Can Difficulties in Language Acquisition and Specific Learning Disabilities be Separated?

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Abstract

This study investigated the prevalence of latent classes at risk for reading and/or math disabilities in elementary-aged children whose first language is Spanish. To this end, children (*N* = 394) in Grades 1, 2, and 3 were administered a battery of vocabulary, reading, math, and cognitive measures in both Spanish and English. Three important findings occurred. First, five latent classes emerged (average achievers, poor achievers, reading disabled, English language learners, Spanish Dominant Achievers) that varied in language and achievement scores. Second, probability estimates indicated that 10% of the total sample was at risk for learning disabilities (below cut-off score), and approximately 40% sample reflected a language acquisition group not at risk for academic difficulties. Finally, the best model for correctly predicting the odds of latent classes differing from average achievers were English measures of STM, naming speed and the executive component of WM. The results support the notion that statistically distinct latent classes emerge under the umbrella of children identified as English learners, and that children at risk for specific learning disabilities can be separated among a heterogeneous sample of children who are acquiring English as a second language.

Keywords: specific learning disability, ELL, working memory, latent class analysis

Can Difficulties in Language Acquisition and Specific Learning Disabilities be Separated Among English Learners?

In the United States, school achievement is lower for English language learners (ELs) who speak Spanish as their first language than other minorities and Caucasian children (e.g., August & Hakuta, 1997; Hemphill & Vanneman, 2011, NAEP, 2011; 2017). In addition, cross-sectional studies have shown that ELs disproportionately experience reading and math difficulties across various age levels (e.g., Kieffer, 2011; Martiniello, 2009). Compounding these aforementioned difficulties is that many of these EL children with reading and math difficulties are not provided appropriate services. For example, national estimates reveal that EL children are underrepresented overall in special education, meaning that a smaller percentage of these children are receiving services than would be expected, given the proportion of the overall population that they represent (e.g., Morgan & Farkas, 2016).

More important, confounds exist in the assessment of children with potential learning problems who are second language learners. These confounds are due in part to attributing difficulties in second language acquisition and reading and/or math achievement to the same cognitive processes as found in children with learning disabilities. In practice, these confounds may lead to English language learners being inappropriately diagnosed with learning disabilities and placed in special education. The opposite situation is also true that children who are at potential risk for learning disabilities are being overlooked and not being provided intervention. In order to circumvent some of these problems, it is necessary to identify the processes in children with learning disabilities from other processes related to second language acquisition. These issues underscore the need for better tools and methods for accurately identifying EL children with serious reading and math difficulties. (The terms EL and emerging bilinguals are used interchangeably throughout the manuscript).

This study has two purposes. The first purpose was to determine if EL children at risk for specific learning disabilities in reading and/or math reflect a discrete latent class of learners. Currently, children at risk for learning disabilities in reading and/or math have been defined by performing below a cut-off score on a norm-referenced standardized reading and/or math test (e.g., Branum-Martin, Fletcher & Stuebing, 2013; Geary, Hoard, Nugent, & Bailey, 2012; Lipka, Lesaux, & Siegel, 2006). However, this selection process of determining children as at risk for learning disabilities has been criticized because of a reliance on artificial cut-off scores (e.g., Branum-Martin et al., 2013; Cirino, Fuchs, Elias, Powell, & Schumacher, 2015). These artificial standards have also been exacerbated when defining risk status among EL students because such children are not tested in their first language (e.g., Peña, Bedore, & Kester, 2016). This is unfortunate because it is commonly assumed that a certain threshold within one's native language is necessary before the cognitive processes and academic performance in the second language can be assessed (e.g., Cummins, 1979).

To address some of the above issues, methodological advances contribute to our understanding of children's academic skills as it relates to EL children, such as modeling the development of discrete processes based on the latent class analysis (e.g., Collins & Lanza, 2010; Muthén, 2006). Latent class analysis (LCA) is a statistical method used to identify subgroups of individuals characterized by similar multidimensional patterns of responses (e.g., Collins, Hyatt, & Graham, 2000). In one sense, LCA is a categorical analog to factor analysis. Instead of defining attributes to a complex covariance structure, LCA posits unobserved classes to explain complex associations in a multidimensional contingency table. Studies that involve the analysis of unobserved classes from a heterogeneous sample are sometimes referred to as mixture models (e.g., Muthén, 2006). A rationale for using latent class or mixture modeling is that although reading and/or math skills can be represented as a continuous outcome variable, the sample may be composed of different groups (or classes) of individuals. The advantage of LCA when compared to other procedures, such as cluster analysis, is that it offers a probabilistic model of the distribution latent classes in the data. In this study, we test the notion that discrete latent classes or mixtures representing different states of academic proficiency exist in EL children who may be identified as at risk or not at risk.

The second purpose of this study was to determine the cognitive processes that correlate with the performance of EL children at risk for achievement difficulties. Current procedures to identify children with potential learning disabilities in reading and/or math assume that such children experience cognitive constraints which impedes their ability to perform efficiently on achievement measures (e.g., Geary, Nicholas, Li, & Sun, 2017; Lesaux, Lipka, & Siegel, 2006). Thus, on the assumption that a discrete subgroup of EL children at risk for learning disabilities in reading and/or math emerges, it is important to know the cognitive processes associated with these risk groups. One of the most often referred to cognitive process underlying both reading and math disabilities is working memory (WM; Cowan, 2014; David, 2012; Peng et al., 2016; 2018; Swanson & Beebe-Frankenberger, 2004), which has also been related to achievement difficulties in emerging bilinguals (e.g., de Abreu, & Engle, 2011; de Abreu & Gathercole, 2012; Linck, Osthus, Koeth, & Bunting, 2013; Swanson, Sáez, & Gerber, 2006; Swanson, Orosco & Lussier, 2015). Although the association between WM and reading and/or math has been established in the literature, the processes of WM that underlie predictions of reading and/or math performance are unclear (see Peng et al., 2016; 2018, for review). Some studies have suggested that the storage component of WM (referred to as verbal short-term memory, STM) plays a major role in academic performance. Other studies have noted that academic difficulties are tied to the executive component of WM (e.g., Peng et al., 2016; 2018; Swanson et al., 2015).

