Journal of Applied Developmental Psychology 50 (2017) 1–14

Contents lists available at ScienceDirect

Journal of Applied Developmental Psychology

Kindergarten readiness profiles of rural, Appalachian children from low-income households

Laura M. Justice, Hui Jiang *, Kiren S. Khan, Jaclyn M. Dynia

The Crane Center for Early Childhood Research and Policy, Ohio State University, 1945 North High St, Columbus, OH 43201, United States

ARTICLE INFO

Article history:
Received 20 April 2016
Received in revised form 22 February 2017
Accepted 26 February 2017
Available online 17 March 2017

Keywords:
Kindergarten readiness
Preschool
Rural education
Latent profile analysis
Language and literacy
Socio-behavioral skills

ABSTRACT

The present study used a person-centered approach to examine profiles of school readiness among entering kindergartners in rural, Appalachian communities. Aims were twofold: to determine the extent to which reliable profiles may characterize kindergartners' school readiness, with readiness encompassing language, literacy, math, socio-emotional skills, and learning-related behaviors; and to identify potential predictors of children's kindergarten readiness profiles. Participants included 396 entering kindergartners. Results of latent profile analysis showed there to be four profiles of kindergarten readiness: global risk (16% of children), academic risk (35%), sociobehavioral risk (13%), and readiness (36%). In general, predictors of profile membership included sex, race, family income, maternal education, and pre-k classroom quality. Study results show that a non-trivial percentage of children (49%) exhibit academic readiness, and 71% exhibit socio-behavioral readiness. This work improves our understanding of profiles of children from rural, Appalachian communities at school entry, and factors that may contribute to positive kindergarten readiness.

1. Introduction

Kindergarten readiness is a multidimensional, theoretical construct representing children's preparedness for participation in formal schooling, which more often than not corresponds to kindergarten entrance in the twenty-first century (Duncan et al., 2007; Hair, Halle, Terry-Humen, Lavelle, & Calkins, 2006; Justice, Bowles, Pence Turnbull, & Skibbe, 2009). It is generally accepted that children who arrive to school "ready to learn" will have more optimal academic achievement over time than children who do not. In support of this point, a considerable number of longitudinal studies have shown that children's language, literacy, math, and social-emotional skills as well as their learning-related behaviors (e.g., attention) at or around kindergarten entry are positively correlated with their future academic achievement (Duncan et al., 2007; McClelland, Acock, Piccinin, Rhea, & Stallings, 2013). Pre-kindergarten programs, especially those that are publicly funded and target enrollment to children from at-risk backgrounds, are correspondingly expected to enhance children's readiness for kindergarten and intervene with those children who are deemed at-risk for not being for ready.

Despite consensus about the importance of kindergarten readiness and the value of improving readiness for children at-risk for being unready, in reality we have limited empirical understanding of how best to determine whether a child is or is not likely to be ready for schooling, which demands a particular level of skills for children to be successful. Indeed, much of the research identifying indicators of kindergarten readiness has relied on variable-centered approaches to examine the relations between specific indices of school readiness, such as letter recognition and phonological awareness, and future achievement indices (Holliday, Cimetta, Cutshaw, Yaden, & Marx, 2014; Stormont, Herman, Reinke, King, & Owens, 2015). While such studies consistently show the positive, predictive relations between school-readiness indices and future achievement variables, they are not particularly helpful for more applied efforts in which we seek to determine whether some children are or are not likely to be school-ready. For instance, assessing children's performance across individual indices of school readiness limits our understanding of how skills across multiple domains interact within children and pattern together to result in qualitatively different readiness characteristics.

Person-centered approaches to studying kindergarten readiness can be helpful in this regard. Such work seeks to determine whether there are profiles of children's readiness scores across multiple measures, just prior to or at kindergarten entry, that correspond to readiness for schooling or, alternatively, a lack of readiness for schooling (e.g., Hair et al., 2006; Pentimonti, Justice, & Kaderavek, 2014). The benefit of profile analyses, such as latent class analysis and cluster analysis, is that they can help to identify how the various dimensions of kindergarten readiness coalesce within clusters, or profiles, of children (Halle, Hair, Wandner, & Chien, 2012). Given that a child's readiness for school reflects a number of different dimensions, including pre-academic skills (math, language, and literacy), social-emotional skills, and learning-

* Corresponding author.
E-mail addresses: justice.57@osu.edu (L.M. Justice), jiang.200@osu.edu (H. Jiang), kirenkh@alumni.upenn.edu (K.S. Khan), dynia.1@osu.edu (J.M. Dynia).

http://dx.doi.org/10.1016/j.appdev.2017.02.004
0193-3973/

related behaviors, profile analyses can explore how skills across these various dimensions exist in combination to define groups of children's readiness characteristics. This methodology allows us to identify subgroups of children that may be at greater risk due to the pattern of functioning across multiple areas of development. Further, by following children's readiness profiles over time, we can begin to understand whether a given profile of school readiness corresponds to specific outcomes of interest, such as academic under-achievement (e.g., Cabell, Justice, Logan, & Konold, 2013) or social adjustment (e.g., Hair et al., 2006).

A handful of studies using profile analyses to better understand kindergarten readiness have appeared in the literature. In an initial application of profile analysis to kindergarten readiness, Hair et al. (2006) studied a nationally representative sample of kindergarteners (from the Early Childhood Longitudinal Study-K) to examine readiness profiles with respect to cognition, social-emotional skills, and physical health. Results showed there to be four profiles characterizing children at kindergarten entry: whereas slightly more than half (54%) of the children fit into one of two generally positive profiles, 46% of children fit into one of two poor-readiness profiles corresponding to social-emotional risk (27% of sample) or health risk (19% of sample). Children in the two poor-readiness profiles were more likely to be from socially and economically disadvantaged backgrounds than those in the positive profiles. Additionally, analyses of first-grade achievement as a function of readiness profiles across a variety of indices (e.g., reading, math, self-control) showed there to be significant repercussions for children with poor school readiness. Children in the two poor-readiness profiles had lower reading and math scores than those in the positive profiles and were rated by their teachers as having less self-control in the classroom.

Several subsequent studies have applied profile analyses to understand school readiness among children considered at-risk. Cabell and her colleagues investigated profiles of school readiness, focusing specifically on language and literacy skills, for children in targeted-enrollment preschool programs, the majority of whom came from low-income households (Cabell, Justice, Konold, & McGinty, 2011; Cabell et al., 2013). These studies showed children to be relatively stable with respect to their profiles from preschool through kindergarten, particularly for children in "at-risk" profiles. There is also some research investigating school readiness patterns in children with language impairment. Pentimonti et al. (2014) investigated profiles of school readiness for children with language impairment (LI), finding there to be four distinct profiles characterizing these youngsters. Children in two profiles (Socially Awkward – 19%; Limited Readiness – 14%) demonstrated patterns of readiness that were significantly weaker than the other groups. Interestingly, the quality of children's preschool experiences was strongly predictive of children's school-readiness profile membership: children were more likely to be in the optimal profile versus one of two at-risk profiles if their preschool classroom had high levels of instructional and emotional support (Pentimonti et al., 2014). The predictive potential of classroom quality as a contextual factor influencing school readiness profile membership is debated in the literature however. A recent examination of school-readiness profiles among participants in Head Start, which showed there to be four distinct profiles of readiness, linked classroom quality to profile membership (Halle et al., 2012), with higher classroom quality being associated with movement to a more strengths-based profile across the year. However, in another study utilizing the same sample (McWayne, Cheung, Wright, & Hahs-Vaughn, 2012), there was no association between classroom quality and profile membership/movement. One possible explanation for this lack of association as acknowledged by the authors is that "measures of individual teacher-student interaction (rather than general sensitivity measures) are needed" (p. 680, McWayne et al., 2012).

In the present study, we examined school readiness among rural, poor children residing in Appalachian communities, adding to the literature concerning development of children in rural settings (Byun, Meece, Irvin, & Hutchins, 2012; Tichnor-Wagner, Garwood, Bratsch-Hines, & Vernon-Feagans, 2016; Vernon-Feagans & Cox, 2013). Appalachia is a large and significant generally rural region of the southeastern United States, with its 204,000 mile^2 transcending 13 states and including 25,000,000 inhabitants (Pollard & Jacobsen, 2012). Much of the Appalachian region is geographically isolated, given the mountainous nature of the topography, contributing in part to long-standing challenges regarding development of both infrastructure and industry.

The present study was conducted in small, rural communities across the Appalachian region of two states, and the children represented in the study were attending preschool programs targeting enrollment to low-income families. These circumstances provide an important and multi-faceted context in which to understand children's development, in this case their school readiness. Most research on school readiness to date has focused on children largely residing in urban and suburban settings (e.g., Winsler et al., 2008; Zhai, Brooks-Gunn, & Waldfogel, 2011), even though millions of children within the United States reside in rural settings. Further, the distinctness of rural and urban settings makes it unclear if findings based on suburban/urban children effectively generalize to rural children (Miller & Votruba-Drzal, 2013). For instance, Halle et al. (2012) examined profiles of school readiness for a national sample of Head Start participants. Of four profiles identified, 47% of children were in profiles exhibiting some facet of risk (cognitive risk profile = 38%; socioemotional risk profile = 9%), whereas 53% were in more advantageous profiles. It is questionable whether these results can generalize to preschoolers in rural settings, as recent work has suggested that rural preschoolers may lag behind their urban and suburban peers in key readiness skills (Miller & Votruba-Drzal, 2013).

Often, rurality is conceptualized based on its distinctiveness from urbanicity; in fact, government organizations define rural settings as those that are "not urban," with the rural/urban distinction based on the density of the population (Hall, Kaufman, & Ricketts, 2006). However, rural settings are not simply "non-urban" and are unique in several important ways. First, rural settings typically have elevated levels of poverty and economic depression compared to urban settings, largely reflecting shifts within the broader economy, such as movements towards 'clean energy' (leading to declines in the coal industry), transfer of local jobs to urban cores, and creation of the 24-h economy (Vernon-Feagans, Burchinal, & Mokrova, 2015). Jobs that are available tend to be low wage, and many adults, especially the less-educated, work nonstandard hours. Nearly one-half of rural children reside in poverty (Strange, Johnson, Showalter, & Klein, 2012) and many live in 'deep poverty' (O'Hare et al., 2013); less than one in five adults has a college degree (Byun, Meece, & Irvin, 2012).

Second, rural settings are, by their nature, relatively isolated and removed from the resources available within suburban and urban contexts. For instance, they may have limited access to health care, especially that which addresses specialized needs (e.g., treatment for extremely preterm birth), and state-of-the-art educational approaches and services (Guarino, Santibanez, & Daley, 2006). This extends to early care and education, with rural parents largely relying on home-based care options for their young children, due in part to limited access to quality center-based programs or inability to pay for such programs (Smith, 2006).

Although the rural context is often considered monolithically, there is variability within the schools and homes of rural children, and this variability appears associated with their academic development (De Marco, Vernon-Feagans, & Investigators, 2015; Tichnor-Wagner et al., 2016). For instance, Tichnor-Wagner and colleagues examined the home-literacy activities experienced by 1100 rural students, showing there to be significant variability among children in their access to literacy materials in the home and the extent to which they engaged in home-literacy activities. Importantly, this variability in home-literacy access and activities was positively associated with children's early-reading achievement, even when controlling for socioeconomic indicators (e.g., maternal education, household income).

