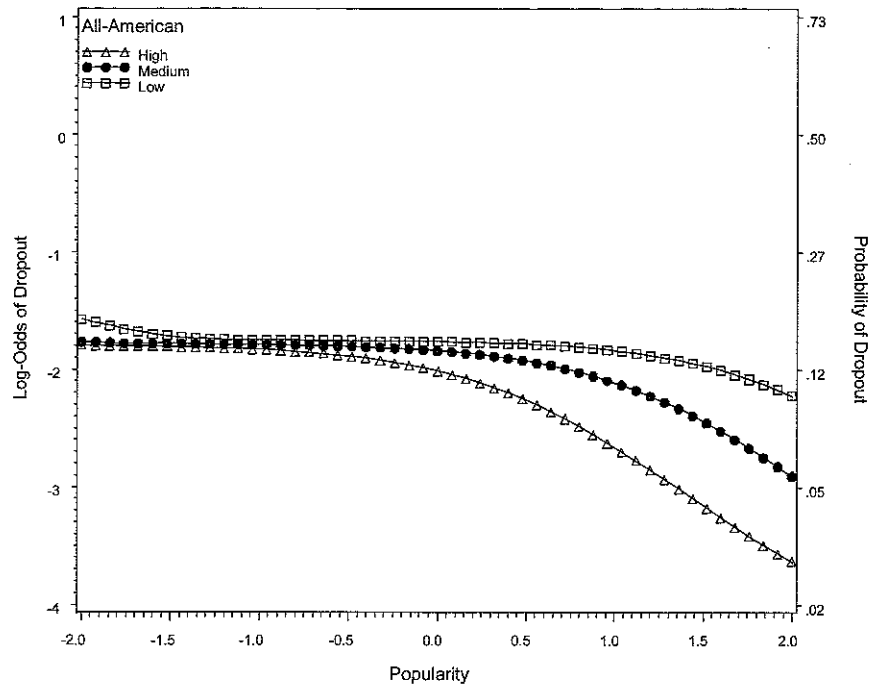
where τ_k is the probability of the event occurring for members of class k and p_{ik} is the posterior probability of class membership given \mathbf{x}_i as defined in Equation 5. In other words, the probability of the event given \mathbf{x}_i is simply a weighted sum of the probabilities of the event of the K classes, where the weights correspond to the posterior probabilities of class membership. Importantly, Equation 6 shows that continuous variation on \mathbf{x}_i need not be discarded in a LPA — each individual can be assigned their own probability of experiencing the dichotomous outcome based on their particular set of observed scores for \mathbf{x}_i .⁶ This observation may partially allay the concern of methodologists that this individualized information would be lost in the estimation of discrete latent classes.

Equally important is the fact that Equation 6 can also be used to translate the predicted probabilities estimated for the discrete latent classes into the same smooth curves previously presented in Figures 11.1 and 11.2, that is, to translate the person-centered results into a variable-centered framework. Specifically, rather than compute predicted values for every configuration of \mathbf{x}_i observed in the sample, we can instead systematically select various configurations of values for \mathbf{x} and use Equation 6 to calculate the model-implied probability of dropout for each selected configuration.⁷ Here, we generate plots in this fashion for the primary purpose of comparing the complex interaction patterns implied by the logistic regression model to the LPA model. Such plots may, however, be of interest in their own right, as they reveal the underlying continuous relations that are implied by the latent profile model. Ideally, theory would suggest that two or three variables are particularly likely to interact and these variables may be used to generate the plots. In the absence of theory, the cluster profiles may suggest important combinations to consider. Additionally, variables whose

⁶In *Mplus*, the posterior probabilities for the sample can be obtained using the command `SAVEDATA: SAVE = CPROB`.

⁷This can be done using a matrix-based programming language such as SAS PROC IML. Alternatively, one could "trick" *Mplus* or other LPA model fitting software into computing these conditional probabilities by first generating an artificial data set with the desired levels of the predictors represented as individual cases and then fitting an identical LPA model to this data but with the parameter values fixed at the estimates from the model fit to the original sample. As with the original sample posterior probabilities, these new probability values can be saved into a new file for use with Equation 6.

FIGURE 11.4
Results of the latent profile analysis for popularity.

