IRTs of the ABCs: Children’s Letter Name Acquisition

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Abstract

We examined the developmental sequence of letter name knowledge acquisition by children from 2 to five years of age. Data from 2 samples representing diverse regions, ethnicity, and socioeconomic backgrounds (n = 1074 & 500) were analyzed using item response theory (IRT) and differential item functioning techniques. Results from factor analyses indicated that letter name knowledge represented a unidimensional skill; IRT results yielded significant differences between letters in both difficulty and discrimination. Results also indicated an approximate developmental sequence in letter name learning for the simplest and most challenging to learn letters -- but with no clear sequence between these extremes. Findings also suggested that children were most likely to first learn their first initial. We discuss implications for assessment and instruction.

Keywords

alphabet; preschool; literacy; assessment; instruction

A consensus has been achieved around the idea that foundational, emergent literacy skills that begin to develop well before the onset of formal literacy instruction are important for the successful development of reading skills (Sulzby & Teale, 1991; Whitehurst & Lonigan, 1998; 2001). Central among these emergent literacy skills are the three areas of alphabet knowledge, phonological awareness, and oral language (Storch & Whitehurst, 2002; Whitehurst & Lonigan, 1998; Lonigan, Schatschneider, Westberg & the National Early Literacy Panel, 2008a). The robust and unique predictive validity of these three skill sets has

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been repeatedly demonstrated in a wide array of studies with varied assessment measures (Catts, Fey, Zhang, & Tomblin, 1999; de Jong & van der Leij, 1999; Naslund & Schneider, 1996; Scarborough, 1989; 1998; Wagner, Torgesen, & Rashotte, 1994; Wagner et al., 1997), including both norm-referenced standardized assessments and researcher-developed measures. Further, there is increasing evidence that all three are causally related to decoding, spelling, or comprehension skill, perhaps especially when instruction combines a focus on more than one of these elements (Lonigan, Schatschneider, Westberg & the National Early Literacy Panel, 2008b; Schneider, Roth, & Ennemoser, 2000; Share & Gur, 1999). Taken together, the body of literature on emergent literacy strongly supports the idea of identified weakness in one or more of these areas as an indicator of later reading difficulty, and also supports the benefit of instructional focus on each of these areas within early childhood classrooms.

Converging findings indicate that, among the three skill areas of phonological awareness, alphabet knowledge, and oral language, alphabet knowledge is the strongest longitudinal predictor of later reading proficiency (Hammill, 2004; Kirby, Parilla, & Pfeiffer, 2003; Leppanen, Aunola, Niemi, & Nurmi, 2008; Lonigan et al., 2008a; Scarborough, 1998; Schatschneider Fletcher, Francis, Carlson, & Foorman, 2004; Torppa, Poikkeus, Laakso, Eklund, & Lyttinen, 2008). In particular, results from the National Early Literacy Report meta-analysis on predictors of conventional literacy skills indicated that alphabet knowledge, measured in preschool and kindergarten and inclusive of both letter name and letter sound assessments, had moderate to strong relations with decoding, comprehension, and spelling outcomes measured at the end of kindergarten or later (Lonigan et al., 2008a). Additional research has shown alphabet knowledge to be a significant, unique predictor of decoding, spelling, and reading comprehension even controlling for, in various combinations, IQ score, oral language, phonological awareness, child age, and socioeconomic status (SES; e.g., Bramlett, Rowell, & Mandenberg, 2000; Lonigan, Burgess, & Anthony, 2000; Leppanen et al., 2008; Lonigan et al., 2008a; Snowling, Gallagher, & Frith, 2003; Storch & Whitehurst, 2002). Alphabet knowledge, along with phonemic awareness, appears to be a key contributor to children’s understanding of the alphabetic principle and its application to decoding single words (Ehri, 1995; Foulin, 2005; Treiman, Tinkoff, & Richmond-Welty, 1996), ultimately supporting fluent reading and comprehending of connected text (Phillips & Torgesen, 2006).

Many of the studies linking alphabet knowledge to reading skill have relied on assessments combining both letter name and letter sound knowledge, leading some to wonder whether it is letter sound knowledge alone that contributes to reading success, rather than letter name knowledge contributing as well (e.g., Feitelson, 1965, 1988; Foulin, 2005). However, quite a few studies support the separability of these two skill areas (e.g., Caravolas, Hulme, & Snowling, 2001; Levin, Shatil-Carmon, & Asif-Rave, 2006; McBride-Chang, 1999), suggesting that letter names in English are acquired before letter sounds in the United States (e.g., Burgess & Lonigan, 1998; McBride-Chang, 1999; Treiman & Kessler, 2003 but cf. Ellefson, Treiman, & Kessler, 2009), and indicating at least an indirect path between letter name knowledge and reading via letter sound knowledge (Foulin, 2005). For example, a number of studies suggest that letter name knowledge facilitates the development of letter sound knowledge (e.g., Ellefson et al., 2009; Foy & Mann, 2006; McBride-Chang, 1999;
Several studies support a relation between letter name knowledge and the ability to connect print and speech by identifying the name of the first letter in words in which the initial letters say their names (e.g., B in ‘beech’ or D in ‘deep’; Bowman & Treiman, 2002; Levin, Patel, Margalit, & Barad, 2002; Riley, 1996; Treiman et al., 1996; Treiman & Rodriguez, 1999). Further, a number of studies support a link between letter name knowledge and spelling skill (e.g., Caravolas et al., 2001; De Abreu & Cardoso-Martins, 1998; Pennington & Lefly, 2001; Shatil, Share, & Levin, 2000; Treiman, 1994). For these reasons, children’s letter name knowledge is increasingly emphasized in preschool curricula, learning standards, and assessments (Justice, Pence, Bowles, & Wiggins, 2006; Piasta, Purpura, & Wagner, 2010), although many preschool curricula, in marked contrast to elementary reading curricula (e.g., Al Otaiba et al., 2008; Crowe, Connor, & Petscher, 2009) still do not include explicit instruction in letter names or sounds (LoCasale-Crouch et al., 2007; Phillips, Clancy-Menchetti, & Lonigan, 2008; Stewart, 2004).

Influences on the Development of Alphabet Knowledge

Children’s capabilities in basic cognitive and phonological processing appear to be implicated in the development of letter name knowledge (e.g., de Jong & Olson, 2004; Molfese et al., 2006; Torppa et al., 2006). Specifically, Torppa et al. (2006) found that phonological memory, phonological awareness, and rapid naming all predicted the rate of growth in 3-to 5-year old children’s letter name knowledge. These results replicated and extended earlier findings of prediction from phonological memory and rapid naming reported by de Jong and Olson (2004). Similarly, Molfese et al. (2006) found that general cognitive ability and phonological awareness predicted increases in letter name knowledge across the course of the preschool year. Overall, the development of alphabet knowledge appears to have a bidirectional relation with the development of phonological awareness (Burgess & Lonigan, 1998; DeJong, 2007; Foy & Mann, 2006; Molfese et al., 2006) and possibly also with the capability to write one’s own name (Bloodgood, 1999; Diamond, Gerde, & Powell, 2008).

A growing body of evidence indicates that child and family characteristics also are related to the development of alphabet knowledge in young children. For example, family SES is a known correlate of children’s average letter name and letter sound identification performance in preschool or kindergarten (Bowey, 1995; Chaney, 1994, Duncan & Seymour, 2000; Korat, 2005; Lonigan, 2003, 2004). In part, these home influences likely stem from findings that the frequency with which parents expose their children to print or intentionally teach about letters predicts children’s alphabet knowledge both concurrently (Evans & Shaw, 2008; Evans, Shaw & Bell, 2000; Haney & Hill, 2004) and longitudinally (Torppa et al., 2008).