In summary, the purpose of this study was to identify whether EL children at risk for learning disabilities reflect a latent class. The study determined if this potential latent class could be differentiated in terms of severity of academic deficiencies from other latent classes and whether this differentiation reflected qualitatively different cognitive processes. To extend the literature in these areas, the study sought to answer two questions:

1: Can a latent classification of EL children at risk for reading and/or math be identified within a heterogeneous sample of English language learners?

Traditionally, as indicated above, children at risk for learning disabilities in reading and/or math are operationally defined by performing below a cut-off point on a norm-referenced achievement measure [studies vary from the 11th to 25th percentile on norm-referenced standardized achievement measures (e.g., Murphy et al., 2007; Swanson et al., 2006;Vukovic & Lesaux, 2013)]. The present study determines the probability of identifying a latent class of participants at risk for learning disabilities using the 16th percentile (85 standard score) as a cut-off point within a sample, that includes a test battery of math, reading, and cognitive abilities. This cut-off was considered a conservative cut-off point because it captures performance below what is considered the average range in normative standard score distributions, As mentioned, LCA is a "model-based clustering" approach that derives clusters using a probabilistic model that describes the distribution of data. Therefore, instead of finding clusters of children with low academic performance, LCA describes the distribution of the data based on a model that assesses probabilities that certain cases are members of certain latent classes. Thus, with the goodness of fit indices, it is possible to test whether a "latent structure" underlies the data.

A further refinement in the sample selection of EL children at risk for learning disabilities includes making sure that such children perform above the cut-off scores (> 16th percentile) on vocabulary measures in L1. This refinement is necessary to establish that risk status resides in the academic domain and not in language (i.e., L1), per se. Likewise, further refinement in sample selection includes establishing that such children's academic difficulties are not due to general intellectual difficulties and/or with biased aptitude measures (e.g., Ferrer et al., 2010, Lohman, Korb, & Lakin, 2008; Lohamn & Gambrell, 2012).

2. Do specific cognitive measures predict latent class membership?

Based on the aforementioned discussion, we determine if cognitive processes related to language acquisition (e.g., phonological storage or STM) can be separated from children at risk for learning disabilities. Clearly, both groups may share some processing difficulties, but one or two processes maybe particularly helpful towards identify EL children with potential risk for learning disabilities in reading and/or math from children experiencing difficulties acquiring English as a second language. For example, it is commonly assumed that deficits in the phonological system (phonological storage) have been attributed to reading disabilities (RD) in English (e.g., Stanovich & Siegel, 1994) and Spanish (e.g., Gonzàlez & Valle, 2000). Studies that are more recent have found that executive processes, primarily those executive processes related to WM, are also significantly related to L2 reading and math performance (e.g., Swanson et al., 2015; Swanson, Kong & Petcu; 2018). For this study, working memory is defined as consisting of a limited capacity system related to the preservation of information while simultaneously processing other information (Baddeley & Logie, 1999). The system reflects controlled attention because information to be recalled is presented in the context of competing information.

In addition to STM and WM, mental operations related to and naming speed and inhibition of the competing language may also play an important role in EL children's academic performance (e.g., Bonifacci, Giombini, Bellocchi, & Contento, 2011; Cooper, 2012). For example, letter and digit naming speed may underlie the general pattern of cognitive difficulties among some emerging bilinguals. Thus, our predictions are that processes related an executive (WM, inhibition) and/or the phonological storage system (STM) play a unique role in predicting a latent class of children at risk for learning disabilities in reading and/or math.

In summary, the present study tested whether various latent classes emerge related to reading and/or math skills among EL children. Measures used to classify children at risk for learning disabilities in either reading and/or math included norm-referenced tests of reading, math and language in both Spanish and English. To enhance our focus beyond academic and vocabulary measures, we also include as part of the classification battery measures of classroom behavior (ADHD) and nonverbal reasoning (fluid intelligence). Specifically, we expected to find latent classes of children at risk for achievement difficulties (i.e., reading and/or math disabilities), children not at risk for achievement difficulties who were proficient in both languages (English and Spanish), and children not at risk who are more proficient in their first language (Spanish) than their second language (English).

Method

Participants

Three hundred and ninety-four (*N*=394) students in grades 1 (*n* =155), 2 (*n* =129) and 3 (*n* =110) from two large school districts in the Southwest United States participated in this study.

The children were designated as EL or emerging bilinguals by their school and were selected from 30 classrooms. [1] These children were selected from urban schools with a high poverty representation (over 98 percent of the children participated in a full or reduced Federal lunch program) as well as a high Hispanic representation (> 95 %). The final sample included 192 boys and 202 girls who returned signed consent forms. School records indicated that children's primary home spoken language was Spanish (> 80%). All children were selected from dual language classrooms in which instruction was provided in both English and Spanish. No significant differences in gender representation emerged across the grades, $\chi^2(df=2, N=394)=2.88, p=.23$.

