### Title

A Latent Transition Mixture Model Using the Three-Step Specification




### Journal

Structural Equation Modeling A Multidisciplinary Journal, 21(3)

### ISSN

1070-5511



### Authors

Nylund-Gibson, Karen
Grimm, Ryan
Quirk, Matt
et al.



### Publication Date

2014-07-03

### DOI

10.1080/10705511.2014.915375

Peer reviewed

*Structural Equation Modeling: A Multidisciplinary Journal*, 21: 1–16, 2014

ISSN: 1070-5511 print / 1532-8007 online
DOI: 10.1080/10705511.2014.915375

# A Latent Transition Mixture Model Using the Three-Step Specification

Karen Nylund-Gibson, Ryan Grimm, Matt Quirk, and Michael Furlong
*University of California, Santa Barbara*

The 3-step method for estimating the effects of auxiliary variables (i.e., covariates and distal outcome) in mixture modeling provides a useful way to specify complex mixture models. One of the benefits of this method is that the measurement parameters of the mixture model are not influenced by the auxiliary variable(s). In addition, it allows for models that involve multiple latent class variables to be specified without each part of the model influencing the others. This article describes a unique latent transition analysis model where the measurement models are a latent class analysis model and a growth mixture model. We highlight the application of this model to study kindergarten readiness profiles and link it to elementary students' reading trajectories. M*plus* syntax for the 3-step specification is provided.

**Keywords**: auxiliary variables, growth mixture modeling, latent class analysis, latent transition analysis, mixture modeling, three-step method

Mixture modeling has become a widely used statistical method in the social and behavior sciences. The ability to identify and understand latent subpopulations in a given population has great appeal because it allows for a richer understanding of a population by identifying the heterogeneity that exists within it. In addition, the use of mixture models potentially allows for a more accurate description of the relationships that exist in the data by relaxing the assumption that relationships are the same for all individuals in a population; rather, relationships can vary across subpopulations. The intersection of mixture modeling with a range of more traditional latent variable models, such as factor mixture models, which combine mixture modeling and the common factor model (see, e.g., Lubke et al., 2007), allows for a wide range of modeling possibilities that might aid in accurately depicting the complexities often seen in social science data.

Over the past 15 years there has been a rapid increase in the applications of mixture models in the social and behavioral sciences. There is a wide range of applications across many disciplines where the use of mixture models has aided in the understanding of educational and psychological phenomena. Latent class analysis (LCA) was used to study the heterogeneity in students' experiences with peer victimization and identified three classes that differed by severity, not type of victimization (Nylund, Bellmore, Nishina, & Graham, 2007). A study by Cleveland, Lanza, Ray, Turrisi, and Mallett (2012) used latent transition analysis (LTA)—considered a longitudinal extension of the LCA model—to study how college freshmen transitioned between latent classes of drinkers and nondrinkers before and after they began college. In another application of mixture modeling, Morin et al. (2011) used growth mixture modeling (GMM) to study heterogeneous developmental trajectories of anxiety in a sample of adolescents.

Most commonly, in applied social science research, mixture models are used in an exploratory fashion. That is, although there is interest in enumerating the latent classes, researchers do not usually have a specific number of classes hypothesized a priori. Equally important as enumerating the number of latent classes is developing an understanding of the individuals that make up the emergent latent classes. By including auxiliary information into the mixture model in the form of covariates (also called predictors or independent variables) or distal outcomes (or consequences), researchers can begin to better understand the characteristics of the individuals who make up the latent classes as

Correspondence should be addressed to Karen Nylund-Gibson, University of California, Santa Barbara, Gevirtz Graduate School of Education, Santa Barbara, CA 93106. E-mail: knylund@education.ucsb.edu

well as the consequences of class membership. In addition to better understanding the heterogeneity, including auxiliary information also provides validity to the emergent latent classes by providing a "substantive check" to the classes and information about how the classes relate to auxiliary variables in a way that is consistent with theory (Muthén, 2003).

## APPROACHES FOR INCLUDING AUXILIARY INFORMATION IN MIXTURE MODELS

There are several approaches to including auxiliary information into mixture models. The most commonly used approach available in most mixture modeling software packages is to regress the latent class variable on the auxiliary variable, considered a one-step approach. As Vermunt (2010) pointed out, there are several disadvantages to this approach; namely, it becomes impractical with a large number of covariates and forces the researcher to make a decision about when to include covariates in the modeling process. Although some recommend including covariates in the mixture model from the beginning (Muthén, 2001), recent simulation studies recommend that the number of classes be decided in a model without the auxiliary variable (Nylund-Gibson & Masyn, 2011). Using the three-step approach, you decide on the number of classes before you include auxiliary information.

One significant disadvantage of the one-step approach is that once the auxiliary variables (e.g., covariates or distal outcomes) are included in a mixture model, the measurement parameters of the latent class model could, and often do, shift depending on the strength of the relationship between the latent class indicators and the covariates or distal outcomes (Asparouhov & Muthén, 2013; Vermunt, 2010). This implies that the item probabilities used to interpret and assign names to the latent classes could change when comparing a model with and without covariates. A significant change in one or more of the item probabilities, the class size, or both could lead to a different interpretation of the latent classes. In fact, it is possible that a model with covariates might result in a different number of classes to be chosen in the class enumeration process.

This change in the measurement parameters of the latent class variable is often unsettling for applied researchers. Although covariates and distal outcomes are important to the modeling process, the measurement of the latent classes is often conceptualized to be independent of the statistical relationship between the covariates or distal outcomes and the latent class variable. In addition, the change in measurement parameters is inconsistent with the motivation to use the latent class variable to capture heterogeneity in a set of outcome variables free from covariate influence. For example, in Nylund, Bellmore, et al. (2007), six indicators of peer victimization were used to capture heterogeneity in victimization experiences. The three latent classes that emerged differentiated victimization experiences by severity. Then, victimization classes were related to auxiliary variables—two covariates (gender and feelings of school safety) and a distal outcome (later depression). Having the auxiliary variables influence the class formation in this example would imply that instead of the latent classes capturing heterogeneity in victimization experiences, the latent classes would capture heterogeneity in victimization experiences, gender, school safety, and depression together. Although the latter is an interesting endeavor, it would likely result in a different set of latent classes than those that emerged when just the victimization experiences were used.

Another approach to including auxiliary information into a mixture model that overcomes the shift in the measurement parameters is the classify–analyze approach. In this two-step approach, an unconditional mixture model is specified and individuals are assigned to a latent class using modal class assignment. Then, in a second modeling step, modal class assignment is read in as data and individuals are compared on the covariates or distal outcomes using a more traditional method to compare groups (e.g., analysis of variance). This approach overcomes the disadvantage of having measurement parameters shift, but it does not account for the imperfect assignment to class and has been shown to be biased, especially when entropy is low (Asparouhov & Muthén, 2013; Clark & Muthén, 2009).

## THREE-STEP PROCESS FOR COVARIATES AND DISTAL OUTCOMES

Recent methodological work has provided a framework for avoiding the measurement parameter shift problem; namely, the three-step method for estimating the effects of covariates and distal outcomes in mixture models (Asparouhov & Muthén, 2013; Vermunt, 2010). This method has been shown to be less biased than older options for estimating these effects, including the pseudo-class draw approach (Asparouhov & Muthén, 2013). This newer three-step method ensures that the measurement of the latent class variable is not affected by the inclusion of covariates or distal outcomes by fixing the measurement parameters of the latent class variable of the model with covariates at values from the unconditional latent class model. As the name suggests, it involves three modeling steps: (a) estimating the unconditional mixture model, (b) assigning individuals to latent classes using modal class assignment, and (c) estimating a mixture model with measurement parameters that are fixed at values that account for the measurement error in the class assignment. Once the model in the third step is specified, auxiliary information is included in this model in the traditional fashion.

## THREE-STEP PROCESS FOR MODELS WITH MORE THAN ONE LATENT CLASS VARIABLE

### Latent Transition Analysis

The three-step process described earlier can also be used in models with more than one latent class variable. Asparahov and Muthén (2013) demonstrated how to use the three-step method for a simple latent transition analysis (LTA) model (Collins & Lanza, 2010; Collins & Wugalter, 1992). LTA is referred to as the longitudinal extension of LCA because it involves multiple latent class variables where LCA is the measurement model for each of the latent class variables. In traditional applications of LTA, the interest is in modeling change in latent class membership over time by regressing the latent class variable at one time point on previous ones. To apply the three-step method described in Asparouhov and Muthén (2013), the manual three-step process is needed where the LCA parameters of the first latent class variable are determined and then the second, independent of the first, and so on.

## THIS ARTICLE

In this article, we illustrate the utility of the three-step method in the context of multiple latent class variables. Specifically, we use this method within the LTA framework where the latent class variables are not repeated measures but instead are two mixture models, namely an LCA and a growth mixture model (see Figure 1). A few other applications of the three-step method have been used (Asparouhov & Muthén, 2013; Vermunt, 2010), but this article is the first to use the three-step method within the LTA framework using different measurement models. This is a novel application for several reasons, one of which is that the measurement invariance of the LTA model does not apply because the latent class variables are not repeated measures, which is the case for most applications of LTA models. Further, LTA with nonrepeated measures is a useful modeling technique that is not widely used but could provide a useful framework to study different developmental changes. In addition, the LTA model used in this article includes an interaction term, where covariates are allowed to influence the probability of transitioning—a specification in LTA modeling that is not widely used. To aid in the understanding of the specification of a complex model like the one used in this article, we provide the M*plus* (Muthén & Muthén, 1998–2012) syntax for all the models involved in the three-step specification, as well as the calculations for the parameters used in the three-step method.