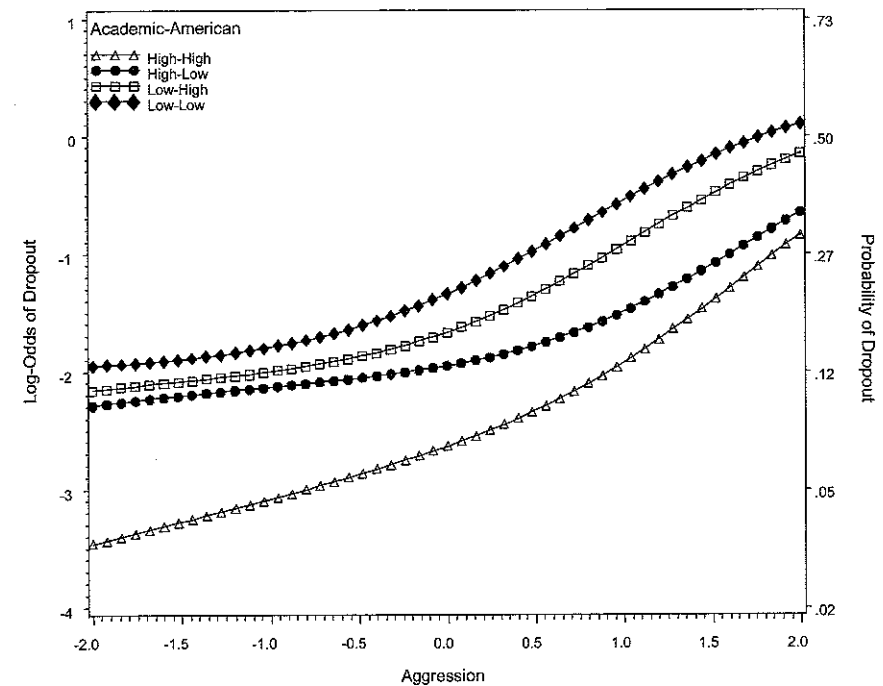


Note. The log-odds and predicted probability of school dropout by the 11th grade as a function of 7th grade popularity at high, medium, and low levels of 7th grade all-American attributes.

means do not differ across classes should not be included in such plots, as they would be noninformative with regard to the outcomes of interest.

In the present case, to generate a graph like Figure 11.1 for the ICS data from the LPA, we calculated predicted probabilities via Equation 6 for fixed values of popularity varying between -2 and 2 at low, medium, and high values of all-American (-1, 0, and 1, respectively) while holding aggression and academic competence constant at their means (0). The obtained predicted probabilities were then translated into log-odds via the transformation shown on the left side of Equation 1. The results are presented in Figure 11.4 and can be directly compared to Figure 11.1. Similarly, to evaluate the aggression \times academic \times all-American interaction, the plots shown in Figure 11.5 were generated for comparison to those previously presented in Figure 11.2. These plots provide

FIGURE 11.5
Results of the latent profile analysis for aggression.



Note. The log-odds and predicted probability of school dropout by the 11th grade as a function of 7th grade aggression for specific combinations of high and low levels of 7th grade academic competence and all-American attributes.

a basis from which to directly compare the results provided by the logistic regression model and the LPA.

COMPARISON OF PERSON-CENTERED AND VARIABLE-CENTERED APPROACHES

We first note a particularly important feature of both Figure 11.4 and 11.5; the curves relating popularity and aggression to the log-odds of dropout are not parallel across the selected levels of other ICS variables. For instance, in Figure 11.4, the curve describing the relation of popularity to the log-odds of dropout when all-American is low is much flatter than the corresponding curve when all-American is high. Similarly, in Figure 11.5, the distances between the curves describing the relation of aggression to log-odds of dropout are not equal for all

values of aggression. The lack of parallelism seen in both of these plots is the hallmark of an interaction (at least as interactions are conventionally defined in linear models). To our knowledge, these figures provide the first verification that interactions can be captured by person-centered methodology.

Given that both the person-centered and variable-centered approaches can capture interactive patterns, what are the differences between the two approaches? First, while the logistic regression model assumes that the log-odds of dropout are linearly related to the ICS variables, the LPA makes no such assumption. This difference is clearly seen by contrasting Figures 11.1 and 11.2 with Figures 11.4 and 11.5. In Figure 11.4, for instance, the effect of popularity on the log-odds of dropout is clearly nonlinear: If an adolescent is unpopular (below the mean), their level of unpopularity is relatively unimportant; but if an adolescent is popular (above the mean), the more popular the better (particularly if they also exhibit all-American attributes). Figure 11.2 leads to broadly the same conclusions, however, the assumption of linearity requires the log-odds of dropout to change (or not) at a constant rate across the entire range of popularity, suggesting that even differences among unpopular adolescents have small effects.