Measures Used for Identifying Latent Classes

The study included group and individual administrations of a battery of tests. The series of tests were counterbalanced into one of four presentation orders. No Spanish and English versions of the same test (except for the Expressive One-word Picture Vocabulary Test, Spanish-Bilingual Edition; Brownell, 2001) were presented simultaneously. All participants were administered both English and Spanish versions of each measure by bilingual graduate students and staff researchers. The mean raw scores and reliabilities for all measures for the current sample described below are provided in the supplement (Supplement Table 4) to this article. Because the normed standardized measures for establishing the latent class are commercially available as well as information on their validity and reliability, they are briefly reviewed here. Additional detail is provided below for the experimental cognitive measures.

Vocabulary: Receptive and Expressive

The Peabody Picture Vocabulary Test (PPVT) (Dunn & Dunn, 2007) was administered in English. In this task, children were presented with four pictures and asked to select the picture that matched the word read aloud in English. The Test de Vocabulario en Imagenes (TVIP) was also administered**.** This measure is similar to the PPVT in the presentation and administration, except that words are read aloud in Spanish (Dunn, Lugo, Padilla & Dunn, 1986). The Expressive One-Word Picture Vocabulary Test -Spanish-Bilingual Edition (EOWPVT-SBE: Brownell, 2001) was used as a measure of English and Spanish speaking vocabulary. The sample Cronbach alpha reliabilities for the receptive and expressive vocabulary measures were .96, .95 for English and .92 and .96 for Spanish measures, respectively.

Reading: Word Identification and Passage Comprehension

The Woodcock-Muñoz Language Survey-Revised (WMLS-R) established a norm-referenced reading level in English and Spanish (Woodcock-Muñoz, Sandoval & Alvarado, 2005). The WMLS-R Spanish and English Word Identification and Passage Comprehension subtests were administered. The sample Cronbach alpha reliabilities for the word identification and comprehension subtests were .95, .90 for English and .89 and .80 for Spanish measures, respectively.

Math: Calculation and Word Problems

The Calculation and Applied Math Problem Solving subtest from the Woodcock-Johnson III (Woodcock, McGrew, & Mather, 2001) was administered for the English presentation and the Calculation and Problemas *Aplicados* from the Batería III Woodcock-Muñoz (Muñoz-Sandoval Woodcock, McGrew, & Mather, 2005) was administered to establish normed referenced math levels in Spanish. Both of these subtests are individually administered and assess children’s early mathematical operations (e.g., counting, addition, and subtraction) through practical problems. The sample Cronbach alpha reliabilities for the calculation and applied problems subtests were .78, .78 for English and .83 and .71 for Spanish measures, respectively.

Fluid Intelligence and Attention

Fluid Intelligence. Fluid intelligence was assessed by administering the Raven Colored Progressive Matrices test (RCMT, Raven, 1976). The RCMT is commonly used to tap fluid intelligence because of its brevity in administration and because of its high correlation with other nonverbal intelligence measures that are assumed to tap reasoning, thinking, or the ability to acquire new knowledge (referred to as Fluid Intelligence). The sample Cronbach alpha was .79.

Attention. The Conners' Teacher Ratings Scales-Revised: Short Form (CTRS–R:S; Conners, 1997) were administered to evaluate problem behaviors by obtaining ratings from teachers. The homeroom teacher was selected for each child and was asked to complete the CTRS–R:S. The primary measure for this study was the Attention-Deficit/Hyperactivity index.

Cognitive Measures Used for Determining Correlates of Latent Class Membership

The cognitive measures assumed related to the latent classification assessed the storage of phonological information (STM, naming speed) and executive processing (inhibition or random generation, the executive component of WM). The convergence of the measures for the English and Spanish versions was established in an earlier study (see Swanson et al., 2015, Swanson, Kudo & Van Horn, 2019 for further discussion), and a full description of each cognitive measure is provided in Swanson et al. (Swanson et al., 2015;Swanson, Kong & Petcu, 2019).

Phonological Storage

Short-term memory. Short-term memory (STM) storage was measured using three tasks. The Forward Digit Span subtest of the Wechsler Intelligence Scale for Children-Third Edition (WISC-III; Wechsler, 1991) assessed STM because it was assumed that forward digit spans presumably involved a subsidiary memory system (the phonological loop). The Word Span task was previously used by Swanson and Beebe-Frankenberger (2004), and assessed the children's ability to recall increasingly large word lists (a minimum of two words to a maximum of eight words). The Phonetic Memory Span task assessed the children's ability to recall increasingly large lists of nonsense words (e.g., des, seeg, seg, geez, deez, dez) ranging from two to seven words per list. The sample Cronbach alpha reliabilities for digit span, word span, and phonetic span were .82, .66, .49 for English measures and .70, .75, and .50 for Spanish measures, respectively.

Naming speed. The Comprehensive Test of Phonological Processing's (CTOPP; Wagner, Torgesen, & Rashotte, 2000) Rapid Digit and Rapid Letter Naming subtests were administered to assess speed in recalling numbers and letters in an English and Spanish version. The sample Cronbach alpha reliabilities for letters and numbers subtests were .96, .95 for English and .96, and .94 for Spanish measures, respectively.

Executive Processing

Central executive. Three complex span measures (tasks that included both a process and storage question) and an updating task were administered. The Conceptual Span, Listening Sentence Span, Digit Sentence and Updating task were administered in English and Spanish to capture the executive component of WM (tasks described in detail in Swanson et al., 2015). The WM tasks required children to hold increasingly complex information in memory while simultaneously responding to a question about the task. Because WM tasks were assumed to tap a measure of controlled attention referred to as updating, an experimental updating task was also administered. The sample Cronbach alpha reliabilities for conceptual span, listening span, digit sentence span and update were .84, .85, .52, .80 for English measures and .83, .86, .52 and .70 for Spanish measures, respectively.