Using an example of kindergarten readiness and elementary reading achievement trajectories, in this article we use an LTA model where the research questions are focused on identifying latent classes in each process, and then modeling changes among latent classes. Specifically, we identified heterogeneity in kindergarten readiness and reading trajectories in elementary school (Grades 2–5). By using the three-step method described earlier, the formation of the trajectory classes in kindergarten was not influenced by reading classes in elementary school, and vice versa. In addition, we included covariates into the model without changing the measurement parameters. We also allowed for the covariates to influence the transition between kindergarten readiness classes and the reading trajectories. That is, the model explores the influence of covariates on how children transition. This model allowed us to better understand the association between variations that are evident in children's kindergarten readiness and long-term reading achievement trajectories through Grade 5.

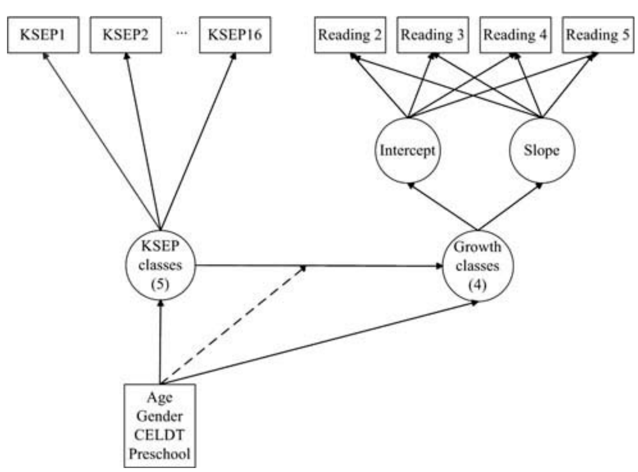


FIGURE 1 Final latent transition analysis model modeling the transitions between kindergarten readiness classes to elementary reading trajectory classes controlling for age, gender, language (CELDT), and prior preschool experiences.
*Note.* KSEP = Kindergarten Student Entrance Profile.

## METHOD

### Sample

During the first month of the 2005 and 2006 academic years, all kindergarten students entering a medium-sized school district in central California were assessed using a universal school readiness screening as part of general education practices. Participants in this study were 2,172 Latino and Latina children who (a) entered kindergarten in the district during this time period, (b) were rated on the school readiness screening, and (c) had values for the predictors included in the model. Of these students, 49.3% were male and 69.9% were English language learners, as reported by the school district. A significant proportion of the children in the district were from families experiencing low socioeconomic circumstances, with approximately 78% of students in the district receiving free or reduced-price lunch services.

The participating K–8 school district is located in a semirural area with a population of about 100,000 people. From 2008 to 2012, 33% of the district's students in Grades 2 through 5 obtained scores of "proficient" or "advanced" scores on the state language arts assessments, compared with 54% of similar-aged students throughout California. On the mathematics standards assessment, 50% of the district's students in Grades 2 through 5 obtained "proficient" (minimum goal for all students) or "advanced" (optimal goal for students) scores, compared to 64% of students statewide during the same time period.

## Measures

*School readiness.* The Kindergarten Student Entrance Profile (KSEP; Santa Maria-Bonita School District, First 5 of Santa Barbara County, & University of California Santa Barbara, 2005) was used as a school readiness screening measure to assess social-emotional, behavioral, physical, and cognitive elements of students' school readiness. The version of the KSEP used in this study had 16 items, with 7 items measuring social-emotional readiness, 3 items measuring physical readiness, and 6 items measuring cognitive readiness. Teachers completed this rating scale by drawing on their observations and professional judgments in the natural classroom setting over at least a 3-week period at the beginning of the school year (for more on the KSEP, see Quirk, Furlong, Lilles, Felix, & Chin, 2011; Quirk, Nylund-Gibson, & Furlong, 2013). A 4-point rating rubric (1 = *not yet,* 2 = *emerging,* 3 = *almost mastered,* 4 = *mastered*) is associated with each individual item that provides an operational definition and an example of the type of behaviors that would be indicative of a child at various levels of mastery. For the purposes of this study, ratings for each item were dichotomized (1 = *mastered* [defined as ratings of *mastered*], 0 = *not mastered* [defined as ratings of *not yet, emerging,* and *almost mastered*); therefore, total scores for individual children ranged from 0 to 16, with a score of 16 indicating that the teacher rated the child at the mastery level on all items. The KSEP is not an assessment of English language proficiency; therefore, children could demonstrate readiness in any language or form of communication.

Previous research has provided evidence of the KSEP's reliability and validity (Furlong & Quirk, 2011; Lilles et al., 2009; Quirk et al., 2011; Quirk et al., 2013). For this sample, the internal consistency (Cronbach's alpha) of the dichotomized 16-item ratings was .90, with subscale reliability coefficients of .85 (social-emotional), .79 (physical), and .74 (cognitive). Total scores for the sample ranged from 0 to 16 ($M = 6.33$, $SD = 4.73$).

*Academic achievement.* The English Language Arts (ELA) and Mathematics subtests of the California Standards Test (CST) were used to assess students' academic achievement in Grades 2 through 5. California schools use the CST to monitor student academic progress from Grades 2 through 11 in comparison to curriculum-based academic standards. Multiple independent item review teams matched items from the ELA portion to a curriculum blueprint covering the areas of word analysis, reading comprehension, literary response and analysis, writing strategies, and written conventions. The ELA scores are reported as scale scores, percentiles, and as standard scores ranging from 1 (*far below basic*) to 5 (*advanced*). Scale scores range from 150 to 600. However, for the purposes of our study, we transformed scale scores to normal curve equivalents (NCEs) because the CST ELA tests are not vertically equated. That is, we could not directly compare scale scores of our sample across years. Transforming scale scores to NCEs allowed us to standardize the scale scores across years and yielded interpretable growth parameters. NCEs have a mean of 50 and a standard deviation of 21.06 and range from 1 to 99 (Haertel, 1987). At values of 1, 50, and 99, NCEs correspond to percentile ranks, but, unlike percentile ranks, NCEs have equal intervals between all scores and are on a linear scale, making them more appropriate for statistical analyses (Haertel, 1987). Internal consistency coefficients for the ELA subtest ranged from .92 to .94 for Latino and Latina students in Grades 2 through 5 (California Department of Education Standards and Assessment Division, 2008–2012). From 2008 to 2012, the estimated proportion of students in Grades 2 through 5 correctly classified as proficient or advanced in ELA ranged from .92 to .94 across all students (California Department of Education Standards and Assessment Division, 2008–2012).

*Predictors.* Four predictors, all of which are theoretically relevant to children's school readiness levels at kindergarten entry and growth in elementary reading, were examined. The predictors included in the model were (a) whether or not the child had previous preschool experience, (b) the age of the child when the KSEP was administered, (c) gender, and (d) English language proficiency.

## Procedure

At the participating district's school, the teachers were trained by the readiness kindergarten transition coordinator on the use of the KSEP prior to the 2005 and 2006 school years. KSEP ratings were recorded for each student on a standard form and scores were recorded in a Microsoft Excel database with an associated student identifier that was used to link readiness data with longitudinal achievement variables. All data were collected by the district as part of general education practices and shared with researchers as part of a collaborative effort to better understand the readiness of the district's students at school entry and its relationship to their later academic achievement. Unique identifiers were removed from the data used for this study to be compliant with the university's Human Subjects Review Board.

### The Analysis Plan

The specification of a complex model that involves two latent class variables with different measurement models requires careful attention to the specification of each component part, thus the analysis was conducted in several steps. First, the cross-sectional LCA was conducted on the KSEP items and the number of classes was decided. Then, covariates and distal outcomes were included in the chosen model to help provide validity to the emergent classes. Next, the GMM model with the reading scores was specified and several different models were studied and compared, resulting in one final GMM model for which covariates were included. Once each of the mixture models (e.g., LCA and GMM) was independently specified and the most plausible model for each was identified, then the manual three-step method was specified.

*Class enumeration.* When fitting a two latent class variable model, the class enumeration process is done separately for each latent class variable. That is, for our example we determined the number of classes for the LCA and GMM models separately. Several indicators of model fit were used because there is no single statistical indicator that is a perfect indicator of which model fits best (Nylund, Asparouhov, & Muthén, 2007). The Bayesian information criterion (BIC; Schwartz, 1978), the most commonly used and trusted fit index for model comparison, was used, where lower values of the BIC indicated better fit. In addition, we compared models that differed in the number of classes using the Lo–Mendell–Rubin (LMR) test and the bootstrap likelihood ratio test (BLRT) to evaluate if adding an additional class significantly improved model fit (for more on these fit indices, see Nylund, Asparouhov, et al., 2007). The entropy of the final model selected is reported in the text but not used for model fit because it is a measure that describes the overall classification of students into the latent classes assuming the model is correct and is not intended for model selection. Entropy ranges between 0 and 1, where 1 is perfect classification and values approaching 1 indicate clear delineation of classes (Celeux & Soromenho, 1996).