Rural contexts are best understood by the opportunities and constraints that young children may face in these settings, not simply in their comparison to urban or suburban settings. Vernon-Feagans et al. (2015) discuss the notion of 'diverging destinies' to reference the distinctiveness of the rural context, especially with respect to the growing gap between lower- and higher-income families within this setting. These authors argue that the very low proportion of college-educated adults in the rural setting creates greater stratification in society reflecting family income and education. Put simply, rural settings can reflect more sharply defined stratification than is observed in suburban and urban settings, with very large differences in the experiences of the educated and the non-educated. Whereas the relatively small, former group of families might have access to the many benefits afforded by society (i.e., enrichment activities for children, specialized health care), the latter do not.

Some scholars have emphasized the role of social capital to help understand the stratification apparent within rural settings, arguing that stratification is not simply a reflection of socioeconomic advantage and disadvantage based on wages and education alone. That is, beyond the role of financial capital (household income) and human capital (educational achievement), social capital within the rural context represents a third type of capital that helps to explain successful and unsuccessful development among rural children, referring in part to the norms, networks, and relationship that children have with their parents (Coleman, 1988; Dyk & Wilson, 1999). Social capital serves to enable some children to achieve certain goals or competencies, such as arriving to school ready to learn, through parents' financial, psychological, and social investments in their children's early school success; on the other hand, social capital can also serve to constrain children's school readiness. In the present study, while we do not examine the role of social capital in understanding young rural children's school readiness, we speculate that distinct profiles that are observed may reflect variability in children's access to financial, human, and social capital within their families, schools, and communities.

In the present study, we expand our understanding of children's school readiness by applying a person-centered approach to examine profiles of school readiness among kindergartners in Appalachia – an understudied and yet culturally distinct population in the United States; the children resided in low-income households and had participated in center-based preschool programs in the year prior. The first aim was to determine the extent to which distinct profiles may characterize the school readiness of rural, Appalachian children entering kindergarten with school readiness encompassing language, literacy, math, socio-emotional skills, and learning-related behaviors. The second aim was to identify potential predictors of children's kindergarten readiness profiles, from among two sets of candidate variables: children's socio-demographic background (sex, race, age, maternal education, household income) and classroom quality (both in terms of instructional and emotional support). The first set of predictors, namely socio-demographic background, was selected based on their prominence in the literature on school readiness. A number of studies have shown that children's profiles are conditional on such background characteristics as sex and household income (e.g., Hair et al., 2006). The second predictor, classroom quality, was selected to examine a potentially malleable contextual factor that has been inconsistently linked to children's school readiness (Keys et al., 2013; Pentimonti et al., 2014). In the current study, classroom quality was conceptualized as the level of instructional support provided by the teacher (such as language modeling, concept development, and structured learning activities) as well as general teacher sensitivity (e.g., Halle et al., 2012; McWayne et al., 2012).

2. Method

2.1. Study overview

Participants in the current study were 383 children who were enrolled during their pre-kindergarten (pre-k) year in a cluster randomized controlled trial (RCT) investigating impacts of an early-literacy curriculum (Authors, In Press) as implemented in rural, Appalachian preschools providing targeted enrollment to children from low-income homes (state-funded Pre-K or Head Start). Enrollment of children was conditional on their pre-k teachers' participation ($n = 99$) in the RCT, with random assignment in the RCT occurring at the classroom level. Eligibility for teachers/classrooms to participate included the following: (1) the classroom prioritized enrollment to children from low-SES backgrounds, (2) the majority of children in a classroom were age-eligible for kindergarten the following year, and 3) the preschool program was located within a rural community in an Appalachia-designated county in one of three states (Ohio, West Virginia, and Virginia).

To identify eligible classrooms for the RCT, the study team generated a list of seemingly eligible preschool programs and made contact with program administrators; subsequently, with administrator permission, information sessions were held for program teachers who could self-select into the study with agreement to the random-assignment procedures. From each enrolled classroom, five children were randomly selected for participation from among those for whom caregiver consent was provided; the overall consent rate was 77%, averaging 14 children per classroom. Children's participation largely comprised participation in assessments in the fall and spring of the RCT year and a follow-up assessment in the subsequent fall (November to December), when most children were in kindergarten. In total, 506 children were enrolled into the RCT in fall of the pre-k year, of whom 427 (84%) were retained for spring assessments; lack of retention was due primarily to child leaving the school (64% of cases), the teacher exiting the study during the RCT year (24% of cases), or the child being absent or dissenting to participate at the spring assessment time-point (12% of cases). The 383 children (76% of initial sample) in the present study are those who were assessed in fall of their kindergarten year; missing data for the remainder were as follows: 46% of children had moved and/or were not available for assessments, 24% could not be located, 15% were not followed because their pre-k teacher had withdrawn from the RCT, 8% were retained in pre-k and did not have follow-up data, 3% of children were chronically absent and could not be assessed, and the remainder were for unknown or other reasons (4%).

2.2. Participants

The majority of children enrolled in this study were Caucasian, non-Hispanic ($n = 338$, 94%) and female ($n = 208$, 54%), with 6% of children identified as African-American ($n = 22$), and 3% of children identified as either Hispanic, Asian/Pacific Islander, American Indian/Native Alaskan, or Other ($n = 10$). The average age of the children was 67 months in the fall of kindergarten ($SD = 3.3$ months, Range = 58 to 77 months). Fewer than 3% of the children were receiving special-education services or were English Language Learners.

Two indices of socioeconomic status for the children were collected (i.e., maternal education and household income). For maternal education, most mothers had a high school diploma as their highest degree earned ($n = 249$, 70%), whereas some had not completed high school ($n = 30$, 8%); only a few had obtained a university degree ($n = 39$, 11%). Seventy-one percent of the families had an annual total family income of less than $35,000 ($n = 246$), whereas 17% had a total family income of $35,001 to $65,000 ($n = 59$) and 12% had a total family income of $65,001 to $85,001 or more ($n = 41$).

2.3. Procedures

During the pre-k year, children's teachers were randomly assigned to one of two experimental conditions or a comparison (business-as-usual instruction) condition. The experimental conditions involved teacher implementation of a 30-week supplemental language and literacy curriculum featuring two instructional lessons per week delivered to the whole class. Treatment impacts are discussed elsewhere (see Authors, In Press).

For the present study, our primary interest is examining children's profiles of school readiness in the fall of kindergarten, and exploring predictors of these profiles from the pre-k year. School readiness profiles were based on 11 measures of children's language, literacy, math, socio-emotional skills and learning-related behaviors. These measures consisted of both direct and indirect assessments collected in November and December of the kindergarten year. Predictors of these profiles were based on two sets of variables: (a) children's socio-demographic background, and (b) children's pre-k experience (instructional quality). These measures were based on data collected at intake into the study, in fall of the pre-k year, and observations made during the children's pre-k year. While treatment condition was also examined as one of the potential predictors of profile membership, no significant or sizeable differences were found between the groups in any of the five domains of school readiness, or in the latent profiles. Therefore, treatment condition was excluded from the main analyses, for purposes of parsimony. We conducted multilevel analyses to account for the clustering effect of pre-k classrooms.

2.4. Measures of school readiness profiles

Children's language, literacy, math, socio-emotional skills, and learning-related behaviors were examined in the fall of the kindergarten year using seven instruments and 11 different measures. For the domains of language, literacy, and learning-related behaviors, multiple measures are available, thus allowing for use of a latent-variable approach in examining profiles.

2.4.1. Language skills

Children's language skills were measured using three subtests of the Clinical Evaluation of Language Fundamentals (CELF; Wiig, Secord, & Semel, 2004). The three subtests included Sentence Structure, Word Structure, and Expressive Vocabulary, thus representing children's skills in grammar, morphology, and vocabulary. These subtests measure the expressive and receptive language skills for children age 3–6 years by asking children to respond verbally to a stimulus picture. Administration of the three core subtests takes approximately 15–20 min and is completed in a 1:1 setting. Every CELF-P2 record form is scored at least twice by two independent staff, first time in the field, and second time in the lab once all data has been collected. For the Sentence Structure and Word Structure subtests, each response is awarded 1 point if correct and 0 points if incorrect. For the Expressive Vocabulary subtest, each response is awarded from 2 to 0 points, depending on the quality of the answer. Points awarded for each subtest are totaled, yielding a raw score, which were used in the current analyses. Adequate levels of reliability have been reported in the examiner's manual (test/retest reliability = 0.77–0.91; Cronbach's α = 0.77–0.95) and in the field study (Cronbach's α = 0.68–0.76).

2.4.2. Literacy skills

Children's literacy skills were measured using two subtests of the norm-referenced Woodcock-Johnson III Tests of Achievement (WJ; Woodcock, McGrew, & Mather, 2001) and one subtest of the Phonological Awareness Literacy Screening-Kindergarten (PALS; Invernizzi, 2010). From the WJ, children were administered the Letter-Word Identification subtest, which examines one's ability to identify letters and words in isolation, and the Word Attack subtest, which examines one's ability to apply phonetic and structural analysis skills to unfamiliar words (both nonsense and infrequently used words). Raw scores for these subtests were used in analyses. From the PALS, children were administered the Spelling subtest, which requires children to write five consonant-vowel-consonant words (e.g., cat). Each is scored for the number of phonemes represented, and partial credit is given for phonetically acceptable substitutions. Up to four points can be received per word, thus scores can range from 0 to 20. According to the examiner's manuals, most of the WJ III tests show strong reliabilities of 0.80 or higher, and PALS Spelling test has reliability of 0.89. Our field study has found consistent results (Word Attack = 0.81; Letter-Word ID = 0.88; PALS Spelling = 0.90).

2.4.3. Math skills

Children's math skills were assessed using the math items of the Academic Rating Scale (ARS-Math; National Center for Education Statistics, 1994). Completed by children's kindergarten teachers in the fall semester, this instrument contains 15 items by which teachers rate child's mathematical thinking, use of perception, and understanding of mathematical problems on a five-point scale (1 = not yet; 2 = beginning; 3 = in progress; 4 = intermediate; 5 = proficient). The items included concrete examples to help the teacher accurately assign a score. For the present study, analyses were based on the average rating across items, with scores ranging from 1 to 5. Reliability ranged from 0.91–0.95 as reported in the technical report, and was 0.93 in the present study.

2.4.4. Social-emotional skills

Children's social-emotional skills were assessed using the Social Skills scale within the Social Skills Rating System (SSRS; Gresham & Elliott, 1990), completed by kindergarten teachers for each child in the fall of the year. This comprises 30 items for which the teacher indicates the frequency that the child demonstrates the behavior or skill using a 3-point rating scale (0 = never, 1 = sometimes, 2 = very often). The items encompass three sub-domains: self-control (e.g., "controls temper in conflict situations with adults"), assertion (e.g., "invites others to join in activities"), and cooperation (e.g., "attends to your instructions"). For the present study, analyses were based on the average rating across the 30 items, with scores ranging from 0 to 2. In the present study, the reliability was 0.92, comparable to what was found in the normative sample (0.90).

2.4.5. Learning-related behaviors

Children's learning-related behaviors were measured using the Learning Behavior Scale (LBS; McDermott, Green, Francis, & Stott, 2000) and two scales from the Teacher-Child Rating Scale task orientation scale (TCRS; Hightower et al., 1986).

The LBS is a teacher-report instrument designed to assess learning behaviors of children when in the classroom. Positive and negative learning behaviors (e.g., "cooperates in class activities sensibly") are assessed using 29 items scored on a three-point scale (0 = does not apply, 2 = most often applies); negative statements are reverse scored. Scores ranged from 0 to 2, and the average rating per item was used for analyses. Internal consistency ranged from 0.75 to 0.85 in the technical reports, and was 0.91 in the current study.

