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Examining Preschoolers' Trajectories of Individual Learning Behaviors: The Influence of Approaches to Learning on School Readiness

Michelle Filomena Maier
University of Miami, mmaier@psy.miami.edu

UNIVERSITY OF MIAMI

EXAMINING PRESCHOOLERS' TRAJECTORIES OF INDIVIDUAL LEARNING BEHAVIORS: THE INFLUENCE OF APPROACHES TO LEARNING ON SCHOOL READINESS

By

Michelle Filomena Maier

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Michelle Filomena Maier

Approved:

____
Daryl B. Greenfield, Ph.D.
Professor of Psychology

____
Terri A. Scandura, Ph.D.
Dean of the Graduate School

____
Rebecca J. Bulotsky-Shearer, Ph.D.
Assistant Professor of
Psychology

____
Heather A. Henderson, Ph.D.
Associate Professor of
Psychology

____
Batya E. Elbaum, Ph.D.
Associate Professor of
Teaching and Learning

____
Seth J. Schwartz, Ph.D.
Associate Professor of Epidemiology
and Public Health

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This study integrated variable- and child-centered techniques to investigate trajectories of four learning behaviors (initiative, persistence, planning, and problem-solving flexibility) and their influence on Head Start preschoolers' academic school readiness. Variable-centered findings revealed differential, quadratic growth trajectories for each of the four learning behaviors. However, where children began the year (intercept), how much they changed across the year (slope), and how much their rate of change changed across the year (quadratic) differed depending on the learning behavior. Initiative and problem-solving flexibility emerged as significant predictors of end-of-year academic school readiness skills, controlling for persistence and planning. There was no evidence of moderation of the relations between learning behaviors and academic skills by child demographic characteristics. Child-centered results provided a more nuanced description of the development of these four learning behaviors. Analyses suggested there may be subgroups of children with different developmental trajectories for each of the four learning behaviors and that these subgroups have significantly different school readiness skills at the end of the year. These findings help extend our current understanding of learning behaviors and, if replicated, may inform the content and timing of early childhood teaching practices and interventions.

This dissertation is dedicated to my parents Thomas and Francine Maier, with all of my love.

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Chapter 1: Introduction

> *...the characteristics we hope to inspire in the children with whom we work are ones that not only equip them for success in school but also prepare them to become competent, resilient, effective human beings in all areas of their lives.* *Early Head Start Resource Center (p. 1)*

Children who display enthusiasm, curiosity, initiative, persistence, and problem-solving flexibility are more likely to benefit from learning opportunities throughout their lives (DiPerna & Elliot, 2002; Hyson, 2008). These learning behaviors, or "learning-to-learn" skills, are captured in the school readiness domain entitled "Approaches to Learning" (ATL). They are considered "domain-general" skills that promote competencies across multiple domains, such as mathematics, language and literacy, as well as growth in these areas into the primary grades (e.g., DiPerna, Lei, & Reid, 2007; McDermott, 1999; Peth-Pierce, 2000). Considered teachable in the preschool classroom, learning behaviors are potential malleable competencies on which interventions aimed at improving school readiness can focus in order to place children on positive academic trajectories.

Head Start and many state early learning standards consider ATL a critical school readiness domain because it promotes learning across multiple academic areas in preschool, the primary grades, and beyond. Even though there is great interest in this domain, its role is not fully understood due to serious gaps in the literature. Currently, only two studies have examined how learning behaviors change during early childhood (Dominguez, Vitiello, Maier, & Greenfield, 2010; McDermott et al., in press). Furthermore, no published studies have explored how this change is related to school readiness outcomes in language, literacy, math, *and* science. The current study attempted to address these gaps, provide a more comprehensive understanding of ATL, and answer important questions that can inform the most appropriate content and timing of early childhood teaching practices and interventions.

The goal of this study was to investigate the influence of Head Start preschoolers' approaches to learning on school readiness by integrating variable- and child-centered techniques. The primary objective was to examine and compare preschool children's growth trajectories for four individual learning behaviors: initiative, persistence, planning, and problem-solving flexibility. A second objective was to employ a variable-centered approach to test the relations between the growth parameters of these trajectories and multiple academic school readiness outcomes. The third objective examined whether these relations were moderated by individual child factors. A fourth objective used a child-centered approach by focusing on the relations among individual preschoolers' growth trajectories; it explored whether there were groups of preschoolers with similar developmental patterns in each of the four learning behaviors and whether these groups varied in their school readiness outcomes.

The Preschool Years

The preschool years are a time of rapid growth and development academically, socially, and physically. These early years are a critical period during which children develop essential skills for establishing positive learning patterns for later school success (Alexander, Entwisle, & Dauber, 1993; National Research Council and Institute of Medicine, 2000). Developmentally appropriate practice suggests that, along with the promotion of academic competencies, preschool educators should foster the development of domain-general skills, such as learning behaviors (Hyson, 2008; Kagan, Moore, &

Bredekamp, 1995). Domain-general skills have the advantage of facilitating competencies across multiple domains in preschool and beyond. Emphasizing the development of these skills during this critical period seems especially important for low-income preschoolers who are at great risk for poor academic achievement (Jencks & Philips, 1998; Reardon, 2003).