Visual-spatial working memory. This component of WM was measured using two tasks (see Swanson & Beebe-Frankenberger, 2004 for review of these tasks). The Mapping and Directions Span task assessed whether the children could recall a visual-spatial sequence of directions on a map with no labels. The sample Cronbach alpha reliabilities for visual matrix and mapping/directions measures were .95 and .80, respectively.

Inhibition. The Random Number and Random Letter Generation Tasks were administered to assess inhibition. Children were first asked to write, as quickly as possible, numbers (or letters) in a non-random sequential order to establish a baseline. They were then asked to write numbers as quickly as possible, out of order, in a 30-second period. Scoring included an index for randomness, information redundancy, and percentage of paired responses to assess the tendency of participants to suppress response repetitions. The sample Cronbach alpha reliabilities of the letters and numbers were .80, .77for English measures and .81, and .82 for Spanish measures, respectively.

Cut-off point

To reduce the number of manifest variables, mean standard scores of subtests of vocabulary (receptive, expressive), reading (word identification, comprehension) and math (calculation, applied problems) were the primary measures. The manifest variables (vocabulary, reading, math, fluid intelligence, and attention) to determine discrete groups were dummy coded as reflecting normative score as at or below the 16^{th} percentile (1 = at or below the 16th percentile, 2 = above the 16^{th} percentile). The 16^{th} percentile (85 standard score) was based on the normative scores from the standardized vocabulary, math, reading and fluid intelligence measures. The Connors scale was in T-scores with high scores representing higher levels of inattention, and therefore the 16^{th} percentile was a T-score of 63.

Procedures

Ten bilingual graduate students or research assistants trained in test administration tested all participants in their schools. One session of approximately 45–60 minutes was required for small group test administration, and two sessions of 45–60 minutes was required for individual test administration. Test administration was counterbalanced to control for order effects.

Statistical Analysis

In order to evaluate the model fit, and because LCA is an exploratory analysis, a series of models were fit, varying the number of latent classes between one and seven (Nylund, Asparouhov, & Muthén, 2007; see Masyn, 2013, for a comprehensive review). A combination of statistical indicators and substantive theory were used to decide on the best fitting model. We used Mplus (Muthén & Muthén, 2012) and SAS (Lanza, Dziak, Huang, Xu & Collins, 2011) software to examine the manifest variables and determine the number of latent classes. The models with different numbers were compared using information criteria (i.e., Bayesian Information Criteria-BIC, Akaike Information Criteria-AIC, and Adjusted BIC). Lower values on these fit statistics indicated a better model fit. Statistical model comparisons included likelihood ratio tests: the Lo-Mendell-Rubin Test (LMR) and the Bootstrap Likelihood Ratio Test (BLRT). Both statistical procedures compared the improvement between neighboring class models (i.e., comparing models with three vs. four classes, and four vs. five, etc.) and provided *p*-values. *P*-values were used to determine if there was a statistically significant improvement in fit for the inclusion of one more latent class. A nonsignificant P-value indicated for a K-class that the previous K-class with a significant P-value fit the data better. Among the information criterion measures, the BIC is generally preferred, as is the BLRT for statistical model comparisons (Nylund et al., 2007). Table 1 shows the indices for the model fit.

Cognitive measures were reduced to latent constructs based on an earlier study (Swanson et al. 2015, 2019). Converting the measures to latent constructs eliminated measurement error and allowed for a focus on shared variance rather than isolated task variance. Latent scores were computed by multiplying the z-score of the target variable by the standardized factor loading weight based on the total sample (see Nunnally & Bernstein, 1994, p. 508, for calculation procedures). Latent variables were specified as indicators of speed (naming speed for numbers and letters), inhibition (random generation of numbers and letters), STM (Digit Forward Span, Word Span, and Phonetic Span), executive processing (Conceptual Span, Listening Span, Digit Sentence Span, updating), and visual-spatial WM (Matrix, Mapping & Directions).

Finally, we used a multilevel logistic model, via SAS PROC GLIMMIX software (SAS, 2010), to analyzed differences between latent classes. The reference group was the latent class considered as average achievers (LC1).

Results

Latent Class Analysis

The indices for determining the number of latent classes are reported in Table 1. Given the indices reported in Table 1, the five and six class models were studied for interpretability. Both the LMR and BLRT yielded non-significant *p*-values for the six-class model, indicating that the five-class model provided an excellent fit to the data. The BIC was lower for five than the six-class model. In addition, adequate sample proportionality and item probabilities for the five-class model were more easily interpreted than the six-class model. The entropy for the five-class model was .79, an acceptable value (Nylund et al., 2007). An online supplement to this article reports tables related to the proportion of the sample in each latent class (gamma estimates), as well as the probabilities (rho estimates) for each measure (manifest variable) for each response category as a function of each latent class for the total sample (Supplement Table 2). Also reported in the supplement are the item probabilities for performance at or *under* the cut-off threshold of the 16^{th} percentile (standard score of 85).

Sample Distribution of Latent Classes (LC)

Means and standard deviations for each of the normed classification measures as a function of the five latent classes are shown in Table 2. Effect sizes (ESs) comparing each latent class across all measures are shown in Table 3 and those ESs at or greater than .80 were considered of large magnitude. The percentage distribution of gender representation across the five latent class (LC) groups for males was 47.77%, 66.67%, 56.67%, 40.91% and 52.49%, respectively. No significant effects were found for gender representation among the five latent classes, χ^2 (4, N = 394) = 4.33, p =.36.