The TCRS is a teacher-report measure that assesses positive and negative aspects of a child's adjustment to school. There are four scales, but for the purposes of the current study, two scales were used (Task Orientation and Behavior Control). For both scales, the teacher rates statements (e.g., "How much do you agree that the child has difficulty following directions?") on a five-point scale (1 = strongly disagree, 5 = strongly agree). Negative statements are reverse scored. For the current study, the Task Orientation scale is a mean of eight items and the Behavior Control scale is a mean of eight items. Mean scores per scale were used in analyses, with a possible range of 1 to 5. In the current study, reliability was 0.94 for Task Orientation and 0.83 for

Behavior Control, consistent with what was reported in the technical manuals (0.85–0.95).

2.5. Predictors of school readiness profiles

2.5.1. Socio-demographic background

Children's socio-demographic characteristics, such as sex, race, age, maternal education, and family income, were determined using caregiver questionnaires completed at study entrance in the fall of pre-k.

2.5.2. Classroom quality

Children's pre-k classroom quality was based on direct observations collected in children's classrooms during the pre-k year, and the observations were scored using the Classroom Assessment Scoring System (CLASS; Pianta, La Paro, & Hamre, 2008). The CLASS is an observational measure that captures the global quality of the classroom across ten dimensions that fall into three general quality domains (Emotional Support, Classroom Organization, and Instructional Support). For the current study, field assessors completed two-hour videotaped classroom observations in the fall, winter, and spring of the pre-k year. Three 20-min cycles were randomly chosen from each of these observations (a total of six hours of video) to be coded by trained and reliable CLASS coders; each cycle is coded for all 10 dimensions based on a holistic 7-point coding scheme for which 1 = low and 7 = high. Twenty percent of cycles were randomly selected to be double-coded, and the intraclass correlations for double-coded video segments using a two-way mixed model across all project timepoints, cohorts, and sites were >0.7 for all domains. For each of the three domains, ratings were averaged across three time points (fall, winter, and spring) to produce summary scores.

2.6. Missing data

Missing data exist in the majority of the outcome measures and predictor variables. Missing data ranged from 0% to 2% for direct measures (e.g., indicators of language and literacy), 6% to 10% for family demographics (e.g., family income, maternal education), and 11% to 13% for teacher ratings of student behavior (e.g., socio-emotional skills scales). There were no missing data for classroom quality variables (i.e., instructional support, emotional support, and classroom organization).

Instead of listwise deleting missing data, which has been shown to produce biased results and low power (Graham, 2012), we used multiple imputation (MI) (Little & Rubin, 1987) to treat missing data. Inclusive imputation (Schafer & Olsen, 1998) was conducted, where the MI models included all outcome measures as well as other variables theoretically or empirically related to the outcomes or rate of missingness (e.g., sex, ethnicity, pre-k scores). To account for the nested nature of the data, a multilevel imputation model was applied by treating classroom effect as a random component. Twenty datasets were imputed (Enders, 2010) using the package "pan" (panel or clustered data in multivariate linear mixed-effects models) (Zhao & Schafer, 2013) in R 3.0.3 (R Core Team, 2014). These datasets were then analyzed by the MI module in Mplus 7.11 (Muthén & Muthén, 2006), where 20 sets of results were obtained and combined to generate the final estimates.

3. Results

3.1. Obtaining factor scores via confirmatory factor analysis (CFA)

We first conducted factor analyses to validate key constructs, and to create summary scores for each of the five school readiness domains. Table 1 provides descriptive statistics and scale reliability for the measures used to represent each domain. Table 2 displays the Pearson correlation coefficients for each pair of measures. Across the three of the five domains that have multiple indicators (language skills, literacy, and learning-related behavior), confirmatory factor analysis (CFA) was conducted and factor scores extracted. Math and social-emotional skills were each measured by one indicator (Academic Rating Scale math and SSRS Social Skills Scale), so CFA was not applied. For language, literacy, and learning-related behavior, CFA models all yielded acceptable fit. The standardized loadings ranged from 0.65 (CELF Sentence Structure) to 0.80 (CELF Word Structure) for language skills, 0.73 (WJ Word Attack) to 0.89 (PALS Spelling) for literacy, and 0.72 (TCRS Behavioral Control) to 0.92 (Learning Behavior Scale) for learning-related behaviors. Based on these CFA models, we extracted factor scores for the constructs of language, literacy, and learning-related behavior. We used these factor scores in all subsequent analyses as the summary scores representing the children's level of development in each specific domain. For the domain of math skills, the ARS math average rating was used as the summary score directly; and for the domain of social-emotional development, the SSRS social skills average rating was used. All summary scores were standardized, allowing each domain of kindergarten readiness to be measured in the same metric in the latent profile analyses.

3.2. Determining the number of profiles via multilevel latent profile analysis (MLPA)

To examine children's profiles of kindergarten readiness, Multilevel Latent Profile Analysis (MLPA) was employed. Latent Profile Analysis (LPA), derived from conventional latent class analysis, is a statistical method for identifying subgroups of related cases from multivariate continuous data (Clogg, 1995; Lazarsfeld, Henry, & Anderson, 1968). The final number of latent profiles is usually determined by theoretical expectation as well as comparison of posterior fit statistics given different choices of number of profiles. For a specific number of profiles, LPA

Table 1
Descriptive data for 11 school readiness indices from fall of kindergarten.

Domain	Measure	Number of item	*M*	*SD*	Reliability (α)	Standardized loading[a]
Language	CELF sentence structure	22	17.60	2.95	0.683	0.653
	CELF word structure	24	17.88	3.80	0.763	0.803
	CELF expressive vocabulary	20	26.65	6.53	0.761	0.726
Literacy	WJ letter-word ID	76	15.54	5.08	0.883	0.812
	WJ word attack	32	3.37	2.32	0.814	0.729
	PALS Spelling	10	9.85	5.78	0.904	0.887
Math	ARS math (average)	15	3.25	0.99	0.967	N/A
Social-emotional	SSRS social skills (average)	30	1.40	0.33	0.926	N/A
Learning-related behavior	LBS (average)	29	1.61	0.31	0.910	0.920
	TCRS task orientation (average)	8	3.63	1.06	0.936	0.906
	TCRS behavior control (average)	8	3.76	0.75	0.826	0.722

Note. CELF = Clinical Evaluation of Language Fundamentals (Wiig et al., 2004); WJ = Woodcock-Johnson III Tests of Achievement (Woodcock et al., 2001); PALS = Phonological Awareness Literacy Screening-Kindergarten (Invernizzi, 2010); ARS = Academic Rating Scale (National Center for Education Statistics, 1994); SSRS = Social Skills Rating System (Gresham & Elliott, 1990); LBS = Learning Behavior Scale (McDermott et al., 2000); TCRS = Teacher-Child Rating Scale (Hightower et al., 1986).

[a] "Standardized loading" refers to the standardized factor loading of each measure to its corresponding domain in the CFA model, as described in the beginning of Results section.

Table 2
Pearson correlation between key indicators for five domains of kindergarten readiness.

Domain	Measure	1	2	3	4	5	6	7	8	9	10
Language	1. CELF sentence structure (SS)	–									
	2. CELF word structure (WS)	0.48	–								
	3. CELF expressive vocabulary (EV)	0.52	0.59	–							
Literacy	4. WJ letter/word ID (WI)	0.31	0.36	0.38	–						
	5. WJ word attack (WA)	0.25	0.33	0.36	0.82	–					
	6. PALS Spelling	0.32	0.44	0.39	0.72	0.65	–				
Math	7. ARS math skills	0.27	0.36	0.36	0.54	0.39	0.52	–			
Social-emotional	8. SSRS social skills (SS)	0.21	0.20	0.23	0.25	0.17	0.26	0.39	–		
Learning-related behavior	9. LBS	0.23	0.24	0.26	0.36	0.25	0.38	0.42	0.74	–	
	10. TCRS task orientation (TO)	0.30	0.32	0.36	0.43	0.31	0.45	0.52	0.75	0.83	–
	11. TCRS behavior control (BC)	0.12	0.12	0.14	0.14	0.09	0.16	0.19	0.68	0.69	0.63

Note. CELF = Clinical Evaluation of Language Fundamentals (Wiig et al., 2004); WJ = Woodcock-Johnson III Tests of Achievement (Woodcock et al., 2001); PALS = Phonological Awareness Literacy Screening-Kindergarten (Invernizzi, 2010); ARS = Academic Rating Scale (National Center for Education Statistics, 1994); SSRS = Social Skills Rating System (Gresham & Elliott, 1990); LBS = Learning Behavior Scale (McDermott et al., 2000); TCRS = Teacher-Child Rating Scale (Hightower et al., 1986).

attempts to estimate the probability that each observation falls into each profile. Following the analysis, the characteristics of the latent profiles can also be determined. To account for the potential clustering of observations due to sample design and research considerations, LPA have been extended to a multilevel context, using the finite mixture modeling framework of latent class analysis (McLachlan & Peel, 2004; Vermunt, 2003). Given the hierarchical nature of data in this study (i.e., children nested in classrooms), We used Mplus (Muthén & Muthén, 2006) software to conduct multilevel LPA (MLPA). In all MLPA models run, the variances and covariances were held equivalent across profiles.

For the present study, we analyzed in the MLPA models the CFA-based summary scores for the language, literacy, and learning-related behavior domains and the scale average scores for the math and socio-emotional domains. Solutions with different number of profiles were run to determine which solution best represented the data. To compare models with different number of profiles, we examined fit statistics such as the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Sample Size Adjusted Bayesian Information Criterion (SSABIC), and Best Log-likelihood based on 120 perturbations of random starting value. For these indices, lower values indicate better fit. In order to test whether the improvement of fit was statistically significant with increasing number of profiles, the Lo-Mendell-Rubin (LMR) Adjusted Likelihood Ratio tests (Lo, Mendell, & Rubin, 2001; Vuong, 1989) were run for each pair of solutions. A lower *p*-value rejects the *k*-1 class model in favor of the *k* class model. We also examined entropy, which indicates how much the profiles are distinct from one another; entropy with values approaching one indicates higher classification accuracy (Celeux & Soromenho, 1996). Note that the fit indices as well as results of likelihood ratio tests typically improve as the number of latent profiles increases, thus favoring a solution with a greater number of profiles. Thus the importance of theory and interpretability also come into play.

Based on theoretical concerns and the comparison of fit indices (Table 3), the 4-profile solution was identified as the best fit for describing profiles of kindergarten readiness for our sample. In terms of fit indices, as expected, AIC, BIC, and SSABIC indices improve when the number of profiles increases, though the amount of improvement decreases. The 4-profile solution has the highest value of entropy among all solutions examined (0.795). The LMR test indicates that model fit improved significantly from the 1-profile solution to the 2-profile solution ($p = 0.010$), and from the 3-profile solution to the 4-profile solution ($p < 0.001$), while beyond 4-profile the solutions did not differ significantly. While the likelihood ratio test suggests a 2-profile solution is appropriate, we chose the 4-profile solution based on theoretical concerns and other fit indices. As shown in the later sections, the 4-profile solution describes the complexity of kindergarten readiness by capturing the variation in academic as well as in socio-behavioral dimensions. For the 4-profile solution, analysis of variance (ANOVA) revealed sizeable between-profile differences for each of the five domains (all $p < 0.001$, Cohen's d range from 1.83 for ARS math skill to 3.48 for learning-related behavior rating).

