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Invited Commentary—Promising Methodological Strategies

Latent class/profile analysis in maltreatment research: A commentary on Nooner et al., Pears et al., and looking beyond

Scott C. Roesch[a,*], Miguel Villodas[b], Feion Villodas[b]

[a] San Diego State University, San Diego, CA, USA
[b] San Diego State University/University of California, San Diego, Joint Doctoral Program in Clinical Psychology, San Diego, USA

Latent class (LCA) and latent profile (LPA; also referred to as continuous LCA) analyses are person-centered statistical techniques that allow researchers to assign individuals to one mutually exclusive class (or profile) based on their responses to observed variables of interest (e.g., maltreatment types). Resultant classes are then substantively characterized by interpreting common patterns of responses within and between the classes/profiles. These techniques, part of a broader class of statistical models referred to as finite mixture models (see McLachlan & Peel, 2000), allow researchers to identify *typologies of people* rather than a *taxonomy of variables* as is customary in research using exploratory or confirmatory factor analysis. The LCA of Nooner et al. (2010) and the LPA of Pears, Kim, and Fisher (2008) both display the usefulness of these techniques with maltreatment data. Moreover, they have extended the limited number of LCA/LPA studies in the maltreatment field (e.g., Romano, Zoccolillo, & Paquette, 2006) by identifying multidimensional class/profile solutions that are more sophisticated than *no maltreatment* class/profile and a *at least one type of maltreatment* class/profile. The primary goal of this commentary is to provide a brief, user-friendly approach to conducting LCA/LPA. To that end, we (1) conceptually describe the goals of LCA/LPA, (2) highlight decision-making rules and practical issues of primary importance when applying LCA/LPA, and (3) identify new applications of finite mixture models as they could potentially be applied in maltreatment research. Throughout this commentary we critique both the Nooner et al. and Pears et al. studies.

While the use of LCA/LPA has increased in recent years with child and adolescent samples (see examples of uses below), the application of this technique has been slower in maltreatment research (however, see McCrae, Chapman, & Christ, 2006; Romano et al., 2006). LCA has been applied to a variety of research designs in the social and behavioral sciences. For example, LCA has been used to identify patterns of co-occurrences for general problem behaviors during adolescence (Fergusson, Horwood, & Lynskey, 1994; Thompson, Brownfield, & Sorenson, 1998), child academic, social, and behavior problems (Reinke, Herman, Petras, & Ialongo, 2008; Tolan & Henry, 1996), temperament, interaction styles, and peer play in infants and toddlers using observational data (Loken, 2004; Webels & von Eye, 1996), and delinquent behaviors among adolescents (D'Unger, Land, & McCall, 2002; Odgers et al., 2007). Moreover, LCA has been used to identify patterns of comorbidity for psychiatric symptoms of affective disorders (Ferdinand, Bongers, et al., 2006; Ferdinand, de Nijs, van Lier, & Verhulst, 2005; Ferdinand, van Lang, Ormel, Verhulst, 2006; van Lang, Ferdinand, Ormel, & Verhulst, 2006; Wadsworth, Hudziak, Heath, & Achenbach, 2001), conduct disorder (Nock, Kazdin, Hirip, & Kessler, 2006) attention-deficit/hyperactivity disorder (ADHD; Althoff, Copeland, et al., 2006; de Nijs, Ferdinand, & Verhulst, 2007; Neumann et al., 1999), ADHD with other psychiatric disorders (Acosta et al., 2008; Volk, Neuman, & Todd, 2005), disruptive behavior disorders (de Nijs, van Lier, Verhulst, 2007; Sondeijker et al., 2005; Storr, Accornero, & Crum, 2007; van Lier, Verhulst, van der Ende, & Crijnen, 2003), hallucinogen dependence syndromes (Stone, Storr, & Anthony, 2006), and nonverbal learning disabilities (Ris et al., 2007).

