ARTICLE

ASSESSING PERSON-CENTERED OUTCOMES IN PRACTICE RESEARCH: A LATENT TRANSITION PROFILE FRAMEWORK

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Advances in statistics provide new methods for analyzing practice data. These advances include person-centered methods (PCMs) that identify subgroups of research participants with similar characteristics. PCMs derive from a frame of reference that is similar to the risk factor perspective in practice. In practice, the delivery of services is often contingent on identifying at-risk populations and then providing interventions to groups based on shared risk profiles. PCMs use this perspective. Moreover, PCMs provide a means for identifying high-risk groups with a precision rarely afforded by routine variable-centered methods. This article describes a latent profile transition analysis (LPTA), one of several PCMs. To demonstrate LPTA, we estimate risk profiles and treatment effects using data from a cohort study of a school-based social skills training program. We define four steps in PCMs analysis, describe key statistical tests, and conclude with a discussion of the strengths and limitations of PCMs for practice research. © 2011 Wiley Periodicals, Inc.

Aggressive behavior in childhood is a significant predictor of conduct problems in adolescence and young adulthood (Dodge & Pettit, 2003). However, designing interventions to disrupt developmental trajectories between early aggressive behavior

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and later conduct problems is challenging because no single set of risk factors adequately accounts for behavior problems. Aggressive behavior, which is behavior intended to harm others, has many different forms. These forms cluster in a range of risk profiles that may require different kinds of practice strategies. Further, risk profiles are often dynamic and likely to change over the course of children's development. Therefore, practitioners, policy makers, and scholars concerned with aggressive behavior, delinquency, and other conduct problems have given increasing attention to developmental studies of changes in risk profiles over time (Singer & Willett, 2003). In addition to the study of developmental patterns, longitudinal designs provide the potential for understanding of the effects of interventions over time, including the effects of interventions on risk profiles.

The growing use of risk assessment – and a risk and protective factor perspective – has paralleled rising interest in person-centered methods (PCMs; Bogat, Levendosky, & Von Eye, 2005; Neely-Barnes, 2010; Nurius & Macy, 2010; Schwalbe, Macy, Day, & Fraser, 2008). PCMs cluster people with similar scores on risk (or other) factors, and these methods enable researchers to analyze changes in groups of similar people (Bogat et al.; Magnusson, 1998; Magnusson & Peel, 2000). PCMs complement general linear models (GLMs), which are dominant in the social and behavioral sciences (Carins & Rodkin, 1998; Fraser, Richman, & Galinsky, 1999; Magnusson).

Thus far, the application of PCM in practice research is limited. Using PCMs can be challenging because of the methodological issues that arise in configuring data, estimating models, and evaluating fit. These issues include (a) accounting for assignment to treatment or comparison conditions, (b) adjusting for nested data (e.g., families nested in neighborhoods), and (c) including covariates and interactions in models. To address these issues, this article describes a longitudinal PCM—latent profile transition analysis (LPTA)—and demonstrates the specification, estimation, and analysis of a LPTA using two waves of data. We begin by comparing traditional and latent class approaches to the study of change. Next, as an analytic example, a LPTA model is applied to data from an evaluation of Making Choices (MC; Fraser, Nash, Galinsky, & Darwin, 2001) (names and citation are masked for review). We conclude by discussing the strengths and limitations of PCMs for practice research.

Variable Centered Methods for Analyzing Change

Typically, change is analyzed using extensions of GLMs such as regression analysis. GLM estimates how variables contribute to practice outcomes. Multiwave GLMs (i.e., based on two or more data collection time points) can include time variant and invariant covariates plus nonlinear terms (Bollen & Curran, 2006). In addition, GLMs accommodates nested or complex survey data and is used to partition variance to examine inter-person and intra-person differences (Bryk & Raudenbush, 1992). Thus, GLMs are powerful statistical techniques that are critically important for practice research. However, to identify subgroup effects within GLMs, researchers must test for interactions between variables. For example, a researcher might code male as 1 to denote the subsample of males and then create an interaction term involving MALE and an intervention indicator to assess intervention effects for males. More complex interactions may be created to identify subgroups of males, e.g., Latino males or young Latino males. These types of analyses require relatively large sample sizes. When samples are small and statistical power is low, GLMs can fail to capture the heterogeneity of small subpopulations (Muthén & Muthén, 2000) that are defined by combinations of three, four, or more variables. Consequently, the intervention effect on a small subsample may be "masked" within overall group means. If only a small fraction of participants show a different intervention outcome, then GLMs may fail to detect it.

