11-1-2019

School Readiness Profiles and Growth in Academic Achievement

Qianqian Pan
University of Kansas, panqianqian2013@gmail.com

Kim T. Trang
University of Kansas

Hailey R. Love
University of Nevada, Las Vegas, hailey.love@unlv.edu

Jonathan Templin
University of Iowa

Repository Citation

Pan, Q., Trang, K. T., Love, H. R., Templin, J. (2019). School Readiness Profiles and Growth in Academic Achievement. *Frontiers in Education, 4* 1-17.
http://dx.doi.org/10.3389/feduc.2019.00127

frontiers in Education

ORIGINAL RESEARCH
published: 01 November 2019
doi: 10.3389/feduc.2019.00127

School Readiness Profiles and Growth in Academic Achievement

Qianqian Pan[1*], Kim T. Trang[1], Hailey R. Love[2] and Jonathan Templin[3]

[1] Department of Educational Psychology, University of Kansas, Lawrence, Kansas, KS, United States, [2] Department of Early Childhood, Multilingual, and Special Education, University of Nevada, Las Vegas, Las Vegas, NV, United States, [3] Department of Psychological and Quantitative Foundations, University of Iowa, Iowa City, IA, United States

The purpose of this research was to identify the presence of different school readiness profiles and to determine whether profiles could differentially predict academic growth. The Early Childhood Longitudinal Study: 2010-11 (ECLS-K: 2011) public data set was used, and participants were 14,954 first-time kindergarteners. The age of entering kindergarten ranged from 44.81 to 87.98 months with a mean of 76.13 months. In Study 1, a six-dimensional construct of school readiness was used: health, self-regulation, social and emotional development, language development, cognitive development, and approaches to learning. Results revealed 41 profiles with the top six school readiness profiles covering 85% of the sample: (1) Positive Development (28%); (2) Comprehensive At-Risk (24%); (3) Personal and Social Strengths (20%); (4) Cognitive and Language Strengths (5%), (5) Health Strength (5%); and (6) Cognitive, Personal and Social Strengths (3%). Study 2 examined whether school readiness profiles could predict children's reading and math achievement growth using growth curve models. Results showed that different school readiness profile membership had unique academic growth patterns and could predict academic growth above and beyond child and family background variables. Moreover, children with the Positive Development profile had higher academic achievement over time. Children with the Personal and Social Strengths profile had the largest growth rates. In sum, findings support the inclusion of self-regulation as another dimension of school readiness and the important role of personal and social skills in the development of reading and math achievement.

Keywords: school readiness, ECLS-K:2011, log-linear cognitive diagnostic models, growth curve models, academic achievement

OPEN ACCESS

Edited by:
Raquel Gilar,
University of Alicante, Spain

Reviewed by:
Angeliki Mouzaki,
University of Crete, Greece
Yong Luo,
Educational Testing Service,
United States

****Correspondence:***
Qianqian Pan
panqianqian2013@gmail.com

Specialty section:
This article was submitted to Educational Psychology, a section of the journal Frontiers in Education

Received: *22 August 2019*
Accepted: *16 October 2019*
Published: *01 November 2019*

Citation:
Pan Q, Trang KT, Love HR and Templin J (2019) School Readiness Profiles and Growth in Academic Achievement. Front. Educ. 4:127. doi: 10.3389/feduc.2019.00127

INTRODUCTION

School readiness skills, including cognitive, social, attentional, and self-regulation skills, lay the foundation for future school success. Considerable research has demonstrated a link between kindergarten cognitive skills and later elementary school achievement (La Paro and Pianta, 2000; Bodovski and Farkas, 2007; Duncan et al., 2007; Claessens et al., 2009). Children entering kindergarten with stronger math and literacy skills tend to have higher math and reading achievement in later grades. There is also evidence that social skills, attention skills, and self-regulation skills are important predictors of academic and behavioral outcomes (La Paro and Pianta, 2000; Trentacosta and Izard, 2007; Claessens et al., 2009; Morgan et al., 2016). Furthermore, prosocial skills predict adult outcomes, such as high school graduation, college degree, and employment (Jones et al., 2015). Presumably, children who are able to regulate their emotions and attention have an easier time attending to academic tasks, which then promotes academic competence. In sum, there is a large body of research evidence demonstrating the importance of both cognitive and personal and social school readiness skills for future school and adult outcomes.

However, not all children enter kindergarten with the necessary school readiness skills. Using data from the Early Childhood Longitudinal Study (ECLS), Kindergarten Class of 1998–99, Wertheimer et al. (2003) estimated that 56% of the nation's young children, or 2.2 million, showed challenges in at least one key area of development before entering kindergarten. More recent data from the ECLS-K:2010-11 illustrated differences in school readiness skills across racial/ethnic groups (Mulligan et al., 2012). Accordingly, many suggest that improving children's school readiness through early childhood education (ECE) is key to reducing the racial achievement differences seen later in education (Heckman, 2006; Duncan et al., 2007). Specifically, publicly-funded early education programs have shown benefits for children who come from socioeconomically-disadvantaged backgrounds and minority children, and these programs help reduce the achievement gap over time (Lee, 2002; Magnuson and Waldfogel, 2016). Moreover, studies have shown that participating in high-quality preschool programs and early interventions can improve all children's health and development (Anderson et al., 2003; Puma et al., 2010).

Yet, while a large body of research supports investment in ECE, there is great disagreement and ambiguity around the underlying theory and conceptualization of school readiness goals within ECE (Snow, 2006; Pretti-Frontczak, 2014). The concept of school readiness has specifically been challenged as often being too narrowly focused on certain literacy and math skills. It has been argued that this narrow focus has led to policies and practices that actually undermine ECE (Pretti-Frontczak, 2014) and have deleterious effects on children with possible special needs (Carlton and Winsler, 1999). These critiques beg the question, what do we mean when we say children need to be ready for school? What skills, knowledge, and abilities are involved in school readiness? To inform interventions or programs that target school readiness skills, we need to better understand the construct of school readiness and its influence on children's later achievement.

SCHOOL READINESS THEORY AND RESEARCH

School Readiness Theoretical Framework

School readiness can be defined generally as the skills, knowledge, and abilities that children need to succeed in formal schooling, which, for most, begins at kindergarten (Snow, 2006). In the last 40 years, research on school readiness has produced many different theories and perspectives (Snow, 2006; Winter and Kelley, 2008). From a maturational perspective, readiness to learn depends on the child's skills and cognitive maturity level (Kagan, 1992). However, more recent perspectives have shifted to a holistic, multidimensional definition of school readiness, emphasizing the importance of personal and social skills and the roles of families and communities (e.g., Diamond, 2010). That is, children need to be ready for school, but schools and communities also need to be ready to support children's future success across multiple developmental domains (Elizabeth Graue, 1992; Pretti-Frontczak, 2014).

Although there is no consensus on an operational definition for school readiness, most researchers rely on the five domains developed by the National Education Goals Panel: health and physical development; emotional well-being and social competence; approaches to learning; communicative skills; and cognition and general knowledge (National Education Goals Panel, 1991). Recent frameworks continue to rely on these general domains and have expanded on them (e.g., U.S. Department of Health Human Services, 2015; Altun, 2018). *Health and physical development* refers to children's health and motor development that support engagement and learning in their environments. *Emotional well-being and social competence* refers to the development of key social skills and attitudes that help build and maintain positive relationships with others. *Approaches to learning* refers to children's attitudes, habits, and learning styles that characterize how they learn. *Communicative skills* refers to language and literacy skills that promote effective communication with others. Lastly, *cognition and general knowledge* refers to ways of thinking and acquiring knowledge that promotes learning. Each domain is a unique aspect of school readiness that needs to be measured and investigated (National Education Goals Panel, 1991).

In recent years, researchers have emphasized the importance of self-regulation in conceptualizing school readiness (Blair, 2002; Blair and Raver, 2015). Self-regulation is used broadly to describe aspects of emotion and behavior regulation that relies in part on development in the prefrontal cortex (Blair and Raver, 2015). In some frameworks, self-regulation is combined with approaches to learning as a general domain (e.g., the Early Childhood Learning and Knowledge Center). However, we argue that the former set of skills can be distinguished from the latter. Positive learning attitudes and beliefs (e.g., growth-mindset, motivation, creativity) are important predictors of child outcomes (Wigfield and Eccles, 2000; Grant and Dweck, 2003). But, these learning attitudes and beliefs are conceptually different from the ability to self-regulate one's emotions, behaviors, and attention in a way that is responsive to specific tasks and demands, which primarily connotes effortful control of cognition and behavior (Liew, 2012). Children can have positive learning orientations but still lack the ability to follow through, inhibit impulses, and focus on achieving goals. In this study, we were interested in investigating the unique contribution of self-regulation processes to children's school readiness ability, and how self-regulation interacts with other domains of school readiness.

Self-regulation offers an important addition to the conceptualization of school readiness because it addresses children's ability to attend to information, use it appropriately, and inhibit behavior that interferes with learning. However, like the broader concept of school readiness, theories and perspectives on self-regulation have focused on various priorities. Within the fields of early childhood and elementary education, three domains of self-regulation are most consistently studied: attentional flexibility, inhibitory control, and working memory (Blair, 2002; McClelland and Cameron, 2011; Lerner, 2015). *Attentional flexibility* is the ability to focus and shift attention. *Working memory* is the ability to work on and actively process information. *Inhibitory control* is the ability to inhibit prepotent responses and activate adaptive responses. Indeed, numerous studies have demonstrated positive social and academic outcomes for children who possess these abilities (e.g., Eiesnberg et al., 1997; Gilliom et al., 2002; Trentacosta and Izard, 2007; Welsh et al., 2010; Curby et al., 2015). For example, Trentacosta and Izard (2007) found that emotion regulation abilities were positively correlated with academic competence. In addition, Curby et al. (2015) found that preschooler's emotion regulation predicted their preliteracy skills. Children who can regulate their emotions may be more able to pay attention to academic tasks and therefore perform better academically. Thus, significant work suggests that school readiness outcomes are dependent on self-regulation abilities.