In addition to the identification of patterns of behaviors and psychiatric symptoms and disorders, LCA has been applied in the examination of the co-occurrence of aspects of the social environment. For example, LCA has been used to identify patterns of environmental risk and protective factors for academic, psychological, and behavior problems (Bowen, Lee, & Weller, 2007; Walrath et al., 2004), adverse life experiences (Shevlin & Elklit, 2008), and peer victimization (Nylund,

* Corresponding author address: Department of Psychology, San Diego State University, 5500 Campanile Drive, San Diego, CA 92182-4611, USA.

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Muthén, & Asparouhov, 2007). Other uses of LCA include the transmission of mother-infant attachment representations using dyadic data (Bailey, Moran, Pederson, & Bento, 2007), assessment and diagnosis procedures for psychological disorders using cognitive diagnosis models (Templin & Henson, 2006), information processing styles in peer relationship scenarios (Sharp, Croudace, & Goodyer, 2007), and the heritability of juvenile bipolar disorder in twins (Althoff, Rettew, Faraone, Boomsma, & Hudziak, 2006).

As noted earlier, both LCA and LPA are person-centered statistical approaches that classify individuals into groups based on their patterns of responses to sets of observed variables (see Gibson, 1959; Hagenaars & McCutcheon, 2002; Lazarfeld & Henry, 1968; McCuthcheon, 1987 for a more technical description of these techniques; see Lanza, Flaherty, & Collins, 2003 for a less technical description). The primary goal is to maximize the *homogeneity* within groups (i.e., individuals within a class/profile should look similar) and maximize the *heterogeneity* between groups (i.e., individuals between classes/profile groups should look different). These groups are represented by a categorical latent variable, as they are not directly known but are inferred from the response patterns on observed variables. In the Nooner et al. study the observed variables were dichotomous items reflecting self-reported physical and sexual abuse, and in the Pears et al. study the observed variables were the severity level of each maltreatment type based on CPS reports. LCA and LPA differ primarily in the type of observed variables used and the descriptive data that emanate from these observed variables. In LCA, observed variables are categorical in nature, whereas in LPA the observed variables are continuous. Please note, however, that categorical and continuous observed variables can be used in the same analysis.

After assessing model assumptions (see Bauer, 2007; McLachlan & Peel, 2000), the determination of the *optimal* number of classes/profiles (referred to as class enumeration) is initiated. This requires the specification and testing of multiple class solutions (1-class, 2-class, 3-class, etc.). From these models, the designation of the "best-fitting" model is determined using a variety of statistical indicators. Those familiar with categorical variable methodology (e.g., log-linear modeling) or structural equation modeling might assume that the likelihood ratio test statistic (G^2) or the log likelihood difference test could be used to determine overall model fit in LCA/LPA. These test statistics can be inaccurate, however, when used in LCA/LPA because the χ^2 distribution (and by implication the test statistic) cannot be approximated when (a) cells indicating response patterns in the multiway contingency table have a zero frequency and (b) comparisons between nested models (e.g., 1-class vs. 2-class) are of interest (see Nylund, Muthén, & Asparouhov, 2007). To overcome the limitations of these more traditional test statistics, the Lo–Mendell–Ruben Adjusted Likelihood Ratio Test (LMRT; Lo, Mendell, & Rubin, 2001) was developed as an inferential statistical test to determine model fit. The LMRT provides an indication of statistically significant improvement in fit for a model with *k* latent classes/profiles as compared to a model with *k–1* latent classes/profiles by approximating the differences between two log likelihood values (instead of using the χ^2 distribution). Thus, a significant LMRT test indicates that a more complex model (e.g., 3-class) provides superior fit to a less complex model (e.g., 2-class). A second inferential test that could be used when evaluating class enumeration is the Bootstrapped Likelihood Ratio Test (BLRT; Arminger, Stein, & Wittenberg, 1999; McLachlan & Peel, 2000). Rather than approximating a log likelihood difference distribution like the LMRT does, the BLRT in effect estimates a "difference" distribution by which different models can be compared, through the use of repeated sampling methods. The conceptual approach of the LMRT and the BLRT are similar in that each are statistically comparing more complex models to less complex models. However, they differ in the underlying distribution that is used to make the statistical determination. Both inferential tests are readily available in statistical software packages such as MPlus (Muthén & Muthén, 2006).