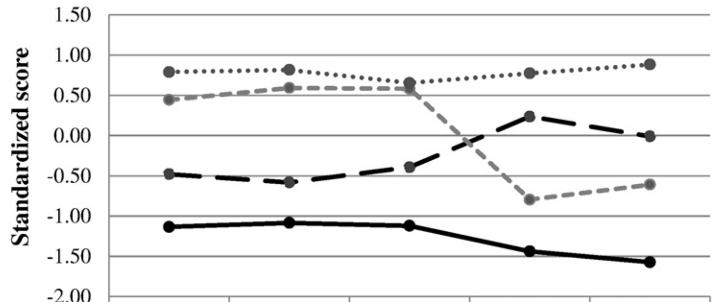
3.3. Describing characteristics of the four latent profiles

We obtained four profiles of kindergarten readiness from the MLPA (Fig. 1). Since these profiles were based on z-scores within each readiness domain, the profiles represent children's standing within this particular sample rather than their standing normatively. For the sample of 383 children, approximately 16% of them were in Profile 1 ($n = 60$), which we refer to as “global risk.” This profile of children was marked by very low scores in all domains (one *SD* below the mean in language, literacy, and math; 1.5 *SD* below the mean in social-emotional skills and learning-related behavior). Around 35% of the children were classified to Profile 2 ($n = 134$), which we refer to as “academic risk.” On average, children in this profile scored about a 0.5 *SD* below the mean in language, literacy, and math skills, yet at the average level in social-emotional (+0.2 *SD*) and learning-related behavior (0 *SD*). Thirteen percent of the children were in Profile 3 ($n = 49$), which we refer to as “socio-behavioral risk.” Children in this profile scored 0.5 *SD* above the sample average in all three academic-related domains, yet were 0.8 *SD* below the mean in social skills, and 0.6 *SD* below the mean in learning-related behavior. Finally, 36% of children ($n = 140$) were in Profile 4, which we refer to as “ready.” Children in this profile were

Table 3
Fit indices for different profile solutions.

Number of profiles	Number of free parameters	Fit indices			Entropy	Smallest group size	Best Log-likelihood	Δ Log-likelihood	Adjusted LRT *p*-value
		AIC	BIC	SSABIC					
2	16	4463.412	4526.580	4475.815	0.776	139	−2215.706	247.906	0.010
3	22	4312.560	4399.417	4329.614	0.771	58	−2134.280	81.426	0.312
4	**28**	**4213.670**	**4324.215**	**4235.375**	**0.795**	**49**	**−2078.835**	**55.446**	**<0.001**
5	34	4155.790	4290.023	4182.146	0.777	49	−2043.895	34.941	0.259
6	40	4125.797	4283.718	4156.805	0.780	27	−2022.898	20.996	0.290

Note. AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; SSABIC = Sample-Size Adjusted Bayesian Information Criterion; Δ Log-likelihood = change in log-likelihood from *k*-1 profile model to *k* profile model; Adjusted LRT = Lo-Mendell-Rubin Adjusted Likelihood Ration test.



	Language Skills	Literacy Skills	Math Skills	Social-Emotional Skills	Learning-Related Behaviors
Profile 1: Global Risk	-1.14	-1.08	-1.12	-1.44	-1.57
Profile 2: Academic Risk	-0.48	-0.58	-0.39	0.24	-0.01
Profile 3: Sociobehavioral Risk	0.44	0.59	0.58	-0.80	-0.61
Profile 4: Ready	0.79	0.82	0.65	0.77	0.88

Fig. 1. Latent profiles of school readiness at the fall of kindergarten: Four profile solution. Note. The figure displays the average score of each profile for each domain. Since we standardized summary scores for all domains (i.e., z-scores), the location on the y-axis indicates where each profile stands as compared to the sample average.

approximately 0.8 *SD* above the mean in language, literacy, social-emotional skills and learning behaviors, and 0.65 *SD* above the mean in math skills. The 4-profile solution indicates that the profiles of kindergarten readiness have complex patterns. While the traditional "high" and "low" groups still exist, for a sizeable amount of the sample (48%), readiness in academic domains does not necessarily mean socio-behavioral readiness, or vice versa.

With the extracted profile membership, we further describe the characteristics of each profile by normative percentile rank scores and scale raw scores (Table 4). The normative percentile rank scores, available for the three language subscales and the socio-emotional scale, are useful for describing the sampled children's standing relative to the population beyond our specific sample. Distributions of the percentile rank scores of language skills and social skills are displayed in Fig. 2. Normative scores for measures in literacy, math, and learning-related behavior domains are not available, so we interpret the children's levels in these domains by comparing the raw scores against the scales' text anchors whenever possible. On average, children from Profile 1 (global risk) ranked 24–31th percentile in language and 16th percentile in social skills. They demonstrated low levels in math skills ($M = 2.1$, 2 = "beginning" on ARS scale) and task orientation ($M = 2.1$ on a 5-point scale), yet average levels in behavior control and learning behavior. Children from Profile 2 (academic risk) ranked 32–41th percentile in language and 52th percentile in social skills. They showed "in progress" math skills, and received positive ratings in all aspects of learning-related behavior. Children from Profile 3 (sociobehavioral risk) ranked average in terms of the national norm (52–55th percentile) in language, demonstrated "intermediate" math skills, and received neutral or

Table 4
Descriptives for school readiness indices across four profiles.

Domain and measures	Score type	Profile 1: Global risk ($n = 60$, 16%) *M* (*SD*)	Profile 2: Academic risk ($n = 134$, 35%) *M* (*SD*)	Profile 3: Sociobehavioral risk ($n = 49$, 13%) *M* (*SD*)	Profile 4: Ready ($n = 140$, 36%) *M* (*SD*)
Language					
CELF sentence structure (SS)	PR[a]	31.01 (21.39)	40.84 (25.32)	54.57 (26.36)	61.87 (25.64)
CELF word structure (WS)	PR	23.54 (19.71)	31.97 (19.82)	52.36 (24.47)	60.13 (27.54)
CELF expressive vocabulary (EV)	PR	26.57 (18.63)	36.46 (20.91)	52.45 (21.37)	60.20 (23.09)
Literacy					
WJ letter/word ID	Raw (0–76)	11.27 (3.50)	13.023 (3.22)	17.67 (2.94)	18.79 (5.23)
WJ word attack	Raw (0–32)	1.93 (1.04)	2.39 (1.09)	4.25 (2.15)	4.60 (2.81)
PALS Spelling	Raw (0–20)	4.22 (3.47)	6.54 (3.91)	13.67 (4.36)	14.09 (4.22)
Math					
ARS math skills (average)	Raw (1–5)[b]	2.14 (0.74)	2.86 (0.76)	3.82 (0.76)	3.89 (0.67)
Social-emotional					
SSRS social skills	PR	16.29 (12.29)	51.68 (21.12)	25.88 (11.57)	68.17 (23.86)
Learning-related behavior					
LBS (avg)	Raw (0–2)[c]	1.16 (0.22)	1.63 (0.21)	1.43 (0.19)	1.85 (0.13)
TCRS task orientation (avg)	Raw (1–5)[d]	2.12 (0.65)	3.57 (0.69)	3.10 (0.65)	4.59 (0.43)
TCRS behavior control (avg)	Raw (1–5)[d]	3.01 (0.66)	3.91 (0.54)	3.14 (0.66)	4.21 (0.54)

[a] PR = Percentile Rank score.
[b] ARS (Academic Rating Scale): 1 = Child has not yet demonstrated skill (Not yet); 2 = Child is just beginning to demonstrate skill but does so very inconsistently (Beginning); 3 = Child demonstrates skill with some regularity but varies in level of competence (In progress); 4 = Child demonstrates skills with increasing regularity and average competence, but is not completely proficient (Intermediate); 5 = Child demonstrates skill completely and consistently (Proficient);
[c] LBS (Learning Behavior Scale): 0 = The positive behavior does not apply (or the negative behavior most often apply); 1 = The positive behavior sometimes apply (or the negative behavior sometimes apply); 2 = The positive behavior most often apply (or the negative behavior does not apply).
[d] TCRS (Teacher Child Rating Scale): For items evaluating positive behavior, 1 = Strongly disagree, 5 = Strongly agree; for items evaluating negative behavior, 1 = Strongly disagree, 5 = Strongly agree.

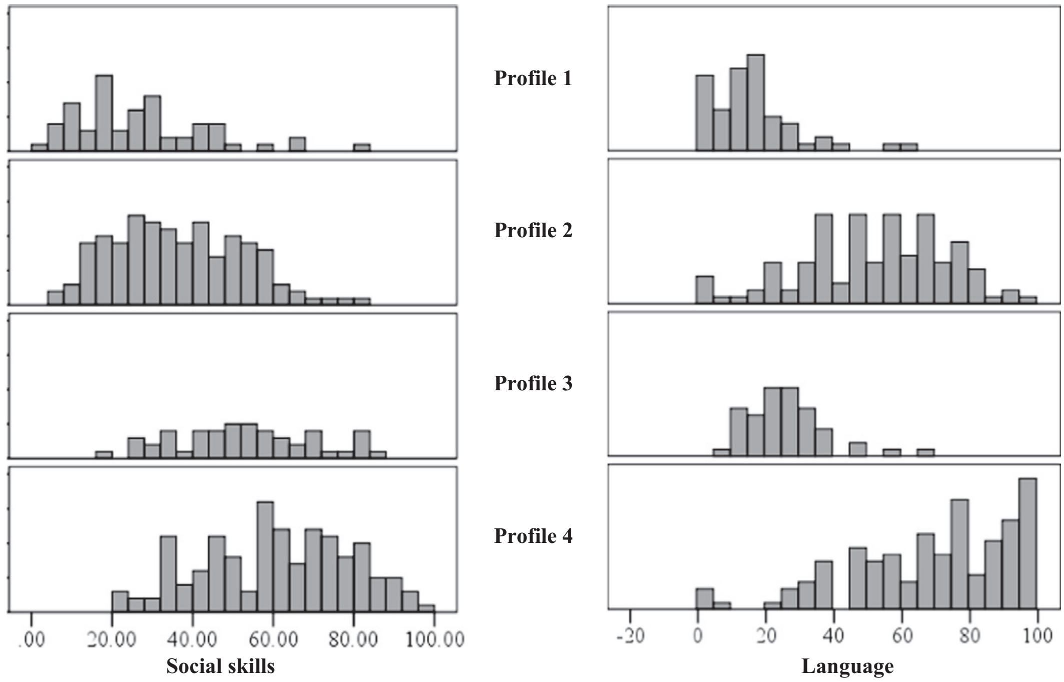


Fig. 2. Percentile ranks (compared to national norm) in overall language skills (CELF total) and social skills (SSRS Social Skills) across four school readiness profiles.

slightly positive ratings in learning-related behavior. On the other hand, their social skills ranked only at the 26th percentile. Finally, children from Profile 4 (ready) scored above average in language (60th percentile), demonstrated "intermediate" math skills, and performed well in social-emotional (68th percentile) as well as behavioral domains (as indicated by high average ratings). Considering these normative standings, the 4-profile classification of kindergarten readiness is appropriate. It is worth noting that our sample is academically disadvantaged in that the academically ready children (Profiles 3 and 4) ranked normatively 50th to 60th percentile in language. In other words, the highest-performing learners in our sample scored only at or slightly above average as compared to the national norm. This is consistent with the observation that the levels of educational achievement within Appalachia region lag behind that of the nation at large.