School Readiness and Academic Trajectories

Understanding the skills children need to support their early learning is important because children's academic trajectories are associated with the skills they have upon kindergarten entry. Previous studies found both main and interaction effects for school readiness skills on children's academic achievement in later grades. A large body of research demonstrates that kindergarten entry cognitive skills (e.g., literacy and mathematics skills) were positively related to later academic performance (McCoach et al., 2006; Duncan et al., 2007; Li-Grining et al., 2010). In contrast, findings on the predictive contributions of children's personal and social skills have been mixed. Some studies suggested no effects of social skills on standardized achievement outcomes (Duncan et al., 2007; Claessens et al., 2009; Romano et al., 2010). However, other studies provided evidence that self-control, approaches to learning (e.g., task persistence, attention), and executive functions contributed to standardized math and reading scores (Bodovski and Farkas, 2007; DiPerna et al., 2007; Li-Grining et al., 2010). Children's approaches to learning (when conceptualized as including self-control, persistence, and attentiveness) were also associated with linear increases in math and reading from kindergarten to fifth grade (Li-Grining et al., 2010).

Furthermore, beyond the main effects of personal and social skills on later academic achievement, there is evidence that personal and social skills interact with cognitive skills to predict later achievement. For example, Cooper et al. (2014) found that among children with low reading skills in kindergarten, those with higher social skills were more likely to have higher reading scores in fifth grade compared to those with lower social skills. Studies that classified children into different school readiness profiles based on the possession of certain cognitive and social skills found that school readiness skills interacted in distinct patterns to predict divergent achievement outcomes (Hair et al., 2006; Halle et al., 2012). Although they used different statistical methods, both Halle et al. (2012) and Hair et al. (2006) found that preschool children can be classified into four distinct profiles based on their strengths and challenges in the social-emotional, cognitive, approaches to learning, and health domains (e.g., profiles included cognitive strength and socio-emotional risk). Importantly, Hair et al. (2006) found that the profiles differentially predicted academic and social outcomes in early elementary school. Children who were classified as having a comprehensive profile (above average for health, socioemotional, language, cognition) were more likely to be rated as having better approaches to learning, self-control, and general health in first grade; they also scored better on standardized math and reading tests. Meanwhile, children in health risk and socio-emotional risk profiles scored the lowest on various outcomes measures (Hair et al., 2006). Overall, previous research provides evidence for school readiness as a multi-dimensional domain and indicates that school readiness profiles can differentially predict child outcomes. In this study, we extend the previous work to include self-regulation as a separate domain of school readiness skills to investigate its unique contributions within school readiness profiles.

Statistical Methods in School Readiness Studies

Traditionally, researchers used linear regression to demonstrate the main effects of school readiness skills on later academic performance (e.g., Duncan et al., 2007). However, as more school readiness skills are added to models, there could be interaction effects between school readiness skills (e.g., a model with four school readiness skills could result in 6 two-way, 3 three-way, and 1 four-way interaction effects) that would be difficult to interpret using linear regression. Therefore, recently, researchers started applying Latent Class Analysis (LCA; e.g., McCutcheon, 1987) in school readiness studies. LCA allows children to be classified into different school readiness profiles, where each profile illustrates a unique pattern of school readiness skills, accounting for the possible interaction effects among these skills. For example, Halle et al. (2012) used LCA to classify children into four profiles: cognitive strength, cognitive risk, approaches to learning strength, and socio-emotional risk. Similarly, Hair et al. (2006) identified four different school readiness profiles (i.e., comprehensive positive development, social/emotional and health strengths, social/emotional risk, and health risk) in the ECKS-K:1998 sample based on a five-dimensional construct of school readiness (physical well-being and motor development, social and emotional development, language development, cognitive and general knowledge, and approaches to learning). Results showed that children with comprehensive positive profiles (strengths in cognitive, health, social/emotional development) had better first-grade math and reading scores compared to those who were classified as at risk in any one area via OLS regression.

However, there is a need for research that uses more advanced statistical methods to identify both the main effects of school readiness skills and interactions between skills. For example, when using LCA to classify children into school readiness profiles, researchers applied several models with different numbers of profiles and compared the model fit indices [e.g., Bayesian information criteria (BIC), likelihood ratio test (LMR-LRT), and bootstrap likelihood ratio test (BLRT)], and the model with the best model fit statistics would be selected as the final model. Then, researchers named profiles by reviewing the patterns of profiles. Therefore, results depended heavily on model fit statistics and samples, which might be subjective and arbitrary. The use of such methods could pose challenges in deciding the number of school readiness profiles, labeling classes, and making inference across studies (Abenavoli et al., 2017). Also, the OLS regression used in previous studies cannot demonstrate the relationships between the school readiness profiles and children's academic trajectories, in terms of the initial status and growth rates (e.g., Hair et al., 2006).

CURRENT STUDY

Building from previous research, the present study aimed to extend current knowledge by (1) conceptualizing school readiness as a multi-dimensional construct that includes self-regulation skills in addition to the five previous dimensions that have been used (health, socioemotional development, language development, cognitive development, and approaches to learning), (2) applying Diagnostic Classification Models (DCMs; Rupp et al., 2010) to classify children into different school readiness profiles, and (3) adopting growth curve models (GCMs; e.g., Hoffman, 2015) to investigate the association between school readiness profile memberships and academic growth, above and beyond background variables.

This research was divided into two studies. Study 1 investigated the school readiness profiles of kindergarteners in the ECLS-K:2011 sample by adopting a six-dimensional construct of school readiness via DCMs. Study 2 investigated how school readiness profiles were associated with children's later academic achievement growth by fitting GCMs.

Study 1

Study 1 addressed the following research question: Using six dimensions of school readiness, what school readiness profiles exist among first-time kindergarteners in the ECLS-K:2011 cohort?

Method

Dataset

The current study used data from the Early Childhood Longitudinal Study-Kindergarten Cohort of 2010-2011 (ECLS-K:2011). The ECLS-K:2011 used a multistage probability sample design to select a nationally representative sample of U.S. children who attended kindergarten during the 2010-2011 school year. A total of six waves of data were released to the public (K-fall, K-spring, Grade 1-fall, Grade 1-spring, Grade 2-fall, and Grade 2-spring) when the current study was conducted. The ECLS-K:2011 provides nationally representative data on children's development, learning and performance at school. Background variables included family, school, and community characteristics, which provided opportunities to investigate the relations among these variables and children's development. More details about this database can be found in the user's manual of ECLS-K:2011 (Tourangeau et al., 2009).

Sample

In Study 1, only the first wave, fall of 2010 kindergarten data was used. The participants were limited to first-time kindergarteners to focus on children's status upon entering formal schooling, reflecting the current investigations' focus on school readiness. Also, children who were one of a set of twins were excluded to remove the potential of dependency within families. A total of 14,954 first-time kindergarteners were included in the data analysis (7,330 females, 7,591 males, and 33 with gender missing). The age of kindergarten entry ranged from 44.81 months to 87.98 months with a mean of 76.13 months. The racial/ethnic distribution of the sample was White (49.0%), African-American (12.8%), Asian (7.5%), Hispanic (24.5%), Others and Multi-Racial (6.1%) and missing (0.2%).

Measures

Table 1 shows the six dimensions of school readiness. The construct, variables, and the re-coding rules designed for the current study was based on previous research (i.e., Hair et al., 2006) and the authors' conceptual knowledge. See Appendix A in **Supplementary Material** for more details on the variables used.

Health. There were four indicators of health. Parents reported on the child's overall health using a scale from 1 to 4. Healthy weight was determined using guidelines from the Center for Disease Control and Prevention (e.g., 5th percentile to less than the 85th percentile) (National Center for Health Statistics, 2000). Low birth weight was defined as <5.5 pounds at birth. Premature was defined as more than two weeks before the due date.

Self-regulation. There were five indicators of self-regulation, which were five scale scores including cognitive flexibility scores measured by Dimensional Change Card Sort tasks (Zelazo, 2006), working memory scores measured by Numbers Reversed tasks (Woodcock et al., 2001), attentional focus scores and inhibitory control scores measured by Children's Behavior Questionnaire (Putnam and Rothbart, 2006), and self-control scores measured by Social Skills Rating System (Gresham and Elliott, 1990). Higher scores indicated higher ability in this area.

Social and emotional development. There were four indicators of social and emotional development. The scales were teacher report and were adapted from the Social Skills Rating Systems, measured on a scale from 1 (Never) to 4 (Very Often). Interpersonal skills measured children's ability to relate and interact with others. Externalizing problem behavior measured children's acting out behaviors. Internalizing problem behavior measured the presence of anxiety, loneliness, low self-esteem, and sadness. Finally, impulsive/overactive measured the presence of child behavior that was considered sudden or excessive given a certain situation.

TABLE 1 | The construct of school readiness.

Dimension		
	Item Number	
Health		
	1	Overall health
	2	Health weight
	3	Low birth weight
	4	Premature
Self-regulation		
	5	Dimensional change card sort
	6	Numbers reversed
	7	Attentional focus
	8	Inhibitory control
	9	Self-control
Social and Emotional Development		
	10	Interpersonal skills
	11	Externalizing problems
	12	Internalizing problems
	13	Impulsive/overactive
Language and Literacy Development		
	14	Reading achievement
	15	Language and literacy (story)
	16	Language and literacy (letters)
	17	Language and literacy (read)
	18	Language and literacy (writing)
	19	Language and literacy (print)
Cognition and General Knowledge		
	20	Mathematics achievement
	21	Mathematical thinking (sort)
	22	Mathematical thinking (order)
	23	Mathematical thinking (relationship)
	24	Science (observe)
	25	Science (classifies)
	26	Science (life science)
Approaches to Learning		
	27	Eagerness to learn
	28	Adaptable
	29	Persistence
	30	Attention
	31	Creativity

Language and literacy development. There were six indicators of language and literacy development. Reading achievement scores were Item Response Theory (IRT)-scaled scores from an individually-administered standardized reading assessment. The assessment measured language use and literacy skills and was developed specifically for the ECLS-K study. Five items from the teacher-reported Academic Rating Scale–Language and literacy were also included. The scale included assessments of children's story comprehension, letter identification, reading, early writing behaviors, and print knowledge. Items were assessed using a scale from 1 (Not yet) to (Proficient).

Cognition and general knowledge. There were seven indicators of cognition and general knowledge. Mathematics achievement scores were IRT-scaled scores from an individually administered standardized mathematics assessment developed for the ECLS-K study. The assessment measured skills in conceptual and procedural knowledge and problem-solving in specific content areas (e.g., number sense, properties, and operations). Three items from the teacher-reported Academic Rating Scale–Mathematical were also included: sorting, ordering, and quantity relationships. Also, three items from the teacher-reported Academic Rating Scale–Science scale were used: observation skills, living and non-living things classification, and understanding of life science concepts. Items were measured on a scale from 1 (Not yet) to (Proficient).