In addition to the LMRT and the BLRT, a number of fit indicators based on information criteria have also been employed, and include the Akaike Information Criteria (AIC; Akaike, 1974), the Bayesian Information Criterion (BIC; Schwarz, 1978), and the sample size-adjusted BIC (Sclove, 1987); each of these information criteria is based on the log likelihood function for individual models (rather than comparing two log likelihood values as the LMRT and BLRT do). All three statistical indicators penalize models for estimating too many parameters; moreover, both versions of the BIC further penalize models by sample size. None of these information criteria can determine model fit for the evaluation of individual models in isolation. A determination of the best-fitting class/profile solution, then, is based on which model has lower values for these fit indicators (lower values indicates better relative fit). Recent simulation studies have identified the sample size-adjusted BIC (Tofighi & Enders, 2007; Yang, 2006) and the BLRT as the most accurate in deciding on number of classes (Bauer, 2007; Henson, Reise, & Kim, 2007; Nylund, Muthén, et al., 2007). However, Nylund et al. also found the BIC to be a good indicator of class enumeration, and a better statistical indicator than the sample size-adjusted BIC, with no significant difference in the power levels between the LMRT and the BLRT.

An underused statistical indicator of class enumeration is entropy (Ramaswamy, DeSarbo, Reibstein, & Robinson, 1993). Entropy is a measure of how well classes or profiles can be distinguished or the percentage of individuals in the sample that were correctly classified given the specific class model. In contrast to other statistical grouping approaches like cluster analysis, individuals in LCA/LPA are assigned a *posterior probability* for each class/profile rather than assigned outright to one and only one class/profile. These posterior probabilities are a function of each individual's response pattern, the number of latent classes/profiles, and the proportion of individuals estimated to be in each class/profile. For example, assume we are statistically evaluating a 3-class model. An individual would have a posterior probability for class/profile 1 (e.g., .65), class/profile 2 (e.g., .25), and class/profile 3 (e.g., .10). Because the posterior probability for this individual is highest in class/profile 1 she would be "assigned" to that class. However, the flexibility of LCA/LPA accounts for the likelihood that there is uncertainty in class/profile membership. Entropy, then, is the aggregate of these posterior probabilities, with values greater than 80% considered noteworthy (Ramaswamy et al.). To underscore the importance of entropy, Lubke and Neale

(2006) identify class/profile separation and classification as a key issue in all finite mixture models. Obviously the number of statistical indicators one could use to determine which class/profile solution might be optimal is quite large. Because the majority of these are available in statistical software packages, it is quite reasonable to recommend that researchers consult all indicators. However, when discrepancies exist in identifying the best-fitting class/profile solution, the BIC, BLRT, and entropy appear to be the most robust indicators that reveal the *true* class/profile structure. Adhering to good statistical practice, both the Nooner et al. and Pears et al. studies used a number of statistical indicators to determine overall model fit. However, neither used what might be the most promising indicator, the BLRT.

