CHILD DEVELOPMENT PERSPECTIVES

Latent Class Analysis for Developmental Research

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ABSTRACT—***In this article, we consider the broad applicability of latent class analysis (LCA) and related approaches to advance research on child development. First, we describe the role of person-centered methods such as LCA in developmental research, and review prior applications of LCA to the study of development and related areas of research. Then we present practical considerations when applying LCA in developmental research, including model selection and statistical power. Finally, we introduce several recent methodological innovations in LCA, including causal inference in LCA, predicting a distal outcome from LC membership, and LC moderation (in which LCA quantifies multidimensional moderators of effects in observational and experimental studies), and we discuss their potential to advance developmental science. We conclude with suggestions for ongoing developmental research using LCA.***

KEYWORDS—*latent class analysis; latent risk classes; latent class moderation*

Latent class analysis (LCA) is a statistical approach that plays an increasingly important role in studies of child development. In this article, we describe several areas where this technique has been critical for scientific advances, outline steps for conducting LCA, and introduce recent methodological developments.

LCA provides a framework for describing population heterogeneity in terms of differences across individuals on a set of behaviors or characteristics, as opposed to describing the variability of a single variable. This distinction has been described as a person-centered approach, in contrast to more traditional variable-centered approaches such as multiple regression analysis. The underlying principle of person-centered approaches is that, rather than quantifying the role of particular variables in a study, a population is organized in terms of a finite number of mutually exclusive and exhaustive subgroups, each comprising similar individuals (1, 2). In other words, each LC represents a subgroup of individuals characterized by a pattern of responses on a set of variables; LCA is used to identify and describe the optimal number of LCs to represent a population.

Finite mixture modeling is a general, person-centered statistical framework for explaining population heterogeneity by identifying unobserved (latent) population subgroups that are inferred from observed variables (3). Table 1 depicts four statistical models for developmental research that fall under the umbrella of finite mixture models, but are distinguished based on two dimensions: type of latent categorical variable (static vs. longitudinal) and type of indicators used to measure them (categorical vs. continuous). For example, models for a static, categorical latent variable can be differentiated in terms of the type of indicators. In LCA, classes are identified based on a set of

Table 1
Finite Mixture Modeling: Common Models Used in Developmental Research.

	Type of categorical latent variable	
Type of indicators	Static	Longitudinal
Categorical	Latent class analysis	Latent transition analysis
Continuous	Latent profile analysis	Growth mixture modeling

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categorical indicators, whereas in latent profile analysis (4), they are identified based on continuous indicators. In this article, we focus on LCA, although the concepts are relevant for models with continuous indicators as well. Longitudinal models involving a categorical latent variable include latent transition analysis (LTA), where individuals may move from one LC to another over time, and growth mixture modeling (GMM), where population subgroups are identified based on common trajectory shapes. We describe these longitudinal models later.

Developmental Questions That Can Be Addressed With LCA

Developmental scientists have long recognized the heterogeneity and complex, multidimensional nature of developmental phenomena (5), as reflected in foundational theories like developmental systems (6), developmental science (7), and the bioecological model of development (8). LCA has been used in the following three ways to address this complexity and enhance our understanding of child development: (a) cross-sectional studies that characterize static, multidimensional constructs, (b) longitudinal studies that identify subgroups of children with common profiles of risk and predictors associated with those profiles, and (c) longitudinal studies that examine development across time.

Cross-Sectional Studies of Multidimensional Constructs

Psychologists have compared groups that differ across mental, emotional, and behavioral symptoms and their related diagnoses. For example, according to the tripartite model of depression and anxiety, although symptoms may be related by common diagnoses, they cluster into three broad groups (general distress, anhedonic depression, and anxious arousal), with some common symptoms across subgroups and some unique to specific subgroups (9). Developmental research on depression and anxiety suggests that, like other developmental issues, they manifest in complex, multidimensional ways throughout life.