As shown in Table 3, LC1 exceeded (ESs > .80) LC2 on seven of the eight measures. Performance weaknesses for LC2 emerged in all domains except for Spanish vocabulary. Based on these comparisons, we characterized this latent class group (LC2) as *poor achievers*. As shown in Table 2, none of the average mean scores for this latent class (LC2) exceeded the 19^{th} percentile (standard score of 87).

For LC3, large ES differences emerged in three out of the eight manifest variables when compared to LC1. Two of the largest ESs were the areas of reading for both the English and Spanish language. As shown in Table 2, the mean reading scores for LC3 were 85.74 and 79.30 in English and Spanish, respectively. In contrast, their average math scores were 99.55 and 90.22 in English and Spanish, respectively. These differences in math scores parallel the discrepancy in vocabulary scores between the two language systems. As shown in Table 2, performance LC3 on the English vocabulary measures (M=94.50) clearly exceeded measures on Spanish vocabulary (M=73.30) measures. Because Fluid intelligence (Raven) scores were in the normal range, this profile fits an operational definition of reading disabilities commonly found in the literature (e.g., Stanovich & Siegel, 1994). We label this latent class as *reading disabilities (RD)*. In general, researchers use the term reading disabilities to identify children with average intelligence but with performance below a certain percentile (e.g., 25th percentile) on norm-referenced standardized reading measure (e.g., Cirino et al. 2015; Siegel & Stanovich, 1994).

Based on the magnitude of ESs, LC4 yielded weak performance relative to average achievers (LC1) on two of the eight measures. This relatively weaker performance of LC4 vs. LC1 was primarily on the English vocabulary and fluid intelligence measures. However, it is important to note that LC4 exceeded (negative ESs) the average achievers (LC1) on Spanish vocabulary, Spanish reading and Spanish math. Thus, we label this latent class as " High Spanish achievers".

Relative to LC1, LC5 yielded weaker performance (ESs > .80) on four of the eight manifest variables. The weaker performances of LC5 children were in the domains of English vocabulary, English reading, English math as well as fluid intelligence. It is important to note, however, that this particular latent class was comparable to average achievers (LC1) in Spanish vocabulary (ES=.07). Thus, we label this group as "Average Spanish achievers".

Correlates of Latent Classes

A multilevel logistic model determined the cognitive variables that uniquely predicted latent classes. Because, the choice of the reference category for generalized logit models affects the results, Brown and Prescott (1999, p. 160) recommended choosing the category with the highest frequency as the reference. The estimates for the multilevel logistic unconditional and conditional models in predicting the odds of being classified in one of the latent classes when compared to average achievers (LC1) as a function of variables external to the classification (cognitive variables) are shown in Table 4. Thus, the four intercept values LC2, LC3, LC4 and LC5 shown in Tables 4 are the latent class comparisons to the average achievers (LC1). For all the conditional models, we have four estimates of the intercept but only one slope associated with the covariate. Thus, covariates remained *constant* across the logits/intercepts within each model. This allowed for the interpretation that the increase in log-odds of falling into a latent class (e.g., LC2) versus LC1 resulted from a one-unit increase in the covariate holding the others covariates constant across all intercepts. Indices for model comparisons included the deviance values, Akaike's Information Criterion (AIC), and Bayesian Criterion (BIC). The Akaike's Information Criterion (AIC) allowed for a comparison of models that were not nested, and the Bayesian Criterion (BIC) allowed for a comparison of nested models. In general, models with lower AIC, BIC and deviance values fit better than models with higher values.

The unconditional model in Table 4 was assumed to have no error at level-1 (Snijders & Bosker, 1999). That is, the level-1 residual follows a logistic distribution with a mean of 0 and a variance of 3.29 (Snijders & Bosker, 1999, p. 227). Thus, only the intercept variance is considered relevant for the analysis. The intraclass correlation was computed as .17 (.67/.67 + 3.29), suggesting that approximately 17% of the variability was accounted for by children nested in classrooms, leaving approximately 83% of the variability to be accounted for by the latent measures (or other unknown factors).

As shown in Table 4, three intercepts for the unconditional model indicated a significant amount of variability in the log odds of being classified as one of the three latent classes relative to average achievers (LC1). As shown, the LC4 (High Spanish achiever) intercept was not significantly different when compared to LC1, suggesting potential differences were related to random effects. A shown in Table 4, Conditional Model 1 entered only Spanish cognitive measures as well as the centered measures of grade and gender. The intercepts were significant for comparisons between LC2, LC3 and LC5 when compared with LC1. As shown, when only Spanish measures were in the analysis, an intercept advantage was found for LC4 relative to LC1. The only significant cognitive measure to emerge for Model 1 was Spanish STM.

Conditional Model 2 entered English cognitive measures into the model. All intercepts were significant as were the measures of English STM, English naming speed, and English executive WM. All intercepts were significant and negative suggesting an advantage for average achievers (LC1) relative to the other latent classes. Model 3 enter all the cognitive variables along with grade and gender. All the intercept values were significant as were measures of English STM, English naming speed, and English WM. In addition, grade level was significant suggesting that increases in grade level were significantly related to the intercept differences. Model 4 tested whether a parsimonious model that included only the significant parameters in the full model (Model 3) provided a better fit to the data than the previous models. As shown, this model substantially reduced the error variance when compared to Model 1 and the unconditional model. The intercept variance for the random effect was reduced by approximately 86% (.67 -.09/.67). As shown, all intercepts were significantly in favor of average achievers, and all intercepts were significantly related to measures of English STM, English naming speed, and the English executive component of WM. Previous studies have found that cross-language differences that emerged on these cognitive measures (in this case English over Spanish measures) are best interpreted as related to ease of access within the preferred language, and not a language-specific cognitive system (Swanson et al., 2015). That is, previous studies has shown L1 and L2 cognitive measures load on the same latent factors (Swanson, Orosco, Lussier, Gerber, & Guzman-Orth, 2011; Swanson, Kudo, & Van Horn, 2019), suggesting that preferred access with a specific language system underlies cross language differences.