Developmental Sequence of Letter Name Knowledge

One relevant issue that has received minimal attention to date is the question of whether there is a discernible sequence in children’s acquisition of letter name knowledge. That is, do young children acquire letter names in idiosyncratic orders or are there aspects of the letters
themselves (e.g., name, orthographic representation) that might render certain letters easier or more difficult to learn? Traditional discussions of letter name knowledge appear to assume letter equivalency in acquisition (e.g., Ball & Blachman, 1988; Ehri & Wilce, 1987; Fugate, 1997; Schneider et al., 2000). However, some studies suggest the possibility of inter-letter differences in children's acquisition of letter names (e.g., Justice et al., 2006; McBride-Chang, 1999). The present study was designed to further investigate the existence of a developmental sequence in letter name acquisition. Current evidence associated with letter-related factors and child-specific factors are addressed in turn.

Letter-related Factors

Studies spanning several decades of research indicate that similarity in the shape of letters can lead to children's difficulties in discrimination and recall of letter names, perhaps particularly with lower case letter presentations (e.g., b and d; p and q) (Courrieu & de Falco, 1989; Gibson, Gibson, Pick & Osser, 1962; Goikoetxea, 2006; Lahey & McNees, 1975; Smythe Stennet, Hardy, & Wilson, 1970; Treiman et al., 2006). Treiman and Kessler (2003) also found that letters that share phonemes in their names with many other letters may be more readily confused; Treiman et al. (2006) extended this finding for English and Portuguese to include an interaction between visual and phonological similarity. In addition, a number of studies have indicated that letters that occur toward the beginning of the alphabetic order, presented to young children in frequent repetitions of the 'ABC song,' are more likely to be known than letters occurring later in that sequence (Justice et al., 2006; McBride-Chang, 1999; Smythe et al., 1970). For example, McBride-Chang (1999) found a beginning of the alphabet effect for both letter names and letter sounds. This study, and at least three others to date (e.g., Justice et al., 2006; Piasta & Wagner, 2010b; Treiman & Broderick, 1998), also found that letters whose names include the letter sound (e.g., B and F, but not W) may be easier to learn than other letters. Mixed evidence exists on whether letters that are more frequent in text are more readily acquired by young children (Levin et al., 2006; Treiman & Kessler, 2003; Treiman et al., 2006; Treiman, Levin, & Kessler, 2007). Studies have more typically used uppercase letter presentation although lowercase letters are often more frequent in actual text, and frequency for individual letters differs by case (Jones & Mewhort, 2004).

Child-related Factors

The most frequently studied individual difference characteristic related to alphabet knowledge is whether or not a particular letter is in the child's name, particularly their first name and especially in the first position within their name (Bloodgood; 1999; Justice et al. 2006; Levin & Aram, 2004; Treiman & Broderick 1998; Treiman & Kessler 2004; Treiman et al., 2006, 2007). For example, Justice et al. (2006) found that children were 1.5 times more likely to know a letter if it was in their first name, and more than 11 times more likely to know the letter if it was in the initial position within their name. More tentative findings have been reported for whether the advantage holds for letters within the child's last name (Treiman & Broderick, 1998). Notably, these effects have been found across several languages and orthographies, including English, Portuguese, and Hebrew. Such findings are consistent with the idea that the concept of “possession” of a letter name may lead to greater
attention to, and memory for, particular letters (Hoorens, Nuttin, Herman & Pavakanun, 1990; Nuttin, 1987). That is, some children seem to have a sense of ownership regarding the letters in their own names, as indicated by anecdotal statements such as “that's my letter” and “I have a b, too.” These findings likely also result from the prominence of the child's name in print at preschools and perhaps in homes.

**Goals of the Present Paper**

Our primary purpose in this study was to explore the developmental sequence of letter knowledge. Substantial recent research has indicated that there are letter- and child-related variables that appear to contribute to whether an individual child is likely to know the name of an individual letter. Of note is that several prior studies evaluated groups of letters (e.g., first half of the alphabet versus second half) rather than each individual letter. Further, data analytic limitations often prevented examination of inter-letter differences while also considering variation among children (see Piasta & Wagner, 2010b for further discussion of this point). The intent of the present study was to continue the descriptive exploration of the developmental acquisition of letter name knowledge in a manner that attends to both inter-child and inter-letter differences. Our core conceptual question was whether there is a reliable sequence in the order of acquisition; by combining data from large samples of children residing in Florida and Texas, we were able to address this question in the largest study to date of English-speaking preschool children. Specifically, the three goals of the study were (a) to examine whether certain letters are more likely to be known than others and to relate knowledge of individual letters to children's skill levels, (b) to examine the extent to which the first letter in children's names might influence the likelihood of knowing specific letters, and (c) to determine how to best optimize measurement of children's letter naming knowledge after accounting for inter-letter differences and inter-child differences.

**Method**

**Participants**

**Florida sample**—The 1074 Florida children in the present study included children from seven archival studies that took place in a midsize city in northern Florida. To be included in the present study sample, children had to be assessed on all 26 letters on a letter name knowledge test (as described in the Measures section); children in these seven archival studies who were not assessed on all 26 letters or who did not have this data captured at the item level were excluded. Thus, the Florida sample included 100% of children who participated in two smaller studies (n = 241; Lonigan et al., 2000; Lonigan, Burgess, Anthony, & Barker, 1998; Piasta et al., 2010), 55% of 1006 children (n = 554; Anthony, Lonigan, Driscoll, Phillips, & Burgess, 2003; Lonigan et al., 2009) who participated in two additional studies in which only some children were assessed on all letters, and a random selection of children (n = 279; Bacon, 2001; Lonigan, et al., 2009; Lonigan, Purpura, Wilson, Walker, & Clancy-Menchetti, 2012) for whom item-level assessment data was collected as part of three additional studies conducted during the same time period. The projects ranged from longitudinal correlational studies to pull-out shared reading and emergent literacy interventions. Baseline performances of children who participated in an intervention were used for the present study. However, for children who participated in
descriptive studies, we selected data from the earliest (or only) time point to include in the present study. The final sample of 1074 Florida children ranged from 2- to 5-years of age and was ethnically diverse (see Table 1). The small number of 2-year-olds in this sample was included to maximize the generalizability and range of scores, given that some 2-year-olds knew some letter names. Florida participants were from both advantaged and disadvantaged backgrounds (i.e., 30% represented multiple cohorts from approximately 60 classrooms in either Head Start, Title 1 public prekindergarten programs or subsidized child care serving primarily children from lower SES backgrounds and 70% were from approximately 30 classrooms in private child care centers that typically serve children from a range of SES backgrounds). Less than 1% of the Florida sample were English learners, and all of the Florida children were able to understand the directions and respond appropriately in English.

**Texas sample**—The Texas sample included children from two research projects conducted in a large city in east Texas. The first study was a longitudinal correlational study (Anthony, Williams, Aghara, Denkelberger, Novak, & Mukherjee, 2010; Anthony Williams, McDonald, & Francis, 2007). The second was a randomized, controlled evaluation of a book rotation program and a program to train parents in optimal shared reading strategies (Anthony, Williams, Xhang, Landry, & Dunkelberger, 2012). Both projects involved testing the same children at multiple points in time during a given school year. For the present study, we randomly selected one wave of data per child. The Texas sample of 500 children attended over 100 classrooms within center-based preschool programs that primarily served families from economically disadvantaged backgrounds, including Head Start centers, public prekindergartens, and private child care centers. The sample of Texas children ranged from 3- to 5-years of age (see Table 1) and also was ethnically diverse. The language of instruction in all centers was English, and all Texas children were either native English speakers or passed a language screening measure before selection into the study. In both the Texas and Florida samples, children with known or obvious sensory, physical, or cognitive impairments were excluded, but children with speech problems or language delays (e.g., as represented by the assessment battery conducted; we were not privy to formal diagnoses) were included.

**Sample comparability**—Demographic comparability of the two samples was tested using chi-square tests of independence. The two samples were not equivalent on gender, $\chi^2 (1) = 6.38, p < .05$, with the Florida sample including a greater percentage of girls. The samples also were not equivalent with regard to ethnicity, $\chi^2 (3)= 581.66, p < .001$, with the Texas sample having greater percentages of Hispanic/Latino and African American children and the Florida sample having a greater percentage of non-Hispanic White children.