Person Centered Methods for Analyzing Change

The term *person centered* describes a variety of statistical approaches for identifying research participants with similar scores on variables of interest (Gibson, 1959; Macy, 2008; Neely-Barnes, 2010). Similar participants are aggregated into clusters, groups, classes, or profiles (these terms are often used interchangeably in the person-centered literature). Latent class analysis (LCA) is perhaps the most common PCMs approach. LCA is a cross-sectional procedure for studying subpopulations with shared scores on categorical or ordinal observations (Muthén, 2001; Reboussin, Reboussin, Liang, & Anthony, 1998; Velicer, Martin, & Collins, 1996). When data are continuous, the term "profile" is used instead of "class," and the modeling approach is called latent profile analysis (LPA).

LCA and LPA are similar to traditional cluster analysis. Traditional cluster analysis methods use estimation procedures that minimize the mean differences between clusters. LCA and LPA differ from cluster analysis in that they are based on latent measurement theory. Latent measurement theory suggests membership in the latent class drives the covariance among the observed variables, similar to a latent construct in a factor analysis (McLachlan & Peel, 2000; Vermunt & Magidson, 2002). The latent approach assumes there are unobserved subgroups comprised of individual participants with similar scores on observed measures. However, the group membership is not known and is inferred through a set of relevant variables determining each participant's association in one of *k* latent classes or profiles.

Latent transition analysis (LTA) and LPTA extend LCA and LPA to longitudinal data by integrating autoregressive modeling (i.e., Markov modeling; Nylund, Muthén, Bellmore, & Graham, 2006) to examine how group membership changes over time. Transitions between profiles from one time point to the next are calculated, and are estimated dependent on baseline profile membership, covariates, and treatment assignment. Thus, LPTA simultaneously estimates (a) discrete profiles, (b) membership in those profiles, and (c) transitions between profiles over time.

LPTA and LTA may be used to study practice effects by comparing the transitions between profiles of research participants assigned to treatment and control conditions (Collins Graham, Rousculp, & Hansen, 1997). In the study described below, we estimated the response to treatment by comparing the transition patterns of children in intervention versus control groups. The data were used to derive profiles based on risk measures, and then treatment assignment and the probability of transitioning between risk profiles were used to estimate a program effect. Alternatively, treatment assignment can be considered as a covariate (cf. Connell et al., 2008; Nylund et al., 2006), but modeling treatment as a covariate requires additional model statements and product terms.

METHOD

To demonstrate LPTA with treatment assignment, we used data from a study of the MC program for third grade children (Fraser et al., 2001). The study used a 4-year

Table 1. Demographic Characteristics of Participants by Cohort

			Race/ethnicity				Gender	
Cohort	Tx	n	Euro Am (%)	African Am (%)	Latino Am (%)	Other (%)	F (%)	M (%)
2000	CC1	177	51 (28.0)	40 (22.6)	75 (42.4)	11 (6.2)	91 (51.4)	86 (48.6)
2001	MC	173	59 (34.1)	38 (22.0)	68 (39.3)	8 (4.6)	83 (48.0)	90 (52.0)
2002	MC+	198	78 (38.4)	50 (15.2)	83 (41.9)	7 (3.5)	95 (48.0)	103 (52.0)
2004	CC2	140	34 (24.3)	20 (14.3)	82 (58.6)	4 (2.9)	74 (52.9)	66 (47.1)
Totals (%)		688	222 (32.3)	128 (18.6)	308 (44.8)	30 (4.4)	343 (49.1)	345 (50.1)

sequential cohort design to estimate program effects across two intervention cohorts and two control cohorts. The nested nature of the data required model constraints to adjust standard errors for the dependence of children within classrooms.

Participants and Design

The sample comprised 688 third grade students from one rural and one suburban school in a Mid-Atlantic state. Four sequential cohorts of students in the third grade were assigned to intervention or control conditions (see Table 1). Cohort 1 served as a control condition and received routine health classes. Cohort 2 received the MC program, and Cohort 3 received MC *plus* additional classroom activities to reinforce the MC content (hereafter MC+). Cohort 4 was lagged one school year and served as the second control condition.

Intervention Procedures

Based on research linking aggressive behavior in childhood to deficits in social information processing competencies, MC is a social-cognitive skills training program for third-grade students (Fraser et al., 2005). Across a seven-unit curriculum, 21 classroom-based lessons provide children with training in social information processing skills. Through these lessons, children learn to encode social cues, interpret the intentions of others, set social goals, generate alternative strategies to achieve goals, and enact strategies that strengthen social relationships. MC classroom exercises were delivered weekly by program specialists with training in psychology, social work, and education. Fully manualized, MC lessons use cooperative learning activities to reduce aggressive behavior and promote engagement, social competence, and peer acceptance.