Table 5 provides a comparison of the four profiles of children with respect to key background characteristics, including children's age, sex, race, ELL status, IEP status, mother's highest level of education, and family annual income. Some background characteristics served to differentiate the profiles of children after correcting for accumulated type-I error rate in multiple comparison. First, sex differentiate Profile 1 (global risk) from the other three profiles, in that the global risk profile consists of a significantly higher percentage of boys (60%; $p = 0.001$)

Family income also significantly correlated with profile membership ($p = 0.004$), in that profiles with academic readiness (Profiles 3 and 4) tended to have a lower percentage of children from poor families (40%) than academically-disadvantaged profiles (Profile 1: 65%; Profile 2: 54%). Finally, maternal education was significantly different across readiness profile ($p < 0.001$). Children classified as "ready" had mothers with more years of formal education.

3.4. Predicting children's kindergarten readiness profiles

Two sets of predictor variables were examined with respect to their potential significance to children's kindergarten readiness profiles: (a) children's socio-demographic background (sex, race, age, maternal education, household income), and (b) pre-k classroom quality (emotional support, classroom organization, and instrumental support). While IEP and ELL status are potentially important predictors of the profile membership, for certain profiles, there are only a very small percentage of children with IEP or ELL status, rendering any related estimates unreliable. Therefore, IEP and ELL status were excluded from the model. Pre-k classroom quality was represented by a latent variable underlying the summary scores of the three CLASS domains. Table 5 provides

Table 5
Background characteristics and preschool experiences corresponding to four readiness profiles.

Characteristic	Profile 1: Global risk (n = 60, 16%)	Profile 2: Academic risk (n = 134, 35%)	Profile 3: Sociobehavioral risk (n = 49, 13%)	Profile 4: Ready (n = 140, 36%)
Background characteristic				
Percentage female	40%	51%	45%	66%
Percentage Caucasian	91%	95%	94%	95%
Percentage ELL	6%	2%	2%	1%
Percentage IEP	7%	3%	0%	2%
Family income (<$20,000)	65%	54%	40%	38%
Age in months	67.17 (3.69)	67.24 (3.22)	67.82 (3.64)	67.71 (3.07)
Maternal education (years)	12.13 (1.11)	12.86 (1.47)	12.87 (1.72)	13.46 (1.89)
Preschool experiences: classroom quality				
Classroom emotional support	5.25 (0.30)	5.34 (0.41)	5.30 (0.32)	5.45 (0.39)
Classroom organization	5.21 (0.44)	5.27 (0.48)	5.35 (0.45)	5.39 (0.45)
Classroom instructional support	2.54 (0.39)	2.62 (0.45)	2.61 (0.32)	2.76 (0.60)

Note. For continuous variables, the characteristics were summarized in the format of *Mean* (*SD*).

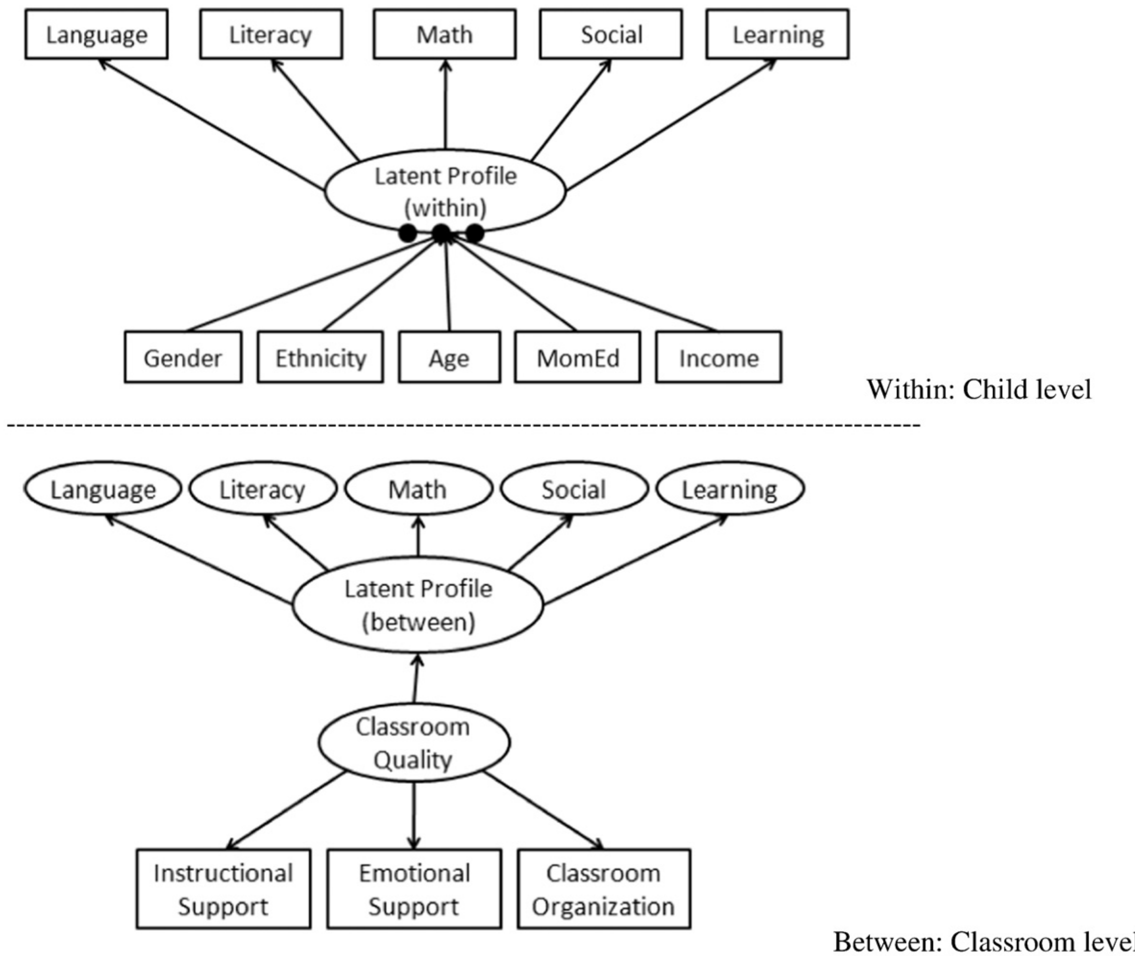


Fig. 3. Predicting membership of latent profile at the child level and at the classroom level. Note. The dark circles attached to the latent profile variable ("Latent Profile") in the child level indicate random intercepts.

descriptive information regarding the classroom quality of the four profiles of children.

Fig. 3 displays the MLPA model used for analyses to examine predictors of profile membership at the child-level ("within") and those at the pre-k classroom level ("between"). All latent variables are represented as circles, while the observed variables are represented as squares. At the child level, it is hypothesized that profile membership is predicted by child characteristics (sex, ethnicity, age, maternal education, and family income). At the classroom level, the random intercepts of latent profiles are modeled as a function of classroom quality, which is a latent variable measured by three CLASS indicators. All indicators of the latent profile and continuous covariates were standardized. Estimation of the multilevel latent profile model uses maximum likelihood estimation via the EM algorithm, with robust standard errors.

Table 6 summarizes the results of the MLPA model that includes the potential predictors. Note that since the profile membership is a categorical variable, the child-level part of the model represents a multinomial logistic regression. In particular, the regression coefficients describe how likely the changes of profile membership occur (i.e., from the reference category to the target category) with one unit of change in the predictors. For easier interpretation, the regression coefficients (in the unit of Logit) were transformed to odds ratios (exponential of the logit, i.e., Exp (B)[1]). The regression coefficients (Logit) were also converted to effect size by dividing by $\pi/\sqrt{3}$, or 1.81 (Chinn, 2000). Whereas statistical tests based on *p*-values are heavily influenced by sample sizes, effect size is only marginally affected by sample size, and thus provides an alternative perspective into the predictive power of the model. In the current study, the smallest group size was 49 (Profile 3). Therefore, we reported not only predictors with a significant *p*-value but also those with interpretable effect size (magnitude > 0.20, which is the threshold for "small" effect size) (Cohen, 1988).

3.4.1. Variables distinguishing global risk and ready profiles

Being a boy ($p = 0.001$, effect size = 0.73), lower levels of maternal education ($p < 0.001$, effect size = 0.30), and lower family income ($p = 0.004$, effect size = 0.20) are associated with increased odds of being in the global risk profile (Profile 1) rather than the ready profile (Profile 4). Specifically, the odds for girls being in the ready profile are 3.7 times as much as the odds for boys. Besides, with one *SD* increase in maternal education (1.7 years of schooling in the sample), we would expect a 70% increase in the odds of being in the ready profile; and with one *SD* increase in family annual income ($23,000 in the sample), a 50% increase in the odds is expected. After controlling for these child characteristics, pre-k classroom quality also significantly predicted profile membership ($p = 0.004$, effect size = 0.68), in that every *SD* increase in pre-k classroom quality is associated with 240% higher odds of being in the ready profile.

3.4.2. Variables distinguishing academic risk and ready profiles

Younger ages ($p = 0.012$, effect size = 0.07), lower levels of maternal education ($p = 0.043$, effect size = 0.12), and lower family income ($p = 0.012$, effect size = 0.11) are associated with increased odds of a

[1] Note that the closer the value of Exp(B) is to 1, the smaller the coefficient is. For example, Exp(B) = 0.1 is associated with a larger coefficient as compared to Exp(B) = 0.9.

Table 6
Coefficient estimates of the four-class latent profile model.

Variables		Profile 1 (global risk) vs. Profile 4 (ready) (reference)				Profile 2 (academic risk) vs. Profile 4 (ready) (reference)				Profile 3 (sociobehavioral risk) vs. Profile 4 (ready) (reference)			
		Logit	*p*	Exp (B)	Effect size (CHINN)	Logit	*p*	Exp (B)	Effect size (CHINN)	Logit	*p*	Exp (B)	Effect size (CHINN)
Level-1 Child and family characteristics	Girl	−1.32	**0.001**	0.27	**−0.73**	−0.59	0.118	0.55	**−0.33**	−1.27	**0.006**	0.28	**−0.70**
	Caucasian	−0.47	0.567	0.63	**−0.26**	−0.05	0.927	0.95	−0.03	0.92	0.748	2.51	**0.51**
	Age in months	−0.11	0.106	0.90	−0.06	−0.12	**0.012**	0.89	−0.07	0.05	0.481	1.05	0.03
	Maternal education	−0.54	<**0.001**	0.58	**−0.30**	−0.22	**0.043**	0.80	−0.12	−0.15	0.406	0.86	−0.08
	Family income	−0.37	**0.004**	0.69	**−0.20**	−0.20	**0.012**	0.82	−0.11	−0.05	0.605	0.95	−0.03
Level-2 Preschool experiences	Classroom quality (latent)	−1.24	**0.004**	0.29	**−0.68**	−0.84	**0.033**	0.43	**−0.46**	−0.37	0.548	0.69	**−0.20**
		Profile 1 (global risk) vs. Profile 3 (sociobehavioral risk) (reference)				Profile 2 (academic risk) vs. Profile 3 (sociobehavioral risk) (reference)				Profile 1 (global risk) vs. Profile 2 (academic risk) (reference)			
		Logit	*p*	Exp (B)	Effect size (CHINN)	Logit	*p*	Exp (B)	Effect size (CHINN)	Logit	*p*	Exp (B)	Effect size (CHINN)
Level-1 Child and family characteristics	Girl	−0.05	0.926	0.95	−0.03	0.68	0.182	1.97	**0.37**	−0.73	0.097	0.48	**−0.40**
	Caucasian	−1.52	0.628	0.22	**−0.84**	−1.11	0.723	0.33	**−0.61**	−0.41	0.606	0.66	**−0.23**
	Age in months	−0.16	0.074	0.85	−0.09	−0.16	**0.012**	0.85	−0.09	0.00	0.942	1.00	0.00
	Maternal education	−0.39	0.057	0.68	**−0.22**	−0.08	0.691	0.92	−0.04	−0.31	**0.016**	0.73	−0.17
	Family income	−0.32	**0.040**	0.73	−0.18	−0.15	0.133	0.86	−0.08	−0.17	0.202	0.84	−0.09
Level-2 Preschool experiences	Classroom quality (latent)	−0.87	0.075	0.42	**−0.48**	−0.47	0.441	0.63	**−0.26**	−0.39	0.294	0.68	**−0.22**

Note. *p*-Values smaller than 0.05 (indicating statistical significance) and effect size larger than 0.2 (indicating small and potentially meaningful effect size) are bolded in the table.

child being in the academic risk profile (Profile 2) rather than the ready profile. The effect size of the abovementioned demographic predictors were however very small (0.07–0.12). Pre-k classroom quality was the only predictor that showed both statistical significance ($p = 0.033$) and moderate effect size (0.46): a one *SD* increase in classroom quality is associated with doubled odds of a child being in the ready profile rather than being in the academic risk profile.