*Three-step method in Mplus.* With just covariates or just distal outcomes, it is possible to use the facilities in M*plus* 7.11 to estimate these effects using the three-step method. The LTA model used in this article requires us to do a manual specification of the three-step model. This involves several model runs for each LCA and GMM model, and then a final model where the three-step variables for each model are combined into one model run. In this final model, the LTA modeling framework is used where the latent class variable from the GMM is regressed on the LCA variable as depicted in Figure 1.

Once the best model is identified for each of the latent class variables (e.g., for the LCA and GMM models), an unconditional model is run where covariates are designated as auxiliary variables (see Appendix A) and a "savedata" command, requesting "cprobabilities" is specified so that M*plus* will create a new data set. In this new data set, all individual values of the class indicators of the mixture model are included (e.g., the KSEP items or NCE reading scores), as well as the posterior probabilities, modal class assignment, and any variables that were specified in the auxiliary command. An important step at this point is to specify covariates or distal outcomes as "auxiliary" variables so that they are included in this newly written data set and can be used later in the three-step procedure (see Appendix A).

This newly written file (called 5clca.dat in Appendix A) is then read in as data in the next model run. In this model, a mixture model is specified to have one indicator—the modal class assignment variable from the first step. In this run, the threshold values for this latent class variable are fixed as specific values. The values then are fixed using the $q_{c1,c2}$ values from the Asparouhov and Muthén (2013), Equation 1. Appendix B illustrates how to hand calculate these values for the LCA model used in this study. The values from the "Average Latent Class Probabilities for Most Likely Latent Class Membership" are from the output file from the first run (Appendix A).[1] Using these values, the mixture model is specified (Appendix C). This same process is done for the GMM model (Appendices D and E). For each model, the three-step process is conducted and the results are compared to ensure that the class sizes match from the first and third steps.

The three-step LTA model is specified using the calculated values from the LCA and GMM latent class variable (see Appendix F). The final LTA model used in this study, depicted in Figure 1, included interactions (Appendix G) for two of the four covariates.

## RESULTS

The results are divided into several subsections. We first present the descriptive statistics for all the variables used in both the LCA and GMM models, including covariates. We then present the class enumeration results for the LCA and GMM models. We present covariate results for both the LCA and GMM models, which helps provide validity for the emergent classes. Finally, we include modeling results for the final model where we link the kindergarten LCA and the elementary school GMM results and include covariates.

[1]Starting in M*plus* 7.1, these values are provided for you, but we included the calculations for pedagogical purposes.

## Descriptive Statistics

Table 1 presents the means and standard deviations for the KSEP items, reading scores, and covariates that were used in the analysis. The KSEP item most often mastered by students was "Separates appropriately from caregiver most days." This was the only item mastered by over half of the sample. Other items that had relatively high frequencies of mastery included "Recognizes own name," "Demonstrates sense of his or her own body in relation to others," "Demonstrates general coordination," and "Stays with or repeats a task." Perhaps not surprising, these items might have had the highest frequencies of mastery because they are nonacademic in nature, as most of these students have not yet experienced formal academic training. Conversely, the item with the lowest amount of students who had attained mastery was explicitly academic in nature, "Writes own name." Similarly, the other items with means less than 0.30 were all related to explicit academic instruction rather than personal traits.

Overall, the mean ELA scores were consistently below the state average for all four academic years. The highest overall achievement scores occurred during fourth grade, and there were decreases in ELA scores during third and fifth grades, with third grade being the larger decrease of the two. In California, the CSTs are read out loud to students in the second grade, but this practice is discontinued beginning in the third grade. This might account for the large decrease in ELA scores. However, on average, the students in this sample never fell below 1 *SD* below the state mean.

TABLE 1
Descriptive Statistics of the Kindergarten Student Entrance Profile (KSEP) Items, Normal Curve Equivalent (NCE) Reading Scores, and Covariates Used in the Final Model

| *Variables* | *M* | *SD* |
|---|---|---|
| KSEP items | | |
| Seeks help | 0.35 | 0.48 |
| Cooperative play | 0.41 | 0.49 |
| Impulse control | 0.38 | 0.48 |
| Stays with task | 0.45 | 0.50 |
| Separates from caregiver | 0.71 | 0.45 |
| New activities | 0.42 | 0.49 |
| Follows rules | 0.37 | 0.48 |
| Uses tools | 0.34 | 0.47 |
| Coordination | 0.46 | 0.50 |
| Body sense | 0.47 | 0.50 |
| Recognizes own name | 0.49 | 0.50 |
| Writes own name | 0.19 | 0.39 |
| Expressive | 0.29 | 0.45 |
| Number sense | 0.29 | 0.45 |
| Recognizes colors | 0.23 | 0.42 |
| Primary shapes | 0.25 | 0.43 |
| NCE ELA scores | | |
| 2nd grade | 42.63 | 16.91 |
| 3rd grade | 33.91 | 18.57 |
| 4th grade | 44.13 | 18.06 |
| 5th grade | 39.43 | 17.75 |
| Covariates | | |
| Age | 5.33 | 0.32 |
| K-CELDT | 2.61 | 2.01 |
| Female | 0.51 | 0.50 |
| Preschool | 0.47 | 0.50 |

*Note.* ELA = English language arts; K-CELDT = Score on the California English Language Development Test in Kindergarten.

## Kindergarten LCA

A series of LCA models were fit starting with a one-class model. We then increased the number of classes by one until nonconvergence was achieved. Fit indices for each model were collected (see Table 2) and compared to aid in selecting the best fitting LCA model among those considered. In this application, the BIC never reached a minimum value; however, we looked for an "elbow" (i.e., the last relatively large decrease in the BIC value; Nylund et al., 2007), which occurred with the five-class model. None of the *p* values for the LMR were nonsignificant, so this was not used to inform our decision. The first nonsignificant *p* value for the BLRT occurred with the four-class model, suggesting the three-class model was preferable. Given that the fit statistics did not unilaterally identify a single LCA model as the correct one, we considered substantive reasons in our decision of which model to retain. We drew on our previous work with similar data (Quirk et al., 2013) to guide our decision, and examined the item profile plots of the three-, four-, and five-class models. This revealed that the five-class model did the best job of explaining the heterogeneity in kindergarten readiness and this was then chosen as the final LCA model. This result is consistent with the LCA results using the KSEP instrument in the Quirk et al. (2013) study.

The item probability plot presented in Figure 2 was used to interpret and label the five emergent latent classes beginning with the two most extreme classes. The top class had the highest probability of receiving mastery ratings across the KSEP items. Thus, this class was labeled *Balanced High* and consisted of 13.5% of the sample. At the opposite extreme, the class at the bottom of the plot had the lowest probability of being rated at the mastery level for all but the last two KSEP items. Thus, this class was labeled *Extremely Low* and consisted of 33.9% of the sample.

The next three classes were labeled based on patterns of being rated at the mastery level on the social-emotional/behavioral (SE) and cognitive items (Cog). The second highest class, denoted with a solid line and squares, had a high probability of being rated at the mastery level for the SE items, but a low probability of being rated at the mastery level on the Cog items. This class was labeled *High SE, Low Cog* and consisted of 13.8% of the sample. The next

TABLE 2
Fit Information for the Latent Class Analysis and Growth Mixture Models

| No. of classes | Log Likelihood | BIC | LMR p Value | BLRT p Value |
|---|---|---|---|---|
| LCA | | | | |
| 1 | −30255.21 | 60694.81 | — | — |
| 2 | −17433.10 | 35150.38 | <.001 | <.001 |
| 3 | −16612.76 | 33671.00 | <.001 | <.001 |
| 4 | −16378.42 | 33363.61 | <.001 | 0.37 |
| 5 | −16178.90 | 33125.87 | <.001 | 0.07 |
| 6 | −16048.46 | 33026.27 | <.001 | 0.05 |
| GMM | | | | |
| 1 | −28397.17 | 56877.60 | — | — |
| 2 | −28377.71 | 56861.40 | .003 | <.001 |
| 3 | −28363.44 | 56855.57 | <.001 | <.001 |
| 4[a] | −28346.68 | 56852.33 | .12 | <.001 |
| 5[b] | −28309.92 | 56824.24 | .09 | <.001 |
| 6 | −28340.01 | 56876.85 | .68 | .10 |

*Note.* BIC = Bayesian information criterion; LMR = Lo–Mendell–Rubin test; BLRT = bootstrap likelihood ratio test; LCA = latent class analysis; GMM = growth mixture modeling.

[a]Intercept variance for Class 1 freely estimated. [b]Residual variance for Class 1 freely estimated.

class, denoted by a solid line with triangles, had a moderate probability of mastery on both the SE and Cog items, and was labeled *Moderate SE, Moderate Cog* and made up 19.7% of the sample. The final class, denoted by a dashed line with circles, had a relatively low probability of mastery across both SE and Cog items. This class was labeled *Low Cog, Low SE* and made up 19.1% of the sample.