Children from low-income families tend to enter the preschool period at an academic disadvantage (Zill et al., 2003). As a result, they begin kindergarten with lower cognitive skills in comparison to their more advantaged peers (Lee & Burkam, 2002; Ramey & Ramey, 2004). Without experiencing a high-quality preschool education, research suggests that these high-risk children are likely to start school up to two years behind their lower-risk peers (Ramey & Ramey, 2004; Stipek & Ryan, 1997). This achievement gap tends to expand over time because these children are likely to attend schools with fewer resources (Lee, Grigg, & Donahue, 2007). Research, however, has shown that children who attend high quality, comprehensive preschool programs begin kindergarten with better academic skills, thus demonstrating preschool programs' potential to ameliorate the negative effects of poverty (Lee & Burkam, 2002). In order to promote not only school readiness but also future academic achievement, enriched learning opportunities are essential early in childhood.

As a comprehensive early childhood intervention program for low-income children, Head Start is dedicated to improving children's readiness in a range of domains, such as language and literacy, mathematics, science, and ATL (U.S. Department of Health and Human Services, 2003). An emphasis on the "whole child", including enhancement of academic skills, as well as ATL, is mandated and part of the model.

Research indicates that children with relatively low cognitive skills develop more negative views of their competencies and more negative attitudes toward school over time (Stipek & Ryan, 1997). Early childhood programs, therefore, aim to prevent the self-perpetuating cycle of lower skills leading to less motivation and enthusiasm for learning in an attempt to place every child on a successful academic trajectory. This is a challenging task; early childhood programs must simultaneously promote a multitude of competencies including cognitive skills, domain-specific skills, social and emotional skills, and approaches to learning. Therefore, ATL are a perfect set of skills to promote in this context because they are domain-general skills that can promote the development of a variety of other school readiness skills.

Learning Behaviors

"Approaches to Learning" (ATL) is a term coined by the National Education Goals Panel and has been adopted as an important school readiness domain by Head Start and many state school readiness standards (Kagan et al., 1995; U.S. Department of Health and Human Services, 2003). ATL, also referred to as learning behaviors or "learning-to-learn" skills, are the ways children think about and engage in learning situations and, ultimately, benefit from such learning opportunities (DiPerna & Elliot, 2002).

Learning behaviors are hypothesized to be observable and teachable behaviors that can help strengthen abilities and facilitate learning across other school readiness domains (Hyson, 2008). This hypothesis is based on a developmental-ecological model of school readiness that focuses on the "whole child" and emphasizes the dynamic interactions between a child and the many characteristics of the changing contexts (or levels of organization) within which the child is embedded (Lerner & Castellino, 2002). Changes within one context are reciprocally related to changes within other levels (Lerner & Castellino, 2002). Within this framework, school readiness may be seen as an accumulation of experiences wherein children build upon previously learned information. When engaged in a learning situation, children utilize many skills and competencies across different school readiness domains (e.g., language development, physical health, social and emotional; Cicchetti & Toth, 1997; McWayne, Fantuzzo, & McDermott, 2004; Snow, 2007). Thus, this perspective conjectures that children's emerging competencies work together to promote development; abilities in one domain can help enhance learning of concepts and development of skills in other domains. For example, a specific mathematic skill such as being able to count may facilitate an understanding of how to measure an object during science time. Learning behaviors such as initiative, persistence, planning, and problem-solving flexibility are perhaps the most domain-general of all skills and, therefore, are hypothesized as foundational skills for ***all*** learning (Hyson, 2008).

A growing body of research supports this hypothesis, indicating that learning behaviors are significantly related to competencies in other school readiness domains and, therefore, may be a very important influence on classroom learning (DiPerna et al., 2007; McDermott, 1999; McDermott, Leigh, & Perry, 2002; Peth-Pierce, 2000). Learning behaviors predict success in language, mathematics, and social skills, above and beyond intelligence or cognitive ability (McDermott, 1999; McDermott et al., 2002). Other studies have revealed that learning behaviors are uniquely related to concurrent reading and mathematics scores as well as growth in these skills between kindergarten and second grade (McClelland, Acock, & Morrison, 2006; McClelland, Morrison, & Holmes, 2000). Similarly, learning behaviors have been shown to have a positive effect on growth in mathematic skills from kindergarten to third grade (DiPerna et al., 2007). A recent study focusing on the direction of effects between learning behaviors and literacy skills found that learning-related behaviors (such as working independently, seeking challenges, accepting responsibility, and paying attention) were positively associated with literacy in third grade, controlling for kindergarten and first grade literacy, gender, ethnicity, and family income (Stipek, Newton, & Chudgar, 2010). Similarly, learning behaviors in third grade were positively related to literacy in fifth grade. Stipek and colleagues (2010) also found some support for a "multiplicative effect of beginning school with strong learning-related behaviors" (p. 392), suggesting that more adaptive learning behaviors early on in a child's educational trajectory lead to better literacy skills, which in turn strengthen learning behaviors.

Development of Learning Behaviors

Learning behaviors begin to develop at an early age; even young infants are enthusiastic and engaged in the world around them (Hyson, 2008). Many children develop positive learning behaviors during the preschool years, especially if they are in supportive environments. For example, children become better able to sustain attention despite distractions and, therefore, become more able to persist at tasks and activities (Hyson, 2008). Around three years of age, children can complete short-term, concrete tasks, but by four and five years of age, they can perform longer-term and more abstract tasks such as finishing an art project started the previous day or setting a goal and following a plan (Hyson, 2008). Additionally, children begin to seek out and engage in new challenges and activities. They become more flexible in how they approach problems and are able to generate several possible alternatives and solutions (Hyson, 2008).