Approaches to learning. There were five indicators of children's approaches to learning. Four teacher-report items measured how often children were: eager to learn, adaptable, persistent, and paid attention. One parent-report item measured children's creativity in work or play. All items were measured on a scale from 1 (Never) to 4 (Very often).

(Note: Correlations among all items used in the analyses can be found in Appendix A in **Supplementary Material**).

Statistical analysis

Diagnostic Classification Models (DCM; Rupp et al., 2010) was applied to classify children into different school readiness profiles, which provide some advantages over LCA used in the previous studies. Compare to LCA as an exploratory analysis model, DCMs are confirmatory latent class models, which can (1) provide an individual mastery status of each latent variable (mastery/non-mastery), often called the latent attribute in the DCM literature, and then (2) classify individuals into pre-determined latent profiles.

Each latent profile illustrates a distinct pattern of mastery status for all latent attributes. For example, suppose a total of 2 binary attributes (A_1, A_2) are measured, then, each individual will have two mastery statuses for each measured attribute (1 = mastery; 0 = non-mastery) and four possible latent profiles: A_1 = (0,0), A_2 = (1,0), A_3 = (0,1), and A_4 = (1,1). A_1 represents non-mastery for all attributes; A_2 represents mastery on Attribute 1 and non-mastery on Attribute 2; A_3 represents mastery on Attribute 2 and non-mastery on Attribute 1, and A_4 represents mastery on both Attribute 1 and Attribute 2. In general, when A binary attributes are estimated, a total of 2^A possible latent profiles could be possible. Therefore, researchers know the number of latent profiles and the meaning of each latent profiles *a priori*. In contrast, the number and meaning of latent profiles provided by LCA were decided after conducting data analyses. Furthermore, model-based classifications in DCMs are more objective and relatively independently; results and interpretation could be compared across studies. Therefore, we chose to use DCM over LCA for these advantages.

A total of six school readiness skills were evaluated in the current study to either be on-track (mastery status) or be off-track (non-mastery status). Thus, there were up to $\mathbf{2^6 = 64}$ distinct school readiness profiles for six binary attributes, and we would know the pattern and meaning of each school readiness profile. Let 0 and 1 represent off-track and on-track for each subdomain. For example, pattern $\mathbf{A_r} = (\mathbf{0},\ \mathbf{0},\ \mathbf{0},\ \mathbf{0},\ \mathbf{0},\ \mathbf{0})$ indicates that child $\mathbf{r}$ is off-track for all attributes, and pattern $\mathbf{A_{r'}} = (\mathbf{1},\ \mathbf{1},\ \mathbf{0},\ \mathbf{0},\ \mathbf{0},\ \mathbf{0})$ indicates child $\mathbf{r}'$ is on-track for the first two attributes but off-track for other attributes.

Data analyses proceed in two steps: First, the alignment between assessment items and school readiness attributes, also called Q-matrix, was specified by the second and third author of the current study by reviewing previous studies and items provided in the ECLS-K:2011 data set, which can be found in Appendix A in **Supplementary Material**.

Second, the Log-linear Cognitive Diagnosis Model (LCDM; Henson et al., 2009), the most general DCM, was applied to (1) determine the mastery status of attributes of individuals, and (2) classify individuals into different school readiness profiles. To achieve these two objectives, first, the item responsibility given by the school readiness profile membership was estimated through Equation (1). Second, the school readiness profile membership probabilities for all possible profiles were estimated through Equation (2) for individuals.

Last, the final school readiness profile for individuals was determined by using the maximum a posteriori (MAP) estimate, which was the largest probability of school readiness profile membership.

$$P(X_r = x_r) = \sum_{c=1}^{C} \nu_c \prod_{i=1}^{I} \pi_{ic}^{x_{ir}} \, (1 - \pi_{ic})^{1-x_{ir}} \tag{1}$$

where, x_r represents a vector of item responses from individual r, π_{ic} represents the certain item response probability for item i given school readiness profile c. So, Equation (1) expresses the probability of observing a vector of item response X_r of an individual is a function of the probability of observing a certain item response and the probability of being in the school readiness profile.

$$\sum_{c=1}^{C} \nu_c = 1 \tag{2}$$

where, ν_c represents the probability of being school readiness c. Since each child is a member of one and only one school readiness profile. Such that, all school readiness profile probabilities are sum up to 1.

Both the item-level fit and test level-fit were evaluated in the current study. Posterior predictive model checking (PPMC, e.g., Rubin, 1984; Meng, 1994; Gelman et al., 1996) was used to assess the item fit. Results from the LCDM were used to simulate a new data set and then generate model-implied correlation coefficients between paired items. Then, the model fit was evaluated by inspecting the discrepancy between model-implied and data-implied correlation coefficients between paired items. Smaller discrepancy indicated better model data fit. In the current study, 0.15 was set as the cut-off value. Therefore, the absolute discrepancy $\leq$0.15 indicated acceptable model-data fit for a pair of items. The mean absolute difference for the item-pair correlations statistic (MADcor, DiBello et al., 2006) was the difference between the data-implied and the model-implied item correlation. For the sake of page limits, more details of estimation and model fit information of the LCDM can be found in Appendix B in **Supplementary Material**.

The data analysis was carried out using Mplus version 7.4 (Muthén and Muthén, 1998–2015) via maximum likelihood estimation.

Results

Model fit

Table 2 presents the proportion of fit and unfit pairs of items for each type of correlation coefficient. The results found 72% of pairs of items showed acceptable model-data fit based on our criteria. Regarding the test fit, MADcor is 0.053. Previous researchers suggested a MADcor value of 0.06 acceptable for the LCDM (e.g., Henson et al., 2009; Lei and Li, 2016). Therefore, the LCDM achieved acceptable model fit and it was plausible to interpret the results from the current LCDM (see Appendix C for more details of item parameter estimates and Appendix D for more details of model fit results in **Supplementary Material**).

Attribute classification

Results showed that the majority of the sample (85.17%) were classified into six school readiness profiles; 23 profiles had zero children, indicating no child showed these patterns of attributes; and 35 profiles had <3% of the sample, indicating these school readiness profiles were less likely to occur. A full description of all possible 64 attribute classifications can be found in Appendix E in **Supplementary Material**. Details of attribute reliability could be found in Appendix F in **Supplementary Material**.

Table 3 shows the proportion of the sample assigned to the top six profiles: (1) Positive Development profile included 28% of children who were on-track for all attributes, except health; (2) Comprehensive At-Risk profile included 24% of children who were off-track for all attributes; (3) Personal and Social Strengths profile included 20% of children who were off-track for health, language development, and cognitive development and on-track for self-regulation, social and emotional development, and approaches to learning; (4) Cognitive and Language Strengths profile included 5% of children who were on-track for language development and cognitive development but off-track for other attributes; (5) Health Strength profile included 5% of children who were only on-track for health; and (6) Cognitive, Personal and Social Strengths profile included 3% of children who were on-track for self-regulation, social and emotional development, cognitive development and approaches to learning but off-track for health and language development.

Discussion

Findings showed that three profiles represented 71.60% of the sample and the top six profiles represented 85.17% of the sample. Other than the inclusion of self-regulation, the top six profiles were conceptually similar to those found in previous studies that classified children as being on- or off-track for school readiness domains (e.g., Hair et al., 2006; Halle et al., 2012). These results indicate that personal and social skills

TABLE 2 | Summary for LCDM model fit statistics.

	N of pairs of categorical items (%)	N of pairs of continuous items	N of pairs of categorical and continuous items	Total pairs of items
Fit[a]	207(75.00%)	10(47.62%)	119(7.83%)	336 (72.26%)
Unfit[b]	69(25.00%)	11(52.38%)	49(29.17%)	129(27.74%)

[a]Fit: the absolute discrepancy between model-implied and data-implied correlation coefficients between paired items ≤0.15.
[b]Unfit: the absolute discrepancy between model-implied and data-implied correlation coefficients between paired items >0.15.

TABLE 3 | Attribute classification results for the top six profiles.

Profile	HEA	SR	SED	LAN	COG	APL	N	Proportion
Positive development	0	1	1	1	1	1	4214	28.18%
Comprehensive at-risk	0	0	0	0	0	0	3566	23.85%
Personal and social strengths	0	1	1	0	0	1	2927	19.57%
Cognitive and language strengths	0	0	0	1	1	0	793	5.30%
Health strength	1	0	0	0	0	0	722	4.83%
Cognitive, personal, and social strengths	0	1	1	0	1	1	514	3.44%

HEA, health; SR, self-regulation; SED, social and emotional development; LAN, language development; COG, cognitive development; APL, approaches to learning. An entry of 0 means off-track on the attribute; an entry of 1 means on-track on the attribute.

appeared to cluster together. That is, children who were on-track for self-regulation were on-track for other personal and social skills while children who were off-track for self-regulation were off-track for other personal and social skills. Cognitive abilities were similarly clustered together. This clustering pattern provides some evidence that self-regulation could be considered a personal and social dimension of school readiness and reflects skills that operate similarly compared to other personal and social skills. Though, it can be considered its own dimension because there were profiles that only included self-regulation skills and those that included self-regulation skills with different combinations of school readiness skills (e.g., a profile with self-regulation mastery and cognitive mastery) (see Appendix E in **Supplementary Material** for a list of all possible profiles from the study).

Study 2

Study 2 addressed the following research question: How does school readiness profile membership predict growth in reading and math achievement from kindergarten to grade 2, after controlling for child demographic and background variables?

Method

Sample

Study 2 used a total of four waves of data[1] from the sample used in Study 1. **Table 4** presents the descriptions of samples of Study 2.

Measures

IRT scores of reading and math achievement assessments were used as outcomes in Study 2. In the ECLS-K:2011 data set, assessments were vertically linked to make it a longitudinal measure of growth in achievement. However, scores for different subject areas were not comparable to each other because of different numbers of questions and content. A set of children and family background variables were used as control variables, including ethnicity, children gender, children disability status, family poverty status, parent education level, single parent household, and mom's age at first birth. More details of these measures could be found in the user's manual for the ECLS-K:2011 (Tourangeau et al., 2009).