**Measures**

**Florida**—The letter name knowledge test administered in Florida required children to respond to the prompt of “What is the name of this letter” when shown an uppercase letter printed in bold Times New Roman 80 point font on a 3 by 5 inch card. Letters were presented one at a time in a fixed nonalphabetic order that had been randomly determined. If children responded with the sound of the letter, they were prompted further with “That’s the
sound it makes, but what is the name of the letter?” Neither letter sounds nor words beginning with the letter or letter sound were accepted as correct responses. All 26 items were administered to children in two of the seven Florida studies (n = 241). However because some very young children (e.g., 2- and 3-year-olds) participated in the other Florida studies, a ceiling rule of five consecutive incorrect items was imposed. To avoid estimation problems related to missing data, the current study only included data from children (n = 833) in these five projects if they were administered all items (i.e., who did not achieve a ceiling before the final item). Note that this selection criterion did not necessarily imply high scores on the measure, as some children repeatedly responded incorrectly to three or four items in a row without reaching the ceiling criterion. As noted below, children’s scores ranged from 0-26 correct. Due to a clerical error, 85% of the Florida sample (n = 913) was not administered the letter W.

**Texas**—The letter name knowledge test administered in Texas required children to respond to the prompt of “What letter is this?” when simultaneously shown the uppercase and lowercase forms of a given letter. Each of the 26 pairs of uppercase and lowercase letters were printed in Arial 30 point font down the center of an 8 ½-by-11 inch piece of paper. An uppercase and lowercase letter pair was presented one pair at a time by sliding a card down the page and exposing the next letter pair. Letter pairs were presented in a fixed nonalphabetic order that had been randomly determined. All 26 items were administered to all children comprising the Texas sample. As in Florida, only the letter name was accepted as a correct response, and children who initially provided the letter sound were prompted, “That's the sound it makes, but what is the name of the letter?” In both samples only the English letter names were scored as correct.

**Procedures**

After receiving parental consent, children were assessed individually at their preschools during the regular program hours. The specific year of data collection and time of year varied within and across cohorts; the complete sample therefore includes children assessed at many different times of the year. All children were assessed by trained research assistants. These research assistants received rigorous training that included observing models, practice sessions with experienced assessors, and certification after flawless administration to a supervisor. Children were assessed for no longer than 45 minutes per session, and for no more than one session per day. The letter knowledge test was administered as one of many tests of emergent literacy, language, and cognition. Although what tests were included in the assessment battery varied by project, the test of letter name knowledge was always administered before the test of letter sound knowledge and there were no other tests in the battery that provided children with corrective feedback concerning letter names.

**Analyses**

The three goals of the present study were accomplished via application of Item Response Theory (IRT). IRT is a measurement framework in which patterns of observed item responses on a given assessment are explained by respondents’ latent or underlying abilities and characteristics of the items themselves (see Embretson & Reise, 2000 for a full treatment of the theory and application of IRT). In the current study, children's success in
naming the 26 letters of the English alphabet constituted the observed item responses, which indexed children’s latent letter naming knowledge.

IRT analysis was ideally suited to address research questions concerning the roles of letter and child factors in letter name acquisition. Both person (responder) and item parameters are explicitly modeled within the IRT framework (Embretson & Reise, 2000), allowing simultaneous examination of both child- and letter-related factors in examining inter-letter patterns in letter name acquisition. Person parameters, commonly termed \( \theta \), correspond to respondents’ latent abilities on the construct measured based on items endorsed. Respondents with greater values of \( \theta \) perform at higher levels (i.e., have higher abilities) than respondents with smaller \( \theta \) estimates. Note that a particular advantage of IRT estimation procedures is that full item-level data is not required for every respondent; \( \theta \) may be estimated from response patterns that are partial or include missing data.

In addition to respondents’ underlying abilities, \( \theta \) estimates are also dependent on the characteristics of items themselves. Two item parameters were directly relevant to the present research. Item difficulties quantify the degree to which an item is difficult or easy; respondents of lower ability levels are less likely to correctly answer items of higher difficulty than items of lower difficulty (i.e., easier items). Item discriminations indicate the extent to which individual items distinguish latent ability levels among respondents. Items with greater discrimination power more precisely distinguish among adjacent ability levels. (A third IRT item parameter, guessing, is mainly applicable to forced or multiple choice assessments and is therefore not relevant to the present study.)

Relations among person and item IRT parameters are generally depicted using item characteristic curves (ICCs). For each item, the probability of endorsement or correctly responding is plotted against \( \theta \) values. These plots result in curves describing the nonlinear relation between the probability of correct response and \( \theta \). Item discriminations are reflected in the slopes of these curves, with higher discriminations indicated by steeper ICCs. Item difficulties determine an ICC’s inflection point and location on the \( \theta \) continuum. The inflection point occurs at the skill level for which chance of success on a particular item is 50% (i.e., probability = .5). Inflection points for easier items occur at lower levels of \( \theta \); inflection points for more difficult items occur at higher levels of \( \theta \). The left-to-right location of the ICCs likewise shifts according to items’ difficulties. Easier items are plotted to the left of more difficult items, as these items are often correctly answered by respondents with lower ability levels. The ordering of items from left to right therefore may be interpreted as representing the general sequence in which items are correctly answered, which was used to address the first aim of the present study.

An assumption of IRT is that item responses are determined only by respondents’ latent ability levels and are independent of other respondent characteristics. This assumption is related to measurement invariance and implies that (a) respondents with the same ability levels ought to have similar item response patterns and (b) similar response patterns ought to

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1 In IRT, the term ability does not refer to capacity to learn, but rather to current skills or knowledge on the measured construct. These current skills or knowledge may or may not reflect underlying capacity.
generate similar ability estimates. If endorsement of items is related to extrinsic factors other than ability level, then there may be bias in item responses and in overall ability estimates. Differential item functioning (DIF) analyses examine the extent to which items behave similarly across defined groups of respondents, in terms of their relations with latent abilities. DIF is detected when one or more item parameters differ based on respondent group membership. DIF analyses were used in the present study to address the second aim, (i.e., examination of whether or not the presence of a letter as the first letter of one's first name influences the correctness of one's response or the “difficulty” of the letter).

The third and final aim of the present study stemmed from initial DIF analyses. That is, because DIF was evident and because DIF undermines the appropriateness of IRT models, it was necessary to modify the IRT measurement model to more appropriately account for inter-letter differences and inter-child differences in the estimation of children's latent letter naming skill. We compared results from a modified IRT model with the unmodified IRT model and with the raw sum scores to investigate the costs associated with less than optimal parameterization.

Our IRT analyses proceeded in four distinct stages. Stage 1 involved three steps to ensure that the Florida and Texas data met the statistical assumptions required for IRT analyses. These steps included exploratory factor analyses to satisfy the assumption of unidimensionality as well as comparisons of multiple IRT measurement models to gauge model fit and guide selection of the most appropriate IRT model for further analysis. Stage 2 represented the IRT analyses of primary interest, addressing the study's goal of investigating inter-letter differences as they relate to children's latent letter naming abilities across the combined Florida- Texas sample. Item parameters and ICCs were investigated for evidence of a discernible sequence of letter name acquisition. Stage 3 explored DIF as a function of the first letter in children's first names. As a result of Stage 3, a fourth and final stage of analysis estimated an alternative IRT model that also adjusted for children's knowledge of their first initials. All models were conducted using Mplus software (Muthén & Muthén, 2008) and maximum likelihood estimation. Each of the 26 items or observed indicators were modeled as binary, categorical data (i.e., 1 = correct, 0 = incorrect). Additional details concerning specific analyses are reported in conjunction with the results of each stage.