3.4.3. Variables distinguishing sociobehavioral risk and ready profiles

As compared to the boys, the odds of a girl being in the ready profile rather than the socio-behavioral risk profile (Profile 3) are 250% higher. Race, while not statistically significant, had moderate effect size (0.51), in that being Caucasian is associated with 150% higher odds of being in the socio-behavioral risk profile instead of the ready profile. Finally, pre-k classroom quality demonstrated a small effect size (0.20), indicating that it is potentially useful in predicting profile membership. Specifically, one *SD* increase in pre-k classroom quality is related with 45% higher odds of being in the ready profile rather than being in the socio-behavioral risk profile.

3.4.4. Variables distinguishing global risk and academic risk profiles

Maternal education ($p = 0.016$, effect size $= 0.17$) was the only significant predictor in distinguishing between the global risk and academic risk profiles. One *SD* increase in maternal education is related to a 30% reduction in the odds of being at-risk in all domains (i.e., global risk) rather than being in the academic risk profile. Moreover, boys (as compared to girls) have twice the odds of being in the global risk profile, while non-Caucasian children (as compared to non-Caucasians) have 50% higher odds of being in the global risk profile, although the coefficients were not significant (sex: $p = 0.10$, effect size $= 0.40$; race: $p = 0.61$, effect size $= 0.23$). Pre-k classroom quality showed a small effect ($p = 0.29$, effect size $= 0.22$). Being in higher-quality pre-k classrooms (one *SD* increase) is related with a 47% increase in the odds of having academic risk only, rather than being globally at risk.

3.4.5. Variables distinguishing global risk and sociobehavioral risk profiles

The only significant predictor that distinguishes global risk and socio-behavioral risk profiles was family income ($p = 0.04$, effect size $= 0.18$). Children coming from poorer families (one *SD* decrease in family income) have 37% higher odds of being at risk across the board rather than having just low socio-behavioral readiness. Maternal education and race, while not statistically significant, were potentially important in differentiating profile membership (effect size $= 0.22$ and 0.84 respectively), in that non-Caucasians or children with lower maternal education levels have higher odds of being globally at risk. Pre-k classroom quality demonstrated marginal significance and a moderate effect size ($p = 0.075$, effect size $= 0.48$). With one *SD* increase in classroom quality, children have 140% higher odds of being in the sociobehavioral risk profile rather than the global risk profile.

3.4.6. Variables distinguishing academic risk and sociobehavioral risk profiles

Child age was the only statistically significant predictor, but the effect size is fairly small ($p = 0.012$, effect size $= 0.09$). Sex and race were not significant predictors, but showed a moderate effect size (0.37 and 0.61). Specifically, girls have doubled odds of being in the academic risk profile rather than sociobehavioral risk profile compared to boys, and non-Caucasians children have tripled odds of being in the academic risk profile as compared to Caucasians. Pre-k classroom quality demonstrated a non-significant, small effect (0.26). Being in higher-quality pre-k classrooms (one *SD* increase) is related with a 59% increase in odds of being in the sociobehavioral risk profile, rather than the academic risk profile.

3.4.7. Summary

Considering the distinctions among the school readiness profiles as a function of the predictors examined, we can summarize as follows. First, sex is useful for differentiating profiles with socio-behavioral risk, in that boys are more likely to be in the profiles with socio-behavioral risk as compared to girls. Second, being Caucasian or coming from families with higher income is related with improved likelihood of being academically ready. Third, maternal education significantly distinguishes the most at-risk children from the rest of the sample. Fourth, pre-k classroom quality consistently demonstrates small to moderate effects on profile membership, and significantly differentiating children with kindergarten readiness from those with academic risks. As shown in Fig. 4, without accounting for any other covariates, the average classroom quality is substantially higher for children in the ready profile as compared to the rest of the sample.

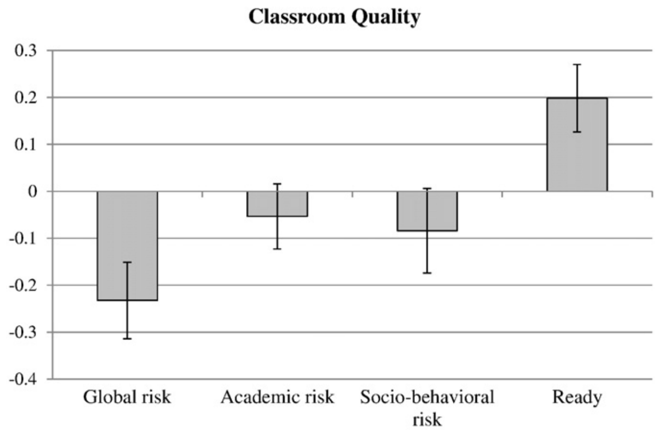


Fig. 4. Mean and standard error of preschool Classroom Quality CFA-based z-scores for four kindergarten readiness profiles. Note. CFA-based z-scores measure the level of classroom quality as compared to the average level of the sample. Standard errors are indicated by the length of standard error bar.

4. Discussion

Rural settings abound within North America, offering children a unique, multi-faceted context in which to grow and learn. With relatively high rates of poverty within rural settings, especially the Appalachian communities in which this study was conducted, it is tempting to consider rural children monolithically, viewing all as vulnerable for difficulties in academic achievement. Indeed, a large body of work finds that children residing in rural areas, tend to lag behind non-rural children in their educational achievement (see Lee & Burkam, 2002). In their analysis using nationally representative data from the Early Childhood Longitudinal Study (Birth Cohort), Miller and Votruba-Drzal (2013) showed that kindergartners in rural settings performed significantly worse than suburban and urban kindergarteners on measures of math and reading. These skill differences may reflect circumstances seen in the homes and preschool experiences of rural children compared to suburban and urban counterparts, as well as variability in children and families' access to social capital. Such findings lend support to the perspective that children's school readiness is dependent upon the context in which this readiness develops, to include home, school, and community environments (see Halle et al., 2012).

The present study presents an important contribution of this work by looking at variability in the form of profiles among entering kindergarteners in rural, Appalachian communities. Although often treated as a singular population of children, results of this study shows the value of considering rural, Appalachian children heterogeneously with respect to their school readiness. Specifically, results of latent profile analyses indicated that there was considerable heterogeneity in children's abilities in this sample, and that these skills patterned together in distinct ways to form four clear profiles. Two main findings regarding these profiles warrant discussion and are detailed below, including examination of patterns in school readiness profiles and an exploration of predictive factors of profile membership.

4.1. Patterns in school readiness profiles

The first major finding of interest is that there were complex patterns in children's school readiness profiles. Importantly, about sixteen percent of children fell into a global risk profile, performing below the mean level of performance in each developmental domain. For example, children in the global-risk profiles ranked in the 24th to 31st percentile on language, and in the 16th percentile on social skills, when compared to an age-matched nationally representative normative population. These findings are consistent with profile analysis results reported by Hair et al. (2006) on a nationally representative sample of first-time kindergarteners showing that children in at-risk profiles were strikingly low in social-emotional skills and tended to perform at least half a standard deviation below their peers on math and cognitive assessments. In fact, a series of studies conducted with children in Head Start classrooms confirm that preschoolers who experience difficulties engaging socially and connecting with learning opportunities (i.e., showing appropriate levels of interest and attention in collaborative learning tasks with teachers and peers), demonstrate low school readiness at kindergarten entry (Downer & Pianta, 2006; Fantuzzo, Bulotsky, McDermott, Mosca, & Lutz, 2003). These results underscore the need to assess multiple dimensions of school readiness including social-emotional and cognitive readiness, in conjunction with assessing progress in the language and literacy domains. These findings also suggest that effective intervention programs for promoting kindergarten readiness should include components targeting a constellation of social-emotional behaviors such as attention, self-regulation, empathy and cooperation.

Of importance is that at least a third of the children were classified as belonging to a "ready" profile, corresponding, on average, to around the 60th percentile on language and 70th percentile on social-emotional skills when compared to a national sample. It is encouraging that a subset of children in this population exhibits a level of skills that schools demand of children at school entry, supporting their transition into formal instruction. Prognostically, with well-developed skills across domains of language, literacy, and social competence, this subset of children is likely to progress well in the primary grades of schooling, based on longitudinal studies (Duncan & Murnane, 2011; McClelland et al., 2013). There is a great need to identify how it is that children experiencing significant economic disadvantage exhibit well-developed readiness skills while many other children do not. Elsewhere in this discussion, we discuss those variables that helped to differentiate children in the 'ready' profile from the three risk profiles.

When examining the nature of the profiles observed among children in this sample, some interesting patterns were apparent. First, in terms of academic skills (language, literacy, math), children within each profile showed consistent levels of skill across oral language (receptive grammar, expressive grammar, and expressive vocabulary), literacy (phonological awareness, emergent reading and writing abilities), and math skills. That is, within a profile children seemed to perform similarly across the three domains – either very low (Global Risk), slightly below or above average (Academic Risk, Sociobehavioral risk), or very high (Ready) – rather than high in some domains and low in others. This consistency within profiles across the academic domains is apparent when looking at Fig. 1.

The inter-profile consistency across academic skills findings is in line with theoretical and empirical research suggesting a strong interdependence among these skills in the years preceding formal reading and writing (Burgess & Lonigan, 1998; Dickinson, McCabe, Anastasopoulos, Peisner-Feinberg, & Poe, 2003; Storch & Whitehurst, 2002; Tabors, Roach, & Snow, 2001; Whitehurst & Lonigan, 1998). For instance, in research focused on the development of language and literacy skills Storch and Whitehurst (2002) proposed that early language and literacy represent two distinct, but interacting and mutually facilitating domains, namely, oral language skills and code-related skills. Consideration of the Global and Academic Risk profiles, our studies show that children are likely to be disadvantaged in both language and literacy skills, rather than one or the other. The findings further show that when language and literacy skills are compromised within a profile of children, math too is compromised.