Researchers have traced the early development of some learning behaviors such as motivation, attention, and problem solving and found, via cross-sectional studies, that the maturity and efficiency of these competencies increase with age. For example, children's mastery motivation, or the desire to affect or master the environment, starts with infant exploration, and by around nine months of age, infants try to control toys and perform simple, goal-directed behaviors; as toddlers, children show more self-consciousness and self-awareness in the behaviors they exhibit (Barrett, Morgan, & Maslin-Cole, 1993). Research on the development of attention indicates that there are age-related changes in the nature of attention as children mature. For example, studies have found increases in children's ability to focus attention and decreases in distractibility from toddlerhood into preschool (Ruff & Capozzoli, 2003; Ruff & Lawson, 1990).

Additionally, studies on children's problem solving show similar developmental patterns. Although six-month-old infants may be able to 'solve' a problem (i.e., use a cloth to retrieve a toy that is out of reach), they do not always do so intentionally, but by eight months, they are less likely to play with the cloth and instead use it to bring the toy closer (Willatts, 1990). However, young infants are unable to use these problem solving skills for more difficult tasks. One study has shown that while 17-month-old children show little specific, goal-directed behavior when asked to use blocks to copy a house built by adults, most two-year-olds are able to do so (Bullock & Lutkenhaus, 1988).

Similarly, kindergartners and older preschoolers, in comparison to younger preschoolers, utilize more complex problem solving strategies to complete difficult tasks (Siegler, 2000; Zelazo, 2000).

Building on these cross-sectional findings, two recent studies have explicitly examined change in Head Start preschoolers' learning behaviors. The first found *linear* growth in global learning behavior scores over the course of one year in two samples of Head Start preschoolers – a large, statewide database and a smaller, local sample of four-year-old Head Start preschoolers (Dominguez, Vitiello, Maier, & Greenfield, 2010). This study also examined child- and classroom-level predictors of this growth, finding that shy children started the year with less adaptive learning behaviors and a supportive preschool environment, particularly one that is well-organized, fostered more growth in positive learning behaviors. The second study also found change over time in both a general factor of learning behaviors (a global learning behaviors score) as well as seven specific subtypes (labeled as strategic planning, effectiveness motivation, sustained focus in learning, vocal engagement in learning, interpersonal responsiveness in learning, acceptance of novelty and risk, and group learning; McDermott et al., in press). Similar to the Dominguez et al. (2010) study, McDermott and colleagues found linear growth over two years for global learning behavior scores. For each of the subtypes, however, they found non-linear growth across the two years (positive linear and cubic growth parameters and negative quadratic parameters); children's scores on the learning behavior subtypes increased, plateaued over the summer months, and increased again during the second preschool year. They also examined the relations among the subtypes and cognitive ability in language, literacy, and math, finding moderate correlations.

Additionally, they found that having stronger learning behaviors (higher scores on the general factor and most of the subtypes) reduced the risk of non-proficiency in cognitive skills at the end of the second preschool year (McDermott et al., in press).

Further empirical research on the developmental trajectories of *individual* learning behaviors, however, is needed. To extend the cross-sectional research on young children's early learning competencies and the two longitudinal studies on change in learning behaviors, the current study longitudinally examined four individual learning behaviors (initiative, persistence, planning, and problem-solving flexibility) during the preschool period. Further, it investigated the influence of these learning behaviors on academic school readiness by integrating variable- and child-focused techniques.

Variable-focused Approach

A variable-focused approach to data analysis focuses on relations among variables with the goal of predicting outcomes (Muthén & Muthén, 2000). The current project examined the influence of initial scores and growth in individual learning behaviors on multiple, academic school readiness outcomes. Different learning behaviors may be important for preschoolers' outcomes depending on academic domain. For example, one study of Head Start preschoolers found differences in the roles persistence and initiative played in relation to different academic outcomes (Maier, 2008). Persistence was shown to be more important than initiative for mathematics outcomes, specifically. Although learning behaviors are often hypothesized to be domain-general, by facilitating learning across *all* school readiness domains, Maier (2008) provided evidence that this assumption must be empirically tested. The current study sought to expand previous research by examining whether initial scores and/or growth in four specific learning behaviors related differentially to multiple school readiness outcomes.

The relations between growth in individual learning behaviors and school readiness outcomes may be influenced by variables such as children's age, sex, or ethnicity. Age-related differences have been found in the learning behaviors of initiative and persistence, suggesting that older preschoolers have more adaptive learning behaviors (Maier, 2008). Further, girls may be better able to pay attention and persist at tasks than boys (McWayne et al., 2004), which may result in greater academic success in comparison to boys. In fact, research has shown that in kindergarten these sex differences in early learning behaviors explain girls' literacy advantage over boys (Ready, LoGerfo, Burkman, & Lee, 2005). Research on learning behaviors in children ages 5 to 17 has found some differences in learning behaviors by ethnicity; in comparison to White children, African American children were more likely to be viewed by teachers as less attentive and Hispanic children more likely to be viewed by teachers as hesitant when providing answers (Schaefer, 2004). In contrast, a study examining the relation between learning behaviors and academic achievement beyond cognitive ability in children ages 6 to 17 found that the form and strength of the relation between learning behaviors and academic achievement was the same across ethnicity and sex (Yen, Konold, & McDermott, 2004). In an attempt to clarify these contradictory findings, the current study also investigated whether child variables, such as age, sex, and ethnicity, moderated the relations between growth in learning behaviors and academic school readiness.