Comparison of Figures 11.2 and 11.5 is equally instructive. As before, the logistic regression model assumes that aggression is linearly related to the log-odds of dropout in Figure 11.2. In contrast, the curvature permitted by the LPA in Figure 11.5 suggests that differences in aggression above the mean are most predictive of the log-odds of dropout (with the exception that low aggression differentially benefits adolescents who are also high in academics and all-American).

Similarly, in the logistic regression model the interactions are also assumed to be linear in form. The assumption implies that the regression lines plotted in Figure 11.1 for popularity at high and low levels of all-American must be simple reflections of one another (i.e., reflections about the regression line plotted at the mean of all-American). In contrast, in Figure 11.4 the curve for high all-American diverges more sharply from the curve for average all-American than does the curve for low all-American. Higher order interactions, such as the three-way interaction between aggression, academics, and all-American plotted in Figure 11.2, are also assumed to be linear with respect to the log-odds in the logistic regression model. In the LPA, interactions are not constrained to have a specific form.

Thus a key advantage of the LPA is that it does not make any specific assumptions about the functional form (e.g., linear, bilinear, etc.) of the predictive relationships in the model. One could counter that if theory suggested the presence of nonlinear effects, then polynomial terms could be added to the logistic regression model (e.g., quadratic or cubic). The inclusion of product

interactions involving polynomial terms would further relax the assumption that the interactions are linear in nature. Adding these terms would, however, increase the complexity of the model considerably, requiring the parsing of additional lower and higher order effects. Generating a coherent interpretation of the model estimates would become correspondingly more difficult. Issues of power also quickly come into play. In contrast, the LPA does not require that nonlinear effects be specified a priori — they emerge naturally through the estimation of the posterior probabilities in Equation 5. Furthermore, profile plots like Figure 11.3 are relatively easy to interpret.

A second key advantage of LPA is that one can consider only those combinations of values on the predictors that are most characteristic of the data patterns in the sample. Specifically, the configurations plotted in Figure 11.3 can be considered as prototypical of the actual data patterns within the sample. Attention can then be focused immediately on these prototypical patterns. In contrast, when using the method of plotting simple slopes with traditional linear models, one must select on an ad hoc basis which configurations of values to consider. Particularly when considering higher order interactions such as the one plotted in Figure 11.2, the particular configurations chosen may be quite uncommon in the sample. For instance, fewer than 2% of the cases in the simulated ICS data have aggression scores below $-.5$, academic scores below $-.5$, and all-American scores above $.5$. Similarly, less than 2% have aggression scores below $-.5$, academic scores above $.5$ and all-American scores below $-.5$. This sparseness is partly responsible for the lack of replication of the middle two lines of Figures 11.2 and 11.5 across the two methods: The predictions made for low levels of aggression are largely based on extrapolations from other regions of the data space and are inevitably closely bound to the different assumptions of the two models. The advantage of LPA is that attention naturally focuses on the configurations represented by the latent class means rather than ad hoc combinations of values that may characterize very few individuals.

THEORY AND METHODOLOGY

Let us now consider how these results inform the debate between theoreticians and methodologists that inspired this chapter. Overall, the results appear to support the intuition of the theoreticians. Analysis of the simulated data indicated that person-centered methodology could indeed recover nonlinear and/or interactive effects. In addition, for the LPA, we demonstrated how such interactions were recovered through the probabilistic basis of the clustering model. Use of a probabilistic clustering model like LPA overcomes one of the most serious concerns of methodologists, that person-centered methodology represents nothing more than a complex categorization scheme that discards infor-

mation on continuous individual differences. In fact, this individual variation in the observed continuous variables can still be taken into account through the probabilistic basis of the model, as we demonstrated with Equation 6. On this point, however, we must also acknowledge that probabilistic clustering approaches have been applied relatively infrequently in person-centered analyses (see Shanahan & Flaherty, 2001, for a rare exception). More commonly used disjoint clustering algorithms, like *k*-means or Ward's method, would not have this important advantage, and hence the concerns of methodologists with these techniques are entirely justified.