Similar to the within-profile consistency observed for academic skills, the same pattern was true when looking within profiles at children's non-cognitive skills of socio-emotional skills and learning-related behaviors. Profiles with relatively higher socio-emotional skills also tended to have higher learning-related behaviors (Ready, Academic Risk profiles), and the reverse was also true. This finding contrasted with Halle et al. (2012), which identified a profile of children demonstrating relative strength in "approaches to learning" relative to socio-emotional skills, whereas children in our sample of slightly older children showed fairly commensurate abilities across learning-related behaviors (behavior regulation, attentive and cooperative behavior, and attitudes towards learning) and socio-emotional skills. It should be noted that only about 11% of children in the Halle et al. (2012) study fell into the approaches to learning strengths profile, and moreover Hair et al. (2006) found that first graders did not show enough variability in terms of learning related behaviors to even be included as a separate dimension in the latent profile analysis. Thus, it appears that motivation and persistence in learning efforts may help differentiate children's school readiness to a greater extent at earlier ages, but become more commensurate with domains of social skill as children grow older.

An interesting finding in the present study was that a 'mixed profile' best represented two of the at-risk groups when looking at patterns across the academic and non-cognitive outcomes. For instance, the Academic Risk profile, corresponding to 35% of the children, exhibited relatively low levels of language, literacy, and math skill with above average levels of social skill and learning-related behaviors. Such mixed profiles have been observed in prior studies examining how multiple aspects of school readiness coalesce in groups in children (e.g., Hair et al., 2006; Halle et al., 2012). An important implication of this finding is that intervention programs designed to promote children's readiness may need to provide additional supports for academic versus social skills depending on the children's readiness profiles.

4.2. Predictive factors of profile membership

The present study also extends prior research by investigating how socio-demographic characteristics as well as the quality of preschool experiences can serve to differentially predict children's school readiness profile membership. In general, children in the global risk profile (low readiness across all domains) were more likely to be non-Caucasian, boys, and belong to socioeconomically disadvantaged families; indeed, family income and maternal education were found to be important predictors distinguishing membership in profiles with academic readiness versus profiles with academic risks. These results are consistent with previous research showing that children from disadvantaged families (i.e., families with low parental educational attainment levels and living in poverty) demonstrate low school readiness in terms of language, cognitive abilities, social-emotional adjustment and physical health (Hair et al., 2006; Halle et al., 2012). This finding may be related to the language and literacy experiences of children reared in poverty. For example, children growing up in low-income households are less likely to experience language and literacy-rich environments (Curenton & Justice, 2008; Justice & Ezell, 2000; Roberts, Jurgens, & Burchinal, 2005; Scarborough & Dobrich, 1994). There is even some evidence that children from lower socio-economic strata show lower language processing abilities compared to their middle and upper class counterparts as early as eighteen months (Fernald, Marchman, & Weisleder, 2013).

The results of this study are particularly informative for showing the importance of even very small differences in socioeconomic status in the school readiness of young children. That is, the children in this study all were residing in poverty, permitting their participating in publicly funded preschool programs that targeted enrollment to low-income families. Nearly three out of four children in the study resided in homes with an annual household income of less than $35,000. It is somewhat astonishing, within such a constrained population, to see that variability in socioeconomic indicators such as income and maternal education is associated with differences in children's school readiness. This work shows that even within the country's poorest families, differential effects of poverty on children's development and learning are apparent.

Maternal education, even when controlling for household income, served as a relatively strong marker for differentiating children in two of the three at-risk profiles (Global Risk, Academic Risk) from the Ready profile. Put simply, having more educated mothers is associated with increased chance of children being school-ready rather than exhibiting global risk or academic risk. The static variable of maternal education likely reflects qualitatively different parent-child interaction patterns that serve to enhance children's early development in academic and non-cognitive domains. For instance, prior research shows that mothers with higher levels of educational attainment display more sensitivity during shared book reading with their children (Roberts et al., 2005), produce more topic continuing responses in conversations with their children (Hoff-Ginsberg, 1991), and engage children in higher order extra textual talk (Curenton, Craig, & Flanigan, 2008). Such processes have strong, positive effects on early language and literacy skills.

A particularly important finding regarding predictors of readiness profiles was the result showing that preschool classroom quality served as a consistently useful predictor of readiness profile membership, serving to differentiate membership across all four readiness profiles. Additionally, the effect of classroom quality on ready versus global risk profile membership was quite large (0.68), and classroom quality significantly distinguishing children in the ready profile from children in the academic risk profile. Of all the predictors studied, classroom quality is the only malleable factor examined, and thus the observed relations between classroom quality and school readiness present important directions for educational research and practice. That is, the findings suggest the significance of ongoing research designed to improve early childhood educators' practices regarding classroom quality, such as work recently conducted to identify the effects of various professional development programs on preschool teachers' classroom quality (see Early et al., 2007).

Interestingly, these results are in contrast with the inconsistent relation between classroom quality and kindergarten readiness profile membership in studies with low-income children enrolled in Head Start programs (Halle et al., 2012; McWayne et al., 2012). One possible explanation for why classroom quality emerged as a significant and consistent predictor of readiness profiles in the current study is the manner in which classroom quality was assessed. The CLASS measure provides an estimate of the quality of teacher-child interactions in a classroom which arguably have a more direct impact on children's language, literacy, and learning behaviors compared to the general classroom environment. Indeed, previous research has linked classroom instructional quality to children's concurrent and long-term academic and social outcomes (Mashburn et al., 2008) as well as to the kindergarten readiness profile membership of children with LI (Pentimonti et al., 2014).

4.3. Limitations and future research

There are three limitations worth noting. First, a constraint that limits our understanding of how specific sub-skills within the developmental domains may pattern together is that composites were created to allow for ease in comparison across multiple domains of kindergarten readiness. Had any of the domains been examined in terms of individual sub-components, it is possible that differences in relative strengths and weaknesses across these domains may have been observed. In support of this idea, there is some empirical support that within the literacy domain, alphabet knowledge and rhyme awareness develop at different rates compared to print knowledge in certain profiles of low-income preschool children (Cabell et al., 2011). Future research should employ person-centered approaches to examining how a more differentiated cluster of skills within each developmental domain pattern together within profiles of children. Second, it should be noted that latent profile analyses and other mixed modeling techniques are extremely sample and measure dependent. Thus, future work should explore whether similar patterns hold for other low-income, rural samples with similar demographic characteristics. Finally, prediction of children's readiness profiles examined two types of capital important to development: financial capital (household income) and human capital (caregiver educational achievement); however, social capital within the rural context represents a third type of capital that helps to explain successful and unsuccessful development among rural children, (Coleman, 1988; Dyk & Wilson, 1999). The present study did not use methods to examine the role of social capital in understanding children's school-readiness profiles, although this is an important direction for future work.

Overall, the present study adds to the extant literature by utilizing a person-centered approach to examine how multiple child-level, family-level, and classroom-level factors pattern together to influence rural Appalachian children's academic and social development. As has been documented in other low-income samples (Neuman, 1996; Payne, Whitehurst, & Angell, 1994; Purcell-Gates, 1996), children in the current study exhibited considerable heterogeneity in their competencies across five different developmental domains. About 30% of children fell into sociobehavioral risk profiles, and about 50% fell into academic risk profiles. Maternal education and family income helped differentiate membership in the global and academic risk profiles, and classroom quality was useful in distinguishing the "ready" profile from the other profiles. Overall, this research helps identify preschool programs as a potential protective factor that helps predict positive school readiness. Our findings suggest that improving access to high quality preschool programs may be a fruitful avenue for preparing children in these communities for the rigors of formal schooling. Also, teacher training targeted at improving the instructional climate of classrooms may be a useful investment for supporting children's readiness and ongoing development in this rural, Appalachian community.

Acknowledgment

The authors are grateful to the numerous families and children who participated in the original research utilized in this study. The original research was supported by R305A080459 from the U.S. Department of Education, Institute of Education Sciences, to Laura M. Justice. Correspondence may be sent to Laura Justice, Crane Center for Early Childhood Research and Policy, Ohio State University, 1945 North High St, Columbus OH, 43210 (justice.57@osu.edu).

References

Burgess, S. R., & Lonigan, C. J. (1998). Bidirectional relations of phonological sensitivity and prereading abilities: Evidence from a preschool sample. *Journal of Experimental Child Psychology*, *70*(2), 117–141.

Byun, S. Y., Meece, J. L., & Irvin, M. J. (2012a). Rural-nonrural disparities in postsecondary educational attainment revisited. *American Educational Research Journal*, *49*(3), 412–437.

Byun, S. -Y., Meece, J. L., Irvin, M. J., & Hutchins, B. C. (2012b). The role of social capital in educational aspirations of rural youth. *Rural Sociology*, *77*(3), 355–379.

Cabell, S. Q., Justice, L. M., Konold, T. R., & McGinty, A. S. (2011). Profiles of emergent literacy skills among preschool children who are at risk for academic difficulties. *Early Child Research Quarterly*, *26*(1), 1–14.

Cabell, S. Q., Justice, L. M., Logan, J. A., & Konold, T. R. (2013). Emergent literacy profiles among prekindergarten children from low-SES backgrounds: Longitudinal considerations. *Early Childhood Research Quarterly*, *28*(3), 608–620.

Celeux, G., & Soromenho, G. (1996). An entropy criterion for assessing the number of clusters in a mixture model. *Journal of Classification*, *13*(2), 195–212. http://dx.doi.org/10.1007/BF01246098.

Chinn, S. (2000). A simple method for converting an odds ratio to effect size for use in meta-analysis. *Statistics in Medicine*, *19*, 3127–3131.

Clogg, C. C. (1995). Latent class models. In B. Arminger, C. C. Clogg, & M. E. Sobel (Eds.), *Handbook of statistical modeling for the social and behavioral sciences* (pp. 311–359). San Francisco, CA: Jossey-Bass.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*. Hillsdale, N.J: L. Erlbaum Associates.

Coleman, J. S. (1988). Social capital in the creation of human capital. *The American Journal of Sociology*, S95–S120.

Curenton, S. M., & Justice, L. M. (2008). Children's preliteracy skills: Influence of mothers' education and beliefs about shared-reading interactions. *Early Education and Development*, *19*(2), 261–283.

Curenton, S. M., Craig, M. J., & Flanigan, N. (2008). Use of decontextualized talk across story contexts: How oral storytelling and emergent reading can scaffold children's development. *Early Education and Development*, *19*(1), 161–187.

De Marco, A., Vernon-Feagans, L., & Investigators, F. L. P. K. (2015). Child care subsidy use and child care quality in low-wealth, rural communities. *Journal of Family and Economic Issues*, *36*(3), 383–395.

Dickinson, D. K., McCabe, A., Anastasopoulos, L., Peisner-Feinberg, E. S., & Poe, M. D. (2003). The comprehensive language approach to early literacy: The interrelationships among vocabulary, phonological sensitivity, and print knowledge among preschool-aged children. *Journal of Education & Psychology*, *95*(3), 465–481.

Downer, J. T., & Pianta, R. C. (2006). Academic and cognitive functioning in first grade: Associations with earlier home and child care predictors and with concurrent home and classroom experiences. *School Psychology Review*, *35*(1), 11–30.

Duncan, G. J., & Murnane, R. J. (2011). *Whither opportunity? Rising inequality, schools, and children's life chances: Rising inequality, schools, and children's life chances*. Russell Sage Foundation.