When comparing the fit indices, the deviance, AIC and BIC values were lower for Model 3 when compared to the other models. However, the parsimonious model (Model 4) reduced the intercept variance related to children nested within classrooms when compared to Models 1 and 2. Model 2 reduced the intercept variance when compared to Model 1.

Discussion

The purpose of this study was to identify whether a discrete class of EL children at risk for achievement difficulties emerged within a heterogeneous sample of elementary school children that varied in L1 and L2 vocabulary, math and reading as well as attention and nonverbal reasoning (fluid intelligence) measures. The results yielded three important findings. First, five latent classes emerged (average achievers, poor achievers, children at risk for reading disabilities, high Spanish achievers, and average Spanish achievers) when setting cut-off scores at or below the 16th percentile on the manifest variables. As expected, the latent class referred to as average achievers outperformed the other latent classes on a host of measures besides achievement. Second, the results showed that children with specific problems in reading (LC3) could be separated for High Spanish achievers (LC4) and Average Spanish achievers (LC5). Finally, when the influence of the various predictors was held constant in a logistic regression analysis, the cognitive variables that uniquely predicted these latent classes were English measures of naming speed, STM and the executive component of WM. Given these general findings, the results related to two questions that directed this study are now addressed.

Question 1: Can a latent classification of EL children at risk of specific learning disabilities be identified within a heterogeneous sample of learners?

The results show that five latent classes emerged related to Spanish and English measures of vocabulary and achievement within a heterogeneous sample of English learners. The latent status membership probabilities for students at risk for specific learning disabilities in L1 and L2 reading were approximately 7% of the total sample. These results are in line with current estimates of reading disabilities. Although the incidence of reading disabilities in public schools has been reported to vary between 5% to 17% (McCandliss & Noble, 2003), more conservative estimates indicate prevalence rates range from 5% to 7% of the general population. Our results also suggested that approximately 10% of the sample (i.e., LC2 and LC3) showed serious achievement difficulties, whereas approximately 38% of the sample was identified by weaknesses only in English language acquisition (English vocabulary, i.e., LC4 and LC5). Thus, the results were able to separate children into latent classes that were primarily related to language acquisition from those with serious achievement difficulties.

Question 2: Do specific cognitive measures predict latent class membership?

In terms of cognitive models that predict latent class status, two were considered. As reviewed in the introduction, these models considered whether STM storage and/or executive processing within the Spanish or English language system played a major role in predictions of latent class status. The results suggested that none of the above models in isolation provided a parsimonious account of the findings. The significant loadings from the full logistic regression model were measures of English STM, naming speed and the executive component of WM. These findings fit the literature attributing EL children's academic difficulties to problems of both storage and executive processing (de Abreu & Gathercole 2012; Swanson et al., 2015). This finding was also supported in recent meta-analyses of the literature on cognition and reading and math disabilities (Peng et al., 2016; 2018) identifying components of WM as playing a key role in separating children with RD and/or MD from children without achievement difficulties.

The results also suggested that when compared to average achievers, EL children at risk for reading disabilities (LC3) perform poorly on measures of storage (E-STM, S-STM, E-speed, S-speed) and executive processing (S-Exec WM); whereas the English executive processing measure (E-executive WM) captured the performance of English language learners not at risk for achievement difficulties (EC=4). Thus, we were able to separate the groups on measures of storage and executive processing. In general, the results suggest that within a heterogeneous sample of EL elementary children, an identifiable group of EL children with L1 and L2 reading problems was identified at the 16th percentile cut-off point. Thus, this study contributes to the emerging literature that EL children with RD represent an identifiable group.

Practical Implications

There are two practical implications related to our findings. First, L1 (Spanish) measures administered in isolation of L2 (English) measures were not particularly well suited to identify children at risk for specific learning disabilities (reading in this case). Second, different cognitive processes separate the latent classes. This finding is particularly important because confounds exist in the assessment of children with potential special needs who are second language learners. These confounds are due in part to attributing difficulties in second language acquisition and reading and/or math disabilities to the same cognitive processes that are involved in second language acquisition.

Limitations

There are at least five limitations to this study. First, although we used conservative cut-off points in identifying children at risk for specific learning disabilities, we have not shown that the identification of latent classes validates a specific cut-off point. Rather the results suggest the measures were able to identify subgroups to the cut-off to which they were applied. Second, we did not establish the stability of reading and/or math performance at the upper middle grades. Although we used a variety of normed referenced measures normed at grades 1 to 3 to capture consistency in low achievement performance, performance across the upper elementary grades was not assessed. Third, we have an absence of intervention and language home usage information. Thus, our study is limited to discussing the risk classification within a heterogeneous sample and not whether a particular intervention program would later influence the classification of children at risk.

Fourth, the design of the study was cross-sectional instead of longitudinal. In order to investigate language dominance and language shift in EL children, longitudinal studies in which the development of linguistic skills is monitored in the course of time are necessary. Finally, the sample yielded minimal variance in SES (98% of the sample was on full federal assistance programs) and therefore the influence of high versus low SES could not be evaluated.