Results

Descriptive Statistics

Children in both samples showed a full range of letter name knowledge. In the Florida sample, children correctly named 17.81 letters on average ($SD = 7.67$, range = 0 to 26). Children in the Texas sample knew slightly fewer letters, averaging 15.61 letters correctly named ($SD = 9.59$, range = 0 to 26). Given the large sample size, the mean difference between the two samples was significant, $t(807.44) = 4.50, p < .001$ although it was relatively small (i.e., effect size of .26). The difference in means was probably due to the greater SES diversity within the Florida sample and to the restriction of a percentage of the Florida sample to only those children who were administered the entire measure.
The descriptive frequency data enabled us to preliminarily explore part of our first goal regarding the letter-specific responses provided by children. Despite demographic differences and a small mean difference, children in the two samples tended to show very similar patterns of relative difficulty among letters (see first three columns of Table 2). For example, children in both samples were most likely to correctly name the letters O, A, B, and C and least likely to name U and V (whereas W was the most infrequently named letter for the Florida sample, it was also the letter with the most missing data). Moreover, this pattern remained unchanged when the samples were combined (see fourth column of Table 2).

We also examined descriptive statistics relevant to our second research goal, addressing the question of whether children’s first name influenced their letter knowledge. The fifth and sixth columns of Table 2 include the percentage of correct responses for children with and without a given letter as the first in their names. For every letter, success rates were higher when letters were the first in children’s names, providing preliminary evidence of children’s first initials influencing their knowledge of particular letters. Differences in success rates were greatest for letters U, Q, and Y, although these letters were also the most infrequently used as first initials. Letters O and A, which were two of the easiest letters, showed the smallest discrepancies for naming skills between children whose names did and did not start with these letters.

**Stage 1: Evaluation of Appropriateness of Data for IRT and Aggregation**

Stage 1 analyses proceeded in the three steps: (1) factor analysis to examine unidimensionality, (2) IRT model comparisons to select the appropriate measurement model, and (3) multiple group analysis to test the equivalence of item parameters in the Florida and Texas samples. Relevant analyses and results for each step are described below.

**Dimensionality of letter names in each sample**—The first step of Stage 1 was to verify the unidimensionality assumption of IRT or, in other words, verify that the 26 letters of the alphabet yielded a single factor that presumably reflects children’s letter name knowledge. We performed sample-specific exploratory factor analysis of the observed binary responses to each of the 26 letters. Examination of eigenvalues revealed clear evidence for a single dominant factor in both the Florida data and the Texas data. (Scree plots are available from the authors upon request.) Moreover, the one-factor models explained the covariance among children’s responses extremely well (CFIs = .999 and .999, TLIs = .999 and .999, RMSEAs = .014 and .025 for Florida and Texas, respectively), given that CFIs and TLIs greater than .95 and RMSEAs less than .05 are generally considered indicative of excellent fitting models (Hu & Bentler, 1999).

**Selection of best IRT model for each sample**—In IRT analysis, it is important to balance data fit with parsimony. Thus, the goal of Step 2 of Stage 1 was to arrive at a model that adequately represented the data using the fewest possible parameters. We compared three binary response models of children’s letter naming skills. The first model, termed the fully constrained model, was not a true IRT model but mimicked the traditional assumption of letter equivalency in the assessment of letter name knowledge by constraining difficulties
and discriminations to be equivalent across all letters. That is, the fully constrained model did not acknowledge any inter-letter differences, as it is traditionally operationalized by simply summing the number of correct responses. The second model was a Rasch or one-parameter logistic (1PL) model in which letters contributed equally to children’s ability estimates (i.e., equivalent discriminations) but difficulty parameters were allowed to vary among letters. The third model was a two-parameter logistic (2PL) model in which both discrimination and difficulty parameters were allowed to vary. Models were statistically compared using the -2 log likelihood test (Tabachnick & Fidell, 1996). The log likelihood value of a model represents the goodness of fit between observed and predicted (i.e., modeled) data. Smaller log likelihood values indicate a better fitting model, and the difference in log likelihood values between two nested models indicates the relative improvement in model fit. The statistical significance of this difference is tested against a chi-square distribution, which is approximated when the log likelihood value is multiplied by -2.

The -2 log likelihood tests comparing the fully constrained, 1PL, and 2PL models revealed that the 2PL model provided the best fit to the data for both the Florida sample (see top panel of Table 3) and the Texas sample (see middle panel of Table 3). Children’s letter naming abilities depended not only on the number of letters named, but also the specific letters to which children correctly responded.

Multiple group IRT—In Step 3 of Stage 1, multiple group IRT analyses were used to assess the stability of item parameters across the Florida and Texas samples prior to collapsing samples into a single data pool (i.e., whether item difficulties, discriminations, or both significantly differed between the two samples). To ensure the same metric of scaling in the two samples, estimation was first linked through constraining the difficulty of letter A to be equivalent across samples. This decision was based on the results of the previous step, which indicated that estimates of the difficulty parameters for the letter A were similar in the two samples. Chi-square tests were used to statistically compare the fit of models in which (1) all item parameters were constrained to be equivalent across samples, (2) only item difficulties were allowed to vary across samples, and (3) both item difficulties and item discriminations were allowed to vary across samples. Chi-square difference tests rather than -2 log likelihood tests as maximum likelihood estimation using numerical integration with robust standard errors is not available in Mplus for multiple group analysis. Equivalence of model parameters across samples supported parameter stability and the use of one large, combined sample.

According to chi-square difference tests, allowing item difficulties to vary provided a better fit than constraining difficulties to be equivalent across samples, χ² (23) = 215.27, p < .001, and allowing item difficulties and discriminations to vary across samples provided a better fit than allowing only difficulties to vary, χ² (9) = 90.73, p < .001. However, chi-square difference tests are overly sensitive when the sample sizes are large like in the present study. In fact, all models, including the model in which both item difficulties and item discriminations were constrained to be equivalent across samples, demonstrated very close fits to the data (CFIs > .99, TLIs > .99, RMSEAs < .06). The Florida and Texas data were therefore combined for all further analyses.
Stage 2: Initial IRT Model for Combined Data

Stage 2 represented the IRT analyses of primary interest, addressing the study's goal of investigating inter-letter differences as they relate to children's latent letter naming abilities. IRT analyses like those above were repeated using the combined dataset. Specifically, we compared the fits of the fully constrained, 1PL, and 2PL models using the -2 log likelihood ratio test. Once the appropriate measurement model was confirmed, item parameters and ICCs were investigated for evidence of a discernible sequence of letter name acquisition.

As was the case in each separate sample, the two-parameter model provided the best fit to the data of the combined sample (see lower panel of Table 3). That is, letters reliably differed in both discriminations and difficulties. Item parameters from this 2PL model are presented in the second and third columns of Table 4. ICCs relating these parameters to letter naming skill are shown in Figure 1. Parameter estimates derived from the combined sample were highly correlated with those derived from separate Florida and Texas IRT analyses ($r > .82$ for discriminations, $r > .99$ for difficulties).

**Letter discriminations**—Differences in discriminations are indicated graphically by the slopes of the ICCs. As depicted in Figure 1, slopes for most letters were fairly consistent, with the exceptions of X and W (dashed lines). Discrimination values in Table 4 ranged from 1.072 (Letter X) to 2.243 (Letter S). Lower values and flatter slopes indicate decreased discrimination power. Thus, correct responses to X and W are less indicative of children's overall letter naming skills than correct responses to most other letters.

**Letter difficulties**—The difficulty parameters in Table 4 indicate that letters differed greatly in their difficulties, ranging from -1.24 (Letter O) to 0.03 (Letter V). Differences in letter difficulties are indicated by the inflection points and left-to-right ordering of letters along the horizontal axis of Figure 1, with easier items located on the left side of the graph. Looking at Figure 1, a typical sequence of letter name learning is apparent in the ordering of letters with similar discrimination values (i.e., slopes). The sequence is clearest for the easiest (O, B, A, and C) and most difficult (V and U) letters. The sequence is less clear for letters that have similar difficulty values and are closely grouped in Figure 1. An example of two such letters is Q and I, the 23rd and 24th most difficult letters. Thus, although letters Q and I tend to be learned after O, B, A, and C and before V and U, some children likely learn Q before I while others learn I before Q.