Duncan, G. J., Dowsett, C. J., Claessens, A., Magnuson, K., Huston, A. C., Klebanov, P., ... Japel, C. (2007). School readiness and later achievement. *Developmental Psychology*, *43*(6), 1428–1446.

Dyk, P. H., & Wilson, S. M. (1999). Family-based social capital considerations as predictors of attainments among Appalachian youth. *Sociological Inquiry*, *69*(3), 477–503.

Enders, C. K. (2010). *Applied missing data analysis*. New York, NY: Guilford Publications.

Early, D. M., Maxwell, K., Burchinal, M., Alva, S., Bender, R. H., Bryant, D., ... Zill, N. (2007). Teachers' education, classroom quality, and young children's academic skills: results from seven studies of preschool programs. *Child development*, *78*(2), 558–580.

Fantuzzo, J., Bulotsky, R., McDermott, P., Mosca, S., & Lutz, M. N. (2003). A multivariate analysis of emotional and behavioral adjustment and preschool educational outcomes. *School Psychology Review*, *32*(2), 185–203.

Fernald, A., Marchman, V. A., & Weisleder, A. (2013). SES differences in language processing skill and vocabulary are evident at 18 months. *Developmental Science*, *16*(2), 234–248.

Graham, J. W. (2012). *Missing data: Analysis and design*. New York, NY: Springer Science & Business Media.

Gresham, F. M., & Elliott, S. N. (1990). *Social skills rating system*. Circle Pines, MN: American Guidance Service.

Guarino, C. M., Santibanez, L., & Daley, G. A. (2006). Teacher recruitment and retention: A review of the recent empirical literature. *Review of Educational Research*, *76*(2), 173–208.

Hair, E., Halle, T., Terry-Humen, E., Lavelle, B., & Calkins, J. (2006). Children's school readiness in the ECLS-K: Predictions to academic, health, and social outcomes in first grade. *Early Child Research Quarterly*, *21*(4), 431–454.

Hall, S. A., Kaufman, J. S., & Ricketts, T. C. (2006). Defining urban and rural areas in US epidemiologic studies. *Journal of Urban Health*, *83*(2), 162–175.

Halle, T. G., Hair, E. C., Wandner, L. D., & Chien, N. C. (2012). Profiles of school readiness among four-year-old head start children. *Early Child Research Quarterly*, *27*(4), 613–626.

Hightower, A. D., Work, W. C., Cowen, E. L., Lotyczewski, B. D., Spinell, A. P., Guare, J. C., & Rohrbeck, C. A. (1986). The teacher-child rating scale: A brief objective measure of elementary children's school problem behaviors and competencies. *School Psychology Review*, *15*(3), 393–409.

Hoff-Ginsberg, E. (1991). Mother-child conversation in different social classes and communicative settings. *Child Development*, *62*(4), 782–796.

Holliday, M. R., Cimetta, A., Cutshaw, C. A., Yaden, D., & Marx, R. W. (2014). Protective factors for school readiness among children in poverty. *Journal of Education for Students Placed at Risk (JESPAR)*, *19*(3–4), 125–147.

Invernizzi, M. A. (2010). *PALS K technical reference*. Virginia State Department of Education.

Justice, L. M., & Ezell, H. K. (2000). Enhancing children's print and word awareness through home-based parent intervention. *American Journal of Speech-Language Pathology*, *9*(3), 257–269.

Justice, L. M., Bowles, R. P., Pence Turnbull, K. L., & Skibbe, L. E. (2009). School readiness among children with varying histories of language difficulties. *Developmental Psychology*, *45*(2), 460–476.

Keys, T. D., Farkas, G., Burchinal, M. R., Duncan, G. J., Vandell, D. L., Li, W., ... Howes, C. (2013). Preschool center quality and school readiness: Quality effects and variation by demographic and child characteristics. *Child Development*, *84*(4), 1171–1190.

Lazarsfeld, P. F., Henry, N. W., & Anderson, T. W. (1968). *Latent structure analysis*. Boston, MA: Houghton Mifflin.

Lee, V. E., & Burkam, D. T. (2002). *Inequality at the starting gate: Social background differences in achievement as children begin school*. ERIC.

Little, R. J., & Rubin, D. B. (1987). *Statistical analysis with missing data*. New York, NY: John Wiley & Sons.

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

Mashburn, A. J., Pianta, R. C., Fau-Hamre, B. K., Hamre, B. K., Fau-Downer, J. T., Downer, J. T., Fau-Barbarin, O. A., Barbarin, O. A., Fau-Bryant, D., Bryant, D., Fau-Burchinal, M., ... Howes, C. (2008). Measures of classroom quality in prekindergarten and children's development of academic, language, and social skills. *Electronics*, 1467–8624.

McClelland, M. M., Acock, A. C., Piccinin, A., Rhea, S. A., & Stallings, M. C. (2013). Relations between preschool attention span-persistence and age 25 educational outcomes. *Early Child Research Quarterly*, *28*(2), 314–324.

McDermott, P. A., Green, L., Francis, J., & Stott, D. (2000). *Preschool learning behaviors scale*. Philadelphia, PA: Edumetric and Clinical Science.

McLachlan, G., & Peel, D. (2004). *Finite mixture models*. New York, NY: John Wiley & Sons.

McWayne, C. M., Cheung, K., Wright, L. E. G., & Hahs-Vaughn, D. L. (2012). Patterns of school readiness among head start children: Meaningful within-group variability during the transition to kindergarten. *Journal of Education & Psychology*, *104*(3), 862–878.

Miller, P., & Votruba-Drzal, E. (2013). Early academic skills and childhood experiences across the urban–rural continuum. *Early Child Research Quarterly*, *28*(2), 234–248.

Muthén, L. K., & Muthén, B. O. (2006). *Mplus (version 4.1)*. Los Angeles, CA: Author.

National Center for Education Statistics (1994). *School and staffing survey 1993–1994; Principal's survey*. Washington, D.C.: National Education Goals Panel.

Neuman, S. B. (1996). Children engaging in storybook reading: The influence of access to print resources, opportunity and parental interaction. *Early Child Research Quarterly*, *11*, 495–514.

O'Hare, W. P., Mather, M., Dupuis, G., Land, K. C., Lamb, V. L., & Fu, Q. (2013). Analyzing differences in child well-being among US states. *Child Indicators Research*, *6*(2), 401–431.

Payne, A. C., Whitehurst, G. J., & Angell, A. L. (1994). The role of the home literacy environment in the development of language ability in preschool children from low-income families. *Early Child Research Quarterly*, *9*, 427–440.

Pentimonti, J. M., Justice, L. M., & Kaderavek, J. N. (2014). School-readiness profiles of children with language impairment: Linkages to home and classroom experiences. *International Journal of Language & Communication Disorders*, *49*(5), 567–583.

Pianta, R. C., La Paro, K. M., & Hamre, B. K. (2008). *Classroom assessment scoring system*. Baltimore: Paul H. Brookes.

Pollard, K., & Jacobsen, L. A. (2012). *The Appalachian region: A data overview from the 2006–2010 American community survey: Chartbook*. Washington, DC: Appalachian Regional Commission.

Purcell-Gates, V. (1996). Stories, coupons, and the TV guide: Relationships between home literacy experiences and emergent literacy knowledge. *Reading Research Quarterly*, *31*, 406–428.

R Core Team. (2014). R: A language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing; 2012. Open access available at: http://cran.r-project.org.

Roberts, J., Jurgens, J., & Burchinal, M. (2005). The role of home literacy practices in preschool children's language and emergent literacy skills. *Journal of Speech, Language, and Hearing Research*, *48*(2), 345–359. http://dx.doi.org/10.1044/1092-4388(2005/024).

Scarborough, H. S., & Dobrich, W. (1994). On the efficacy of reading to preschoolers. *Developmental Review*, *14*(3), 245–302. http://dx.doi.org/10.1006/drev.1994.1010.

Schafer, J. L., & Olsen, M. K. (1998). Multiple imputation for multivariate missing-data problems: A data analyst's perspective. *Multivariate Behavioral Research*, *33*(4), 545–571.

Smith, K. (2006). *Rural families choose home-based child care for their preschool-aged children*. The Carsey School of Public Policy at the Scholars' Repository, 9 Retrieved from http://scholars.unh.edu/carsey/9/

Storch, S. A., & Whitehurst, G. J. (2002). Oral language and code-related precursors to reading: Evidence from a longitudinal structural model. *Developmental Psychology*, *38*(6), 934–947. http://dx.doi.org/10.1037/0012-1649.38.6.934.

Stormont, M., Herman, K. C., Reinke, W. M., King, K. R., & Owens, S. (2015). The kindergarten academic and behavior readiness screener: The utility of single-item teacher ratings of kindergarten readiness. *School Psychology Quarterly*, *30*(2), 212–228.

Strange, M., Johnson, J., Showalter, D., & Klein, R. (2012). *Why rural matters 2011–12: The condition of rural education in the 50 states. A report of the rural school and community trust policy program*. Rural School and Community Trust.

Tabors, P. O., Roach, K. A., & Snow, C. E. (2001). Home language and literacy environment: Final results. In D. K. Dickinson, & P. O. Tabors (Eds.), *Beginning literacy with language: Young children learning at home and school* (pp. 111–138). Baltimore, MD: Paul H. Brookes.

Tichnor-Wagner, A., Garwood, J. D., Bratsch-Hines, M., & Vernon-Feagans, L. (2016). Home literacy environments and foundational literacy skills for struggling and nonstruggling readers in rural early elementary schools. *Learning Disabilities Research and Practice*, *31*(1), 6–21.

Vermunt, J. K. (2003). Multilevel latent class models. In R. M. Stolzenberg (Ed.), *Sociological methodology. Vol. 33*. (pp. 213–239). Boston, MA: Blackwell Publishing.

Vernon-Feagans, L., & Cox, M. (2013). The family life project: An epidemiological and developmental study of young children living in poor rural communities. *Monographs of the Society for Research in Child Development*, *78*(5), 1–150 (vii).

Vernon-Feagans, L., Burchinal, M., & Mokrova, I. (2015). *Diverging destinies in rural America: Families in an era of increasing inequality*. Springer, 35–49.

Vuong, Q. H. (1989). Likelihood ratio tests for model selection and non-nested hypotheses. *Econometrica*, *57*(2), 307.

Whitehurst, G. J., & Lonigan, C. J. (1998). Child development and emergent literacy. *Child Development*, *69*(3), 848–872. http://dx.doi.org/10.1111/j.1467-8624.1998.tb06247.x.

Wiig, E. H., Secord, W. A., & Semel, E. (2004). *Clinical evaluation of language fundamentals preschool* (2nd ed.). San Antonio, TX: Harcourt Assessment.

Winsler, A., Tran, H., Hartman, S. C., Madigan, A. L., Manfra, L., & Bleiker, C. (2008). School readiness gains made by ethnically diverse children in poverty attending center-based childcare and public school pre-kindergarten programs. *Early Child Research Quarterly*, *23*(3), 314–329.

Woodcock, R. W., McGrew, K. S., & Mather, N. (2001). *Woodcock-Johnson III Test of Cognitive Abilities*. Itasca, IL: Riverside Publishing.

Zhai, F., Brooks-Gunn, J., & Waldfogel, J. (2011). Head start and urban children's school readiness: A birth cohort study in 18 cities. *Developmental Psychology*, *47*(1), 134.

Zhao, J., & Schafer, J. L. (2013). *Pan: Multiple imputation for multivariate panel or clustered data. R package version 0.9*.