*Covariates in KSEP LCA.* Four covariates—age, gender, preschool experience, and English language proficiency—were included in the analysis and served to help validate the classes. These covariates are a subset of the ones used in the Quirk et al. (2013) study. Comparing the emergent latent classes across the LCA model with and without covariates, there were no large shifts in the emergent latent classes. That is, the profiles remained stable, as did the relative size of the latent classes. Thus, in this context, because the entropy is high and the classes do not substantially change once covariates are included, the covariate results using the three-step method will likely not differ much from the more traditional approach of regressing the latent class variable on the covariates.

Covariate results were consistent with those found in Quirk et al. (2013) and are in line with substantive predictions. For example, having prior preschool experience was a consistent predictor of being in the *Balanced High* class. Furthermore, the odds ratio for the *Extremely Low* class showed that students with preschool experience were almost 17 times more likely to be in the *Balanced High* class. Additionally, age and English language proficiency consistently differentiated the *Balanced High* class from the others. Specifically, students who were older or more proficient in English were more likely to be in the *Balanced High* class than each comparison class. Gender only differentiated

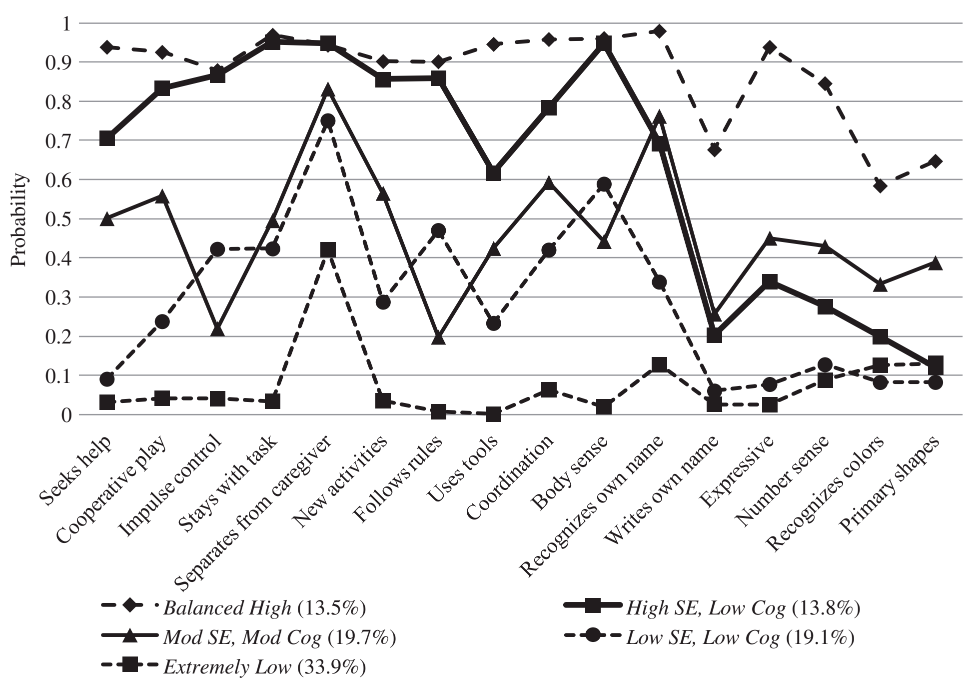


FIGURE 2 Item probability plot for the latent class analysis of Kindergarten Student Entrance Profile items.

*Note.* Cog = Cognitive; SE = Social-emotional/behavioral.

the *Balanced High* class from the *Mod SE, Mod Cog*, and *Extremely Low* classes, with females more likely to be in the *Balanced High* class.

## Elementary School GMM

A series of GMM models were fit using the NCE reading scores from second through fifth grade. A similar model selection process was performed for the GMM models as the LCA models. The bottom panel of Table 2 presents the fit statistics for the GMM models that were considered. The lowest BIC value (56824.24) indicated a five-class solution. The nonsignificant LMR value of the four-class solution indicated a three-class solution was the best fit to the data. However, the nonsignificant BLRT value of the six-class model indicates the five-class model is again the preferred solution. Although most of the fit statistics seemed to indicate the five-class solution was the appropriate model, substantive interpretation of the classes must also play a key role in the process of model selection. When we examined the growth patterns for the five-class solution, one latent growth class only made up 0.4% of the sample and two of the other classes were not very well differentiated. The four-class model resulted in latent classes that identified different growth trajectories with reasonably sized classes; we thus determined this was a plausible and interpretable solution to describe heterogeneity in NCE growth trajectories. Additionally, this model had the next lowest BIC value, which provided some statistical evidence for the validity of the four-class solution. The entropy for this model was .48, which is considered low. However, none of the models had an entropy value greater than .65.

As with the LCA, the mean plot in Figure 3 was used to interpret and label the classes using the growth plot. Because NCEs have a mean of 50, we used this value as a reference for the class names. Subsequently, the top class had mean ELA scores greater than 50 at all four occasions and was named *Above Average*. This class made up 17% of the sample. The bottom class was named *Very Low*, reflecting the fact that the mean ELA scores for this class were more than a standard deviation below the mean at all four time points. This class consisted of 14.8% of the sample. The class depicted with a dashed line and diamonds was termed *Low Average*, as they were slightly below the mean for 3 of the 4 years. This was the largest class and made up 45.3% of the sample. Finally, the class depicted with a solid line and squares was labeled *Low* and constituted 22.9% of the total sample.

## Covariates in GMM

Three covariates were used in the GMM analysis and were related to the latent class variable: age, gender, and preschool experience. Unlike in the LCA results, comparing the classes of the four-class GMM model with and without covariates showed significant differences. Figure 3 shows the mean trajectory plot for the final chosen unconditional (i.e., without covariates) GMM, and Figure 4 shows the mean trajectory plot for the conditional (i.e., with covariates) GMM. Comparing the two figures, we see that both the nature of the profiles and the sizes change with the inclusion of covariates. For example, we see that the *Low Average* class performs much more similar to the *Very Low* class when there are covariates (see Figure 4) as opposed to performing more similar to the *Low* class with the model without covariates. One of the most notable differences between the models is that there is less variation in the three lower performing classes in the conditional model. This is especially apparent when we compare Grades 2, 4, and 5. The mean scores

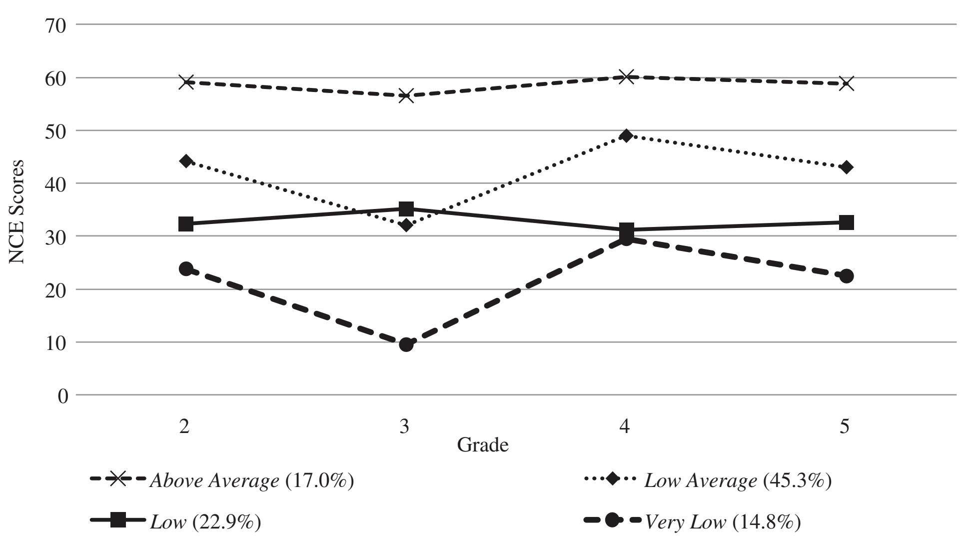


FIGURE 3 Mean normal curve equivalent (NCE) scores for the four-class unconditional growth mixture modeling solution.

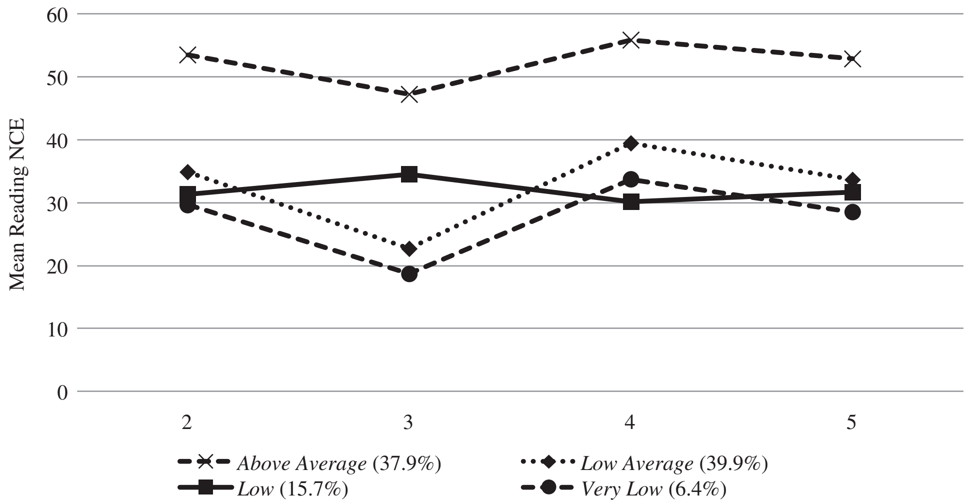


FIGURE 4 Mean normal curve equivalent (NCE) scores for the four-class growth mixture modeling solution with covariates.

of the lower performing classes are clustered substantially closer together in the conditional model than the unconditional model. Another key difference between the models is the *Above Average* class has lower NCE scores across all four grades, but a higher proportion of the sample in the conditional model compared to the unconditional model.