Measures

Pretest and posttest data were collected from classroom teachers using the Carolina Child Checklist-Teacher Form (CCC-TF; Macgowan, Nash, & Fraser, 2002). The CCC-TF is adapted from the Social Health Profile (Fast Track Project, 1997), which itself was adapted from the Teacher Observation of Classroom Adaptation–Revised (Werthamer-Larsson, Kellam, & Wheeler, 1991). The CCC-TF is a 37-item scale used to obtain teachers' ratings of children's risk behaviors. The analysis used subscales from the CCC-TF measuring the following: overt aggression (OvAgg; $\alpha = .79$), social aggression (RelAgg; $\alpha = .80$), cognitive concentration (CogCon; $\alpha = .97$), and social competence (SocCom; $\alpha = .91$), and two items that indicated whether a teacher perceived a student was liked or disliked by classroom peers (Liked; $\alpha = .81$). Each item was rated on a 6-point Likert scale, ranging from 0 (*never*) to 5 (*always*). Before composites were calculated, negatively worded items were reverse coded so higher values would indicate a more desired state (e.g., disliked by peers = 5 indicated a child was *never* disliked by peers). For a detailed description of the psychometric properties of the CCC-TF, see Macgowan et al.

Data Analysis Strategy

Two general issues arise in PCMs with longitudinal data. These issues include determining (a) the number of groups across data collection waves and (b) the form of the model (Neely-Barnes, 2010; Vermunt & Magidson, 2002). To address these issues in a systematic fashion, Nylund and colleagues (2006) recommended a four-step strategy. The first step is to examine the descriptive, distributional, and correlational properties of the variables of interest. In the second step, LCA or LPA models (depending on whether variables are categorical or continuous) are fit cross-sectionally at each data collection wave. These models are fit by successively increasing the number of groups and comparing different models using parameter estimates, fit indices, and meaningful substantive interpretation in terms of prior research and theory. In the third step, solutions are estimated simultaneously across all waves of data. Using fit statistics (for a review, see McCutcheon, 2002; Muthén & Muthén, 2000), the multiwave models—in our case, LPTA—are examined for consistency and theoretical relevance. In the fourth step, using the best fitting multiwave model, transition patterns of group membership from one point to another, and posterior probabilities are estimated. Posterior probabilities provide a measure of how distinct the estimated group profiles are and how well individual participants are classified into particular profiles (Muthén, 2002).

Evaluating model fit. Beginning with Step 2 of the analysis strategy, the bootstrapped likelihood ratio test (BLRT) and the Bayesian information criterion (BIC; Schwartz, 1978) are used to select the number of profile groups (Nylund, Asparouhov, & Muthén, 2007). The BLRT provides significance testing for the ratio of a model with k groups to a model with $k-1$ groups (Nylund et al., 2007). Similar to the BLRT, the Lo-Mendall-Rubin is a ratio test (LMR; Lo, Mendall, & Rubin, 2001) of a model with k groups against a model with $k-1$ groups.

In assessing fit, entropy (Celeux & Soromenho, 1996), Akaike information criterion (AIC; Akaike, 1974), and the BIC are used. Entropy is a summary statistic of all posterior probabilities derived by the model. There are no recommended cutoff values for entropy, although values approaching 1 indicate meaningful differences between profile groups (Celeux & Soromenho). AIC is a measure of the extent to which a model fits the data, while minimizing the number of parameters used to estimate it. Similarly, the BIC describes the extent to which a model reproduces the covariance matrix of the data, while simultaneously reducing the number of parameters required to estimate the model (Krueger et al., 2002). Models with lower AIC and BIC values are preferred.

When determining the fit and ultimately the selection of a solution using the BIC, Raferty argued that BIC differences greater than 10 equate to "150:1 odds" that the model having the smaller BIC value is preferred (Raferty, 1995, p. 133). However, model parsimony should be balanced with the substantive interpretation, which is typically derived from theory and prior research, of the profile groups. Substantive meaning is considered paramount in specifying one well-fitting solution over another (Kline, 2004; McCutcheon, 2002; Muthén & Muthén, 2000).

Estimation of the latent profile transition model with an intervention. All of the analyses for the current study were completed with Mplus 6.0 (Muthén & Muthén, 2010), though other statistical programs may be used to estimate these models (e.g., Latent GOLD, SAS [Proc LCA and Proc LTA], STATA, and WinLTA). Follow-up analyses of posterior probabilities and transition patterns were completed using SPSS 18.0 (SPSS, 2010).