Statistical analysis

The Growth Curve Model (GCM) was used to analyze children's academic growth in reading and math achievement across time. After inspecting the growth trajectory for each subject across time (see **Figure 1**), both reading and math achievement showed linear growth trajectories across time, on average[2]. Therefore, a two-level linear growth model was adopted in the current study. A total of four waves of data, including kindergarten–fall, kindergarten–spring, grade 1–spring and grade 2–spring[3] were used in the data analyses. At Level 1, individual's test scores were predicted by the length of his/her receiving formal education (in months). Also, a random intercept and a random slope of the time variable (the length of time in formal education) were assumed, meaning that each child could have his/her own initial

[1]kindergarten–fall, kindergarten–spring, grade 1–spring and grade 2–spring. Due to the sample design, only one-third of the original samples were selected in grade 1 – fall and grade 2 – fall, so, these two waves of data were not included in the GCMs.

[2]The average test scores were the saturated means, which was calculate by using Full Information Maximum Likelihood (FIML) to reduce the impacts of missing data at grade 1 – fall and grade 2 – fall.

[3]A total of six waves of data were available in the ECLS: K-2011 database, including kindergarten – fall, kindergarten – spring, grade 1 – fall, grade 1 – spring, grade 2 – fall, and grade 2 – spring. However, only a subsample (40%) of the total sample was selected for grade 1 – fall and grade 2 – fall data collection by design. So, only four waves of data were used in the current study to avoid the impacts of missing data.

TABLE 4 | Descriptive statistics of children demographic and background variables ($N = 14{,}954$).

Background variables[a] Categorical variables	N	%
Ethnicity		
White	7,331	49.02
Black	1,907	12.75
Hispanic	3,659	24.47
Asian	1,115	7.46
Others	908	6.07
Missing	34	0.23
Gender		
Male	7,591	5.76
Female	7,330	49.02
Missing	33	0.22
Disability Status		
Students without disability	8,613	57.60
Students with disability	2,111	14.12
Missing	4,230	28.29
Poverty Status		
Not poverty	8,597	57.49
Poverty	2,716	18.16
Missing	3,641	24.35
Parent Education Level		
High school	2,940	19.66
Middle school or lower	1,736	11.61
College	4,447	29.74
Bachelor degree	2,731	18.26
Master degree or higher	1,748	11.69
Single Parent Household		
Not a single parent household	9,650	64.53
Single parent household	2,953	19.75
Missing	2,351	15.72
Teenage Mom		
Not a teenage mom	9,105	6.89
Teenage mom	3,041	2.34
Missing	2,808	18.78
Continuous variables	**Mean**	**SD**
Age at entering the kindergarten	67.17	4.16
Household income	1.71	5.57
Parent occupational prestige	44.84	12.03
Outcome variables[b]		
Reading—Kindergarten fall	46.91	11.54
Reading—Kindergarten spring	61.40	13.44
Reading—Grade 1 spring	84.59	15.50
Reading—Grate 2 spring	96.63	12.03
Math—Kindergarten fall	31.71	11.40
Math—Kindergarten spring	45.31	12.18
Math—Grade 1 spring	67.15	15.26
Math—Grate 2 spring	81.40	13.58

[a] *Background variables were control variables in GCMs, including both categorical and continuous variables.*
[b] *Outcome variables were outcome variables in GCMs.*

level of the achievement at kindergarten entry as well as his/her own growth rates (Equation 3). At Level 2, a set of child and family background variables, as well as the school readiness profiles, were used as the predictors of Level 1 intercept and slope to investigate if school readiness profiles were associated with individual's academic growth above and beyond background variables (Equation 4 and 5). More details of GCMs can be found in Appendix G in **Supplementary Material**.

$$Y_{it} = \beta_{0i} + \beta_{1i} Time_{ti} + \epsilon_{it} \tag{3}$$

$$\beta_{0i} = \gamma_{00} + \sum_{k=1}^{K} \gamma_{0k} X_{ki} + u_{0i} \tag{4}$$

$$\beta_{1i} = \gamma_{10} + \sum_{k=1}^{K} \gamma_{1k} X_{ki} + u_{1i} \tag{5}$$

In Equation (3), Y_{it}, represents the test score for child i at time t, which can be expressed as a linear combination of a random intercept, β_{0i}, which represents each child had his/her own initial starting point, and the product of a random slope, β_{1i}, which represents each child had his/her own growth rates, and timing variable of child i, $Time_{ti}$, which is the length of receiving formal education in months, and the time specific error, ϵ_{it}.

In Equations (4,5), a set of K time-invariant variables predicted the random intercept and random slope, which included child background and demographic variables and school readiness profile membership. γ_{00} is the Level 2 intercept for Level 1 intercept; $\gamma_{01} - \gamma_{0k}$ are coefficients for time-invariant variables for the Level 1 intercept, representing the effects the time-invariant variables on the between-person variation in the intercept; and u_{oi} is the Level 2 residual for Level 1 intercept. γ_{10} is the Level 2 intercept for the Level 1 slope; $\gamma_{11} - \gamma_{1k}$ are coefficients for time-invariant variables for the Level 1 slope, representing the effects the time-invariant variables on the between-person variation in the slope; and u_{1i} is the Level 2 residual for Level 1 slope.

The total R^2, the squared correlation between the observed test scores and the test scores predicted by the model fixed effects was calculated to represent the variance explained by the time-invariant predictors. The pseudo-R^2 value for the proportion reduction in each random effect variance was calculated to evaluate the effect size of adding school readiness profile membership into the model. Additionally, Log-likelihood values were used to evaluate the relative model fit. Smaller values indicate better model fit. Residual maximum likelihood (REML) was used in estimating and reporting all model parameters. Denominator degrees of freedom was estimated by using the Satterthwaite method (Satterthwaite, 1946). The significance of fixed effects was evaluated with univariate Wald tests. The GCM analysis was generated using SAS Studio via PROC MIXED (SAS Institution, 2016).

Unrepresentative samples and missing data

To provide national-level estimates, the current study used one sampling weight variable (W6C6P_20) provided by ECLS-K:2011 to account for the unrepresentativeness and missing

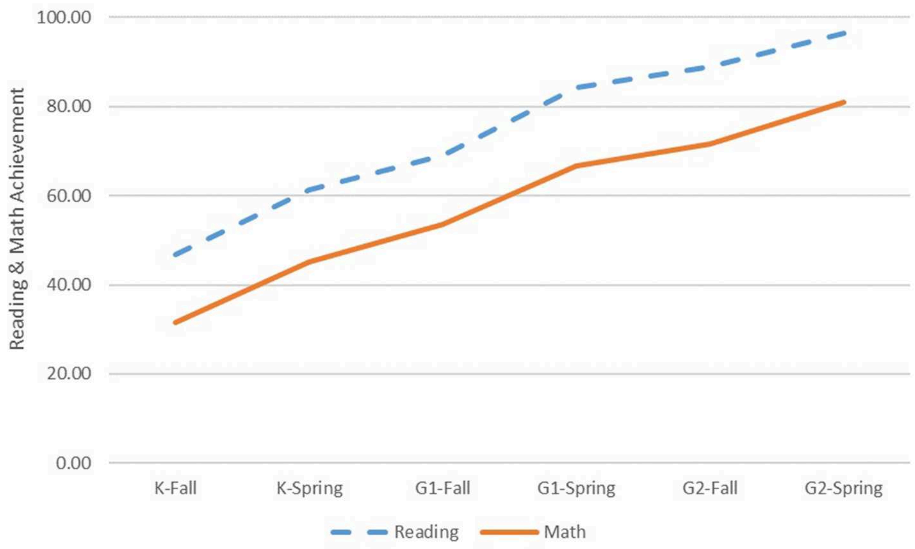

FIGURE 1 | Data-implied average reading and math growth trajectory across time.

data (Bernstein et al., 2014). This sampling weight variable adjusted for nonresponse associated with child assessment data from both kindergarten rounds, spring first grade and spring second grade, as well as parent data from fall kindergarten or spring kindergarten.

Results

Descriptive statistics

The descriptive statistics for child test scores, background, and demographic variables are presented in **Table 4**. For categorical variables, the first category was treated as the reference group in the GCMs. Continuous background and demographic variables were centered at the mean before entering into the GCMs.

Growth model results

Reading achievement growth Children's reading achievement scores across four measurement occasions were predicted from a set of child background and demographic variables as the baseline model (Reading Model 1). As shown in **Table 6**, 73.76% of the total variance in the reading achievement was explained by including the length of education, and child background and demographic variables. **Table 6** presents the estimated coefficients, where the intercept and slope parameters represent the reading achievement and growth rates for the average child who was in all reference groups. Moreover, there was a negative covariance between the intercept and the slope, which indicates that a higher initial level of reading achievement was associated with a slower growth rate.

For Reading Model 1, in terms of time-invariant predictors, some factors were related with higher initial level of reading achievement, including being an Asian child, chronologically older children at kindergarten entry, females, higher family income, higher parent occupation prestige, and higher parental education level. Also, the following variables were associated with lower initial levels of achievement: disability status, poverty status, having a teenage mother, and living in a single-parent household. Results revealed that there was a negative relationship between intercept variance and slope variance, indicating that a higher initial level of reading achievement was associated with a lower growth rate. In addition, results found two types of factors that were related to the lower growth rate: (1) sociodemographic factors, including race (i.e., Black and Hispanic children had a lower growth rate), having a disability, and family income under the poverty threshold; and (2) factors associated with high initial level of reading achievement (i.e., Asian children, chronologically older children at kindergarten entry, and having parents with a higher education level).

In Reading Model 2, as shown in **Table 5**, school readiness profile membership was added as an additional predictor of the intercept and the linear slope. Profile membership was treated a dummy variable and the Comprehensive At-Risk profile was the reference group. Results found that the total cumulative R^2 from Model 2 is $R^2 = 77.64\%$, approximately a 3.9% increase due to the addition of school readiness profile membership. In terms of the pseudo-R^2, school readiness profile membership accounted for 26.00% of random intercept variance, 6.57% of random slope variance, and 0.84% of the residual variance. In addition, smaller negative Log-likelihood values in the Model 2 indicate that Model 2 fit the data better than Model 1. Intercept, slope, and coefficients of other time-invariant predictor estimates are presented in **Table 6**. Results showed all other profiles except for Health Strength profile had significantly higher initial reading level compared to Comprehensive At-Risk profile. Regarding to the growth rates, comparing to the reference profile, Positive Development profile, Cognitive and Language Strengths, and Health Strength profile had significantly lower growth rates, however, Personal and Social Strengths profile and Cognitive, Personal and Social Strengths profile had significantly higher growth rates.