Stage 3: DIF Analysis of First Letters in Children’s First Names

The Stage 3 DIF analysis examined the research question of whether children's skill at naming letters was influenced by whether the letter was the first in their names. For these analyses, a second set of 26 observed variables coded whether or not a specific letter was the first in a given child's name (i.e., first initial). The effect of the first letters of children's names was tested using DIF procedures described by Muthén and colleagues (Muthén, 1989; Muthén, Kao, & Burstein, 1991). The Muthén technique conditions the item responses and latent skill level on the potential source(s) of item bias. Figure 2 presents this theoretical model as applied to letter data. The right side of the figure constitutes the IRT measurement model; the left side comprises a structural model in which item responses and latent skill...
were regressed on the set of 26 dummy codes indicating children's first initials. The structural model indicates the extent to which first initials influence letter naming responses and overall letter naming skill. The measurement model provides IRT parameterization, conditional on first initial effects. This parameterization included two difficulty estimates for each letter: one for children for whom the letter is not their first initial and one for those having the letter as their first initial. DIF is indicated in cases of significant path coefficients for the effects of first initials on individual letter responses, indicating a reliable difference in the difficulties.

Prior to examination of item responses, paths between indicators and latent skill were considered (i.e., dashed lines in Figure 2). These paths represented the direct influence of children's first initials on their letter naming skill. Such paths were not theoretically meaningful, as significant effects would indicate that children's skills are inherently related to the names they are given. This phenomenon would result in differing latent skill estimates for children with different first initials, regardless of letter responses. Although these direct effects were initially tested for the sake of completeness, none of the direct paths from first initial indicators to latent ability were significant (all ps > .059). Thus, these direct paths were subsequently fixed to 0.

Statistical results of the DIF analysis are presented in the fourth through eighth columns of Table 4. Letter discriminations and letter difficulties for children who did not have the letter as a first initial were highly consistent with results for the combined sample 2PL model presented above (rs > .99). Difficulties for letters that were the first initials in children's names, however, were much lower than previous difficulty estimates. This pattern held for all letters, with changes in difficulty magnitudes ranging from 0.39 (Letter A) to 9.36 (Letter H).

The magnitudes of DIF effects were examined by converting path coefficients to log odds, a more meaningful and interpretable metric given the use of logit parameterization. The log odds represent differences in likelihoods of correctly naming letters between children who did and did not have given letters as first initials. For example, children with the first initial A were approximately 3 times more likely to correctly name Letter A than children with other first initials. The log odds revealed particularly strong advantages for having certain letters as first initials, including K, R, G, and V (see the seventh column in Table 4). Children with these first initials were over 20 times more likely to correctly name these letters than children with other initials. Similarly strong advantages would likely have been seen for Letters H, Q, U, and Y, as may be noted from the particularly low difficulties for these letters when they served as the first letters of children's names. In fact, all children whose names began with these letters correctly named their first initials; the lack of variation in the joint distribution thus prevented the model from arriving at stable estimates of the log odds for these four letters.

Finally, significance tests for the effects of first initials on letter responses were evaluated. As noted, insufficient variability for Letters H, Q, U, and Y prevented estimation of standard errors and p-values for these letters. Of the remaining letters, all but five effects were
statistically significant. Overall, letter responses appeared to be based both on children’s latent letter naming skill and the first letters of their names.

**Stage 4: IRT Model Adjusting for First Letters in Children’s Names**

The evidence presented above suggests that children's letter naming skills may be affected by both inter-letter and inter-child differences. The IRT models of Stage 1 and 2 showed that letters varied in both difficulty and discrimination, with letter naming skills depending on the specific pattern of letters known. The DIF model of Stage 3 showed that children were more likely to correctly name the first letters in their names, even after controlling for their latent ability. In Stage 4, to address our third research goal, a final IRT model accounting for these influences on children's letter naming skills was thus estimated, in which children's responses to their first initial were considered as a separate observed item, akin to a 27th letter. Children's responses for this item were coded as for all other letter response items, as correct or incorrect, regardless of the specific letter that was first in their names. For example, if Joseph and Anna correctly named J and A, respectively, both would receive scores of 1 on this new item. Responses to the specific letter (e.g., J and A) were considered missing.

Consideration of “first letter of first name” as a separate item in Stage 4 conferred a number of advantages. First like the DIF models of Stage 3, it controlled for the advantage in letter naming for children's first initials when estimating parameters of other letters and when estimating children's latent letter naming abilities; however, it greatly simplified estimation of item parameters relative to the DIF model. Second unlike any prior models examined, item parameters for responses to first initials, as a single entity, could be compared to those of other letters by placing both on the same scale. Third, the more parsimonious model of Stage 4 bypassed the problems associated with variability in the joint distributions of letter responses and first initials. That is, the lack of children with first initials H, Q, U, or Y who were unfamiliar with the names of these letters did not pose a problem for estimating the Stage 4 model, which results in more accurate and stable item and person parameter estimation. Finally, the item parameters generated by the IRT model of Stage 4 were compared to those generated by the IRT model of Stage 2 (i.e., a model not taking first initials into account). Latent skill estimates from these two IRT models were also compared to each other and to letter knowledge indexed as a total raw score to examine the amount of agreement among these several different means of quantifying children's letter name knowledge.

**Letter parameters**—The item parameters estimated in Stage 4 are presented in the last columns of Table 4, and ICCs are presented in Figure 3. As anticipated, the first letter of children’s names had the lowest difficulty and was the easiest letter for children to name (see the leftmost curve within Figure 3). The discriminations and difficulties for other letters were highly comparable to those estimated by the earlier Stage 2 IRT model ($r > .98$). Discriminations were generally similar across letters with the exceptions of X and W, which were generally less discriminating than other letters. Letters O, B, A, and C continued to be the easiest letters to name after one's first initial. Letters U and V were the most difficult. Letter sequence shifted slightly for those letters of similar difficulties in the initial IRT
model. For instance, letters L and F reversed their relative positions when children's first initial was controlled.

**Letter naming abilities**—Latent letter naming ability estimates, thetas, were computed and compared for the IRT models of Stage 2 and 4. As per typical IRT parameterization, theta estimates had a mean of zero and standard deviation of approximately one (actual \(SD = .94\)). Theta estimates from the Stage 2 model ranged from -2.09 to 1.26. Estimates were the same for children with equivalent response patterns. For example, children whose response patterns indicated correctly naming the first 10 letters of the alphabet (i.e., Letters A through J) had estimates of -0.70. Theta estimates based on the Stage 2 model correlated at \(r = .96\) with total raw scores that ranged from 0 to 26.

Theta estimates based on the Stage 4 IRT model ranged from -2.12 to 1.26 and also correlated at \(r = .96\) with total raw scores. Unlike the Stage 2 IRT model estimates, however, the Stage 4 IRT model estimates were based on both response patterns and first initials. To illustrate, consider children who correctly named Letters A through J and had equal skill estimates under the Stage 2 IRT model. In the final IRT model, those children with A as a first initial (an easy letter) had theta estimates of -0.67; children with G as a first initial (a more difficult letter) had theta estimates of -0.70. Higher estimates resulted for the former group because these children were able to name a more difficult letter (G) without the advantage of this letter being their first initial. Despite the increased sensitivity of the Stage 4 model, latent estimates from the Stage 2 and Stage 4 IRT models correlated at \(r > .99\).

**Discussion**

Our primary goals in this article were to explore the developmental sequence of letter name knowledge and to examine the possible influence of the first letter in children's names as informing this development. Studies to date have only partially investigated these questions, using less sophisticated methods that did not allow for simultaneous consideration of both letter and child factors. Using the largest sample of preschool-age children to date in a study with this focus, and methods that did allow analyses of the joint influence of both letter and child factors, this study replicated and extended findings from prior studies indicating that there are significant inter-letter differences in how readily children acquire naming knowledge of each of the 26 letters in the English alphabet. Specifically, IRT analyses demonstrated that letters varied significantly in both their difficulty and in their discrimination, and in how indicative they were of a child's underlying letter name knowledge. These findings held very consistently across ethnically- and skill- diverse samples of children from two different areas of the country.