Child-focused Approach

Complementing variable-focused techniques (examining the relations among variables) with child-focused approaches that consider intragroup variation and focus on relations among individuals is important for data analysis (Muthén & Muthén, 2000). Conventional growth modeling assumes children are from a single population and, therefore, a single growth trajectory satisfactorily describes that population (Jung & Wickrama, 2007). However, there may be unobserved heterogeneity (i.e., different subgroups, or classes) within the population, invalidating this assumption and oversimplifying the different growth patterns that may represent continuity and change among children in different subgroups (Jung & Wickrama, 2007). A person-centered approach, such as growth mixture modeling, can more fully capture information about interindividual differences in intraindividual change because it can categorize children into distinct groups based on similarities in their growth trajectories. Such research is especially important for children at risk, as child-centered analyses may help in accurately portraying children's development (e.g., Aber, Gephart, Brooks-Gunn, & Connell, 1997; McWayne et al., 2004; Roeser, Eccles, & Sameroff, 1998).

One previous study utilized growth mixture modeling to examine former Head Start children's reading and math achievement in primary school, finding evidence for heterogeneous growth trajectories from first through third grade (Kreisman, 2003). Specifically, Kreisman (2003) found two groups that represented different developmental trajectories for both reading and math: one group that started with slightly below average achievement, with a slight to moderate decline by third grade; the other group started with extremely low achievement, with a steady improvement to third grade. Although this study focused on the developmental trajectories of children's academic skills, rather than learning behaviors, and did not examine the children while they were in Head Start, it is likely that these differential trajectories for school readiness skills began in preschool. Therefore, this study highlights the importance of not assuming one common pattern of growth in school readiness skills for all Head Start children.

Although the Kreisman (2003) study examined academic skills and not learning behaviors, there was one previous study that applied a child-centered approach when examining learning behaviors. Using hierarchical cluster analysis, Head Start preschoolers were grouped by common learning behavior profiles (Angelo, 2006). Additionally, the relation between these groups and kindergarten and first-grade academic outcomes was investigated. Analyses produced six distinct learning behavior types: *Advanced Proficient*, *Proficient High Attention and Attitude*, *Proficient High Motivation*, *Less Proficient Low Motivation*, *Less Proficient Low Attention and Attitude*, and *Deficient* (Angelo, 2006). The children in the most adaptive types had better outcomes in kindergarten and first grade. The subgroups also differed based on sex and age, with the *Advanced Proficient* type including more girls and more five-year-olds than expected, and the *Less Proficient* type including more boys. In addition, the *Less Proficient Low Attention* and *Deficient* types contained more three-year-olds than expected. These results are consistent with research indicating that girls and older preschoolers tend to have more positive learning behaviors (Childs & McKay, 2001; McWayne et al., 2004; Schaefer, 2004). Furthermore, these child-focused analyses provide valuable information about subgroups of preschoolers, particularly regarding potential risk for negative academic outcomes (Angelo, 2006).

Although Angelo's (2006) study offers useful descriptive and predictive information regarding profiles of learning behaviors, child-centered analyses have not yet been utilized in the context of *specific* learning behavior growth. The current study explored whether distinct patterns of growth in *specific* learning behaviors could be empirically identified and, further, whether these differential patterns of growth were related to academic school readiness outcomes at the end of the year. Identifying specific groups of children with similar developmental patterns in an individual learning behavior is a critical step for determining differentiated and targeted instruction in Head Start.

Summary

Current research has established that learning behaviors (1) are part of a school readiness domain of great importance to Head Start and many early childhood programs, (2) are positive influences on other school readiness domains, such as mathematics and language and literacy, and (3) are developing during the preschool period. However, many of these studies have examined learning behaviors at only one point in time as either predictors or outcomes. While two studies have examined overall change in learning behaviors (Dominguez et al., 2010; McDermott et al., in press) and one study has focused on change in specific subtypes of learning behaviors (McDermott et al., in press), more empirical research is needed. Further, little research has examined whether different learning behaviors have the same effect on different academic school readiness domains. Finally, no studies have explored whether there are groups of preschoolers with similar developmental patterns of individual learning behaviors and whether these groups differ in their school readiness.

Current Study

This purpose of the current study was to (1) examine change in four preschool learning behaviors across the school year and (2) investigate the influence of these learning behaviors on multiple academic readiness skills by integrating variable- and child-centered techniques. The current study addressed the following four research questions in a sample of three- to five-year old Head Start children:

1. *How do initiative, persistence, planning, and problem-solving flexibility change over the course of the preschool year?* It was hypothesized that children would show positive change in each learning behavior over the course of the preschool year and that there would be differences in the rates of change across the four learning behaviors.
2. *Is change in individual learning behaviors associated with variations in other school readiness domains?* It was expected that change in each learning behavior would be positively associated with school readiness outcomes. Given past research showing that persistence, in comparison to initiative, was more related to mathematics outcomes, it was expected that persistence would predict math outcomes more strongly than the other domains.
3. *Do individual child factors moderate the influence of change in specific learning behaviors on other school readiness domains?* Given previous research findings indicating that older children and female preschoolers tend to exhibit more positive learning behaviors, it was hypothesized that that the effect of change in learning behaviors on outcomes would be stronger for older children and for girls. No specific moderation hypotheses were posited for child ethnicity.

4. *Are there subgroups of preschoolers with similar developmental patterns? Do these subgroups vary in their school readiness?* It was hypothesized that these analyses would find subgroups of preschoolers with similar developmental patterns in individual learning behaviors and that these subgroups would vary in their school readiness. Specific hypotheses regarding what the subgroups would look like were not posited.