Mplus allows for the creation of a latent variable to indicate treatment assignment. It also provides controls for nested data and the specifications needed to compare different latent profile solutions. The "Knownclass" command allows an estimation of effects for intervention and comparison treatment groups separately. The "Cluster" command controls for the violation of the independence assumption inherent in nested data. This command assigns penalties in the calculation of standard errors to result in robust statistical tests (i.e., similar to a Huber-White correction Asparouhov & Muthén, 2008). In the current study, students were nested in 33 classrooms and two schools. Given the nesting of classrooms in only two schools, school-level effects were fixed as other covariates such as race/ethnicity and gender.

Model specification. LPTA models can be used to estimate program effects by comparing the transition patterns of participants in treatment and control conditions (Collins et al., 1997). In LPTA, an LPA is estimated across each data wave to identify participants with similar profiles and to classify participants into profile groups. Next, LPTA uses autoregressive modeling to estimate the probability of participants transitioning among profile groups between two data collection waves. These transitions are conditioned on treatment assignment and other covariates. In this way, LPTA estimates: (a) discrete profiles across all waves of data, (b) participant membership in profile groups, and (c) person-level probabilities of transitioning among profiles between data collection waves. A technical description of the model specification is attached as an appendix.

RESULTS

Shown in Figure 1, four latent risk profile groups fit the data. Based on substantive interpretations, we labeled them as follows: high risk (HR), moderate risk with high aggression (MRHA), moderate risk with low aggression (MRLA), and low risk (LR). The results are organized according to the four-step modeling process described above.

Step 1: Examine the Descriptive and Distributional Properties of the Data

All four cohorts were statistically similar on time 1 measures and demographic characteristics (e.g., race and gender). Table 1 presents the gender and race/ethnicity of each cohort. Table 2 shows the correlations, means, standard deviations, and skewness of the model variables.

Step 2: Conduct a Cross-Sectional Analysis With LPA

LPA models were estimated without covariates and then with covariates. Shown in Table 3 with covariates, the BIC drops in magnitude from a two-group to a five-group

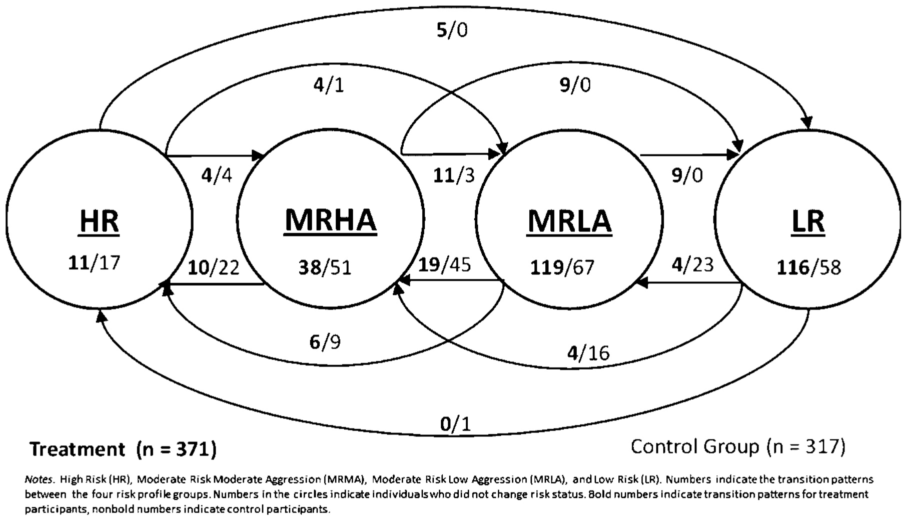


Figure 1. Transition pattern diagram for four-profile model. *Note*: Numbers indicate the tranisiton patterns between the four risk profile groups. Numbers in the circle indicate individuals who did not change risk status. Bold numbers indicate transition patterns for treatment participants; nonbold numbers indicate participants.

Table 2. Sample Correlations, Means, and Standard Deviations (N = 688)