LCA helps us address these phenomena by identifying and describing subgroups of individuals with varying dimensions of developmental problems such as substance use (10), sexual risk behavior (11), and behavior that put them at risk for obesity (12). For example, one study identified three LCs of peer victimization among urban, middle school students (13). In contrast with previous studies that classified students according to a single dimension of victimization—either severity or type (e.g., physical, verbal, and relational)—this study incorporated both into the LCA model to find that classes were defined primarily by severity rather than type of victimization during middle school. That is, victims of one type of aggression likely experience other types as well.

LCA also informs our understanding of profiles and patterns in other developmentally relevant, multidimensional constructs like personality and temperament (14), racial identity (15), and parenting styles (16). For example, one study used national data to identify six LCs of preschool children in terms of their broad profiles of health and development (17). Most Mexican children belonged to one of the four classes: 39% in the low cognitive achievement class, 29% in the healthy class, 15% in the developmental problems class, and 12% in the low social skills class. By including measures of physical conditions, functional problems, and development into a single LCA model, this study captured the multidimensional nature of ethnoracial disparities in health and development among youth.

Longitudinal Studies of Multiple Risks

Traditionally, the impact of exposure to ecological risk on developmental outcomes has been examined, one factor at a time or by summing up the number of risks to which an individual is exposed (i.e., cumulative risk index) to predict an outcome in a regression model. However, theoretically and conceptually, developmentalists understand that risks do not occur in isolation and any one ecological factor gains meaning only in relation to other aspects of the person–environment system (8). LCA allows us to examine risk from this perspective by identifying subgroups of individuals who are exposed to intersections of risks at varying ecological levels. In several recent studies, this approach was used to examine how early profiles of sociodemographic and family risks are related to later physical, cognitive, academic, social, and behavioral outcomes for children (18, 19).

One study explored exposure to 13 risk factors from six ecological levels (child, family, parenting, classroom, school, and neighborhood) during kindergarten, examining the association between this exposure and academic and behavioral problems in fifth grade (20). Four LCs were identified (two parents, low risk; single parent/history of problems; single parent, multilevel risk; and two parents, multilevel risk); children characterized by multilevel risk had the most negative outcomes. In studies using LCA to identify risk profiles, even within high-risk populations, the combinations of risk to which individuals are exposed are substantially heterogeneous and specific patterns matter in terms of their associations with later outcomes.

Longitudinal Mixture Models to Study Development

LTA has shed light on developmental processes that are best characterized by shifts between discrete stages, rather than smooth increases or decreases along a single quantitative dimension. LTA (21–24) is a direct extension of LCA to repeated measures data in which an individual's LC membership is not assumed to be stable over time. Researchers measure an LC at two or more times, and estimate the probability of class membership at Time 1 and the incidence of transitions from Times 1 to 2, Times 2 to 3, and so on. Examples of LTA include studies on developmental transitions in the legitimacy of parental authority (25), racial identity statuses (15), and alcohol use behaviors (26).

Another useful mixture model for studying development is GMM (27). Researchers use GMM to describe population heterogeneity in individuals' growth trajectories (i.e., change over time in the level of a continuous outcome, typically estimated as a linear or quadratic function). Building directly on the growth curve modeling framework, where repeated measures data are used to estimate average parametric growth curves to reflect mean population change on an outcome, GMM identifies subgroups of individuals characterized by particular trajectories. This framework has been used widely over the past two decades in child development research, including longitudinal studies of acculturation (28), perceived racial discrimination (29), and self-esteem (30). It is valuable for examining phenomena in which two or more developmental trajectories are hypothesized, such as in Moffitt's (31) dual taxonomy of antisocial behavior.

PRACTICAL CONSIDERATIONS

The mathematical details of LCA have been widely disseminated (21, 32–34). In general, LCA estimates two sets of parameters. The first set is the LC membership probabilities (i.e., the estimated proportion of individuals in each class). The second is the item response probabilities, representing how likely class members are to provide different responses to each categorical indicator (i.e., the probabilities of particular responses to indicators given class membership). These probabilities are similar conceptually to factor loadings in factor analysis. The item response probabilities provide information about how well each indicator measures the latent variable. In an overview of LCA that matched a five-class model of adolescent depression symptomatology to data on eight symptoms of depression in a national sample of 11th-grade students (35), the LC membership probabilities represented the proportion of adolescents in each depression class. One example of an item response probability is the likelihood that an individual in the sad and disliked class would endorse the statement "People dislike me."