Summary

In summary, this study yielded three important findings. First, latent classifications of children with learning disabilities and children with difficulties in second language acquisition could be identified among a sample of elementary school EL children. The results provide support for the notion that children at risk for special education needs within a heterogeneous EL sample reflect a discrete class of learners. Second, approximately 10% of the sample would be considered eligible for special education (LC2 and LC3) and approximately 40% of the children would be at risk of being misdiagnosed. Finally, English cognitive measures related to storage and executive processing were the only cognitive measures that consistently predicted latent class status. Overall, the results support the notion that children at risk for specific learning disabilities reflect a latent class group that can be separated from a heterogeneous sample of children who vary in attention, fluid intelligence and L1 and L2 measures of vocabulary, reading and math.

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Table 1

Fix Indices for Seven Latent Class Models

	LC1	LC2	LC3	LC4	LC5	LC6	LC7
Log-likelihood:	-1616.41	-1523.45	-1498.3	-1478.96	-1467.77	-1457.87	-1454.9
AIC:	474.3	306.38	274.08	253.41	249.02	247.21	259.27
BIC:	506.11	373.97	377.46	392.58	**423.98**	457.96	505.8
CAIC:	514.11	390.97	403.46	427.58	**467.98**	510.96	567.8
Adjusted BIC	480.73	320.03	294.96	281.53	**284.37**	289.79	309.08
Entropy	1	0.78	0.67	0.72	0.79	0.75	0.78
Degrees	247	238	229	220	211	202	193
LMR (p-value)	-	0	0.056	0.049	0.70	0.53	0.09
BLRT (p-value)	-	0	0	0	0.012	0.051	0.17

Note. LC=Latent Class*,* AIC = Akaike's Information Criterion; BIC = Bayesian Information Criterion; CAIC and Adjusted BIC corrected for sample size; LMR = Lo-Mendell-Rubin Test; BLRT = Bootstrap Likelihood Ratio Test.

Table 2

Normative Descriptive Scores as a Function of Latent Class

	LC1 (N=224)		LC2 (N=13)		LC3 (N=30)		LC4 (N=66)		LC5(N=61)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Manifest Variables[a]										
E-Vocab	105.56	14.50	82.14	5.38	94.50	11.89	72.96	8.65	79.74	15.96
S-Vocab	83.74	14.07	81.87	9.80	73.30	9.00	90.68	13.31	82.85	11.6
E-Read	105.70	12.13	77.36	12.37	85.74	13.42	98.24	9.34	78.52	10.12
S-Read	107.16	12.13	78.23	9.02	79.30	5.09	114.22	12.62	100.91	13.99
E-Math	103.55	10.14	77.84	8.52	99.85	8.69	95.95	9.54	87.73	11.99
S-Math	100.28	9.34	80.25	6.18	90.22	13.42	103.54	8.90	94.00	10.67
Fluid Intell.	105.63	14.78	87.45	8.50	97.90	15.74	93.33	16.18	88.32	14.73
Inattention[b]	50.05	9.26	59.30	3.87	54.68	11.11	48.60	7.81	56.15	11.54
Correlated variables[c]										
E-STM	0.49	1.54	-0.67	1.30	-1.37	1.36	-0.26	1.63	-0.88	1.38
S-STM	0.36	1.61	-0.65	1.42	-1.43	1.59	-0.01	1.71	-0.51	1.4
E-Speed	-0.51	1.00	1.57	1.61	0.88	2.13	0.27	1.55	1.07	2.19
S-Speed	-0.16	1.28	1.04	2.53	1.19	2.42	-0.48	1.09	0.50	1.74
E-inhibition	0.14	0.97	0.09	0.78	-0.24	0.98	-0.18	1.05	-0.15	0.82
S-Inhibition	0.10	0.72	-0.25	0.82	-0.29	0.64	-0.20	0.71	0.03	0.59
E-Exec WM	0.50	1.48	-0.86	0.51	-0.61	1.00	-0.68	0.93	-0.75	1.09
S-Exec WW	0.20	1.61	-1.33	1.26	-1.37	1.11	0.47	1.68	-0.48	1.32
Visual-Spatial WM	0.21	1.16	-1.23	0.50	-0.30	0.87	0.03	1.27	-0.37	1.01

Note. [a]Standard normed scores, [b]T-score [c]z-scores E=English, S=Spanish., LC=latent class; LC1=average achiever, LC2=poor achiever, LC3=reading disability, LC4=High Spanish achiever , LC5=Average Spanish Achiever, STM=Short-Term Memory or Phonological Loop; Speed=Naming Speed, Inhibition=random Generation Tasks, Exec=executive component of working memory, WM=working memory.