On average across the subsamples the children correctly named roughly 60% of the letter names. This rate is slightly higher than that from Worden and Boettcher (1990) who found that four-year-olds from middle-income families named 54% of the letters. Our sample included mostly 4- and 5-year-old children from a wide variety of SES backgrounds; the rate of correct responses we found exceeds that for samples of exclusively at-risk children (e.g., children attending Head Start; U.S. Department of Health and Human Services, 2006). An increase in the performance of young children since 1990 may also be attributed to

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substantial national and state initiatives targeting letter knowledge over the past two decades (e.g., Early Reading First, and standards for Head Start and state early learning programs).

The results partially support the idea of a common developmental sequence in which letters are learned by young children, in the absence of a formal letter knowledge instructional sequence. That is, letters show a range in likelihoods of being known at a given point in child development, as shown both by the simple percent correct frequencies and by the IRT-based difficulty parameters. The common sequence of learning letter names is more apparent at the extreme ends of letter knowledge. That is, there appears to be a small subset of letters that are more readily acquired by young children (e.g., O, A, and B), and a few that pose particular challenges (e.g., U and V). In contrast, a clear sequence of development is not apparent during middle stages of letter knowledge development, which appear to be more idiosyncratic, as evidenced by the closer clustering of the ICCs for many letters in Figures 1 and 3. These findings are generally consistent with results from studies of kindergarten-age children (e.g., Alonzo & Tindall, 2007). For example, using a 1PL Rasch model with kindergarten children, and, notably, a fluency based measure rather than an untimed measure as was used in the present study, Alonzo and Tindall (2007) also found that the uppercase letters A, B, and O were among letters with the lowest difficulty parameters, whereas uppercase letters U, Q, and V were among those with the highest difficulty parameters. The ease of acquisition for letters A and B likely relate to the ubiquity of the alphabet song and the alphabetic order sequence in many preschool classrooms. The letter O may be readily named because learning its name requires mapping a novel phonological sound to a familiar orthographic shape, rather than the novel to novel association required for most other letters.

One clear interpersonal variation in letter name acquisition supported by this study is the impact of the first letter of a child's first name. Consistent with theories suggesting that children, and adults, may have a sense of “possession” or affinity for letters included in their names (Hoorens et al., 1990; Nuttin, 1987), and with the prominence given to print displays of names in many early childhood classrooms, children were significantly, and in some cases, substantially more likely to know a letter if it began their given name. Of note is that this finding holds for letters across the range of difficulty and discrimination, such that the first-initial advantage may be particularly profound for letters that a child would otherwise not yet be likely to identify. Moreover, the first-initial effect appears robust enough to render this letter, regardless of which specific letter it is, the letter children are most likely to know.

Although children are most likely to learn the name of their first initial before the names of all other letters, our results indicated that including the first-initial effect in the IRT models did not meaningfully alter the general pattern or values of difficulty, discrimination, or the overall sequence of letter acquisition. Further, the estimate of letter naming skill was virtually identical with and without considering the first-letter effect. In fact, both of the IRT-estimated latent skill scores (e.g., from the 2PL models with and without the first-letter effect) were strongly related to the simple sum scores of raw letter naming responses.
Relevance for the Assessment of Letter Naming Knowledge

An appropriate interpretation of the present findings suggests that how one chooses to assess young children’s letter name knowledge likely should depend on the intended purpose for the assessment, amount of resources available, and the skills of the population under study. If the goal of the assessment is to index individual differences in children at a single point in time and resources are available to assess all children on all letters, then raw total scores are sufficient, and IRT-based theta scores are unnecessary. This conclusion is reassuring given the typical use of this basic metric in many educational and research settings in which IRT analysis is not easily applied. If however, there are resource limitations that make a shorter and thus quicker assessment more appealing, these findings can be a guide toward the development of instruments with a sampling of letters representing the full range of children’s skills. Further, there appear to be a number of letters with some degree of redundancy in difficulty, discrimination, or both, which may allow for multiple parallel forms to be generated for the purposes of progress monitoring. Such measures could be particularly useful in the context of response-to-instruction systems that may require frequently repeated assessments of children’s letter knowledge, and in the context of intervention and program evaluation research that targets letter knowledge as an indicator of curricular or programmatic impact (e.g., state-funded prekindergarten programs, Head Start Family and Child Experiences Survey ongoing studies; Hulsey et al., 2011).

The use of an IRT model to inform the creation of these short-form instruments appears particularly necessary given that the raw sum score is not actually on an interval scale (i.e., the difference in the latent skill gain between the 3rd and 4th letter acquired is not equal to the skill gain between the 14th and 15th letter acquired) As such, growth trajectories that use an IRT-based interval scale of theta scores will be more reliable. As an example, Alonzo and Tindal (2007) used their Rasch model (1PL) to develop progress monitoring probes for fluency of naming uppercase and lowercase letters for use in kindergarten and 1st grade. The present results also call for caution, however, when utilizing assessments or curriculum-based probes that feature a subset of letters whose selection is not informed by IRT findings. Such assessments may unintentionally under- or over-estimate children’s letter name knowledge based on the particular letters that are selected (e.g., predominantly using only easier letters such as A, B, and O or a series of more difficult letters such as V, U, and Q).

Relevance for the Instruction of Letter Knowledge

The finding that children appear to most readily learn the first letter of their name, and that there may be certain other letters they may be more likely to already know, has the possibility of adding some concrete suggestions to an area of instruction particularly in need of empirically-based practices (Phillips & Piasta, in press; Piasta et al., 2010; Piasta & Wagner, 2010a). Despite the wealth of data supporting the concurrent and longitudinal linkage between letter knowledge and decoding skill, there is no clear research consensus on the best tactics for teaching children letter names or sounds (but cf. Piasta et al., 2010, for some new evidence). Traditional curricula are currently implemented by many programs, including the majority of Head Start centers, which serve an at-risk group of children (Lonigan, Farver, Phillips, & Clancy-Menchetti, 2011). These preschool curricula and many educational leaders focused on ages 3 to 5 often shy away from systematic introductions of
individual letters, preferring more implicit, incidental instructional methods (Heroman & Jones, 2004; Morrow, 2007). Perhaps as a consequence, preschool educators who want to use more intentional instructional planning have often had little more than intuition on which to rely when deciding the order, manner, and strategies with which to teach children these aspects of print knowledge. However, many newer, literacy-focused preschool curricula systematically introduce all letters, most often in alphabetic order (e.g., 7 of 10 curricula recently reviewed by the third author, see also Justice et al., 2006). Further, most curricula for kindergarten and first grade students include a specific sequence of letter name and sound instruction (e.g., letters with high frequency in consonant-vowel-consonant words, Carnine, Silbert, Kame' enui & Tarver, 2009; Juel, Paratore, Simmons, & Vaughn, 2008). In addition, there does seem to be some degree of best practice convergence on the notion that children’s own names can be a meaningful starting place for letter knowledge instruction, as evidenced by the prevalence of this strategy in numerous preschool curricula (e.g., Hohmann, 2005; Lonigan, Menchetti, Phillips, McDowell, & Farver, 2007) and in the suggestions of authors writing for an audience of early childhood educators (e.g., Morrow, 2007; Venn & Jahn, 2004).

One implication of our findings is that this strategy is aligned with the empirical evidence, if one determines that it would be reasonable and beneficial to begin letter knowledge instruction for 3- and 4-year-old children with a personally relevant letter that the child is quite likely to already know. This logic would also be consistent with theories of motivation and learning that suggest that initial success may be important for ongoing motivation toward learning a challenging skill or concept (e.g., akin to the concept of teaching within children’s zone of proximal development; Bedrova & Leong, 2007; Berk & Winsler, 1995; Moreno, 2010). Regarding the implications of these findings for the instruction of other letters, there are several empirical questions that would need to be first resolved. That is, one could see arguments made both for a strategy that followed the logic of beginning with the first letter in one’s name and then moved to easy letters, such as B, A, and O. The common use of alphabetic order has some overlap with this strategy. In contrast, one could also envision a strategy in which those letters were sequenced later, or even skipped, on the argument that many children would likely acquire them without targeted instruction. Another instructional strategy worth investigation is that after introducing the letter of a given child’s first initial, one might move to the first initials of peers, and then other letters that are in the child’s and peers’ names. Alternatively, teachers might follow the model of some elementary reading curricula and introduce letters in order of prominence in written language. Intervention studies are clearly needed to evaluate these and other testable instructional models with children in several age groups. In addition, future research should build on Piasta et al. (2010) to explore the relative benefits of instruction on letter names, letter sounds, and the combination for preschool-age children, as well as to compare outcomes for instruction on upper and lower case letters.