Because the class variable is latent, an individual's true class membership is unknown. Rather, an individual's probability of belonging to each LC can be calculated as a function of his or her observed data and the parameter estimates. Researchers often use these posterior probabilities to assign individuals to the LC corresponding to their maximum probability, although this can result in attenuated effects between LC membership and other variables of interest (36, 37). When the goal is to include covariates as predictors of class membership, researchers can do this directly in the LCA model—in other words, they do not need to classify individuals based on posterior probabilities. LCA with covariates enables researchers to describe the composition of classes and identify antecedents that can identify individuals likely to belong to particular classes. The underlying statistical model is multinomial logistic regression; this model is traditionally used to estimate associations between covariates and an observed categorical outcome. In LCA, this regression model allows the categorical outcome to be latent.

In addition to predicting LC membership from covariates, it can be useful to include a grouping variable such as sex or treatment condition to examine group differences. These differences can emerge in the class membership probabilities (i.e., certain classes may be more prevalent for certain groups), the item response probabilities (i.e., the structure of the LCs may vary across groups), or the multinomial logistic regression coefficients (i.e., a grouping variable may moderate the association between a covariate and LC membership).

The key assumption in LCA is that the indicators are conditionally independent given LC. In other words, any observed associations among the items can be explained by the LC variable. If all indicators are independent from one another in the overall sample, a single LC would be sufficient. However, this is seldom the case with real data. Selecting an optimal LC model is one of the most important considerations when conducting LCA. The identification of any model with two or more LCs must be examined before it can be considered during the selection process. In LCA, having positive degrees of freedom is a necessary but far from sufficient requirement to confirm that a model is identified. A model is considered to be identified sufficiently when many sets of starting values converge on the solution corresponding to the maximum likelihood value (see 21).

Model selection typically occurs by comparing models with different numbers of LCs, for instance, using information criteria (e.g., Akaike information criterion (AIC), Bayesian information criterion (BIC)) that balance the trade-off between model fit and parsimony; greater parsimony provides greater generalizability to other samples. A common approach is to fit a one-class model to a particular data set; it is possible to use only one starting value to assess identification of a one-class model because the solution is calculated directly, as opposed to estimated using an iterative procedure. Then a two-class model is estimated using many (e.g., 100) sets of starting values. If the model is identified sufficiently (i.e., many sets of starting values converge on the solution with the maximum likelihood value), it is retained as a candidate model from which to select a final model. A three-class model is then run and retained as a candidate model; this process continues until the number of LCs is too large to achieve model identification. This process of selecting a final model is typically done prior to adding covariates or grouping variables (see 21, for more on model identification and selection).

Potential Limits

Several limits merit consideration when conducting LCA. First, this approach typically is considered an exploratory approach. The nature of finite mixture models is such that researchers often interpret the estimated LCs as representing the true subgroups in a population. However, any LC structure identified using LCA should be considered a heuristic for describing population heterogeneity. Statistical power is one factor that is directly linked to the ability to detect true, underlying LCs (see 38), so solutions should not be interpreted as the set of true population subgroups. Second, researchers need to provide practical recommendations for handling missing data in LCA. For missingness on LC indicators, full information maximum likelihood (FIML) is an appropriate approach and is available in all modern LCA software. However, missing data on a covariate or grouping variable present a more complex problem. Multiple imputation is likely the best approach since FIML cannot accommodate missingness on exogenous variables. But this approach holds challenges unique to LCA; for example, researchers would need to consider model selection and interpretation within each imputed data set prior to combining parameter estimates across imputations.

Software and Online Resources

The dominant software packages for conducting LCA include SAS PROC LCA (39), Mplus (40), and Latent Gold (41). The first comprehensive book on this method (21) provides a conceptual overview and technical details on model fit, model selection, multiple groups LCA, incorporating covariates, and longitudinal modeling using LTA. Resources are also available online (e.g., http://methodology.psu.edu/, http://www.statmodel.com/examples/webnote).