Chapter 2: Method

Participants

Data for the current study were collected on 279 preschoolers from 30 classrooms in six centers in a large Head Start Program in Miami-Dade County. One center with two classrooms was excluded from the current study because its computers did not have internet access and, therefore, its teachers were unable to report on children's learning behaviors. This resulted in a final sample of 260 preschoolers from 28 classrooms in five centers. Children's ages at the beginning of the school year ranged from 36 to 59 months (M = 48.07, SD = 6.49). Fifty-one percent were female. Sixty seven percent were Black or African American, 25% Hispanic or Latino, 5% White, 2% Asian, and 1% did not report ethnicity. All children met the poverty eligibility criteria for the Head Start Program.

All 28 lead teachers were female; 18 were Hispanic or Latino (64.3%), 8 were Black or African American (28.6%), 1 was Asian (3.6%), and 1 did not report ethnicity. Teachers reported the number of years they had been a preschool teacher, which ranged from 0 to 30 years (M = 12, SD = 8). All but one teacher reported highest education level obtained: 10 teachers completed a CDA (Child Development Associate credential) or other associate's degree (35.7%), 14 completed a bachelor's degree (50.0%), and 3 completed a master's degree (10.7%).

Procedure

The six Head Start centers were selected from a pool of centers that met the following criteria: (1) were located within 20 miles of the university's campus, (2) had at least two Head Start classrooms, and (3) were using the online version of the Galileo

System for the Electronic Management of Learning. Thirty classrooms across the six centers consented to participate. After IRB approval, the research team notified center directors and teachers and explained the project. After directors and teachers consented, parent information letters were sent home to all children in the sample. Parents who did not want their child to participate were asked to sign the information letter and return it to their child's teacher. Children were selected by first stratifying each classroom by age and gender and then randomly selecting 10 children per classroom so that there would be an even number of boys and girls as well as younger and older preschoolers.

Learning behaviors were assessed throughout the school year by teachers, as part of the routine assessment conducted throughout this Head Start program. Teachers are required to update each child's school readiness progress, including their learning behaviors score, at least three times during the year (at the beginning, middle, and end of the year). Because the program asks teachers to update a child's score whenever they see evidence of growth, many children have more than three time points. These administrative data, along with student demographic information, were requested at the end of the school year by the researchers.

Direct assessments of the academic outcomes (science, mathematics, and language and literacy) were collected by independent, trained assessors in the spring semester of the school year. The measure of language and literacy and mathematics was collected first, followed by the science assessment. Before each assessment, children provided verbal assent as they were asked if they wanted "to come and play some games". After each assessment, children were given stickers for their participation.

Measures

Learning behaviors. Teachers completed the Approaches to Learning subscale of the Galileo System for the Electronic Management of Learning (Galileo; Bergan et al., 2003) throughout the year. Teachers are trained to complete the Galileo in accordance with typical Head Start procedures in the local Head Start programs. The Galileo is an Item Response Theory (IRT)-based measure that allows teachers to assess and track the growth and development of children's skills across the eight school readiness domains established by Federal Head Start standards, including Approaches to Learning (U.S. Department of Health and Human Services, 2003).

Galileo's items are aligned specifically with the Head Start Child Outcomes Framework (U. S. Department of Health and Human Services, 2003). The developers of Galileo itemized the broad, general indicators under each Head Start school readiness domain into specific, observable items on which children could be easily rated. Each domain has several subskills with multiple items that represent important skills for that domain (e.g., "maintains interest in an activity for an appropriate period of time"). The items are binary and ordered by difficulty. Teachers indicate whether or not the child has mastered a given item.

The Approaches to Learning domain has 30 items across five subscales (*initiative and curiosity*, *learning about objects and events*, *engagement and persistence*, *goal setting and planning*, and *reasoning and problem solving*), allowing more specific and observable definitions of specific learning behaviors (see Table 1 for a list of the items). Because learning about objects and events is not one of the learning behaviors under investigation in the proposed study, the items from this subscale were not used. For the current study, raw scores on each of the subscales were used.

Factor analytic studies conducted by the developers provide support for the validity of the structure of the Approaches to Learning scale. All items loaded significantly on their assigned subscale, with loadings ranging from .54 to 1.00 (Bergan, Guerrera Burnham, Feld, & Bergan, 2009). Additionally, the five subscales significantly loaded on a single underlying factor (Approaches to Learning), with loadings ranging from .39 to .90 (Bergan et al., 2009). Cronbach's alpha for the ATL subscale has been reported as .94, indicating a high level of internal consistency (Bergan et al., 2009).

Academic school readiness. Language and literacy, as well as mathematic, skills were directly assessed using the Learning Express (McDermott, Fantuzzo, Waterman, Angelo, Warley, Gadsden, et al., 2009), a criterion-referenced direct assessment of school readiness. This is a newly developed tool that is one of the only academic assessments designed and validated specifically for low-income, at-risk preschool children. Although this measure is sensitive to change over time (McDermott et al., 2009), it was only used in the current study as an outcome measure. Children were assessed individually by a trained assessor using a large flip-book of pages that depict pictures, letters, and/or numbers. The assessor reads a prompt and asks the child to respond either by pointing to or verbalizing an answer. The test has four subscales that are administered in this order: Vocabulary (58 items), Mathematics (57 items), Listening Comprehension (37 items), and Alphabet Knowledge (52 items). There are two equated forms of the test (A and B), allowing for valid and reliable retesting. Each subscale includes a set of items ordered by difficulty, and each item is scored as either correct or incorrect. Raw scores are converted to an interval-level score according to IRT analysis.