To further aid in the determination of the optimal number of classes/profiles, the interpretability of each class or profile must be considered. When evaluating the numerous statistical indicators identified above, it is quite common that inconsistencies in determining which class/profile solution fits best will occur, as was found in both the Nooner et al. and Pears et al. studies. Thus, the interpretability of each class/profile could facilitate the determination of whether or not a specific class solution is more consistent with past theory and empirical research. There are two primary model parameters that are useful in this regard: (1) conditional response probabilities (CRP) in LCA and conditional response means (CRM) in LPA; and (2) latent class probabilities (LCP) in both LCA and LPA. CRPs and CRMs are analogous to factor loadings (Lanza & Collins, 2008). CRPs refer to the probability for each observed variable *within* a latent class being present; for example, a CRP value of .90 for an observed variable in class 1 would reflect that 90% of the individuals within this class endorsed or evidenced this variable (e.g., indicated *yes* for "hit with a dangerous object"). CRMs refer to the mean for each observed variable *within* a latent profile; for example, a CRM value of 4.25 for an observed indicator of the severity of sexual abuse would be the average for this variable for participants in this profile. Thus, these classes/profiles are substantively characterized by interpreting responses within and between classes. This characterization is largely descriptive and can be based on clinical cut-points, norms, and standard deviations for target observed variables.

LCPs indicate the prevalence of each case in a class and are analogous to factor scores (Lanza & Collins, 2008). Once classes/profiles are substantively interpreted the probability or the proportion of cases within each class/profile helps identify the prevalence of class/profile membership. For example LCP values of .80 for a normative class (no maltreatment), .15 for a primarily neglect class, and .05 for a primarily sexual abuse class would reflect that the sample has generally (80%) not been maltreated. However, the latter two classes would identify groups of youth that have been maltreated. It should be noted that small classes (those with LCP values <.05) could be considered spurious, a condition often associated with extracting too many classes/profiles (Hipp & Bauer, 2006). This is potentially a problem in the Nooner et al. study, where three of the four classes have LCP values between .03 and .06. This appears to be less of a problem in the Pears et al. study where the smallest profile had an LCP value of .09. This is not to say that small classes/profiles are always statistical anomalies, but rather that validation of these classes is required to demonstrate their stability, as was done in both the Nooner et al. and Pears et al. studies (see also a recent study by Bradshaw, Buckley, & Ialongo, 2008).

Finally, we would like to briefly discuss three important issues in applying LCA/LPA: (1) small sample sizes, (2) missing data, and (3) local solutions (optima). Because LCA/LPA are latent variable techniques large sample sizes are generally required. While these approaches have been used successfully with smaller sample sizes (e.g., Bailey et al. [2007] used 76 dyads, Acosta et al. [2008] used 107 children, and Pears et al. [2008] used 117 children), unstable class/profile solutions can result. The simulation study by Nylund, Muthén, et al. (2007) found that the only statistical indicator of overall model fit that performed reasonably well with a sample size of 200 was the BLRT. Second, missing data are allowable on the observed variables of an LCA/LPA if the data are missing at random. However, if an observed variable is determined to be missing not at random (MNAR or non-ignorable missingness), then the maximum likelihood estimation procedure commonly employed will likely result in biased parameter estimates (Little & Rubin, 1987). MNAR occurs when the reason for missingness on an observed variable is a function of the observed variable itself; for example, when extreme physical abuse would preclude an adolescent from completing a self-report physical abuse measure. When data are deemed MNAR one can stratify the sample by missing data pattern and then aggregate over strata to eliminate any bias. Examples of this latent pattern mixture modeling approach are available (see Lin, McCulloch, & Rosenheck, 2004; Roy, 2003). Third, statistical indicators of overall model fit (e.g., BIC) are based on likelihood functions. The mathematical goal of these functions is to identify the most accurate solution/model (referred to as the global solution). However, finite mixture models in general are known to have likelihood functions that perform erratically (referred to as local optima; see Hipp & Bauer, 2006). These local optima then can *trick* the applied user into thinking they have identified the best solution. To overcome this, programs such as MPlus evaluate models with multiple sets of starting values to help determine if the global likelihood can be replicated, and thus indicate the correct class/profile solution.

What lies beyond LCA/LPA?

