Contact Email: jillpentimonti@gmail.com

Title: Examining Early Learning Profiles at Pre-K Entry

Choice of Conference Section: Early Childhood Education

Authors:
Jill Pentimonti, American Institutes for Research, jillpentimonti@gmail.com
Virginia Buysse, American Institutes for Research, vbuysse@air.org
Aleksandra Holod, American Institutes for Research, aholod@air.org

Presenting Author: Jill Pentimonti

Abstract

Background/Context

Understanding the impact of pre-k programs is a complex endeavor. It involves understanding multiple pieces of a puzzle consisting of components such as different delivery contexts, program features, teacher qualifications, and child characteristics. With respect to child characteristics, it is well established that children enter pre-k classrooms with widely varying skill levels and divergent early learning experiences (Phillips et al., 2017). However, it is often challenging to capture and communicate children's early learning variability across multiple dimensions using a single assessment or battery of assessments. Creating early learning profiles at pre-k entry can be used to typify groups of children who differ in terms of various dimensions of learning, in this case, language and literacy development. The results are useful for measuring the gains that children make in pre-k to evaluate program impacts and to plan and evaluate instructional interventions. By focusing on profiles of language and literacy learning, this study builds on previous research that has used these methods to create profiles of groups of pre-k children who differ across dimensions of both social-emotional development and academic learning (Denham, Bassett, Mincic, Kalb, Way, Wyett, & Segal, 2012; McWayne, Fantuzzo, & McDermott, 2004).

Purpose

In the present work, we used person-centered methods to examine whether there may be reliable profiles that characterize children's early language and literacy skills as they enter pre-k, and the extent to which profile membership may be associated with gender and dual language learner (DLL) status.

Setting and Participants

Participants were 400 children enrolled in the New York City *Pre-K for All* program. At entry to pre-k, on average children were 4 years, 2 months old. A total of 51% of the children in the sample were male and 26% were DLLs. Children's early language and literacy skills were screened in the fall of their pre-k year with the Preschool Early Literacy Indicator (PELI; Kaminski, Abbott, Bravo, Aguayo, & Latimer, 2014) which measures the following skills: (a) alphabet knowledge, (b) vocabulary, (c) listening comprehension, and (d) phonological awareness. See Table 1 for descriptive statistics across PELI subtests.

Analysis

To address the two research aims of this study, two phases of analyses were conducted. First, we utilized latent class analysis (LCA) to classify individuals into classes based on individual responses (Samuelsen & Dayton, 2010). LCA determine group membership from a person-centered approach based on children's early language and literacy skills. In this study, we used Latent Profile Analysis (LPA), a subtype of LCA, which is conceptually identical to LCA except that the LPA indicators are continuous; in LCA, the indicators are categorical (Logan & Petscher, 2010). Second, we utilized multinomial logistic regression to examine the relations between profile membership and gender and DLL status.

Findings

Our first study aim was to explore profiles of PreK children in regard to their early language and literacy skills. LPA-derived models were tested for 2- through 5-group solutions, using a variety of model fit indices to evaluate the data. In all analyses, standardized scores were used to allow for comparison of scores across measures. Table 2 provides the model fit indices for all models (group sizes of two through five). Using the recommendations of Logan and Petscher (2010), multiple indices were examined to determine that a 5-group solution was the most appropriate fit for the data. The first two indices are the Akaike Information Criteria (AIC; Kaplan, 2000) and Bayesian Information Criterion (BIC; Kaplan, 2000); the AIC and BIC evaluate model parsimony, with lower values indicating a more parsimonious model fit. Model results showed that both of these indices declined as the number of groups tested increased. Additionally, the Lo-Mendell-Rubin Likelihood Ratio Test (TECH11; Lo, Mendell, & Rubin, 2001) was used as a model fit index as reported in the MPlus program (Muthén & Muthén, 2019). TECH 11 demonstrates whether the model being tested fits significantly better than a model with one less group as indicated with significant *p*-values ($p < 0.05$). TECH 11 was significant for the Group 5 model ($p < .01$). Finally, entropy values offer information about group membership classification and are indicators of model fit. In examining entropy, values greater than 0.80 indicate a good separation of the identified groups (Ramaswamy, DeSarbo, Reibstein, & Robinson, 1993). For these data, entropy was acceptable for all five models. To sum, accounting for all model fit indices, the 5-group model was determined to be the best fit for our data. In order to visually examine the nature of the five groups identified by the LPA, we graphed children's school readiness standardized scores by group (see Figure 1).

The second research aim was to predict membership in the five identified profiles with respect to gender and DLL status. First, a multinomial logistic regression was performed to model the relationship between gender and membership in the five profiles. This model was not statistically significant, χ^2 (4, N = 400) = 40.43, p = .67; therefore, children's gender showed no significant difference in profile membership. Second, a model was conducted to understand relationship between profile membership and children's DLL status. A significant relation was found between profile membership and children's DLL status. Children who were DLLs were more likely to be placed in Profile 1 (in which scores were low across all dimensions of language and literacy) than Profiles 2-5. Model results are presented in Table 3.

Conclusion

Our results indicate that there are several different early learning profiles at children's entry pre-k. Specifically, DLLs exhibit a typology across dimensions of language and literacy (alphabet knowledge, vocabulary, listening comprehension, and phonological awareness) that differs from non-DLL groups. These results warrant further research to substantiate these findings for DLLs and to determine whether these patterns persist over time.