Variable-centered models are also capable of capturing complex relationships, as was the case with the logistic regression model. Typically, nonlinear or interactive effects are specified through the inclusion of polynomial or product terms. Such terms may or may not readily capture the complex nature of the effects and, even when adequate, partition the effects of variables into lower and higher order components that can make coherent holistic interpretations difficult. The plotting of simple slopes at specific configurations of values for moderator variables can aid in the interpretation of complex interactions. As our example showed, however, there is no guarantee that the specific combinations of values chosen are actually representative of common configurations in the sample or population. In part, this is due to the fact that these values are typically chosen on the basis of univariate statistics computed for each variable separately (e.g., standard deviations or quartiles), and these statistics may not reveal relative sparseness at the multivariate level. The person-centered approach avoids each of these difficulties. The specific nature of complex effects need not be specified a priori nor assumed to have a particular form. Furthermore, modal configurations within the data are identified at the outset. This facilitates holistic interpretations by focusing attention on the relations between these specific configurations and outcomes of interest, obviating the need to select ad hoc combinations of values that may or may not be representative of the actual patterns in the data.

We have intentionally highlighted the advantages of the person-centered approach here in part to challenge methodologists to consider the potential of these models more seriously. In the past, methodologists have often shown little interest in such models. For instance, when Gibson (1959) developed the latent profile model, he hoped that it would be considered a viable alternative to the continuous linear factor analysis model of Thurstone (1935). However, subsequent comparisons of the two models have often been relatively dismissive of latent profile analysis. For example, in their compendium on latent variable modeling, Bartholomew and Knott (1999) introduced LPA with the remark "The latent profile model can be thought of as a factor model with a discrete (multivariate) prior distribution... For this reason we shall not give

an extended treatment to latent profile models," (p. 22). True to their words, Bartholomew and Knott dedicated only 4.5 pages to LPA, primarily to draw a comparison to traditional factor analysis (the subject of a 27 page chapter). Moreover, while empirical applications of factor analysis and other linear modeling approaches abound, there are comparatively few examples of latent profile analysis or other person-centered methodology in the substantive literature. We hope that the results presented here will encourage both methodologists and applied researchers to explore the possible advantages of latent profile analysis and related models for capturing complex relations between variables.

But there are drawbacks to person-centered approaches as well. For instance, while we have shown how probabilistic clustering models can recover complex nonlinear and/or interactive effects, we have not evaluated their performance for this purpose. Bauer (2005) presented results indicating that clustering models can provide unbiased and reasonably efficient estimates of continuous nonlinear bivariate relations, but it is unclear whether these results will carry over to more complex patterns involving multiple variables. In addition, direct comparisons between person-centered and variable-centered models will be of importance. For instance, variable-centered methods may outperform person-centered methods if the assumption of linearity (or bilinearity) is only modestly violated. Because variable-centered models often require fewer parameters, they may well produce more accurate and stable results with small samples than person-centered models, even when higher order effects are of primary interest. Much future research will be required to investigate and compare the finite sample performance of these models. To motivate these investigations, we would like now to discuss two areas of research where we believe the person-centered approach holds great promise, namely, the modeling of person-context interactions and developmental change.

CAPTURING PERSON-CONTEXT INTERACTIONS

There is a certain irony involved in the use of person-centered approaches for modeling interactionist theories of human development: In their focus on the person, context effects are often marginalized, despite the theoretical emphasis on interactions both within and between levels of developmental systems. This is clear even in the empirical example that we used in this chapter, where the variables were distinctly personal, in keeping with the majority of empirical applications we have seen. Several possible approaches to modeling context effects can, however, be considered.

One possibility is to define clusters or classes on the basis of both intrapersonal and contextual variables. The resulting configurations will then capture

potential interactions between the two types of variables in the way shown here. For instance, in the Cairns, Cairns, and Neckerman (1989) study that motivated our empirical example, socioeconomic status (SES) was included among the measures that were clustered to identify the individual profiles. The obtained profiles then indicated how patterns of individual functioning within specific levels of SES predicted school dropout. Clearly, one could also include several finer grained contextual variables alongside variables measuring personal characteristics.

A second strategy is to separately cluster on intrapersonal variables and contextual variables and then to examine the associations between the two sets of clusters. For instance, Xie, Cairns, and Cairns (2001) conducted parallel cluster analyses of the ICS and other measures for both individuals and the peers with whom they affiliated. Individual and peer clusters were then crossed both to determine their correspondence (typically high) and to determine whether particular combinations of individual and peer cluster membership were related to teen parenthood. Xie, Cairns, and Cairns (2001) found that, for girls, peer cluster membership was the dominant factor predicting teen motherhood. In contrast, for boys, individual and peer cluster membership interacted such that boys in high risk clusters who affiliated with peers also occupying high risk clusters were the most likely to become teen fathers.