Figure 2 shows the data-implied growth trajectories for the top six school readiness profiles[4], which illustrates the growth trajectories of reading achievement of the top six school readiness profiles. Children who had a Positive Development profile had higher initial reading levels and maintained that status over time. Children who were off-track for some cognitive attributes but on-track for personal and social attributes (Personal and Social Strengths) had lower initial reading achievement levels but eventually caught up to the reading achievement of children who were on-track for cognitive skills and language and literacy by the end of second grade (Cognitive and Language Strengths). Children who had less on-track attributes (Comprehensive At-Risk and Health Strength profiles) had a lower initial level and maintained that status over time.

Math achievement growth

Similar to the analysis conducted for reading achievement, math achievement across four measurement occasions were first predicted from a set of child background and demographic variables as the baseline model (Math Model 1). **Table 5** shows that 76.00% of the total variance in the math achievement was explained by including the education time and child background and demographic variables. Compare to the development of reading, there was a positive relationship between intercept variance and slope variance, indicating that a higher initial level of math achievement was associated with a higher growth rate.

For Math Model 1, regarding time-invariant predictors, results found several factors that were associated with a lower initial level of math achievement compared to the reference group: race (i.e., Black and Hispanic children had a lower initial level of math achievement), having a disability, having a parent with lower than a high school education, being from a single-parent household, and having a teenage mother. Other factors were found to be related with the higher initial level of math achievement: being an Asian child, high family income, having a parent with a college education and above, and having a parent with higher occupational prestige. Some factors were associated with a lower growth rate, including being Black or Hispanic, having a disability, family income under the poverty threshold, and single-parent household status. Also, females had lower growth rates even though females and males had the same initial level upon kindergarten entry. Similar to the results from the reading growth models, older age at kindergarten entry was also related to a higher initial math achievement level and a lower growth rate of math achievement.

In Math Model 2, school readiness profile membership was added as an additional predictor for intercept and slope. Profile membership was treated a dummy variable, and the Comprehensive At-Risk profile was the reference group. As shown in **Table 5**, a total of 79.45% of the total variance was explained, indicating a 3.50% increase in variance explained due to the addition of school readiness profile membership. Regarding the pseudo-R^2, school readiness profile membership

TABLE 5 | Summary of variance components estimates and model fit statistics for growth models.

	Reading model 1				Reading model 2					Math model 1				Math Model 2				
Variance Components	**Est.**	**SE**	***z*** [a]	***p*** [b]	**Est.**	**SE**	***z*** [a]	***p*** [b]	**R^2** [c]	**Est.**	**SE**	***z*** [a]	***p*** [b]	**Est.**	**SE**	***z*** [a]	***p*** [b]	**R^2** [c]
Intercept	86.45	2.50	34.55	<0.01	63.97	2.04	31.42	<0.01	0.26	67.65	1.89	35.83	<0.01	5.47	1.54	32.88	<0.01	0.25
Slope	0.03	<0.01	12.74	<0.01	0.03	<0.01	12.22	<0.01	0.07	0.03	<0.01	15.91	<0.01	0.03	<0.01	15.90	<0.01	0.01
Covariance [d]	−0.41	0.06	−6.75	<0.01	−0.28	0.05	−5.25	<0.01		0.30	0.04	7.20	<0.01	0.30	0.04	7.89	<0.01	
Residual	19321	243.04	79.49	<0.01	19219	24.55	79.90	<0.01	0.01	14034	175.22	8.09	<0.01	13963	173.48	8.49	<0.01	0.01
Total R^2	0.74						0.78			0.76				0.79				
Total R^2 change							Total R^2 change	0.04									0.03	
Model Fit Statistics																		
−2LL		161246			159842					155955	154657							

[a] *z is plausible z-value.* [b] *p is the plausible p-value.* [c] *R^2 is pseudo R^2.* [d] *Covariance: covariance between the intercept and the slope.*

[4]The average observed test scores.

TABLE 6 | Summary of fixed effect estimates in growth models.

	Reading model 1				Reading model 2				Math model 1				Math model 2			
	Est.	SE	t [e]	p [f]	Est.	SE	t [e]	p [f]	Est.	SE	t [e]	p [f]	Est.	SE	t [e]	p [f]
Fixed Effects																
Intercept	42.08	0.58	72.97	<0.01	38.76	0.58	67.25	<0.01	26.80	0.50	53.23	<0.01	23.37	0.50	46.45	<0.01
Ethnicity																
Black	1.03	0.54	1.92	0.06	0.72	0.49	1.48	0.14	−2.37	0.47	−5.04	<0.01	−2.54	0.42	−5.97	<0.01
Hispanic	−0.59	0.45	−1.31	0.19	−0.27	0.41	−0.65	0.51	−2.30	0.39	−5.83	<0.01	−1.90	0.36	−5.29	<0.01
Asian	5.08	0.77	6.57	<0.01	4.55	0.72	6.34	<0.01	2.55	0.67	3.80	<0.01	2.24	0.62	3.59	<0.01
Other	1.31	0.67	1.96	0.05	1.03	0.61	1.68	0.09	0.68	0.59	1.16	0.25	0.48	0.53	0.90	0.37
K_age [a]	0.52	0.04	13.61	<0.01	0.28	0.04	7.92	<0.01	0.70	0.03	21.05	<0.01	0.49	0.03	15.85	<0.01
Female	1.26	0.31	4.00	<0.01	0.30	0.29	1.01	0.31	−0.36	0.27	−1.33	0.18	−1.34	0.25	−5.27	<0.01
SWD [b]	−2.54	0.40	−6.33	<0.01	−1.21	0.37	−3.30	<0.01	−3.13	0.35	−8.94	<0.01	−1.89	0.32	−5.87	<0.01
Income [c]	0.16	0.05	3.15	<0.01	0.07	0.05	1.45	0.15	0.25	0.04	5.64	<0.01	0.16	0.04	4.09	<0.01
Poverty	−1.23	0.58	−2.13	0.03	−0.97	0.53	−1.85	0.06	−0.97	0.51	−1.92	0.05	−0.71	0.46	−1.55	0.12
Parent Education Level																
Middle School or Lower	−2.09	0.71	−2.94	<0.01	−1.64	0.65	−2.53	0.01	−1.94	0.62	−3.13	<0.01	−1.58	0.57	−2.79	0.01
College	1.27	0.47	2.73	0.01	0.91	0.42	2.15	0.03	1.15	0.41	2.81	<0.01	0.84	0.37	2.28	0.02
Bachelor	4.87	0.56	8.66	<0.01	3.58	0.51	6.97	<0.01	4.41	0.49	8.99	<0.01	3.29	0.45	7.35	<0.01
Master or higher	6.32	0.66	9.58	<0.01	4.70	0.60	7.81	<0.01	5.90	0.58	1.26	<0.01	4.57	0.53	8.69	<0.01
Occupation Prestige [d]	0.07	0.02	4.18	<0.01	0.05	0.01	3.29	<0.01	0.05	0.01	3.48	<0.01	0.03	0.01	2.50	0.01
Single Parent Household	−1.78	0.44	−4.07	<0.01	−1.33	0.40	−3.36	<0.01	−1.43	0.38	−3.73	<0.01	−0.98	0.35	−2.81	<0.01
Teenage Mom	−1.35	0.44	−3.07	<0.01	−0.93	0.40	−2.33	0.02	−1.06	0.38	−2.78	0.01	−0.77	0.35	−2.20	0.03
School readiness profile [g]																
Positive development					11.93	0.42	28.14	<0.01					1.83	0.37	29.25	<0.01
Personal and social strengths					3.38	0.46	7.36	<0.01					4.34	0.4	1.82	<0.01
Cognitive and language strengths					1.2	0.67	15.15	<0.01					8.15	0.59	13.88	<0.01
Health strength					−1.48	0.76	−1.95	0.05					−1.95	0.66	−2.95	<0.01
Cognitive, personal and social strengths					2.75	0.82	3.37	<0.01					5.29	0.71	7.42	<0.01
Slope	1.74	0.02	94.11	<0.01	1.73	0.02	85.59	<0.01	1.77	0.02	98.41	<0.01	1.77	0.02	98.41	<0.01
Ethnicity																

(Continued)

TABLE 6 | Continued

	Reading model 1				Reading model 2				Math model 1				Math model 2			
	Est.	**SE**	***t*** [e]	***p*** [f]	**Est.**	**SE**	***t*** [e]	***p*** [f]	**Est.**	**SE**	***t*** [e]	***p*** [f]	**Est.**	**SE**	***t*** [e]	***p*** [f]
Black	−0.09	0.02	−5.45	<0.01	−0.09	0.02	−5.42	<0.01	−0.18	0.01	−12.00	<0.01	−0.18	0.01	−12.07	<0.01
Hispanic	−0.03	0.01	−2.36	0.02	−0.03	0.01	−2.32	0.02	−0.06	0.01	−4.32	<0.01	−0.06	0.01	−4.32	<0.01
Asian	−0.10	0.03	−3.53	<0.01	−0.09	0.03	−3.28	<0.01	0.02	0.02	0.88	0.31	0.02	0.02	1.01	0.31
Other	−0.03	0.02	−1.51	0.13	−0.03	0.02	−1.40	0.16	−0.04	0.02	−2.05	0.05	−0.04	0.02	−1.96	0.05
K_age [a]	−0.01	0.00	−5.41	<0.01	−0.01	0.00	−4.15	<0.01	−0.01	0.00	−7.70	<0.01	−0.01	0.00	−7.31	<0.01
Female	0.04	0.01	3.55	<0.01	0.03	0.01	3.12	<0.01	−0.06	0.01	−6.11	<0.01	−0.06	0.01	−6.32	<0.01
SWD [b]	−0.05	0.01	−3.76	<0.01	−0.05	0.01	−3.73	<0.01	−0.05	0.01	−4.27	<0.01	−0.04	0.01	−3.74	<0.01
Income [c]	0.00	0.00	0.15	0.88	0.00	0.00	0.17	0.87	0.00	0.00	−0.65	0.51	0.00	0.00	−0.81	0.42
Poverty	−0.08	0.02	−4.48	<0.01	−0.08	0.02	−4.43	<0.01	−0.05	0.02	−3.15	<0.01	−0.05	0.02	−3.01	<0.01
Parent Education Level																
Middle School or Lower	−0.02	0.02	−0.90	0.37	−0.03	0.02	−1.23	0.22	0.01	0.02	0.37	0.71	0.01	0.02	0.26	0.79
College	0.01	0.01	0.82	0.41	0.01	0.01	1.00	0.32	0.02	0.01	1.67	0.10	0.02	0.01	1.59	0.11
Bachelor	−0.02	0.02	−1.04	0.30	−0.01	0.02	−0.56	0.58	−0.01	0.02	−0.86	0.39	−0.01	0.02	−0.79	0.43
Master or higher	−0.04	0.02	−2.01	0.04	−0.03	0.02	−1.40	0.16	−0.02	0.02	−1.14	0.26	−0.02	0.02	−1.04	0.30
Occupation prestige [d]	0.00	0.00	−0.73	0.47	0.00	0.00	−0.58	0.56	<0.01	<0.01	−0.49	0.62	0.00	0.00	−0.39	0.70
Single parent household	0.00	0.01	0.14	0.89	0.01	0.01	0.45	0.65	−0.03	0.01	−2.24	0.03	−0.02	0.01	−1.79	0.07
Teenage mom	0.01	0.01	0.68	0.50	0.01	0.01	0.42	0.68	−0.03	0.01	−2.24	0.03	0.00	0.01	0.00	1.00
School readiness profiles [g]																
Positive development					−0.05	0.02	−3.13	<0.01					<0.01	0.01	0.36	0.72
Personal and social strengths					0.08	0.02	5.1	<0.01					0.07	0.01	4.74	<0.01
Cognitive and language strengths					−0.09	0.02	−3.83	<0.01					<0.01	0.02	0.04	0.97
Health strength					−0.07	0.03	−2.55	0.01					−0.05	0.02	−2.26	0.02
Cognitive, personal and social strengths					0.06	0.03	2.18	0.03					0.07	0.03	2.64	0.01