Limitations and Suggestions for Future Research

Although the largest and most diverse evaluation of preschool-age children’s letter-specific alphabetic knowledge to data, this study is not without limitations. Alphabetic knowledge was only assessed expressively, tapping recall rather than recognition, which may
demonstrate a different pattern of acquisition. Likewise, although the Texas sample viewed uppercase and lowercase letters together, the Florida sample only were presented with uppercase letters, and there was not a way to separately evaluate children's performance on lowercase letters. Thus, both of these are areas in need of further study to determine if the present results would generalize across case and across task specifics. A joint assessment of both uppercase and lowercase name knowledge would likely increase the range of underlying skill estimates and would increase the accuracy of both item parameters.

Whereas we were able to simultaneously evaluate both inter-letter and inter-child factors, we were not able to analyze the impact of other inter-letter distinctions, including alphabetic order, the relation of the letter name to the letter sound (Treiman et al., 1998; Piasta et al., 2010), the frequency of each letter in spoken or written language, the frequency with which children are incidentally exposed to specific letters (e.g., in classroom peer names or environmental print), or age of acquisition of specific speech sounds. Whereas it is likely that many of these features are quite similar across letters and would thus not necessarily add to the reliability of item parameters, these are empirical questions designated for future investigations. Future studies will need to explore other inter-child distinctions, including whether the letter appears anywhere in a child's name (Treiman & Broderick, 1998) or appear in peers' or siblings' names, and the child's skill on related emergent literacy skills (e.g., phonological awareness, expressive language; Piasta & Wagner, 2010b). Future research is warranted that can relate children's letter name knowledge at multiple points in time to the instructional context. Related areas in need of further exploration include whether children are differentially responsive to instruction on individual letters, and whether such variability (e.g., such as within a dynamic assessment or short-term learning trial context) would be conditioned on underlying skill at baseline.

The sample, although quite diverse ethnically, included only children who were English speaking. Additional research with children learning to read in other alphabetic languages, and with English learners, is needed to determine whether these findings would generalize. Although the results from the combined Texas and Florida sample closely mirrored those from the separate samples, we do note some small but significant differences in the demographic characteristics of the two samples. In particular, the Texas sample included a sizable proportion of Hispanic children, whereas there were none in the Florida sample, and the proportions of non-Hispanic white children were quite different. We also were not able to ascertain the impact of classroom-level variables on children's letter name knowledge, such as peers' influence, curriculum, or the type or quality of instruction during the current or prior school years. We leave such studies of children's letter name learning, in terms of gains across time, to future research endeavors.

Conclusion

In sum, the present results suggest that children's acquisition of letter names depends on both inter-letter and inter-child factors. Acquisition of letter names follows a fairly predictable sequence in the early and late stages of letter name acquisition. The children in these samples represented almost 200 classrooms from a full range of center-based early childhood programs, including Head Start, public prekindergarten, and private childcare,
which served children from a range of socioeconomic backgrounds. These aspects of diversity lend confidence to the current findings. We encourage researchers and practitioners alike to consider the implications of these results in their pursuit of best practices for fostering children's alphabet knowledge development.

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Fig. 1.
Item characteristic curves for 26 letters as derived from the initial 2PL IRT model. When read left to right, the figure key presents letters in order of difficulty (at .50 probability of correct response). For example, O was the least difficult letter to name whereas V was the most difficult.
Fig. 2.
Theoretical DIF model depicting the effect of children's first initials on letter responses and latent letter naming ability.
Fig. 3.
Item characteristic curves for 26 letters and the first letters of children's names as derived from the final, adapted 2PL IRT model. When read left to right, the figure key presents letters in order of difficulty (at .50 probability of correct response). Thus, the first letter of children's first names (FLFN) was the least difficult for children to name whereas V was the most difficult.
### Table 1
Demographic information for Florida and Texas samples and the combined sample.

<table>
<thead>
<tr>
<th></th>
<th>Florida sample</th>
<th>Texas sample</th>
<th>Combined sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td>54.8% girls</td>
<td>48.0% girls</td>
<td>47.3% girls</td>
</tr>
<tr>
<td>2-years-old</td>
<td>2.8%</td>
<td>0.0%</td>
<td>1.9%</td>
</tr>
<tr>
<td>3-years-old</td>
<td>19.7%</td>
<td>14.4%</td>
<td>18.0%</td>
</tr>
<tr>
<td>4-years-old</td>
<td>49.1%</td>
<td>59.0%</td>
<td>52.3%</td>
</tr>
<tr>
<td>5-years-old</td>
<td>26.8%</td>
<td>26.4%</td>
<td>26.8%</td>
</tr>
<tr>
<td>6-years-old</td>
<td>1.6%</td>
<td>0.02%</td>
<td>1.0%</td>
</tr>
<tr>
<td>Non-Hispanic White</td>
<td>60.8%</td>
<td>11.2%</td>
<td>45.0%</td>
</tr>
<tr>
<td>African-American</td>
<td>30.2%</td>
<td>49.4%</td>
<td>36.3%</td>
</tr>
<tr>
<td>Hispanic</td>
<td>0.0%</td>
<td>33.2%</td>
<td>10.5%</td>
</tr>
<tr>
<td>Other/ mixed ethnicity</td>
<td>4.2%</td>
<td>3.6%</td>
<td>4.0%</td>
</tr>
<tr>
<td>Unreported ethnicity</td>
<td>4.8%</td>
<td>2.6%</td>
<td>4.1%</td>
</tr>
<tr>
<td>Mean age (months)</td>
<td>54.30 (SD = 8.05)</td>
<td>55.00 (SD = 6.41)</td>
<td>54.33 (SD = 8.07)</td>
</tr>
</tbody>
</table>
Table 2

Percentage of correct responses (n) by letter and percentage of correct response conditioned on first name initial across samples and for the combined sample.