Last, one could analyze a single set of variables that are constructed to measure the individual's transactions with his/her environment. Very little attention has been devoted to measures that capture such transactions by simultaneously referring to aspects of both person and context. One simple possibility, however, is suggested by Shanahan and Flaherty's (2001) analysis of how much time teenagers spent engaged in several domains (e.g., in the workplace, school, with peers, parents). Such measures are behavioral, and yet begin to describe the social worlds that youth construct and participate in.

Further thought should be given to these and other ways of optimally modeling context effects from a developmental systems perspective.

DEVELOPMENT

A second apparent inconsistency in the use of person-centered approaches for modeling developmental systems is that there are relatively few options for modeling change over time. As noted by Bergman (1998), two general strategies have been considered. The first strategy is to classify individuals into categories based on their patterns of change on a specific variable of interest (e.g., aggression or alcohol use). Here, three approaches have been proposed. The first approach is to cluster analyze or conduct an LPA on the repeated measures across time for a single construct. The results can then be described as

longitudinal profiles. An advantage of this approach is that the repeated measures need not be commensurate. For instance, when studying a construct that shows heterotypic continuity, the measurement of the construct might change from one age to the next. With commensurate measurement across time, the longitudinal profiles can be thought of as trajectories of change over time. One may then wish to impose a specific structure on these trajectories, such as a linear or quadratic trend. Imposing such a structure on an LPA model leads to the latent class growth model of Nagin (1999).

In Nagin (1999) approach, latent trajectory classes are defined similarly to the LPA. All individuals within a class are presumed to share a common class trajectory (true scores). The only difference is that the class trajectory (true scores) are assumed to follow a particular polynomial trend over time. If the assumption of homogeneity within classes is relaxed, then the growth mixture model of Verbeke and Lesaffre (1996) is obtained, a model that has recently been extended and popularized by B. Muthén and Shedden (1999). In the general growth mixture model, each individual is assumed to follow a unique trajectory, however, within each latent class, the individual trajectories are normally distributed around the class mean trajectory. That is, there is both between-class and within-class heterogeneity in change over time (fixed and random effects).

The increasing popularity of latent class growth models and growth mixture models, particularly in research on developmental psychopathology and substance use, attests to their appeal for examining heterogeneous patterns of change. The complexity of these models will, however, often preclude modeling change in more than one or two variables simultaneously. The strategy of forming longitudinal clusters is thus not really person-centered because it is not suited to modeling the possible interactions that may occur among a set of variables over time.

An alternative advocated by Bergman (1998) is to identify configurations of variables at each point in time and then to link configurations over time. The potential of this strategy to identify new patterns as they emerge developmentally is particularly appealing. However, linking configurations over time also has drawbacks. First, transition patterns are typically examined between successive waves of assessment, requiring relative age homogeneity within wave and ignoring potentially lagged trends between, say, Wave I and Wave III that are not mediated by Wave II. Furthermore, interpretation can become considerably more cumbersome as the number of waves increases, particularly if there are more than a few within-wave clusters.

A second limitation of this strategy concerns implementation. Typically, individuals are assigned to clusters at each point in time and then movement is examined from one cluster to another over time. In addition to introducing

classification errors that may bias estimates of the frequencies of these transitions, if the individual probabilities of class membership are not retained then information on potentially important individual differences is likely to be obscured. A latent transition analysis is an alternative probabilistic clustering approach that would avoid these difficulties (Collins, Hyatt, & Graham, 2000; Lanza, Flaherty, & Collins, 2002).

CONCLUSIONS

Capturing emergent and changing person-context interactions is unequivocally one of the most significant methodological challenges that developmental researchers face. A key goal of this chapter was to suggest that the person-centered approach may well play an important role in addressing this challenge in the future. We demonstrated that some person-centered methods, namely probabilistic clustering models, appear to be particularly well-suited to capturing complex interaction patterns within time. We also suggested several possible ways that these models could be extended to examine interaction patterns over time. Our hope is that this initial demonstration of the promise of these models will help to spur research by other methodologists and applied researchers to further evaluate the usefulness of these models for studying person-context interactions in human development.

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