[a]*K_age is Kindergarten Entry Age and centered at 60 months.* [b]*SWD is student with disability.* [c]*Income is family income and centered at 10.* [d] *Occupation Prestige is parent occupation prestige and centered at 45.* [e]*t is the plausible t value.* [f]*p is the plausible p value.* [g]*Profile of comprehensive at-risk was the reference group. All none-zero school readiness profiles were included in the Model 2, because of the page limits, regression coefficients of top 6 school readiness profiles were reported. A full description of regression coefficients for all none-zero school readiness profiles could be found in Appendix E (**Supplementary Material**).*

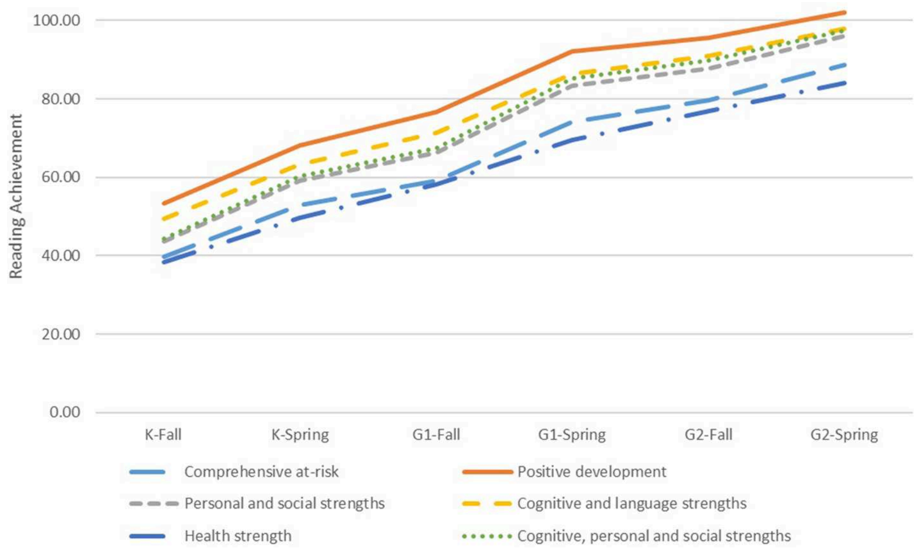

FIGURE 2 | Data implied reading growth trajectories across top 6 profiles.

accounted for 25.39% of random intercept variance, 1.11% of random slope variance, and 0.51% of the residual variance. Furthermore, smaller negative Log-likelihood values obtained from Math Model 2 indicate that Math Model 2 fit the data better than Math Model 1. **Table 6** shows the intercept, slope, and coefficients of other time-invariant predictor estimates of Math Model 2. Results showed Health Strength profile had significantly lower initial math level and all other profiles had significantly higher initial math level, compared to the Comprehensive At-Risk profile. Regarding the growth rate, comparing to the rerefence profile, Health Strength profile had significantly lower growth rates; in contrast, Personal and Social Strengths profile and Cognitive, Personal and Social Strengths profile had significantly higher growth rates.

As shown in **Figure 3**, similar results were found for the impact of school readiness profiles on the development of math achievement. Children in the Positive Development profile membership had higher initial achievement and maintained that status over time. At-risk profile membership (Comprehensive At-Risk and Health Strength profiles) was associated with lower initial achievement and maintained that status over time. However, children in the Personal and Social Strengths and Cognitive, Personal and Social Strengths profile caught up to their peers in the Cognitive and Language Strengths profile by the end of second grade, even though these children started behind their peers at kindergarten entry. The gap between children who were on-track for personal and social skills and children who were on-track for cognitive and language skills were closed over time as the former children demonstrated a higher growth rate compared to their peers starting around the spring semester of kindergarten.

Discussion

Results from Study 2 showed that school readiness profile membership could uniquely predict children's academic growth trajectories in both reading and math achievement, above and beyond child demographic and background variables. In other words, children's membership in different school readiness profiles could impact their academic growth. Furthermore, based on the data-implied growth trajectories for the top six profiles, children with the Positive Development profile entered kindergarten ahead and continued to perform higher than their peers, indicating the importance of children starting school with necessary school readiness skills. These findings were consistent with previous studies that show preschool cognitive skills could predict later academic achievement (e.g., Duncan et al., 2007; Pagani et al., 2010; Romano et al., 2010). However, it is notable that children who were on-track for personal and social attributes (e.g., self-regulation, social and emotional development, and approaches to learning) but off-track for cognitive attributes (e.g., language development, cognitive development) were able to catch up their peers by second grade in both reading and math achievement. Overall, these results provide evidence for the importance of personal and social skills in children's academic growth, as suggested by previous studies (e.g., Rimm-Kaufman et al., 2002; Bodovski and Farkas, 2007; DiPerna et al., 2007; Li-Grining et al., 2010). Additionally, findings support the inclusion of personal and social skills, including self-regulation, as components of school readiness that are important for children's continued academic achievement (Blair and Raver, 2015).

GENERAL DISCUSSION

The current study viewed school readiness as a six-dimensional construct, comprised of health, social and emotional development, language and literacy development, cognitive development, approaches to learning, and self-regulation. The inclusion of self-regulation in our conceptualization of

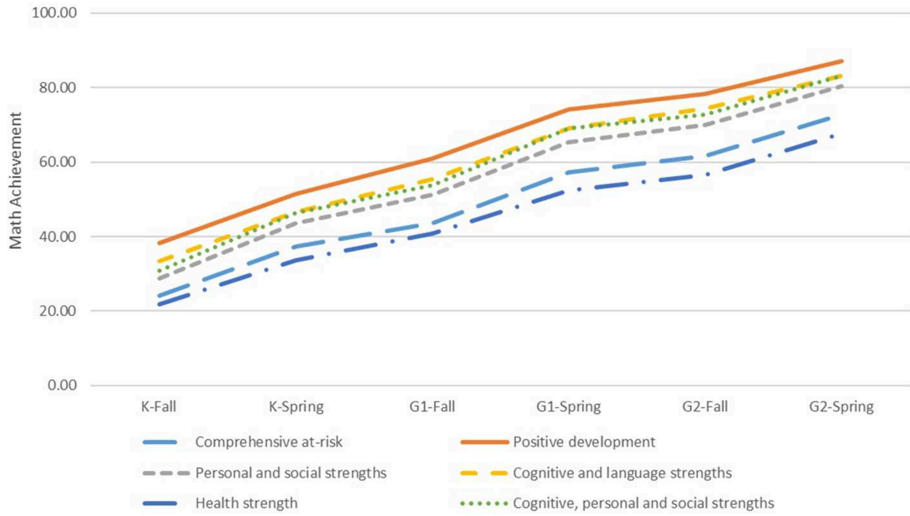

FIGURE 3 | Data implied math growth trajectories across top 6 profiles.

self-regulation was based on theory (e.g., Blair and Raver, 2015) and empirical evidence of its contributions to later achievement (e.g., Trentacosta and Izard, 2007; Welsh et al., 2010). This research extended previous work (Hair et al., 2006; Halle et al., 2012) by including self-regulation as a distinct domain in assessing the relations between children's school readiness and later academic achievement and using more recent, advanced statistical methods.

Study 1 applied Log-linear Cognitive Diagnostic Model (LCDM) to classify children into up to 64 possible pre-defined school readiness profiles. This approach overcame the limitations of general Latent Class Models used in previous studies because the LCDM classified children in a confirmatory model, such that the number of school readiness profiles and the label of each school readiness profile were known before the data analysis. Results showed that 85% of children were classified into the top six profiles: Positive Development (28%), Comprehensive At-Risk (24%), Personal and Social Strengths (20%), Cognitive and Language Strengths (5%), Health Strength (5%), and Cognitive, Personal and Social Strengths (3%). Other than the inclusion of self-regulation, the top six profiles were conceptually similar to those found in previous studies that classified children as being on- or off-track for school readiness domains (e.g., Hair et al., 2006; Halle et al., 2012).

Identifying school readiness profiles is important because they indicate the key developmental areas that children need support before entering kindergarten. Further, the profiles can be used to understand how school readiness attributes may group or interact with each other to inform practice. Importantly, these profiles allow a conceptualization of school readiness strengths and "risk" based on children's knowledge and skills, rather than purely based on familial and social backgrounds. In other words, these profiles allow a conceptualization of school readiness risk that focuses on attributes early childhood educators and interventionists can intervene on.

Based on this conceptualization, school readiness intervention programs and programs that supplement general high-quality ECE could be tailored to the school readiness profile that children belong to. That is, rather than delivering a general school readiness intervention or program to a group of children deemed "at-risk" due to their socioeconomic status or other family characteristics, educators and interventionists could focus on tailoring school readiness-focused instruction and intervention to distinct domains and/or profiles of school readiness. If high-quality ECE is conceived as a Tier 1, universal support for children's school readiness, interventions and embedded instruction tailored to children's school readiness profile could be added as a Tier 2 support for children identified as belonging to a profile other than the global Positive Development profile. This reflects a tiered system of support that has already shown benefits for children identified to have developmental delays or disabilities (e.g., Greenwood et al., 2011). Future research could explore the feasibility and effectiveness of such tailored intervention based on school readiness profiles.