Variable	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*
1 Cohort	1												
2 Gender	0.05	1											
3 Race/Eth	−0.01	0.01	1										
4 OvAgg*	−0.05	−0.06	0.30	1									
5 RelAgg*	0.30	0.04	0.13	0.73	1								
6 CogCon*	0.00	−0.08	−0.23	−0.38	−0.38	1							
7 SocCom*	0.05	−0.06	−0.31	−0.63	−0.62	0.71	1						
8 Liked*	0.06	0.00	−0.16	−0.55	−0.52	0.49	0.70	1					
9 OvAgg**	0.02	−0.01	0.25	0.61	0.54	−0.32	−0.46	−0.32	1				
10 RelAgg**	0.22	0.37	0.05	0.47	0.70	−0.30	−0.42	−0.33	0.75	1			
11 CogCon**	0.03	−0.87	−0.19	−0.28	−0.28	0.76	0.54	0.33	−0.44	−0.41	1		
12 SocCom**	0.06	−0.09	−0.25	−0.45	−0.48	0.58	0.70	0.48	−0.64	−0.67	0.74	1	
13 Liked**	−0.35	−0.01	−0.03	−0.33	−0.65	0.34	0.40	0.38	−0.45	−0.75	0.39	0.55	1
M	1.40	1.70	0.50	0.41	0.98	3.19	3.23	4.04	0.54	1.15	3.19	3.24	3.61
SD	1.08	1.42	0.50	0.55	0.76	1.04	0.89	0.85	0.68	0.83	1.09	0.94	0.98
Skew	0.03	−0.01	−0.06	1.71	0.60	−0.26	0.01	−0.88	1.72	0.48	−0.26	−0.22	−0.20

Note: OvAgg = overt aggression; RelAgg = relational aggression; CogCon = cognitive concentration; SocCom = social competence. Correlations rounded to second decimal place; coding for cohort: 0 = 2000, 1 = 2001, 2 = 2002, 3 = 2004; coding for gender: 0 = male, 1 = female; coding for race/ethnicity: 0 = White, 1 = African American, 3 = Latino, 4 = Other (Collapsed Asian [2] & Native American [5]); * = T1; ** = T2.

profile model. However, the differences in the BIC and LMR from a five-group to a six-group profile model were farther away from zero, indicating the best fitting model contained fewer than six profiles. In addition, the LMR for a five-profile model was not significant for the Wave 1 and Wave 2 LPAs. Further, entropy decreased for the five-group profile model in Wave 2 indicating that this model did not distinguish as

Table 3. Latent Profile Analysis Model Fit Using Cross-Sectional Data

	Wave 1 groups					*Wave 2 groups*				
Fit stats	*2*	*3*	*4*	*5*	*6*	*2*	*3*	*4*	*5*	*6*
BIC	10,861.81	10,294.22	10,042.97	9,960.644	9,775.682	11,502.11	10,989.86	10,789.05	10,604.53	10,297.58
BLRT	−5,965.59	−5,345.97	−5,026.23	−4,864.68	−4,766.93	−6,332.34	−5,666.11	−5,374.05	−5,237.72	−5,109.52
LMR	1,209.03	623.56*	315.08*	150.364	−6.545	1,299.3	569.59*	265.90*	250.01	152.672
Entropy	0.87	0.858	0.866	0.896	0.905	0.848	0.866	0.875	0.872	0.862

Notes: BIC = Bayesian information criteria; BLRT = bootstrapped likelihood ratio test; LMR = Lo Mendall Rubin.
* = p-value > .00.

Table 4. Latent Profile Transition Analysis Fit Using Both Data Points

Fit stats	*♯*	*LgLkd*	*AIC*	*BIC*	*LgLkd χ^2*	*Entropy*
Number of profiles	2	−9,996.114	20,116.23	20,397.324	81.211	0.946
	3	−9,370.752	18,929.5	19,355.681	116.793	0.926
	4	−9,040.289	18,348.58	18,956.107	135.307*	0.922
	5	−8,748.888	17,861.78	18,686.926	206.215	0.939
	6	−8,619.452	17,714.9	18,793.946	207.424	0.927

Notes: ♯ = number of groups in latent transition analysis model; LgLkd = log likelihood; AIC = Akaike information criteria.
* = p-value > .000.

well among profile groups at Wave 2. Thus, the cross-sectional LPA models suggest a four-group profile model fit the data at both waves.

Steps 3: Conducting a Longitudinal Analysis With LPTA

LPTA models were estimated without covariates and then with covariates. Shown in Table 4 with covariates, the improved BIC between the two-group and five-group profile models confirmed the cross-sectional LPA models. Two-group and three-group profile models appear to have acceptable fit. However, the log likelihood chi-square showing the ratio between the constrained (fewer free parameters) and freely estimated (more free parameters) models suggested the data do not fit either model well. At first review, the five-group profile model appeared to fit adequately. However, a closer review showed that the number of parameters required to estimate the five-group profile model sacrifice parsimony without improving overall fit (cf. Kline, 2004; Raferty, 1995). Thus, based on both the fit of cross-sectional LPAs and the fit of the multiwave LPTA models, the findings suggested the four-group profile LPTA model fits the data well.