Science outcomes were directly assessed using an IRT-based instrument, the Science Assessment (Greenfield, Dominguez, Greenberg, Fuccillo, Maier, & Penfield, 2010). Children were assessed individually by a trained assessor using a large flip-book of picture pages. The assessor reads a prompt and asks the child to respond by pointing, verbalizing, sequencing, measuring, or sorting. Because there currently are no measures of preschool science, this direct assessment of preschoolers' science content knowledge and process skills was recently developed and designed specifically for use with Head Start preschoolers. Development of the Science Assessment was supported by a three-year Institute of Education Sciences development grant.

Preliminary analyses indicate that the assessment is sensitive to detecting change across the school year (Greenfield et al., 2010). Additionally, scores on the Science Assessment have been shown to be positively correlated (.48 to .66) with math, vocabulary, listening comprehension, and alphabet knowledge skills (as assessed by the Learning Express) and vocabulary skills (as assessed by the Peabody Picture Vocabulary Test; Greenfield, Dominguez, Fuccillo, Maier, & Greenberg, 2009).

Data Analytic Plan

Structure of data. Data for the current study had a hierarchical structure in which preschoolers were nested in classrooms. The learning behaviors data were in repeated-measures form, in which individual measurements of learning behaviors were nested within children, and children were nested within classrooms. Additionally, there were missing observations and unequally spaced observations across preschoolers. The number of observations of learning behaviors ranged from 2 to 31 (M = 14.30, SD = 7.15). In order to make the data more manageable, the time structure of the learning behaviors data was modified to make five equally-spaced "buckets" across the year (Time point 1 = August 18 – October 15; Time point 2 = October 16 – December 15; Time point 3 = December 16 – February 15; Time point 4 = February 16 – April 15; and Time point 5 = April 16 – June 12). For each child, the total number of items reported as 'mastered' within each bucket (i.e., a two month period) was counted. If a child did not have any scores within a given bucket's time period, the child was considered to have missing data for that time point.

Data analysis approach. Structural equation modeling (SEM) was chosen for the data analytic approach because it allowed for the examination of growth over time, permitted the inclusion of simultaneous observed and/or latent outcomes in a single model, and was capable of executing growth mixture modeling analyses (Kline, 2005). All analyses were conducted in M*plus* Version 6, and the multilevel nature of the data was taken into account by using a sandwich estimator to compute standard errors (Muthén & Muthén, 2007). To account for missing data, full information maximum likelihood estimation was used to estimate parameters under the assumption that data were missing at random (e.g., McArdle et al., 2004). This type of estimation uses all available data for each case when estimating parameters and, therefore, increases the statistical power of estimated parameters (Enders & Bandalos, 2001).

For all analyses, fit of the model to the data (i.e., whether the proposed functional form was consistent with the data) was evaluated using standard fit indices: chi-square (χ^2), comparative fit index (CFI), standardized root mean square residual (SRMR), and root mean square error of approximation (RMSEA). A nonsignificant chi-square, a CFI of .90 or greater, a SRMR of .08 or lower, and a RMSEA of .08 or lower reflect good model fit (Kline, 2005).

Analyses. Analyses were conducted to answer the primary questions of this study as follows:

1. *How do the learning behaviors of initiative, persistence, planning, and problem-solving flexibility change over the course of the preschool year?*

Multilevel latent growth modeling was used to examine change over the course of one year in four learning behaviors. A separate multilevel latent growth model was conducted for each learning behavior, given the mathematical complexity involved in estimating several growth models in a single analysis. Multilevel modeling was used only to account for the nestedness of the data; no child- or classroom-level predictors were included in these models.

Several different models were conducted for each learning behavior: no growth model, linear growth model, and nonlinear growth models (i.e., latent basis model, quadratic growth model, and cubic growth model). In a latent basis model, all but two time points are freely estimated, allowing the 'shape' of the nonlinear change to be estimated in an exploratory, data-driven way (Ram & Grimm, 2007) rather than forcing the 'shape' to be quadratic or cubic. In the current study, the second, third, and fourth time points were freely estimated. Models were first conducted with error variances constrained to be equal across time, a common assumption in hierarchical linear modeling (Llabre, Spitzer, Siegel, Saab, & Schneiderman, 2004). Next, models were conducted allowing error variances to vary across time. Model fit was assessed using the previously discussed standard fit indices, and nested models were compared using chi-square difference tests. Because the models took into account the hierarchical structure of the data, the Satorra-Bentler scaled chi-square test was used (Satorra & Bentler, 2001).

2. Is change in individual learning behaviors associated with variations in other school readiness domains?

A "multistep" model fitting approach (Ram et al., 2005) was used to examine whether baseline scores and change over time in each learning behavior differentially related to academic school readiness outcomes:

Latent growth modeling. First, when the four best-fitting growth models from the previous question were determined, the individual child intercept and growth estimates (slope and quadratic) estimated from M*plus* were saved to a data file (cf. Ram et al., 2005).

Confirmatory factor analysis. Second, three of the academic outcomes from the Learning Express (vocabulary, listening comprehension, and alphabet knowledge) were combined into a latent variable representing children's language and literacy outcomes. Latent variables are measured indirectly through the variance that is shared between several observed variables (i.e., vocabulary, listening comprehension, and alphabet in the current study) using confirmatory factor analysis. This model is just identified, and therefore model fit was not assessed.