Additional latent variable models building on LCA/LPA have been developed and are applicable to maltreatment researchers. For example, combination or hybrid models (see Muthén, 2006) merge the logic and estimation procedures of LCA/LPA and factor analysis. This approach allows variables within each class/profile of the LCA/LPA to be correlated, thus accounting for within-class heterogeneity. Individuals within a class are similar, but they are certainly not identical to one another. Allowing observed variables to correlate within a class can explain (or reduce) this variation further. For example, when using maltreatment *subtype* variables (neglect, sexual abuse, and physical abuse) as the observed indicators, a common correlation might emerge among the variables in one class that represents the severity of maltreatment. One could also move from the exploratory LCA/LPA conducted by Nooner et al. and Pears et al. and conduct confirmatory LCA/LPA (Lanza, Collins, Lemmon, & Schafer, 2007; Laudy, Zoccolillo, Boom, Tremblay, & Hoijtink, 2005 and Sharp et al., 2007 for examples) where equality constraints are applied to conditional response probabilities/means to represent different theoretical orientations that are of interest. One could also test for class structure differences as a function of ethnicity, gender, and/or culture, for example, using a multiple group LCA/LPA (see Diener, 2003).

Popular theories of developmental psychopathology suggest that as children develop, they master stage salient skills or processes via representational models, which may play an integral role in more complex behavioral and cognitive processes later in development (Cicchetti, 2006; Cicchetti & Valentino, 2006). Disruption of the acquisition of these skills or processes could interfere with future cognitive abilities or information processing skills. Cicchetti and Valentino (2006) further review empirical evidence for the role of maltreatment in the disruption of developmental processes, underscoring the importance of applying longitudinal data analytic models in order to understand changes in these processes over time. Latent transition analysis (LTA) is the longitudinal extension of LCA/LPA and is therefore much more suited for these types of research questions. It is quite common for youth to move between classes/profiles along the developmental course. For example, a group of youth may move from a no maltreatment class/profile at age 12 to a sexual abuse/physical abuse class/profile at age 14. The transition (movers) or stability (stayers) in class/profile membership can be explicitly modeled in LTA and used for predictive purposes (see Chung, Park, & Lanza, 2005; Reinke et al., 2008 for examples). Moreover, this model can be extended to comparing change across two or more processes across time (associative latent transition analysis; see Flaherty, 2008).

LTA (and repeated measures LCA/LPA [see Hill, Degnan, Calkins, & Keane, 2006]) is a grouping technique that is employed when no underlying growth trajectory is expected over time. Building on the conceptual underpinnings of latent growth curve modeling and LCA/LPA, growth mixture modeling (GMM; Muthén, 2004; Nagin, 2005) identifies classes/profiles of individuals that share a common growth trajectory over time. For example, assume that severity of physical abuse is measured in a sample of youth at 6, 8, 10, 12, and 14 years of age. GMM could empirically identify one group of youth that (linearly) increase in severity over time (at risk group); one group of youth that start out high in physical abuse but the growth trajectory declines across time (a "recovery" group); and a group of youth that have consistently low physical abuse across time (a normative group). These classes/profiles of trajectories, then, could be predicted by early childhood variables (e.g., home environment) or used to predict distal outcome variables (e.g., dropout rates in high school).

Final thoughts

LCA/LPA are useful tools for describing individual differences in the response patterns of individuals on observed variables. Moreover, these techniques are easily implemented using statistical software packages such as Latent Gold (Vermut & Magidson, 2005), Proc LCA (see Lanza, Collins, Schafer, & Flaherty, 2005), MPlus (Muthén & Muthén, 2006), poLCA (Linzer & Lewis, 2007), SPlus (see Loken, 2004), and LCAP (see Neumann et al., 1999). Ease and accessibility, however, are no substitute for rigorous and repeated assessment and confirmation of class/profile structures. As noted by Bauer (2007), confidence in classes or profiles derived from finite mixture models only comes from confirming the class/profile structure across samples, types of observed variables, and so on, and establishing strong convergent and discriminant validity with target antecedent, concomitant, and outcome variables. Both the Nooner et al. and Pears et al. applications of LCA/LPA are a good first step towards this end.

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