Step 4: Assess the Substantive Meaning of the Model

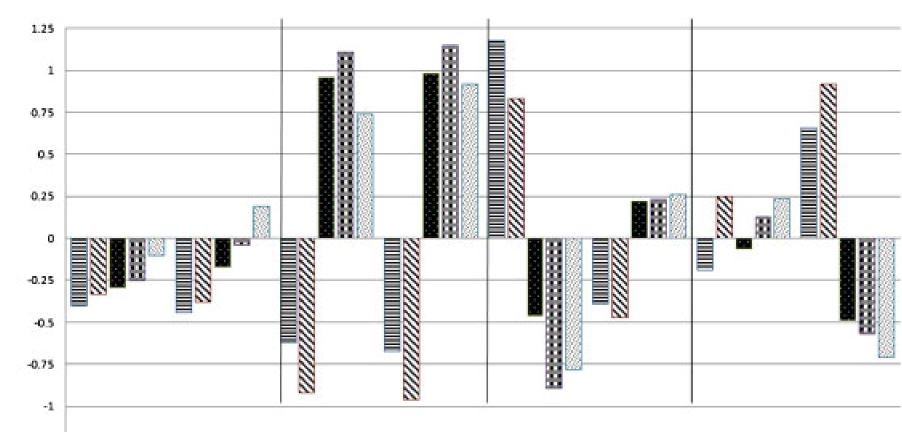
The final test for model selection is substantive (McCutcheon, 2002; Muthén & Muthén, 2000). Prior to assessing the effects of the MC program, we examined the four-group profile model in light of prior research and theory. We reviewed studies of school-based interventions designed to reduce or prevent conduct problems. In the four-group profile LPTA solution, the percentage of children in each cohort fitting the HR profile was between 6% and 8%. This is similar to percentages of high-risk children observed in school-based prevention projects such as the Fast Track Project (9%; Conduct Problems Prevention Research Group, 2002) and the Seattle Social Development Project (5% to 10%; Ayers et al., 1999). It is also similar to estimates of high-risk children from the Office of Juvenile Justice and Delinquency Prevention (8%; 2001) and comprehensive school service delivery programs (5% to 10%; Sugai & Horner, 2008). Further, studies of risk factors associated with bullying behavior have found four groups of students, with the highest risk group constituting 9.9% of the sample (Pepler, Jiang, Craig, & Connolly, 2008).

The transition patterns of children by treatment condition between risk profiles are shown in Figure 1. Each child in each cohort fits one of 16 possible transition patterns. The bold numbers represent transition patterns of participants in the two MC cohorts, which were combined for parsimony. Nonbold numbers represent the two comparison cohort, which were also combined for this report. The patterns in

Figure 1 include students who digressed (i.e., transitioned from a lower risk profile group into a higher risk group as shown by arrows on the bottom of the figure and pointing to the left), students who stayed (i.e., remained in the same profile from Time 1 to Time 2 as shown by the numbers in the circles), or students who progressed (i.e., transitioned from a higher risk profile group into a lower risk group shown by arrows at the top of the figure and pointing to the right).

Using the numbers in Figure 1, the percentages of *digressors*, *stayers*, or *progressors* were calculated by examining the percentage of individuals fitting each transition pattern. The percentages of participants fitting a digressor, stayer, or progressor pattern were then compared across treatment conditions to estimate the treatment effect for individuals with differing risk profiles. Last, we exported posterior probabilities from Mplus into SPSS (though any program might be used) to further study transition patterns. We considered these follow-up analyses exploratory and compared the demographic characteristics and pretest scores of digressors, stayers, and progressors.

Once posterior probabilities for students who fit a digressing, staying, or progressing transition were exported, we transformed each participants' original raw scores from the variables used to conduct the model analyses to z-scores. Use of z-scores enabled us to assess the substantive meaning of the profiles by comparing the subsample groups. Figure 2 displays the profiles for students who stayed in the MRLA profile, students who stayed in the LR profile, students who fit a progressing transition pattern, and students who fit a digressing transition pattern. Among students who had a probability of remaining in the MRLA category, 26.9% were in Control 1 and 9.1% were in the lagged Control 2. By contrast, 26.9% of students were in MC (Cohort 2) and 37.1% of students were in the MC+ (Cohort 3) intervention cohorts (see Fig. 1). The interaction of MC treatment and group membership was significant for students who stayed in the MRLA profile, χ^2(3 degree of freedom [*df*]; $n = 186$) $= 22.306$,