Structural model. Third, the intercept and growth estimates from Question 1 were entered as predictors in a structural equation model of the two observed academic school readiness outcomes, science and mathematics; and the language and literacy latent variable. Due to multicolinearity between the language and literacy latent and the other two school readiness outcomes (*r* = .81 for mathematics and *r* = .91 for science), this model was unable to converge. Therefore, two separate structural models were conducted: one with the language and literacy latent variable as the outcome and the other with both math and science scores as outcomes. These structural models took into account the multilevel nature of the data. Model fit was also determined through the previously discussed standard fit indices.

3. *Do individual child factors moderate the influence of change in specific learning behaviors on other school readiness domains?*

To examine this question, three subgroup comparisons (across age, sex, and ethnicity) were explored using multiple group analysis with the final models retained from Question 2. This allowed for examination of which relations (i.e., path coefficients), if any, differed based on age, sex, and/or ethnicity. When using multiple group analysis, models were estimated within each group concurrently. The path coefficients were specified first to be constrained equal across the groups (three-year-olds vs. four- and five-year-olds [henceforth called "four-year-olds"]; males vs. females; African American/Black vs. Hispanic/Latino). If the model with all paths constrained equal across the two groups did not fit the data well, then models that freely estimated individual path coefficients were tested. These multilevel, nested models were compared using the Satorra-Bentler scaled chi-square difference test (Satorra & Bentler, 2001).

4. *Are there subgroups of preschoolers with similar developmental patterns? Do these subgroups vary in their school readiness?*

Multilevel latent growth mixture modeling (LGMM; Muthén & Muthén, 2000) was used to determine whether distinct subgroups, or classes, of preschoolers can be empirically identified based on their baseline scores and growth trajectories for each learning behavior. LGMM can be viewed as a confirmatory form of cluster analysis (Muthén, Khoo, Francis, & Boscardin, 2003). For each learning behavior, the analysis empirically grouped preschoolers according to similarities in their intercepts and slopes, allowing identification of distinct classes of preschoolers. Unlike latent class growth analysis which assumes that the individual growth trajectories within any given class are homogenous, growth mixture modeling is more flexible as it allows variation in the mean intercept and growth estimates within each class (Jung & Wickrama, 2008). This approach uses an iterative process to attain parameter estimates as well as posterior estimates of the probability of each child's membership in each of the possible classes (Ram & Grimm, 2007).

First, 2-class solutions (labeled "2-$\text{Class}_{\text{Means}}$") that allowed only the mean growth parameters (intercept, slope, and quadratic) to be freely estimated between the two classes were conducted for each learning behavior. The model fit of this 2-class solution was compared to the model fit of the 1-class baseline model (i.e., the final models from Question 1) by (1) conducting a chi-square difference test based on loglikelihood values and scaling correction factors, (2) using relative fit information criteria, including the Bayesian Information Criterion (BIC), Akaike Information Criteria (AIC), and Adjusted BIC (ABIC; Burnham & Anderson, 2004; Ram & Grimm, 2009; Schwartz, Mason, Pantin, & Szapocznik, 2009), and (3) using the Adjusted Lo-Mendell-Rubin likelihood ratio test (LMR-LRT), which compares the current model to a model with one fewer class (Nylund, Asparouhov, & Muthén, 2007). A significant loglikelihood difference test, a significant LMR-LRT, and lower values on the relative fit information criteria all indicate better fit (Muthén, 2003; Nylund et al., 2007); Raftery (1995) specifies that BIC differences of 10 or greater can be regarded as important.

If after examining the fit indices it was deemed that a 2-Class$_{\text{Means}}$ solution could reasonably fit the data, 2-, 3-, and 4-class solutions were estimated. For each number of classes, different models were specified that allowed for differences between the classes in: (1) the intercept, slope, and quadratic *means*, (2) intercept, slope, and quadratic *means + variances*, (3) intercept, slope, and quadratic *means + variances + latent variable covariances*, and (4) intercept, slope, and quadratic *means + variances + latent variable covariances + residual variances*. In order to determine the most reasonable representation of the observed data, these models were compared using the BIC, AIC, Adjusted BIC, and the Adjusted LMR-LRT. Furthermore, classification quality was considered by examining the entropy values, or summary values of the individual class probabilities (Muthén, 2004). Possible values for entropy range from 0 to 1, and higher values signify greater accuracy of the class solution (Hix-Small, Duncan, Duncan, & Okut, 2004).

Finally, the class solution that was deemed the most reasonable representation of the observed data was retained and distal outcomes (academic school readiness outcomes in mathematics, science, and language and literacy) were added to the model in order to determine whether the classes varied in their school readiness. The Wald chi-square test was used to examine whether the class means on the school readiness outcomes were significantly different from one another (Asparouhov, 2007).

Chapter 3: Results

Preliminary analyses were conducted to examine all variables for outliers, normality, skewness, and kurtosis. Descriptive statistics for child age and the academic school readiness outcomes can be found in Table 2. Bivariate correlations can be found in Table 3. All academic school readiness outcomes were significantly and positively correlated with one another and with child age.