Table 3

Effect Size Comparisons among Latent Classes

Name	1[a] vs. 2	1 vs. 3	1 vs. 4	1 vs. 5	2 vs. 3	2 vs. 4	2 vs. 5	3 vs. 4	3 vs. 5	4 vs. 5
Manifest	Measures									
E-Vocab	**1.65**	0.78	**2.43**	**1.74**	-1.19	1.12	0.16	2.21	1.00	-0.53
S-Vocab	0.13	0.77	-0.50	0.07	0.93	-0.69	-0.09	-1.43	-0.88	0.63
E-Read	**2.33**	**1.62**	0.65	**2.32**	-0.64	-2.11	-0.11	-1.16	0.64	2.03
S-Read	**2.41**	**2.41**	-0.58	0.50	-0.16	-2.97	-1.71	-3.21	-1.82	1.00
E-Math	**2.55**	0.37	0.76	**1.50**	-2.55	-1.93	-0.86	0.42	1.10	0.76
S-Math	**2.18**	**1.02**	-0.35	0.65	-0.85	-2.73	-1.37	-1.27	-0.32	0.97
Fluid Intell.	**1.25**	0.52	**0.81**	**1.17**	-0.75	-0.39	-0.06	0.28	0.64	0.32
Inattention	**-1.02**	-0.49	0.16	-0.62	0.48	1.46	0.30	0.68	-0.13	-0.77
Cognitive	Measures									
E-STM	0.76	**1.22**	0.48	**0.91**	0.52	-0.26	0.15	-0.72	-0.36	0.41
S-STM	0.63	**1.11**	0.23	0.55	0.51	-0.38	-0.10	-0.85	-0.63	0.32
E-speed	**-2.00**	**-1.17**	-0.68	**-1.18**	0.35	0.83	0.24	0.35	-0.09	-0.42
S-speed	**-0.87**	**-0.93**	0.26	-0.47	-0.06	1.07	0.29	1.03	0.35	-0.68
E-inhib	0.05	0.39	0.32	0.31	0.36	0.27	0.30	-0.06	-0.10	-0.03
S-inhib	0.48	0.55	0.42	0.10	0.06	-0.07	-0.44	-0.13	-0.53	-0.35
E-Exec WM	**0.94**	0.77	**0.86**	**0.89**	-0.28	-0.21	-0.11	0.07	0.13	0.07
S-Exec WM	**0.96**	**1.01**	-0.17	0.44	0.03	-1.11	-0.65	-1.20	-0.71	0.63
Visual-WM	**1.27**	0.45	0.15	0.51	-1.19	-1.06	-0.91	-0.28	0.07	0.35

Note. E=English, S=Spanish. **Bold**=Effect sizes (Hedges g) > .80 when compared to latent class 1(LC1). 1[a] = LC1=average achiever, 2= LC2=poor achiever,3= LC3=reading disability, 4= LC4=High Spanish Achiever, 5= LC5=Average Spanish achiever, STM=Short-Term Memory or Phonological Loop; Speed=Naming Speed, Inhibition=Random Generation Tasks, Exec=executive component of working memory, WM=working memory.

Table 4

Estimates for Two-Level Generalized Linear Polytomous Model (N=394).

	Unconditional		Model 1		Model 2		Model 3		Model 4	
Fixed Effects	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Intercept LC2	-3.59***	0.33	-5.36***	0.80	-5.96***	0.66	-6.23***	0.72	-5.92***	0.65
Intercept LC3	-2.29***	0.23	-3.32***	0.63	-3.73***	0.45	-4.11***	0.52	-3.70***	0.43
Intercept LC5[a]	-1.06***	0.30	-1.80**	0.60	-2.31***	0.42	-2.62***	0.48	-2.27**	0.39
Intercept LC4	-0.26	0.19	-1.04	0.60	-1.54***	0.42	-1.86***	0.47	-1.43**	0.39
Grade			0.26	0.29	0.46*	0.20	0.58**	0.22	0.42*	0.18
Gender			-0.02	0.12	-0.08	0.12	-0.06	0.13		
E-STM					-0.38**	0.15	-0.42*	0.18	-0.42**	0.14
S-STM			-0.51***	0.16			-0.09	0.17		
E-speed					0.51***	0.15	0.48*	0.20	0.50***	0.14
S-Speed			0.23	0.14			0.04	0.12		
E-Inhibition					-0.13	0.14	-0.006	0.16		
S-Inhibition			-0.21	0.14			-0.22	0.15		
E-Exec WM					-0.79***	0.19	-0.87***	0.21	-0.79***	0.18
S-Exec WM			-0.16	0.15			0.14	0.16		
Visual-spatial WM			-0.02	0.12	0.03	0.12	0.07	0.13		
Error Variance	0.67**	0.30	0.98*	0.46	0.12	0.15	0.16	0.19	0.09	0.13
Model Fit										
Deviance	933.80		680.71		664.53		593.28		697.69	
AIC	943.80		704.71		688.53		625.28		715.69	
BIC	950.81		720.70		704.94		646.60		728.30	

Note. [a] Logistic output was organized by cell size and therefore the intercept to LC5 was reported before LC4. E=English, S=Spanish. LC2=poor achiever, LC3=specific reading disability, LC4=High Spanish achiever, LC5=Average Spanish Achiever. , STM=Short-Term Memory or Phonological Loop; Speed=Naming Speed, Inhibition=Random Generation Tasks, Exec=executive component of working memory, WM=working memory.SE= standard error,*$p < .05$, ** $p < .01$, *** $p < .001$, Deviance= Chi-square value for the correspondence between model and data, AIC= Akaike's Information Criterion, BIC= Bayesian Information Criteria.

Footnotes

[1] Four large elementary urban schools from two large metropolitan areas in the U.S. southwest participated in this study. Children who participated in this study were initially identified as EL by the school district, not by special education status. Of the total sample, only three students had IEPs. Data were not available to the researchers on how Tier 1 intervention was implemented in the schools. Two of the elementary public schools, according to a state report, yielded the lowest percentage in reading and math score proficiency within the state. Minority (Hispanic) enrollment was 95% of the study body which was higher than the state average. In addition, the current study included two urban charter schools also with a high Hispanic (> 95%) representation. State reports indicated that one of the charter schools at the time of testing (2017-2018) reported that only 35% of children were proficient in reading and 29% were at proficient in math. A state report on the second charter school also indicated that only 33% of the elementary children were proficient in reading and 29% proficient in math on state measure.