	Time 1	Time 2	Time 1	Time 2	Time 1	Time 2	Time 1	Time 2
	MRLA (n = 186)		LR (n = 174)		Progressor (n = 50)		Digressors (n = 159)	
OvAgg	-0.4	-0.44	-0.62	-0.67	1.18	-0.39	-0.19	0.66
RelAgg	-0.33	-0.38	-0.92	-0.96	0.83	-0.47	0.25	0.92
CogCon	-0.29	-0.17	0.96	0.98	-0.46	0.22	-0.06	-0.49
SocCom	-0.25	-0.04	1.11	1.15	-0.89	0.23	0.13	-0.57
Liked	-0.1	0.19	0.74	0.92	-0.78	0.26	0.24	-0.71

Figure 2. Profiles for MRLA and LR stayers, progressors, and digressors. *Note*: OvAgg = overt aggression; RelAgg = relational aggression; CogCon = cognitive concentration; SocCom = social competence.

$p < .0001$, $\eta^2 = .18$. A comparison of students who stayed in the LR category showed that 25.9% were from Control 1 and 7.3% were from Control 2. By contrast, 32.2% were in the MC condition, and 37.3% were in MC+. The stayer transition pattern in the LR profile group was significantly related to exposure to MC, $\chi^2(3\ df;\ n = 217) = 26.203$, $p < .0001$; $\eta^2 = .20$. Similarly, for students whose transition pattern fit one of the three possible progressing patterns (represented by the arrows at top and pointing to the right in Fig. 1), only 13.5% were from Control 1 and 3.8% were from Control 2. By contrast, 34.5% of students in the MC and 48.1% of students in the MC+ intervention groups fit a progressing transition pattern. The interaction between exposure to MC and fitting a progressing transition pattern was significant, $\chi^2(3\ df;\ n = 52) = 21.749$, $p < .0001$; $\eta^2 = .18$.

For students whose transition pattern fit one of the three digressing patterns (represented by the arrows on the bottom and moving to the left in Fig. 2), 22.7% were in Control 1 and 50.8% were from Control 2. By contrast, only 13.6% of students in the MC and 12.9% of students in the MC+ groups fit a digressing transition pattern. The interaction between treatment and a digressing pattern was significant, $\chi^2(3\ df;\ n = 159) = 110.889$, $p < .0001$; $\eta^2 = .40$). Finally, of the 18 students who progressed from the HR profile to a lower risk profile, 13 students were in one of the MC treatment conditions, $\chi^2(18\ df;\ n = 18) = 54.00$, $p < .0001$; $\eta^2 = .90$). Although the subsample is small, the effect of MC on high-risk children appears to be large.

Supplemental descriptive analyses can help illuminate transition patterns. In our data, as compared with females, males were more likely to have membership in the HR group profile ($\beta = 1.381$; $p = .017$), and less likely to have membership in the MRLA group profile ($\beta = -1.91$; $p = .003$). These findings are consistent with previous studies examining gender differences in aggressive behavior (e.g., Crick & Gropeter, 1995). In fact, compared with females, males were 4.4 times more likely to have membership in the HR profile at Time 1. However, when compared with females, males in the sample were only 1.24 times as likely to have membership in the HR profile at Time 2.

DISCUSSION

PCMs provide useful tools for parsing intervention effects. They complement traditional GLMs approaches and may be helpful when theory, prior research, and practice suggest outcomes may vary by small subgroups, e.g., subgroups of moderate risk children distinguished by different types of aggressive behavior (Bogat et al., 2005; Carins & Rodkin, 1998; Collins, Murphy, & Bierman, 2004; Fraser et al., 1999; Magnusson, 1998; Nurius & Macy, 2010). This article has described and demonstrated the application of LPTA in a community setting. An LPTA was applied to an evaluation of a social-skills training program in two elementary schools. In so doing, we provided a guide for person-centered analysis, showing how to (a) account for assignment to treatment and control conditions, (b) manage nested data, and (c) include covariates and interactions in models. Overall, the paper demonstrates the use of LPTA to explore intervention effects on subsamples that may be obscured in GLM approaches.

We also show how to use treatment assignment in a latent variable context. By examining treatment and control group membership at baseline along with changes in risk profile group membership over time, researchers can use LPTA to estimate treatment effects on small and theoretically important subsamples. Such group profile transition patterns and their associated treatment effects can be conditioned on covariates, including individual and community characteristics. By including both the intervention and control group participants in our analysis, we provide for two comparisons. The first shows that some risk profiles in the intervention group fair better than others when the intervention is provided. The second—a counterfactual for what might have happened to children in the treatment condition if they had not received treatment—shows that the comparison condition fairs worse. Depending on the strength of the design (e.g., whether participants were randomized, presence of post randomization confounds such as differential attrition), inferences about the effect of treatment on risk status—as indicated by changes in profile membership—may be drawn. In particular, our finding of a relatively large MC treatment effect for high-risk children is notable.