Study 2 identified the unique contribution of school readiness profiles to academic growth, above and beyond demographic and family variables. In general, children who were well prepared in the cognitive attributes had the highest performance over time. It is noteworthy that children who were not well prepared in cognitive attributes but well prepared in personal and social attributes (e.g., self-regulation, social and emotional development, and approaches to learning) started off with lower reading and math achievement compared to children on-track for cognitive skills, but they closed the gap with their peers by second grade. Moreover, children who were not well prepared in both cognitive and personal and social attributes had the lowest initial levels and maintained that status through second grade. These findings suggest that personal and social skills, such as self-regulation, social and emotional development, and approaches to learning, could help children with lower cognitive preparation catch up to their peers over time. These skills may be important because they help children attend to learning, regulate their emotions and behavior, learn and play with peers, and appropriately attend to and use new information. Previous studies suggested that self-regulation was positively related to the motivation and engagement for learning activities (e.g., Blair, 2002). Also, social and emotional competence could impact children's opportunities for learning by influencing the ways they interact with classroom adults and peers. Valiente et al. (2007, 2008) found that children with greater emotional regulation challenges were less likely to participate in class, were absent from school more often, and reported liking school less than their peers with greater emotional regulation. Thus, these growth trajectories indicate the importance of personal and social skills as contributors to school readiness and academic achievement.

Study 2 also indicated that self-regulation operates similarly compared to other personal and social attributes. We separated self-regulation as its own domain based on theory, and previous research indicates it does operate differently from other skills often grouped as approaches to learning. Specifically, research indicates that self-regulation supports academic achievement by reducing challenging behaviors that interfere with learning and improving interactions with other children (e.g., Montroy et al., 2014). Similarly, other research indicates that self-regulation may uniquely support attention and reasoning abilities (Blair et al., 2015). Thus, the growth trajectories identified in the present study in conjunction with the previous research indicate the significance of self-regulation as a distinct attribute that complements other personal and social skills to contribute to school readiness and academic achievement. Given the importance of personal and social skills for children's academic growth, particularly if a child is off-track on cognitive and language development, such skills should be treated as distinct abilities requiring specific instructional strategies, similar to the ways academic knowledge is divided into content areas. The present investigation represents one step toward further parsing out the specific personal and social skills that early childhood educators and interventionists can target to support children's school readiness.

In sum, results from Study 1 and Study 2 suggest that children can generally be characterized according to a six-dimensional conceptualization of school readiness that includes health, social and emotional development, language and literacy development, cognitive development, approaches to learning, and self-regulation. The present investigation also found that the particular combination of school readiness skills children possess upon kindergarten entry can impact their future growth and development, with personal and social skills allowing children to catch up if they start kindergarten behind their peers in cognitive and language development. The six-dimensional conceptualization of school readiness put forth by this study advances a more nuanced view of school readiness that accounts for the needs of the whole child rather than only academic or cognitive knowledge (Diamond, 2010). It is important that early childhood educators and other professionals are intentional in providing opportunities to develop children's school readiness skills, and defining these skills with more specificity can allow more targeted instruction and intervention. Early education programs should emphasize both cognitive, and personal and social skills as they prepare children for kindergarten as that dual focus could have lasting effects on children's academic achievement.

LIMITATIONS AND FUTURE STUDY

Although the ECLS-K:2011 data set is nationally representative, only a portion of the data was publicly available. The public data set provides scale scores for measures rather than the original item responses. Even though most measures had high reliabilities, we cannot exclude measurement error when applying the LCDM to classify children into different profiles. Future studies should analyze the item responses directly to get measurement-error-free estimates. Also, future studies can apply the same model to other cohorts of ECLS dataset to cross-validate the findings from the current study. The present study contributes to a growing body of literature arguing for the importance of self-regulation as a nuanced skill that significantly impacts children's academic achievement. Future research can build on these findings by continuing to explore the unique contributions of self-regulation to school readiness, including the specific mechanisms through which it impacts children's academic achievement. For example, future studies can look at different aspects of self-regulation (e.g., emotional and cognitive), and how they contribute to children's school readiness and academic achievement. Finally, future research could explore the feasibility and effectiveness of tailoring interventions to children's school readiness profiles. This might be done within the context of a response-to-intervention framework in which high-quality ECE is supplemented by targeted instruction based on children's school readiness profile. Considering the importance of both cognitive, and personal and social skills in children's academic achievement, early childhood educators should treat each skill as worthy of targeted support.

DATA AVAILABILITY STATEMENT

The datasets analyzed for this study can be found in the Early Childhood Longitudinal Program (ECLS-K:2011) (https://nces.ed.gov/ecls/datainformation2011.asp).

AUTHOR CONTRIBUTIONS

QP drafted the manuscript, conducted and interpreted the statistical analyses. KT drafted the literature review. KT and HL formed the measures and wrote the literature review and discussion. JT provided expertise on data analysis and feedback to the manuscript.

ACKNOWLEDGMENTS

We thank Dr. Lesa Hoffman for sharing her wisdom with us in specifying and interoperating the growth curve models, which improved the manuscript greatly.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/feduc.2019.00127/full#supplementary-material

REFERENCES

Abenavoli, R. M., Greenberg, M. T., and Bierman, K. L. (2017). Identification and validation of school readiness profiles among high-risk kindergartners. *Early Childhood Res. Q.* 38, 33–43. doi: 10.1016/j.ecresq.2016.09.001

Altun, D. (2018). A paradigm shift in school readiness: a comparison of parents', pre-service and in-service preschool teachers' views. *Int. J. Prog. Edu.* 14, 37–56. doi: 10.29329/ijpe.2018.139.4

Anderson, L. M., Shinn, C., Fullilove, M. T., Scrimshaw, S. C., Fielding, J. E., Normand, J., et al. (2003). The effectiveness of early childhood development programs: a systematic review. *Am. J. Prevent. Med.* 24, 32–46. doi: 10.1016/S0749-3797(02)00655-4

Bernstein, S., West, J., Newsham, R., and Reid, M. (2014). *Kindergartners' Skills at School Entry: An Analysis of the ECLS-K*. Mathematica Policy Research.

Blair, C. (2002). School readiness: Integrating cognition and emotion in a neurobiological conceptualization of children's functioning at school entry. *Am. Psychol.* 57:111. doi: 10.1037/0003-066X.57.2.111

Blair, C., and Raver, C. C. (2015). School readiness and self-regulation: a developmental psychobiological approach. *Annu. Rev. Psychol.* 66, 711–731. doi: 10.1146/annurev-psych-010814-015221

Blair, C., Ursache, A., Greenberg, M., Vernon-Feagans, L., and Family Life Project, I. (2015). Multiple aspects of self-regulation uniquely predict mathematics but not letter-word knowledge in the early elementary grades. *Dev. Psychol.* 51, 459–472. doi: 10.1037/a0038813

Bodovski, K., and Farkas, G. (2007). Mathematics growth in early elementary school: the roles of beginning knowledge, student engagement, and instruction. *Element. Schl. J.* 108, 115–130. doi: 10.1086/525550

Carlton, M. P., and Winsler, A. (1999). School readiness: the need for a paradigm shift. *Schl. Psychol. Rev.* 28:338.

Claessens, A., Duncan, G., and Engel, M. (2009). Kindergarten skills and fifth-grade achievement: Evidence from the ECLS-K. *Econ. Educ. Rev.* 28, 415–427. doi: 10.1016/j.econedurev.2008.09.003

Cooper, B. R., Moore, J. E., Powers, C., Cleveland, M., and Greenberg, M. T. (2014). Patterns of early reading and social skills associated with academic success in elementary school. *Early Educ. Dev.* 25, 1248–1264. doi: 10.1080/10409289.2014.932236

Curby, T. W., Brown, C. A., Bassett, H. H., and Denham, S. A. (2015). Associations between preschoolers' social–emotional competence and preliteracy skills. *Infant Child Dev.* 24, 549–570. doi: 10.1002/icd.1899

Diamond, A. (2010). The evidence base for improving school outcomes by addressing the whole child and by addressing skills and attitudes, not just content. *Early Educ. Dev.* 21, 780–793. doi: 10.1080/10409289.2010.514522

DiBello, L. V., Roussos, L. A., and Stout, W. (2006). "A review of cognitively diagnostic assessment and a summary of psychometric models," in *Handbook of Statistics*, Vol. 26, eds C. R. Rao and S. Sinharay (Elsevier), 979–1030. doi: 10.1016/S0169-7161(06)26031-0

DiPerna, J. C., Lei, P.-W., and Reid, E. E. (2007). Kindergarten predictors of mathematical growth in the primary grades: An investigation using the Early Childhood Longitudinal Study–Kindergarten cohort. *J. Educ. Psychol.* 99:369. doi: 10.1037/0022-0663.99.2.369

Duncan, G. J., Dowsett, C. J., Claessens, A., Magnuson, K., Huston, A. C., Klebanov, P., et al. (2007). School readiness and later achievement. *Dev. Psychol.* 43:1428. doi: 10.1037/0012-1649.43.6.1428

Eiesnberg, N., Guthrie, I. K., Fabes, R. A., Reiser, M., Murphy, B., Holgren, R., et al. (1997). The relations of regulation and emotionality to resiliency and competent social functioning in elementary school children. *Child Dev.* 68, 295–311. doi: 10.1111/j.1467-8624.1997.tb01941.x

Elizabeth Graue, M. (1992). Social interpretations of readiness for kindergarten. *Early Childhood Res. Q.* 7, 225–243. doi: 10.1016/0885-2006(92)90006-K

Gelman, A., Meng, X.-L., and Stern, H. (1996). Posterior predictive assessment of model fitness via realized discrepancies. *Stat. Sin.* 6, 733–760.

Gilliom, M., Shaw, D. S., Beck, J. E., Schonberg, M. A., and Lukon, J. L. (2002). Anger regulation in disadvantaged preschool boys: strategies, antecedents, and the development of self-control. *Dev. Psychol.* 38:222. doi: 10.1037/0012-1649.38.2.222

Grant, H., and Dweck, C. S. (2003). Clarifying achievement goals and their impact. *J. Pers. Soc. Psychol.* 85, 541–553. doi: 10.1037/0022-3514.85.3.541

Greenwood, C. R., Bradfield, T., Kaminski, R., Linas, M., Carta, J. J., and Nylander, D. (2011). The response to intervention (RTI) approach in early childhood. *Focus Except. Child.* 43, 1–22.