In the LCA, most of the covariates proved to be significant predictors of class assignment. However, this was not the case for the GMM. It should be restated that the California English Language Development Test (CELDT) score was not included as a covariate in the GMM due to model convergence difficulties. Gender was the only significant covariate in the GMM model, and this result was limited to the *Low* and *Very Low* classes when using the *Above Average* class as the reference class. That is, there were no gender differences when comparing the *Above Average* and *Low Average* classes. However, boys were slightly more than twice as likely to be in the *Low* and *Very Low* classes instead of the *Above Average* class.

### Results of the Combined LTA Model

After establishing the models for the LCA and GMM models, the combined LTA model was fit using the three-step specifications from the independent LCA and GMM models. When doing this, the class percentage (i.e., class size) remained the same for each part of the model as a result of the three-step specification. First, a model without covariates was fit and then the final LTA model with covariates was fit (see Figure 1).

Table 3 presents the transition probabilities describing the patterns of change of students from the kindergarten readiness classes to the elementary school reading trajectory classes based on the unconditional model. The results indicate that the students in the *Balanced High* class in kindergarten had a .55 probability of transitioning into the *Above Average* reading trajectory class in elementary school, the class with consistently above-average reading scores in elementary school. Another way to interpret this is that 55% of the students who were in the *Balanced High* class transitioned into the *Above Average* reading trajectory class. The next most likely class they transitioned into was the *Low Average* reading trajectory class, which is the second highest reading trajectory class. It was very unlikely (e.g., low probability) that a student in the *Balanced High* class would transition into the *Low* or *Very Low* class.

TABLE 3
Latent Transition Analysis Transition Probabilities Based on the Unconditional Latent Transition Analysis Model

| | *GMM Classes* | | | |
|---|---|---|---|---|
| *K Readiness Classes* | *Very Low* | *Low* | *Low Average* | *Above Average* |
| Extremely Low | 0.25 | 0.25 | 0.42 | 0.08 |
| Low SE, Low Cog | 0.16 | 0.24 | 0.51 | 0.09 |
| High SE, Low Cog | 0.08 | 0.18 | 0.66 | 0.08 |
| Mod SE, Mod Cog | 0.07 | 0.29 | 0.40 | 0.24 |
| Balanced High | 0.06 | 0.11 | 0.28 | 0.55 |

*Note.* Cog = Cognitive; GMM = growth mixture modeling; SE = Social-emotional/behavioral.

Forty percent of the students in the *Mod SE, Mod Cog* class transitioned into the *Low Average* class. The next two likely classes these students would transition to are the *Low* class (29%) and the *Above Average* (24%) class. Most (66%) of the students in the *High SE, Low Cog* class transitioned into the *Low Average* class. The next likely class for these students to transition to would be the *Low* class.

Just over half (51%) of the students in the *Low SE, Low Cog* class transitioned into the *Low Average* class. The next most likely classes were the Low class (24%) or the *Very Low* (16%) class. It was rare (9%) that students in this class transitioned to the *Above Average* class. Finally, of the students in the *Extremely Low* class, 42% transitioned into the *Low Average* class, and then just over half transitioned into either the *Very Low* (25%) or *Low* (25%) class. Like the *Low SE, Low Cog* class, students in the *Extremely Low* class were very unlikely to transition into the *Above Average* class.

## Covariate Results of the Final LTA Model

Tables 4 and 5 present the covariate results for the final LTA model. Note that the class percentages for both the LCA and GMM models remain the same as the unconditional three-step model, again one of the advantages of the three-step method. The final LTA, depicted in Figure 1, included the regression of the two latent class variables on the set of covariates. This model included an interaction term that allowed for the transition probabilities to be different based on the covariates. All four covariates were allowed to influence the transition probabilities, but only the covariates of age and prior preschool experience yielded results. Covariate results are presented first for the regression of the latent class variable on the covariates (Table 4) and then the interaction terms (Table 5). The *Balanced High* class was the reference class for the kindergarten readiness classes and the *Above Average* was the reference class for the elementary reading trajectory classes. A summary of the key covariate findings follows.

The covariate results in Table 4 are consistent with those found in the two independent analyses. The relationship of the covariates with the kindergarten readiness classes found that there was a consistent, positive effect of prior preschool experience and English language proficiency (CELDT); specifically across all the latent classes, students who went to preschool and who had higher English language proficiency were more likely to be in the *Balanced High* class. With the exception of the *High SE, Low Cog* class, older students were significantly more likely to be in the *Balanced High* class, as were female students.

With respect to elementary reading trajectory classes, there was a consistent gender effect. Specifically, female students were more likely to be in the *Above Average* class

TABLE 4
Covariate Table for the Final Model That Included Interaction Effects

| | *Effect* | *Logit* | *SE* | *Logit/SE* | *p Value* | *OR* |
|---|---|---|---|---|---|---|
| K readiness classes | | | | | | |
| Mod SE, Mod Cog | Age | −0.66* | 0.32 | −2.11 | 0.04 | 0.51 |
| | CELDT | −0.13* | 0.04 | −3.20 | 0.00 | 0.87 |
| | Female | −1.05* | 0.20 | −5.21 | 0.00 | 0.35 |
| | Preschool | −0.66* | 0.23 | −2.93 | 0.00 | 0.52 |
| High SE, Low Cog | | | | | | |
| | Age | −0.47 | 0.34 | −1.41 | 0.16 | 0.62 |
| | CELDT | −0.40* | 0.06 | −7.17 | 0.00 | 0.67 |
| | Female | 0.02 | 0.24 | 0.09 | 0.93 | 1.02 |
| | Preschool | −1.21* | 0.25 | −4.86 | 0.00 | 0.30 |
| Low SE, Low Cog | | | | | | |
| | Age | −1.04* | 0.30 | −3.47 | 0.00 | 0.35 |
| | CELDT | −0.42* | 0.05 | −8.66 | 0.00 | 0.66 |
| | Female | −0.52* | 0.19 | −2.66 | 0.01 | 0.60 |
| | Preschool | −1.53* | 0.22 | −7.09 | 0.00 | 0.22 |
| Extremely Low | | | | | | |
| | Age | −1.67* | 0.29 | −5.73 | 0.00 | 0.19 |
| | CELDT | −0.39* | 0.04 | −9.43 | 0.00 | 0.67 |
| | Female | −1.08* | 0.19 | −5.83 | 0.00 | 0.34 |
| | Preschool | −2.71* | 0.21 | −12.92 | 0.00 | 0.07 |
| Reading trajectory classes | | | | | | |
| Low Average | CELDT | −0.34* | 0.08 | −4.50 | 0.00 | 0.71 |
| | Female | −0.53 | 0.33 | −1.58 | 0.11 | 0.59 |
| Low | CELDT | −0.27* | 0.07 | −3.69 | 0.00 | 0.76 |
| | Female | −0.83* | 0.34 | −2.46 | 0.01 | 0.44 |
| Very Low | CELDT | −0.37* | 0.10 | −3.76 | 0.00 | 0.69 |
| | Female | −1.02* | 0.33 | −3.12 | 0.00 | 0.36 |

*Note.* Cog = Cognitive; OR = odds ratio; SE = Social-emotional/behavioral. CELDT = California English Language Development Test.
*$p < .05$.

TABLE 5
Interaction Effects of Age and Preschool Experience in the Final Latent Transition Analysis Model