In part, the benefits of PCMs stem from the flexibility these methods afford in teasing out treatment effects within samples. For example, a child's risk of aggressive behavior is often correlated with a mix of individual and environmental risk factors. Alternative combinations of more than two or three risk factors are not easily modeled as interactions in GLMs. Accordingly, PCMs enable researchers to investigate how their interventions might (or might not) interact with complex risk profile groupings. PCMs can also provide information about participant groups that benefitted from an intervention even if the sample as a whole did not appear to benefit. PCMs may also provide information about participants who fail to benefit when the sample as a whole did benefit. In addition, modeling outcomes by person-centered groupings holds potential to reduce the gap between research and practice. In research, findings tend to be expressed as average effects across entire samples. In practice however, findings and services tend to be expressed in person-centered metrics (e.g., "The program affects high-risk children.").

In spite of their potential advantages, PCMs have limitations. First, as with all analyses, alternative and more parsimonious models that better represent the data should always be sought (Bauer & Curran, 2004; Muthén, 2003). Second, the use of PCMs are relatively new (Macy, 2008). As a result, pitfalls in applying these models are not yet fully understood. Third, PCMs are subject to the same confounds for making causal inferences as routine variable-centered methods (e.g., differential attrition within treatment groups but also within classes or profiles). Fourth and as in traditional cluster analysis, the groups derived from PCMs do not represent "real world" groups (e.g., peer cliques). Rather, the groups represent shared variance on measures. Similar to other statistical analyses, PCMs are subject to misspecification and unobserved heterogeneity. To confirm outcomes, we emphasize finding support for models in prior research. Moreover, it may be advisable to use an estimation–validation process where half of a sample is randomly selected to calibrate a model and the other half is reserved to validate that model (Byrne, Shavelson, & Muthén, 1989; Kline, 2004). This is similar to the strategy of reproducing outcomes with an independent sample (Bauer & Curran; Muthén, 2003). Unfortunately, these kinds of validation approaches tend to require large samples. In considering validation by replication strategies, experts warn that a sample size of 300 may be needed (Penn State, n.d.). This, of course, would be dependent upon other factors, such as the number of indicators used to estimate a model, the reliability of measures, the number of groups imposed on the model, and the number of model constraints (i.e., measurement invariance).

Like variable-centered methods, PCMs include a variety of analytic tools. Readily available, these analytic techniques provide increasingly sophisticated means for making refined distinctions in practice research. Prudence is warranted because the properties of estimators continue to evolve. However, in conjunction with GLMs, the application of PCMs have the potential to provide insight on practice effects for small subgroups within an overall sample.

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APPENDIX

Suppose data were collected on n youth using p items assessing risk factors at t time points. If $y_{it} = (y_{i1t}, \ldots, y_{ipt})$ is a column of responses to p items for individual i at time t, and $x_{it} = (x_{i1t}, \ldots, x_{iqt})$ represents a column of responses to q covariates. Both p items and q covariates may be categorical or continuous as well as time variant or invariant. In the structural equation framework with a multiwave design, a group of p responses assessing risk factors and q covariates are conceptualized as causes of membership in latent states at time t and time $t+1$.

This framework may be used to investigate the transition of individuals between groups conditional upon treatment assignment. To this end, the transition probability for individual i is estimated by $\tau_{ikm} = P(\mathrm{C}_{it} = k \mid \mathrm{C}_{it+1} = m,\ x_{it})$. In this autoregressive equation (i.e., the probability of profile membership based on previous profile membership), the latent class variable C_{it+1} with m profiles is regressed on the latent class variable C_{it} with k profiles. Thus, τ_{ikm} is the transition probability estimated in the autoregressive component of the model for each individual i to be in latent profile m at time point $t+1$, conditional upon membership in latent profile k at time point t. When covariate x_{it} is included, the membership of individual i in latent profile m is conditioned on both the prior profile membership and the value of the covariate for individual i.

Ultimately, the LTA and LPTA framework estimates four sets of parameters: (a) gamma parameters (γ) or the number of discrete profiles estimated at each wave of data; (b) delta parameters (δ) or the proportion of individuals in each profile; (c) the tau parameters (τ) or the case-based probabilities for membership in a particular latent state at time $t+1$ conditional on latent profile membership at time t (e.g., the probability of a student moving to another latent state at time $t+1$ conditional on membership at time t); and (d) the rho parameters (ρ), which represent measurement error.