Gresham, F. M., and Elliott, S. N. (1990). *Social Skills Rating System (SSRS).* American Guidance Service.

Hair, E., Halle, T., Terry-Humen, E., Lavelle, B., and Calkins, J. (2006). Children's school readiness in the ECLS-K: Predictions to academic, health, and social outcomes in first grade. *Early Childhood Res. Q.* 21, 431–454. doi: 10.1016/j.ecresq.2006.09.005

Halle, T. G., Hair, E. C., Wandner, L. D., and Chien, N. C. (2012). Profiles of school readiness among four-year-old Head Start children. *Early Childhood Res. Q.* 27, 613–626. doi: 10.1016/j.ecresq.2012.04.001

Heckman, J. J. (2006). Skill formation and the economics of investing in disadvantaged children. *Science* 312, 1900–1902. doi: 10.1126/science.1128898

Henson, R. A., Templin, J. L., and Willse, J. T. (2009). Defining a family of cognitive diagnosis models using log-linear models with latent variables. *Psychometrika* 74, 191–210. doi: 10.1007/s11336-008-9089-5

Hoffman, L. (2015). *Longitudinal Analysis: Modeling Within-Person Fluctuation and Change*. New York, NY: Routledge.

Jones, D. E., Greenberg, M., and Crowley, M. (2015). Early social-emotional functioning and public health: The relationship between kindergarten social competence and future wellness. *J. Inform.* 105, 2283–2290. doi: 10.2105/AJPH.2015.302630

Kagan, S. L. (1992). Readiness past, present, and future: Shaping the agenda. *Young Child.* 48, 48–53.

La Paro, K. M., and Pianta, R. C. (2000). Predicting children's competence in the early school years: a meta-analytic review. *Rev. Educ. Res.* 70, 443–484. doi: 10.3102/00346543070004443

Lee, J. (2002). Racial and ethnic achievement gap trends: Reversing the progress toward equity? *Educ. Res.* 31, 3–12. doi: 10.3102/0013189X031001003

Lei, P.-W., and Li, H. (2016). Performance of fit indices in choosing correct cognitive diagnostic models and Q-matrices. *Appl. Psychol. Meas.* 40, 405–417. doi: 10.1177/0146621616647954

Lerner, R. M. (2015). Promoting positive human development and social justice: Integrating theory, research and application in contemporary developmental science. *Int. J. Psychol.* 50, 165–173. doi: 10.1002/ijop.12162

Liew, J. (2012). Effortful control, executive functions, and education: bringing self-regulatory and social-emotional competencies to the table. *Child Dev. Perspect.* 6, 105–111. doi: 10.1111/j.1750-8606.2011.00196.x

Li-Grining, C. P., Votruba-Drzal, E., Maldonado-Carreño, C., and Haas, K. (2010). Children's early approaches to learning and academic trajectories through fifth grade. *Dev. Psychol.* 46:1062. doi: 10.1037/a0020066

Magnuson, K., and Waldfogel, J. (2016). Trends in income-related gaps in enrollment in early childhood education: 1968 to 2013. *AERA Open* 2, 1–13. doi: 10.1177/2332858416648933

McClelland, M. M., and Cameron, C. E. (2011). Self-regulation and academic achievement in elementary school children. *N. Direct. Child Adolesc. Dev.* 2011, 29–44. doi: 10.1002/cd.302

McCoach, D. B., O'connell, A. A., Reis, S. M., and Levitt, H. A. (2006). Growing readers: A hierarchical linear model of children's reading growth during the first 2 years of school. *J. Educ. Psychol.* 98:14. doi: 10.1037/0022-0663.98.1.14

McCutcheon, A. L. (1987). *Latent Class Analysis*. Thousand Oaks, CA: Sage. doi: 10.4135/9781412984713

Meng, X.-L. (1994). Posterior predictive p-values. *Ann. Stat.* 22, 1142–1160. doi: 10.1214/aos/1176325622

Montroy, J. J., Bowles, R. P., Skibbe, L. E., and Foster, T. D. (2014). Social skills and problem behaviors as mediators of the relationship between behavioral self-regulation and academic achievement. *Early Childhood Res. Q.* 29, 298–309. doi: 10.1016/j.ecresq.2014.03.002

Morgan, P. L., Farkas, G., Hillemeier, M. M., and Maczuga, S. (2016). Science achievement gaps begin very early, persist, and are largely explained by modifiable factors. *Educ. Res.* 45, 18–35. doi: 10.3102/0013189X16633182

Mulligan, G. M., Hastedt, S., and McCarroll, J. C. (2012). *First-Time Kindergartners in 2010-11: First Findings from the Kindergarten Rounds of the Early Childhood Longitudinal Study, Kindergarten Class of 2010-11 (ECLS-K: 2011).* NCES 2012-049. National Center for Education Statistics.

Muthén, L. K., and Muthén, B. O. (1998–2015). Mplus User's Guide, 8th Edn. Los Angeles, CA: Muthén & Muthén.

National Center for Health Statistics (2000). *Clinical Growth Charts*. Retrieved from: https://www.cdc.gov/growthcharts/clinical_charts.htm

National Education Goals Panel (1991). *Goal 1 Technical Planning Group Report on School Readiness*. Washington, DC: NEGP. Retrieved from https://www2.ed.gov/pubs/AchGoal1/goal1.html

Pagani, L. S., Fitzpatrick, C., Archambault, I., and Janosz, M. (2010). School readiness and later achievement: A French Canadian replication and extension. *Dev. Psychol.* 46, 984–994. doi: 10.1037/a0018881

Pretti-Frontczak, K. (2014). Stop trying to make kids "ready" for kindergarten. *Young Except. Child.* 17, 51–53. doi: 10.1177/1096250614523346

Puma, M., Bell, S., Cook, R., Heid, C., Shapiro, G., Broene, P., et al. (2010). *Head Start Impact Study*. Final Report. Administration for Children & Families.

Putnam, S. P., and Rothbart, M. K. (2006). Development of short and very short forms of the children's behavior questionnaire. *J. Pers. Assess.* 87, 102–112. doi: 10.1207/s15327752jpa8701_09

Rimm-Kaufman, S. E., Early, D. M., Cox, M. J., Saluja, G., Pianta, R. C., Bradley, R. H., et al. (2002). Early behavioral attributes and teachers' sensitivity as predictors of competent behavior in the kindergarten classroom. *J. Appl. Dev. Psychol.* 23, 451–470. doi: 10.1016/S0193-3973(02)00128-4

Romano, E., Babchishin, L., Pagani, L. S., and Kohen, D. (2010). School readiness and later achievement: replication and extension using a nationwide Canadian survey. *Dev. Psychol.* 46:995. doi: 10.1037/a0018880

Rubin, D. B. (1984). Bayesianly justifiable and relevant frequency calculations for the applied statistician. *Ann. Stat.* 12, 1151–1172. doi: 10.1214/aos/1176346785

Rupp, A. A., Templin, J., and Henson, R. A. (2010). *Diagnostic Measurement: Theory, Methods, and Applications*. New York, NY: Guilford Press.

SAS Institution (2016). *SAS Studio 3.5 User's Guide*. Retrieved from http://support.sas.com/documentation/cdl/en/webeditorug/68828/PDF/default/webeditorug.pdf

Satterthwaite, F. E. (1946). An approximate distribution of estimates of variance components. *Biometr. Bull.* 2, 110–114. doi: 10.2307/3002019

Snow, K. L. (2006). Measuring school readiness: conceptual and practical considerations. *Early Educ. Dev.* 17, 7–41. doi: 10.1207/s15566935eed1701_2

Tourangeau, K., Nord, C., Lê, T., Sorongon, A. G., and Najarian, M. (2009). *Early Childhood Longitudinal Study, Kindergarten Class of 1998-99 (ECLS-K): Combined User's Manual for the ECLS-K Eighth-Grade and K-8 Full Sample Data Files and Electronic Codebooks*. NCES 2009-004. National Center for Education Statistics.

Trentacosta, C. J., and Izard, C. E. (2007). Kindergarten children's emotion competence as a predictor of their academic competence in first grade. *Emotion* 7, 77–88. doi: 10.1037/1528-3542.7.1.77

U.S. Department of Health and Human Services (2015). *Supporting the School Readiness and Success of Young African American Boys Project: Reflections on a Culturally Responsive Strength-Based Approach*. Retrieved from: https://eclkc.ohs.acf.hhs.gov/sites/default/files/pdf/young-african-american-boys-project-guide.pdf

Valiente, C., Lemery-Chalfant, K., and Castro, K. S. (2007). Children's effortful control and academic competence: mediation through school liking. *Merrill Palmer Q.* 53, 1–25. doi: 10.1353/mpq.2007.0006

Valiente, C., Lemery-Chalfant, K., Swanson, J., and Reiser, M. (2008). Prediction of children's academic competence from their effortful control, relationships, and classroom participation. *J. Educ. Psychol.* 100, 67–77. doi: 10.1037/0022-0663.100.1.67

Welsh, J. A., Nix, R. L., Blair, C., Bierman, K. L., and Nelson, K. E. (2010). The development of cognitive skills and gains in academic school readiness for children from low-income families. *J. Educ. Psychol.* 102, 43–53. doi: 10.1037/a0016738

Wertheimer, R. F., Moore, K. A., Hair, E. C., and Croan, T. (2003). *Attending Kindergarten and Already Behind: A Statistical Portrait of Vulnerable Young Children.* Washington, DC: Child Trends. doi: 10.1037/e317232004-001

Wigfield, A., and Eccles, J. S. (2000). Expectancy-value theory of achievement motivation. *Contemp. Educ. Psychol.* 25, 68–81. doi: 10.1006/ceps.1999.1015

Winter, S. M., and Kelley, M. F. (2008). Forty years of school readiness research: What have we learned? *Childhood Educ.* 84, 260–266. doi: 10.1080/00094056.2008.10523022

Woodcock, R. W., Mather, N., McGrew, K. S., and Wendling, B. J. (2001). *Woodcock-Johnson III Tests of Cognitive Abilities*. Itasca, IL: Riverside Publishing Company.

Zelazo, P. D. (2006). The Dimensional Change Card Sort (DCCS): a method of assessing executive function in children. *Nat. Protoc.* 1:297. doi: 10.1038/nprot.2006.46

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.