| *K Readiness Class* | *Reading Trajectory Class* | *Effect* | *Logit* | *SE* | *Logit/SE* | *p Value* | *OR* |
|---|---|---|---|---|---|---|---|
| Balanced High | Very Low | Preschool | 0.17 | 1.28 | 0.13 | 0.90 | 1.18 |
| | | Age | 2.90 | 3.18 | 0.91 | 0.36 | 18.19 |
| | Low Average | Preschool | −0.20 | 1.18 | −0.17 | 0.87 | 0.82 |
| | | Age | 0.21 | 1.20 | 0.18 | 0.86 | 1.24 |
| | Low | Preschool | −0.45 | 1.14 | −0.39 | 0.69 | 0.64 |
| | | Age | 0.96 | 2.62 | 0.37 | 0.72 | 2.61 |
| High SE, Low Cog | Very Low | Preschool | −6.90* | 3.14 | −2.20 | 0.03 | 0.00 |
| | | Age | −7.32 | 4.97 | −1.47 | 0.14 | 0.00 |
| | Low Average | Preschool | −7.87* | 2.87 | −2.74 | 0.01 | 0.00 |
| | | Age | −7.25 | 4.13 | −1.76 | 0.08 | 0.00 |
| | Low | Preschool | −8.33* | 2.96 | −2.81 | 0.01 | 0.00 |
| | | Age | −9.11* | 4.40 | −2.07 | 0.04 | 0.00 |
| Mod SE, Mod Cog | Very Low | Preschool | −0.55 | 1.44 | −0.38 | 0.70 | 0.58 |
| | | Age | −11.18* | 4.60 | −2.43 | 0.02 | 0.00 |
| | Low Average | Preschool | 1.27 | 0.77 | 1.65 | 0.10 | 3.55 |
| | | Age | 1.32 | 1.51 | 0.88 | 0.38 | 3.74 |
| | Low | Preschool | 1.01 | 0.77 | 1.32 | 0.19 | 2.76 |
| | | Age | −1.11 | 1.43 | −0.77 | 0.44 | 0.33 |
| Low SE, Low Cog | Very Low | Preschool | −0.31 | 0.74 | −0.41 | 0.68 | 0.74 |
| | | Age | −0.02 | 1.25 | −0.02 | 0.99 | 0.98 |
| | Low Average | Preschool | −0.22 | 0.77 | −0.29 | 0.77 | 0.80 |
| | | Age | 0.57 | 1.12 | 0.51 | 0.61 | 1.77 |
| | Low | Preschool | −0.98 | 0.83 | −1.18 | 0.24 | 0.38 |
| | | Age | 0.51 | 1.27 | 0.40 | 0.69 | 1.67 |
| Extremely Low | Very Low | Preschool | 0.47 | 0.94 | 0.50 | 0.62 | 1.59 |
| | | Age | −0.67 | 0.91 | −0.74 | 0.46 | 0.51 |
| | Low Average | Preschool | −0.72 | 1.13 | −0.64 | 0.52 | 0.49 |
| | | Age | −2.92* | 1.08 | −2.71 | 0.01 | 0.05 |
| | Low | Preschool | −0.90 | 1.11 | −0.81 | 0.42 | 0.41 |
| | | Age | −2.85* | 1.11 | −2.57 | 0.01 | 0.06 |

*Note.* Cog = Cognitive; OR = odds ratio; SE = Social-emotional/behavioral.
$^*p < .05$.

compared to the *Low* and *Very Low* classes, but were equally likely to be in the *Low Average* and *Above Average* classes (see Table 4). Also, there was a consistent finding that students with higher English language proficiency were significantly more likely to be in the *Above Average* class compared to all the other classes.

*Interaction results.* The other two covariates, age and prior preschool experience, were included in the model and were allowed to have an interaction on the transition probabilities. That is, we tested to see if these variables changed the probability of a student transitioning among the kindergarten readiness classes and the reading trajectory classes. Table 5 presents the results of the interaction. There were several key findings here. For students who were in the *Extremely Low* kindergarten readiness class, results indicated that there is an interaction for age for two of the possible transitions. Specifically, older students who were in the *Extremely Low* kindergarten readiness class were significantly less likely to transition into the *Low Average* class relative to the *Above Average* class (−2.92, $p < .05$). Also, older students who were in the *Extremely Low* kindergarten readiness class were significantly less likely to transition into the *Low* class relative to the *Above Average* class (−2.85, $p < .05$). In other words, older students who were in the *Extremely Low* class were more likely to transition to better reading trajectory classes that had higher NCE scores.

There were several effects of age and prior preschool experiences for students who were in the *High SE, Low Cog* kindergarten readiness class. There was a consistent interaction effect for prior preschool experience for students in this class, indicating that students who went to preschool were significantly more likely to be in the *Above Average* class relative to any of the other reading trajectory classes (see Table 5). There was one age effect for students in the *High SE, Low Cog* kindergarten readiness class. Older students in this class were significantly less likely to end up in the *Low* reading class compared to the *Above Average* class (−11.18, $p < .05$). There was no interaction with age and the other reading trajectory classes. There were no interactions for age and prior preschool experience for students who were in the *Balanced High* or *Low SE, Low Cog* classes.

## DISCUSSION

In this article we present a flexible way to use the three-step method for a longitudinal model that involves the estimation of two mixture models. The example we used to illustrate this involved modeling heterogeneity in kindergarten readiness and linking it to heterogeneity in middle school reading trajectories. By providing an example of a complex LTA model that involved different measurement models for the latent class models as well as the syntax for these models, this article helps to provide building blocks for other mixture models that would benefit from using the three-step method.

The application of this model to study the relationship between kindergarten readiness and its link to elementary reading trajectories extended previous work examining the relationship between Latino and Latina children's readiness and subsequent academic achievement. First, the five readiness classes identified in this study were virtually identical to those identified by Quirk and colleagues (2013), providing a replication of these readiness classes with an additional cohort of Latino and Latina students. Second, the associations between readiness classes and subsequent achievement were consistent with previous research (Quirk et al., 2011; Quirk et al., 2013), with results providing additional evidence that Latino and Latina children's readiness levels, particularly cognitive readiness, at kindergarten entry are predictive of subsequent achievement through Grade 5. In addition, this study found that children's reading achievement trajectories remained fairly stable across the elementary grades, which is consistent with previous research on reading achievement trajectories across the elementary grades (Juel, 1988; Phillips, Norris, Osmond, & Maynard, 2002). Specifically, these findings revealed a discouraging trend amongst the Latino and Latina children from our sample, with the majority of students falling into a consistent pattern of below-average reading achievement across the elementary grades. Finally, the relationships yielded from the covariates examined were consistent with patterns found in previous studies, with preschool experience and age emerging as the most influential factors differentiating children's readiness classes and longitudinal reading achievement. Overall, the findings from this study suggest that Latino and Latina children who enter school unprepared for the social-emotional and cognitive demands of kindergarten are at extremely high risk of remaining on below-average reading achievement trajectories throughout the elementary grades, with very few students closing achievement gaps that persist from Grades 2 through 5.

### Limitations

As in any study, there are several limitations that should be mentioned. We focus on how to specify the three-step LTA model in M*plus,* but it should be noted that these models can be specified in other mixture modeling software such as Latent Gold (Vermunt & Magidson, 2005). In our application, we do not include distal outcomes predicted by the growth model and it should be noted that the manual three-step method easily allows for one or more distal outcomes to be included. Also, we do not allow the covariates in the GMM model to directly influence the growth parameters, only the latent class variable, which might in part explain why there are shifts in the latent classes' prevalence. In this article, we focused on modeling ideas, and are not able to focus fully on the potentially important contributions this study makes to understanding kindergarten readiness and its link to elementary reading trajectories.

### Future Directions

The three-step method provides a robust modeling framework that allows for a new way to estimate and specify mixture models. By having a model with fixed measurement parameters, we are more in line with our measurement wishes—that our auxiliary variables do not influence the measurement of the latent class variable. Using the three-step method is advantageous, however, because it becomes more time efficient to specify complex models that involve multiple latent class variables, which opens the door to more easily computed complex mixture models. For example, LTA with three time points or a higher order model (e.g., the Mover–Stayer model [Langeheine & van de Pol, 2002], once the three-step specification was calculated) could be estimated much more efficiently. Also, using the framework presented in this article it becomes more straightforward to have a latent class variable as a mediator or as another variable that is in a larger structural equation model.

## REFERENCES


Asparouhov, T., & Muthen, B. (2013). *Auxiliary variables in mixture modeling: 3-step approaches using M*plus (pp. 1–48). Los Angeles, CA: Muthén & Muthén. Retrieved from http://www.statmodel.com/examples/webnotes/webnote15.pdf

California Department of Education Standards and Assessment Division. (2008–2012). *California Standards Tests Technical Report: Spring 2008–2012 administrations*. Retrieved from http://www.cde.ca.gov/ta/tg/sr/technicalrpts.asp

Celeux, G., & Soromenho, G. (1996). An entropy criterion for assessing the number of clusters in a mixture model. *Journal of Classification*, *13*, 195–212.

Clark, S., & Muthen, B. (2009). *Relating latent class analysis results to variables not included in the analysis*. Retrieved from http://www.statmodel.com/download/relatinglca.pdf

Cleveland, M. J., Lanza, S. T., Ray, A. E., Turrisi, R., & Mallett, K. A. (2012). Transitions in first-year college student drinking behaviors: Does pre-college drinking moderate the effects of parent- and peer-based intervention components? *Psychology of Addictive Behaviors: Journal of the Society of Psychologists in Addictive Behaviors*, *26*, 440–450.

Collins, L. M., & Lanza, S. T. (2010). *Latent class and latent transition analysis: With applications in the social, behavioral, and health sciences*. New York, NY: Wiley.

Collins, L. M., & Wugalter, S. E. (1992). Latent class models for stage-sequential dynamic latent variables. *Multivariate Behavioral Research*, *27*, 131–157.

Furlong, M., & Quirk, M. (2011). The relative effects of chronological age on Hispanic students' school readiness and grade 2 academic achievement. *Contemporary School Psychology*.

Haertel, E. (1987). Scores and scales for school achievement. *Studies in Educational Evaluation*, *13*, 61–71.

Juel, C. (1988). Learning to read and write: A longitudinal study of 54 children from first through fourth grades. *Journal of Educational Psychology*, *80*, 437–447.

Langeheine, R., & van de Pol, F. (2002). Latent Markov chains. In J. A. Hagenaars & A. L. McCutcheon (Eds.), *Applied latent class analysis* (pp. 304–341). Cambridge, UK: Cambridge University Press.