ADVANCES IN LCA

LC variables have been used in developmental studies for several decades, yet our research questions continue to increase in complexity. Once an LC variable is identified, researchers want to explore that construct more deeply. Among their questions: What characterizes individuals in each class? What early factors predict membership? Can causal inferences be drawn about possible determinants of class membership? What are the consequences of class membership? Does the effect of a behavioral intervention vary across LCs? Ongoing research is focused on expanding the capabilities of LCA so researchers can address these questions. Next, we summarize three recent advances.

Drawing Causal Inferences in LCA

Including covariates in LCA has been well understood for more than 20 years (42). This approach estimates the LCA parameters and multinomial logistic regression coefficients linking covariates with a multinomial outcome. As with any regression analysis, in the absence of randomization to levels on the predictor, conclusions drawn from the logistic regression coefficients in LCA cannot be interpreted as causal. However, advances in causal inference techniques such as propensity score methods (43) lay the foundation for estimating causal effects of covariates in LCA. A didactic introduction to propensity score methods may be useful to psychologists (44). Integrating propensity score techniques and LCA with covariates in the analysis of longitudinal data was proposed only recently, but shows promise for advancing developmental science (45).

Predicting a Distal Outcome From LC Membership

Naively assigning individuals to the LC corresponding to their largest posterior probability and using that variable in a subsequent analysis (i.e., standard classify–analyze, or three-step, approaches) results in bias, specifically attenuation, of the estimated association between LC membership and an outcome (46). Techniques are being developed to address this bias in various ways, including a new model-based, one-step approach (37) and several improved three-step approaches (36, 46). This research is crucial for ensuring that LCA can continue to address increasingly complex developmental questions.

LC Moderation

LC moderation is a new framework for examining differential effects and is characterized by a multidimensional moderator variable (i.e., an LC variable). This approach allows researchers to identify types of individuals that show stronger or weaker effects of interventions. In this framework, LCs are derived on the basis of multiple individual characteristics (e.g., baseline risk level) that together may explain heterogeneity in effects. This framework was first described in work that focused on subgroup analysis (i.e., differential effects of nonrandomized exposures or randomized interventions; 47). Most commonly, differential effects are examined using standard moderation analysis, with the outcome predicted as a function of a hypothesized moderator (e.g., gender), intervention condition, and the interaction between the two. LCA has been used to model adolescent risk profiles identified by a combination of individual-, peer-, and family-level risk factors, and that LC variable was treated as a moderator of an intervention effect (47).

Another study used LCA to create a multidimensional, latent moderator of family and home characteristics hypothesized to explain the differential impact of Head Start on children's outcomes (48). The moderator comprised five LCs: married/lower risk (29%), married/Spanish/lower education (17%), single/Food Stamps/depression (37%), single/higher education/full-time work (13%), and single/Spanish/lower education (4%). The effect of Head Start on cognitive, behavioral, and relationship skills varied across classes, with a significant, long-term impact detected for certain groups (e.g., married/Spanish/lower education) but little or no impact for others (e.g., married/lower risk).

LOOKING AHEAD

Compared to more traditional analytic approaches such as multiple regression, LCA allows researchers to characterize individuals more holistically in terms of their behavior, health status, exposure to risk, development, or response to an intervention. Many of the most pressing issues in child development have been addressed using variable-centered methods, perhaps most commonly multiple regression and random effects modeling. LCA offers a new lens for examining the same issues, providing complementary empirical evidence that advances theory and has important clinical implications.

Work remains to advance LCA methodology to accommodate increasingly complex questions in child development. For example, researchers may wish to consider multidimensional mediators that are measured using an LC model. Researchers are also investigating the most optimal ways to estimate more complex models such as this. As social and behavioral researchers continue to integrate big data into their research—including data from electronic medical records, ecological momentary assessments, and physical activity monitors—LCA may prove useful for detecting common patterns in these data. We expect LCA to play an increasingly important role in research on child development.

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