References

Denham, S.A., Bassett, H., Mincic, M., Kalb, S., Way, E., Wyett, T, & Segal, Y. (2012). Social-emotional learning profiles of preschoolers' early school success: A person-centered approach. *Learning and Individual Differences,* 22(2), 178-189

Kaminski, R., Abbott, M., Aguayo, K., Latimer, R., & Good III, R. (2014). The Preschool Early Literacy Indicators: Validity and benchmark goals. *Topics in Early Childhood Special Education, 34*(2), 71-82. DOI: 10.117/0271121414527003

Kaplan, D. (2000). Structural equation modeling: Foundations and extensions. Thousand Oaks, CA: Sage

Lo, Y., Mendell, N. R., & Rubin, D. B. (2001). Testing the number of components in a normal mixture. *Biometrika*, *88*(3), 767-778.

Logan, J. A., & Petscher, Y. (2010). School profiles of at-risk student concentration: Differential growth in oral reading fluency. *Journal of school psychology*, *48*(2), 163-186.

McWayne, C., Fantuzzo, J., McDermott, P.A. (2004). Preschool competency in context: An investigation of the unique contribution of child competencies to early academic success. *Developmental Psychology,* 40(4), 633-645.

Muthén, L. K., & Muthén, B. (2019). Mplus. *The comprehensive modelling program for applied researchers: user's guide*, *5*.

Phillips, D., Lipsey, M. W., Dodge, K. A., Haskins, R., Bassok, D., Burchinal, M. R., & Weiland, C. (2017). Puzzling it out: The current state of scientific knowledge on pre-kindergarten effects. A consensus statement. *Issues in pre-kindergarten programs and policy*, 19-30.

Ramaswamy, V., DeSarbo, W. S., Reibstein, D. J., & Robinson, W. T. (1993). An empirical pooling approach for estimating marketing mix elasticities with PIMS data. *Marketing Science*, *12*(1), 103-124.

Samuelsen, K. M., & Dayton, C. M. (2010). Latent class analysis. *The reviewer's guide to quantitative methods in the social sciences*, 173-184.

Table 1. *Descriptive Statistics for Children's School-Readiness Skills (N=400)*

	Range	*M*	*SD*
Alphabet knowledge	0-26	14.02	9.71
Vocabulary	0-34	15.10	9.81
Listening comprehension	0-21	10.01	5.76
Phonological awareness	0-15	4.73	5.24

Table 2. *Fit Indices from Model Testing*

Groups	AIC	BIC	TECH 11	Entropy
2	10435.46	10487.34	0.00	0.92
3	10290.31	10362.15	0.00	0.83
4	10168.39	10260.19	0.03	0.86
5	**10064.41**	**10176.17**	**0.01**	**0.86**

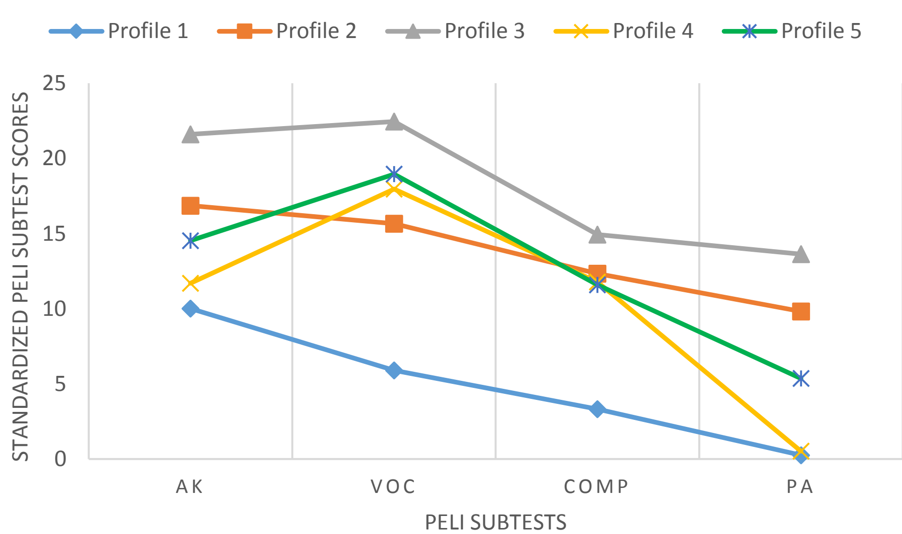
AIC = Akaike Information Criteria, BIC = Bayesian Information Criterion, TECH 11 = Lo-Mendell-Rubin Likelihood Ratio Test

Table 3. *Results of Multinomial Logistic Regression Analyses*

DLL Status	Intercept	Estimate	Standard Error of Estimate	Odds Ratio
Profile 1 vs. 2	-2.12	27.19	0.41	0.12*
Profile 1 vs. 3	-2.58	25.96	0.51	0.08*
Profile 1 vs. 4	-1.84	31.27	0.33	0.16*
Profile 1 vs. 5	-1.80	18.96	0.41	0.15*

* p <.05

Figure 1. *Early language and literacy skills by profile.*



AK = Alphabet Knowledge, VOC = Vocabulary, COMP = Listening Comprehension, PA = Phonological Awareness