Lilles, E., Furlong, M., Quirk, M., Felix, E., Dominguez, K., & Anderson, M. (2009). Preliminary development of the Kindergarten Student Entrance Profile. *The California School Psychologist*, *14*, 71–80.

Lubke, G. H., Muthén, B., Moilanen, I. K., McGough, J. J., Loo, S. K., Swanson, J. M., Yang, M. H., Taanila, A., Hurtig, T., Järvelin, M. R., & Smalley, S. L. (2007). Subtypes versus severity differences in attention-deficit/hyperactivity disorder in the Northern Finnish Birth Cohort. *Journal of the American Academy of Child & Adolescent Psychiatry*, *46*, 1584–1593.

Morin, A. J. S., Maïano, C., Nagengast, B., Marsh, H. W., Morizot, J., & Janosz, M. (2011). General growth mixture analysis of adolescents' developmental trajectories of anxiety: The impact of untested invariance assumptions on substantive interpretations. *Structural Equation Modeling*, *18*, 613–648.

Muthén, B. (2001). Latent variable mixture modeling. In G. A. Marcoulides & R. E. Schumacker (Eds.), *New developments and techniques in structural equation modeling* (pp. 1–33). Hillsdale, NJ: Erlbaum.

Muthén, B. (2003). Statistical and substantive checking in growth mixture modeling: Comment on Bauer and Curran (2003). *Psychological Methods*, *8*, 369–377.

Muthén, L. K., & Muthén, B. O. (1998–2012). *Mplus user's guide*. Los Angeles: Muthen & Muthen.

Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling*, *14*, 535–569.

Nylund, K., Bellmore, A., Nishina, A., & Graham, S. (2007). Subtypes, severity, and structural stability of peer victimization: What does latent class analysis say? *Child Development*, *78*, 1706–1722.

Nylund-Gibson, K., & Masyn, K. (2011). *Including auxiliary variables in latent class analysis*. Paper presented at the annual meeting of the Western Psychological Association, Los Angeles, CA.

Phillips, L. M., Norris, S. P., Osmond, W. C., & Maynard, A. M. (2002). Relative reading achievement: A longitudinal study of 187 children from first through sixth grades. *Journal of Educational Psychology*, *94*, 3–13.

Quirk, M., Furlong, M. J., Lilles, E., Felix, E., & Chin, J. (2011). Preliminary development of a kindergarten school readiness assessment for Latino students. *Journal of Applied School Psychology*, *27*, 77–102.

Quirk, M., Nylund-Gibson, K., & Furlong, M. J. (2013). Exploring patterns of Latino/a children's school readiness at kindergarten entry and their relations with Grade 2 achievement. *Early Childhood Research Quarterly*, *28*, 437–449.

Santa Maria-Bonita School District, First 5 of Santa Barbara County, & University of California Santa Barbara. (2005). *Kindergarten Student Entrance Profile*. Santa Barbara, CA: University of California Santa Barbara.

Schwartz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics*, *6*, 461–464.

Vermunt, J. K. (2010). Latent class modeling with covariates: Two improved three-step approaches. *Political Analysis*, *18*, 450–469.

Vermunt, J. K., & Magidson, J. (2005). *Technical guide for Latent Gold 4.0: Basic and advanced*. Belmont, MA: Statistical Innovations.

## APPENDIX A
## STEP 1 FOR THE LCA MODEL

```
Data: File is KSEP_Mplus.dat;

Variable: Names are IDSort SMID Cohort KSEP_AGE BirthMo Gender
    Presch KSEPProg Sp_Ed_K K_CELDT Ethnic KSEP_A KSEP_B
    KSEP_C KSEP_D KSEP_E KSEP_F KSEP_G KSEP_H KSEP_I
    KSEP_J KSEP_K KSEP_L KSEP_M KSEP_N KSEP_O KSEP_P
    KSEP64 B_KSEP_A B_KSEP_B B_KSEP_C B_KSEP_D B_KSEP_E
    B_KSEP_F B_KSEP_G B_KSEP_H B_KSEP_I B_KSEP_J B_KSEP_K
    B_KSEP_L B_KSEP_M B_KSEP_N B_KSEP_O B_KSEP_P
    KSEP16 KSEPLang ELA2_SS ELA2_PR MATH2_SS MATH2_PR
    ELA3_SS ELA3_PR MATH3_SS MATH3_PR ELA4_SS ELA4_PR
    MATH4_SS MATH4_PR ELA5_SS ELA5_PR MATH5_SS
    MATH5_PR K_School Age_KSEP K_SpEd;

    Usev = B_KSEP_A B_KSEP_B B_KSEP_C B_KSEP_D B_KSEP_E
    B_KSEP_F B_KSEP_G B_KSEP_H B_KSEP_I B_KSEP_J B_KSEP_K
    B_KSEP_L B_KSEP_M B_KSEP_N B_KSEP_O B_KSEP_P
    Age_KSEP K_CELDT Gender Presch;
    categorical = B_KSEP_A B_KSEP_B B_KSEP_C B_KSEP_D
    B_KSEP_E B_KSEP_F B_KSEP_G B_KSEP_H B_KSEP_I
    B_KSEP_J B_KSEP_K B_KSEP_LB_KSEP_M B_KSEP_N
    B_KSEP_O B_KSEP_P;

idvariable=smid;
auxiliary= Age_KSEP K_CELDT Gender Presch;

Missing are all (999);
classes = c(5);

Analysis: type=mixture;

Output: tech11 tech14 sampstat;

savedata:
   file is 5clca.dat;
   save=cprob;
   missflag=9999;
```

## APPENDIX B
## CALCULATING VALUES FOR THE LOGIT VALUES USED IN THE THIRD STEP

Using the two following tables taken from the Step 1 file for the LCA run (the Appendix B output file) from M*plus*. We calculate the probabilities using the following equations, described on page 4 of Asparouhov and Muthén (2013).

Average Latent Class Probabilities for Most Likely Latent Class Membership (Row) by Latent Class (Column)

| | *1* | *2* | *3* | *4* | *5* |
|---|---|---|---|---|---|
| 1 | 0.842 | 0.001 | 0.039 | 0.064 | 0.054 |
| 2 | 0.001 | 0.934 | 0.061 | 0.005 | 0.001 |
| 3 | 0.029 | 0.068 | 0.822 | 0.081 | 0.001 |
| 4 | 0.051 | 0.006 | 0.106 | 0.817 | 0.020 |
| 5 | 0.067 | 0.001 | 0.001 | 0.020 | 0.913 |

*Note*. Values that were zero were converted to 0.0001 for the sake of calculation.

## Classification of Individuals Based on Their Most Likely Latent Class Membership

| *Latent Classes* | | |
|---|---|---|
| 1 | 280 | 0.12891 |
| 2 | 734 | 0.33794 |
| 3 | 520 | 0.23941 |
| 4 | 367 | 0.16897 |
| 5 | 271 | 0.12477 |

$$q_{c_1=1,c_2=1} = \frac{0.842\,(280)}{0.842\,(280) + .0001\,(734) + 0.029\,(520) + 0.051\,(367) + .067\,(271)} = 0.819216$$

$$q_{c_1=2,c_2=1} = \frac{0.001\,(737)}{0.842\,(280) + .0001\,(734) + 0.029\,(520) + 0.051\,(367) + .067\,(271)} = 0.000255$$

Doing this calculation for all cells in the table, we get the following values for $q_{c_1,c_2}$

| $q_{c_1,c_2}$ | *1* | *2* | *3* | *4* | *5* |
|---|---|---|---|---|---|
| 1 | 0.819216 | 0.000002 | 0.020918 | 0.048568 | 0.055998 |
| 2 | 0.000255 | 0.948051892 | 0.085768 | 0.009947 | 0.000272 |
| 3 | 0.052400 | 0.048899163 | 0.818790 | 0.114156 | 0.000193 |
| 4 | 0.065038 | 0.003045135 | 0.074519 | 0.81264 | 0.027184 |
| 5 | 0.063092 | 0.000002 | 0.000005 | 0.01469 | 0.916353 |

To calculate the logits for each class which are used in the input file of the third step, we calculate the following, $\log\left(\frac{q_{c_1,c_2}}{q_{K,c_2}}\right)$. Thus, using the values from above, we obtain

$$logit_{q_{c_1=1,c_2=1}} = \log\left(\frac{0.819216}{0.063092}\right) = 2.563758177$$

$$logit_{q_{c_1=2,c_2=1}} = \log\left(\frac{0.000255}{0.063092}\right) = -5.510887505$$

Doing these calculations for all possible combinations results in the following set of logit values that are used in the third step (see Appendix C). Note that there are four rows of $c_1$ because the last class is the reference class.

| | *1* | *2* | *3* | *4* | *5* |
|---|---|---|---|---|---|
| 1 | 2.563758 | 0.032670782 | 8.301403 | 1.195822 | −2.79508 |
| 2 | −5.51089 | 13.13418401 | 9.712434 | −0.3899 | −8.12293 |
| 3 | −0.18569 | 10.16953506 | 11.96862 | 2.050427 | −8.46761 |
| 4 | 0.030376 | 7.393319863 | 9.571852 | 4.01315 | −3.51776 |

Note that in M*plus* 7.1, these values are provided to you in the output of the Step 1 run in a table labeled "Logits for the Classification Probabilities for the Most Likely Latent Class Membership (Row) by Latent Class (Column)."