<table>
<thead>
<tr>
<th>Letter</th>
<th>Florida sample</th>
<th>Texas sample</th>
<th>Combined Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Overall</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(n)</td>
<td></td>
<td>(n)</td>
</tr>
<tr>
<td>A</td>
<td>83.61% (1074)</td>
<td>73.80% (500)</td>
<td>80.50% (1574)</td>
</tr>
<tr>
<td>B</td>
<td>85.38% (1074)</td>
<td>72.00% (500)</td>
<td>81.13% (1574)</td>
</tr>
<tr>
<td>C</td>
<td>80.15% (1073)</td>
<td>68.80% (500)</td>
<td>76.54% (1573)</td>
</tr>
<tr>
<td>D</td>
<td>72.53% (1074)</td>
<td>57.92% (499)</td>
<td>67.90% (1573)</td>
</tr>
<tr>
<td>E</td>
<td>74.30% (1074)</td>
<td>61.40% (500)</td>
<td>70.20% (1574)</td>
</tr>
<tr>
<td>F</td>
<td>68.06% (1074)</td>
<td>59.40% (500)</td>
<td>65.31% (1574)</td>
</tr>
<tr>
<td>G</td>
<td>64.43% (1074)</td>
<td>54.82% (498)</td>
<td>61.39% (1572)</td>
</tr>
<tr>
<td>H</td>
<td>73.09% (1074)</td>
<td>61.80% (500)</td>
<td>69.50% (1574)</td>
</tr>
<tr>
<td>I</td>
<td>63.78% (1074)</td>
<td>52.71% (499)</td>
<td>60.27% (1573)</td>
</tr>
<tr>
<td>J</td>
<td>63.50% (1074)</td>
<td>62.12% (499)</td>
<td>63.06% (1573)</td>
</tr>
<tr>
<td>K</td>
<td>71.14% (1074)</td>
<td>63.20% (500)</td>
<td>68.61% (1574)</td>
</tr>
<tr>
<td>L</td>
<td>69.18% (1074)</td>
<td>58.00% (500)</td>
<td>65.63% (1574)</td>
</tr>
<tr>
<td>M</td>
<td>73.28% (1074)</td>
<td>58.20% (500)</td>
<td>68.49% (1574)</td>
</tr>
<tr>
<td>N</td>
<td>63.87% (1074)</td>
<td>54.82% (498)</td>
<td>61.01% (1572)</td>
</tr>
<tr>
<td>O</td>
<td>91.06% (1074)</td>
<td>75.15% (499)</td>
<td>86.01% (1573)</td>
</tr>
<tr>
<td>P</td>
<td>74.95% (1074)</td>
<td>63.33% (499)</td>
<td>71.27% (1573)</td>
</tr>
<tr>
<td>Q</td>
<td>63.04% (1074)</td>
<td>53.60% (500)</td>
<td>60.04% (1574)</td>
</tr>
<tr>
<td>R</td>
<td>72.44% (1074)</td>
<td>61.80% (500)</td>
<td>69.06% (1574)</td>
</tr>
<tr>
<td>S</td>
<td>76.54% (1074)</td>
<td>63.53% (499)</td>
<td>72.41% (1573)</td>
</tr>
<tr>
<td>T</td>
<td>73.93% (1074)</td>
<td>60.12% (499)</td>
<td>69.55% (1573)</td>
</tr>
<tr>
<td>U</td>
<td>58.10% (1074)</td>
<td>47.60% (500)</td>
<td>54.76% (1574)</td>
</tr>
<tr>
<td>V</td>
<td>50.37% (1074)</td>
<td>44.89% (499)</td>
<td>48.63% (1573)</td>
</tr>
<tr>
<td>W</td>
<td>47.83% (161)*</td>
<td>60.80% (500)</td>
<td>57.64% (661)</td>
</tr>
<tr>
<td>X</td>
<td>68.81% (1074)</td>
<td>67.20% (500)</td>
<td>68.30% (1574)</td>
</tr>
<tr>
<td>Y</td>
<td>70.30 (1074)</td>
<td>49.20 (500)</td>
<td>63.60 (1574)</td>
</tr>
<tr>
<td>Z</td>
<td>67.69 (1074)</td>
<td>56.20 (500)</td>
<td>64.04 (1574)</td>
</tr>
</tbody>
</table>
Note. Due to a clerical error W was omitted for assessment for most of the Florida sample.
Table 3

IRT model comparisons for the separate and combined samples.

<table>
<thead>
<tr>
<th>Model</th>
<th>log likelihood value</th>
<th>-2 log likelihood test</th>
<th>Difference$^a$</th>
<th>df</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Florida sample (N = 1074)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constrained</td>
<td>-11,255.27</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>One-parameter logistic model</td>
<td>-10,323.99</td>
<td>1802.58</td>
<td>24</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>Two-parameter logistic model</td>
<td>-10,263.25</td>
<td>121.47</td>
<td>26</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td><strong>Texas sample (N = 500)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constrained</td>
<td>-5148.13</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>One-parameter logistic model</td>
<td>-4807.13</td>
<td>682.00</td>
<td>24</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>Two-parameter logistic model</td>
<td>-4760.36</td>
<td>93.58</td>
<td>26</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td><strong>Combined sample (N = 1574)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constrained</td>
<td>-16,398.08</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>One-parameter logistic model</td>
<td>-15,225.78</td>
<td>2344.60</td>
<td>24</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>Two-parameter logistic model</td>
<td>-15,135.24</td>
<td>181.08</td>
<td>26</td>
<td>&lt;.001</td>
<td></td>
</tr>
</tbody>
</table>

Note.

$^a$ Difference from model presented immediately above.
Table 4

Letter parameters for IRT and DIF models in the combined sample.

<table>
<thead>
<tr>
<th>Letter</th>
<th>Stage 2 2PL IRT model</th>
<th>Stage 3 DIF model</th>
<th>Stage 4 2PL IRT model accounting for first initial</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Discrimination</td>
<td>Difficulty</td>
<td>Discrimination</td>
</tr>
<tr>
<td>A</td>
<td>1.77</td>
<td>-0.99</td>
<td>1.78</td>
</tr>
<tr>
<td>B</td>
<td>1.54</td>
<td>-1.06</td>
<td>1.55</td>
</tr>
<tr>
<td>C</td>
<td>1.81</td>
<td>-0.83</td>
<td>1.950</td>
</tr>
<tr>
<td>D</td>
<td>1.80</td>
<td>-0.54</td>
<td>1.87</td>
</tr>
<tr>
<td>E</td>
<td>1.76</td>
<td>-0.62</td>
<td>1.86</td>
</tr>
<tr>
<td>F</td>
<td>1.98</td>
<td>-0.45</td>
<td>2.00</td>
</tr>
<tr>
<td>G</td>
<td>1.77</td>
<td>-0.34</td>
<td>1.82</td>
</tr>
<tr>
<td>H</td>
<td>1.86</td>
<td>-0.59</td>
<td>1.94</td>
</tr>
<tr>
<td>I</td>
<td>1.71</td>
<td>-0.31</td>
<td>1.72</td>
</tr>
<tr>
<td>J</td>
<td>1.67</td>
<td>-0.40</td>
<td>1.80</td>
</tr>
<tr>
<td>K</td>
<td>1.73</td>
<td>-0.57</td>
<td>1.87</td>
</tr>
<tr>
<td>L</td>
<td>2.13</td>
<td>-0.46</td>
<td>2.23</td>
</tr>
<tr>
<td>M</td>
<td>1.54</td>
<td>-0.58</td>
<td>1.63</td>
</tr>
<tr>
<td>N</td>
<td>1.82</td>
<td>-0.33</td>
<td>1.88</td>
</tr>
<tr>
<td>O</td>
<td>1.83</td>
<td>-1.24</td>
<td>1.82</td>
</tr>
<tr>
<td>P</td>
<td>2.06</td>
<td>-0.63</td>
<td>2.06</td>
</tr>
<tr>
<td>Q</td>
<td>1.68</td>
<td>-0.31</td>
<td>1.69</td>
</tr>
<tr>
<td>R</td>
<td>2.17</td>
<td>-0.56</td>
<td>2.29</td>
</tr>
<tr>
<td>S</td>
<td>2.24</td>
<td>-0.66</td>
<td>2.30</td>
</tr>
<tr>
<td>T</td>
<td>1.76</td>
<td>-0.60</td>
<td>1.79</td>
</tr>
<tr>
<td>U</td>
<td>1.62</td>
<td>-0.15</td>
<td>1.63</td>
</tr>
<tr>
<td>V</td>
<td>1.86</td>
<td>0.03</td>
<td>1.89</td>
</tr>
<tr>
<td>W</td>
<td>1.20</td>
<td>-0.55</td>
<td>1.20</td>
</tr>
<tr>
<td>X</td>
<td>1.07</td>
<td>-0.66</td>
<td>1.07</td>
</tr>
<tr>
<td>Y</td>
<td>1.59</td>
<td>-0.42</td>
<td>1.59</td>
</tr>
<tr>
<td>Letter</td>
<td>Stage 2 2PL IRT model</td>
<td>Stage 3 DIF model</td>
<td>Stage 4 2PL IRT model accounting for first initial</td>
</tr>
<tr>
<td>--------</td>
<td>-----------------------</td>
<td>-------------------</td>
<td>--------------------------------------------------</td>
</tr>
<tr>
<td></td>
<td>Discrimination</td>
<td>Difficulty</td>
<td>Not first letter of name</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Discrimination</td>
</tr>
<tr>
<td>Z</td>
<td>1.71</td>
<td>-0.43</td>
<td>1.74</td>
</tr>
<tr>
<td>First letter</td>
<td></td>
<td></td>
<td>First letter of name</td>
</tr>
<tr>
<td>b</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note.

\( ^a \) Estimates for these letters were unstable due to lack of variability in the joint distributions.

\( ^b \) Item coding whether children correctly responded to the first letters of their first names.