## APPENDIX C
## STEP 3 FOR LCA MODEL

```
Data: file is merged.dat;
Variable:
   Names = nce2 nce3 nce4 nce5 smid i s ci cs cprob1g cprob2g cprob3g
   cprob4g cg ksepa ksepb ksepc ksepd ksepe ksepf ksepg kseph ksepi
   ksepj
   ksepk ksepl ksepm ksepn ksepo ksepp age kcdldt gender presc cprob1l
   cprob2l cprob3l cprob4l cprob5l cl;

   missing are all (9999);
   nominal=cl;
   usevar= cl;
   classes=c1(5);

   analysis: type=mixture;
       starts=0;

   Model:
     %c1#1%
       [cl#1@2.563758177];
       [cl#2@-5.510887505];
       [cl#3@-0.185686799];
       [cl#4@0.030376041];
     %c1#2%
       [cl#1@0.032670782];
       [cl#2@13.13418401];
       [cl#3@10.16953506];
       [cl#4@7.393319863];


     %c1#3%
       [cl#1@8.301402614];
       [cl#2@9.712434258];
       [cl#3@11.96862057];
       [cl#4@9.571852307];


     %c1#4%
       [cl#1@1.195821592];
       [cl#2@-0.389904153];
       [cl#3@2.050426872];
       [cl#4@4.013149848];


     %c1#5%
       [cl#1@-2.795081052];
       [cl#2@-8.122930766];
       [cl#3@-8.467610983];
       [cl#4@-3.51776058];
```

## APPENDIX D
## STEP 1 FOR GMM

```
Data: File is KSEP_Mplus_NCE.dat;
Variable:
    Names are IDSort SMID Cohort KSEP_AGE BirthMo Gender
    Presch KSEPProg Sp_Ed_K K_CELDT Ethnic KSEP_A
    KSEP_B KSEP_C KSEP_D KSEP_E KSEP_F KSEP_G
    KSEP_H KSEP_I KSEP_J KSEP_K KSEP_L KSEP_M
    KSEP_N KSEP_O KSEP_P KSEP64B_KSEP_A B_KSEP_B
    B_KSEP_CB_KSEP_D B_KSEP_E B_KSEP_F B_KSEP_G
    B_KSEP_H B_KSEP_I B_KSEP_J B_KSEP_K B_KSEP_L B_KSEP_M
    B_KSEP_N B_KSEP_O B_KSEP_P KSEP16 KSEPLang ELA2_SS
    ELA2_PR MATH2_SS MATH2_PR ELA3_SS ELA3_PR MATH3_SS
    MATH3_PR ELA4_SS ELA4_PR MATH4_SS MATH4_PR ELA5_SS
    ELA6_PR MATH6_SS MATH6_PR K_School Age_KSEP K_SpEd
    MATH5_SS E_NCE2 E_NCE3 E_NCE4 E_NCE5;

    Usev = E_NCE2 E_NCE3 E_NCE4 E_NCE5;
    Missing are all (999);
    Classes = c(4);

    Analysis: type=mixture;
      starts = 500 100;
      process=8;

    Model:
      %overall%
      i s | E_NCE2@0 E_NCE3* E_NCE4* E_NCE5@1;

    %c#1% i
      i;

    Plot: type=plot3;
    series = E_NCE2 E_NCE3 E_NCE4 E_NCE5(*);

    Output: tech1 tech11 tech14 sampstat;
```

## APPENDIX E
## STEP 3 FOR GMM

```
data: file is merged.dat;

Variable:
    Names = nce2 nce3 nce4 nce5 smid i s ci cs cprob1g cprob2g cprob3g
    cprob4g cg ksepa ksepb ksepc ksepd ksepe ksepf ksepg kseph ksepi
    ksepj ksepk ksepl ksepm ksepn ksepo ksepp age kcdldt gender presc
    cprob1l cprob2l cprob3l cprob4l cprob5l cl;

missing are all (9999);
nominal=cg;
usevar= cg;
classes=c2(4);

Analysis: type=mixture;
   starts=0;

Model:

  %c2#1%
     [cg#1@11.21770963];
     [cg#2@9.893657578];
     [cg#3@9.228930143];

  %c2#2%
     [cg#1@0.282194847];
     [cg#2@2.476637782];
     [cg#3@0.229667677];

  %c2#3%
     [cg#1@0.240097661];
     [cg#2@1.394279801];
     [cg#3@2.384519776];

  %c2#4%
     [cg#1@-5.728501062];
     [cg#2@-0.604537082];
     [cg#3@-1.790119257];
```

## APPENDIX F
## STEP 3 FOR COMBINED LTA MODEL

```
data: file is mergedfinal.dat;
variable:
    names = KSEP_A KSEP_B KSEP_C KSEP_D KSEP_E KSEP_F
    KSEP_G KSEP_H KSEP_I KSEP_J KSEP_K KSEP_L KSEP_M
    KSEP_N KSEP_O KSEP_P SMID AGE CELDT GENDER PRESCH
    CPROB1 CPROB2 CPROB3 CPROB4 CPROB5 Cl E_NCE2 E_
    NCE3 E_NCE4 E_NCE5 CG;

missing are all (9999);
nominal=cl cg;
usevar= age celdt gender presch cl cg;
classes=c1(5) c2(4);

Analysis:
   type=mixture;
   starts=0;

Model:
   %overall%
   c2 on c1;

Model c1:
   %c1#1%
      [cl#1@2.565];
      [cl#2@-11.051];
      [cl#3@-11.051];
      [cl#4@0.034];

   %c1#2%
      [cl#1@0.000];
      [cl#2@13.762];
      [cl#3@10.795];
      [cl#4@8.020];

   %c1#3%
      [cl#1@ 6.236];
      [cl#2@7.639];
      [cl#3@9.898];
      [cl#4@7.503];

   %c1#4%
      [cl#1@1.209];
      [cl#2@-0.427];
      [cl#3@ 2.063];
      [cl#4@4.026];

   %c1#5%
      [cl#1@-2.787];
      [cl#2@-13.729];
      [cl#3@-10.441];
      [cl#4@-3.542];
```

```
Model c2:
    %c2#1%
    [cg#1@6.612539444];
    [cg#2@5.288487392];
    [cg#3@4.623759957];

  %c2#2%
    [cg#1@0.282194847];
    [cg#2@2.476637782];
    [cg#3@0.229667677];

  %c2#3%
    [cg#1@0.240097661];
    [cg#2@1.394279801];
    [cg#3@2.384519776];

  %c2#4%
    [cg#1@-5.728501062];
    [cg#2@-0.604537082];
    [cg#3@-1.790119257];
```

## APPENDIX G
## STEP 3 FOR COMBINED LTA MODEL WITH COVARIATES AND COVARIATE INTERACTIONS

```
data: file is mergedfinal.dat;
   variable:
   names = KSEP_A KSEP_B KSEP_C KSEP_D KSEP_E KSEP_F
   KSEP_G KSEP_H KSEP_I KSEP_J KSEP_K KSEP_L KSEP_M
   KSEP_N KSEP_O KSEP_P SMID AGE CELDT GENDER PRESCH
   CPROB1 CPROB2 CPROB3 CPROB4 CPROB5 Cl E_NCE2
   E_NCE3 E_NCE4 E_NCE5 CG;

missing are all (9999);
nominal=cl cg; !CL = latent class ; CG = growth mixture model
usevar= age celdt gender presch cl cg;
classes=c1(5) c2(4);

Analysis:
  type=mixture;
  starts=0;

Model:
  %overall%
  c2 on c1;
  c1 on age celdt gender presch;
  c2 on celdt gender;

Model c1:
  %c1#1%
  [cl#1@2.565];
  [cl#2@-11.051];
  [cl#3@-11.051];
  [cl#4@0.034];

  C2 on presch age;
  %c1#2%
  [cl#1@0.000];
  [cl#2@13.762];
  [cl#3@10.795];
  [cl#4@8.020];
  c2 on presch age;

  %c1#3%
  [cl#1@ 6.236];
  [cl#2@7.639];
  [cl#3@9.898];
  [cl#4@7.503];
  c2 on presch age;

  %c1#4%
  [cl#1@1.209];
  [cl#2@-0.427];
  [cl#3@ 2.063];
  [cl#4@4.026];

  c2 on presch age;
  %c1#5%
  [cl#1@-2.787];
  [cl#2@-13.729];
  [cl#3@-10.441];
  [cl#4@-3.542];

  c2 on presch age;
Model c2:
  %c2#1%
  [cg#1@6.612539444];
  [cg#2@5.288487392];
  [cg#3@4.623759957];

  %c2#2%
  [cg#1@0.282194847];
  [cg#2@2.476637782];
  [cg#3@0.229667677];

  %c2#3%
  [cg#1@0.240097661];
  [cg#2@1.394279801];
  [cg#3@2.384519776];

  %c2#4%
  [cg#1@-5.728501062];
  [cg#2@-0.604537082];
  [cg#3@-1.790119257];
```