Question 1: Change over Time

In order to examine change over time in initiative, persistence, planning, and problem-solving flexibility, several multilevel latent growth curve models (with error variances both constrained and unconstrained across time) were conducted for each learning behavior: no growth model, linear growth model, quadratic growth model, cubic growth model, and latent basis model. See Table 4 for the model fit indices for the models that converged normally. For initiative, the best fitting model was the quadratic model in which error variances were freely estimated across time. The Satorra-Bentler scaled chi-square different test indicated that this initiative model provided a significantly better fit than a quadratic model with constrained error variances, $\chi^2\ \Delta\ (4, N = 260) = 11.909, p = .018$. For persistence, planning, and problem-solving flexibility, the best fitting models were quadratic models with error variances constrained across time. Although the model fit indices for the cubic models with constrained error variances looked excellent, these models did not provide significantly better fit over the more parsimonious quadratic models, $\chi^2\ \Delta\ (5, N = 260) = 10.311, p = .07$; $\chi^2\ \Delta\ (5, N = 260) = 4.770, p = .445$; and $\chi^2\ \Delta\ (5, N = 260) = 4.094, p = .536$ for the persistence, planning, and problem-solving flexibility models, respectively.

For all four learning behaviors, the slope estimates were positive and significant, indicating that children's initiative, persistence, planning, and problem-solving flexibility scores increased by .93, .70, .41, and .33 points, respectively, every two months. The mean quadratic estimates were significant for initiative and problem-solving flexibility but not for persistence and planning. Although the mean quadratic estimates for persistence and planning were not significantly different from zero, there was significant variability in the quadratic estimates across children. The quadratic estimate for initiative was negative (-.10), suggesting that change in initiative slowed down over time. The quadratic estimate for problem-solving flexibility, however, was positive (.08), indicating that change in problem-solving flexibility skills increased at a slightly faster rate over time. There was significant variance in children's initial scores and in both the slope and quadratic estimates for each learning behavior. See Table 5 for the growth parameter estimates associated with the final latent growth models conducted for each learning behavior.

Question 2: Prediction to Academic School Readiness

A "multistep" model fitting approach (Ram et al., 2005) was used to examine whether the growth parameters associated with each learning behavior differentially related to academic school readiness outcomes. First, the individual intercept and growth parameters estimated for each child in the previous analyses were saved to a data file. These estimates were then used in a structural equation model as predictors of a latent variable of language and literacy as well as of math and science scores.

Confirmatory factor analysis. Using confirmatory factor analysis, three of the academic outcomes from the Learning Express (vocabulary, listening comprehension, and alphabet knowledge) were used as indicators of a latent variable representing children's language and literacy. All three indicators loaded significantly and positively onto the latent variable, with standardized loadings of .73, .72, and .60 for vocabulary, listening comprehension, and alphabet scales, respectively. Because this model is just identified, model fit indices were unavailable.

Structural models. Finally, the intercept and growth estimates for all four learning behaviors were entered as predictors of school readiness outcomes. First, they were simultaneously entered as predictors of the language and literacy latent factor and, second, of the two observed academic school readiness outcomes, science and mathematics. For the model with the language and literacy latent variable as the outcome, the initiative intercept (B = 8.45, SE = 3.63, p = .02), initiative slope (B = 54.14, SE = 23.73, p = .02), initiative quadratic slope (B = 259.91, SE = 124.48, p = .04), and problem-solving flexibility quadratic slope (B = 76.17, SE = 32.04, p = .02) significantly predicted language and literacy, controlling for the other learning behaviors. For every one-point change in the initiative intercept, there was an 8.45-point increase in the language and literacy outcome at the end of the year. For every 0.01-point change in the initiative slope, there was a 0.54-point increase in the language and literacy outcome at the end of the year. For every 0.01-point change in the initiative quadratic slope, there was a 2.60-point increase in the language and literacy outcome at the end of the year. For every 0.01-point change in the problem-solving flexibility quadratic slope, there was a 0.76-point increase in language and literacy. The inclusion of these variables explained 26% of the variance in the language and literacy latent variable. Model fit indices indicated excellent fit of the model to the data, χ^2 (24, N = 255) = 19.548, p = .72; CFI =

1.00, RMSEA = 0.00, SRMR = .02. See Figure 1 for a graphical representation of these results.

For the model with math and science scores as the outcome measures, the initiative intercept (*B* = 9.26, *SE* = 4.40, *p* = .04), initiative slope (*B* = 51.91, *SE* = 25.76, *p* = .04), initiative quadratic slope (*B* = 292.56, *SE* = 138.51, *p* = .04), and problem-solving flexibility quadratic slope (*B* = 93.67, *SE* = 39.23, *p* = .02) significantly predicted math outcomes, controlling for the other learning behaviors. For every one-point increase in the initiative intercept, there was a 9.26-point increase in math outcomes. For every 0.01-point increase in the initiative slope, there was a 0.52-point increase in math. For every 0.01-point increase in the initiative quadratic slope, there was a 2.93-point increase in math. For every 0.01-point increase in the problem-solving flexibility quadratic slope, there was a 0.94-point increase in math.

Finally, the problem-solving flexibility slope (*B* = 28.37, *SE* = 12.08, *p* = .02) and quadratic slope (*B* = 139.70, *SE* = 45.74, *p* = .002) significantly predicted science outcomes, controlling for the other learning behaviors. For every 0.01-point increase in the problem-solving flexibility slope, there was a 0.28-point increase in science. For every 0.01-point increase in the problem-solving flexibility quadratic slope, there was a 1.40-point increase in science. Learning behaviors explained 22% of the variance in the math outcomes and 18% of the variance in science outcomes. Because this model was just identified, model fit indices were unavailable. See Figure 2 for a graphical representation of these results.

Question 3: Moderation by Child Factors

To examine whether any relationships among learning behaviors and academic school readiness outcomes differed by child demographics, three group comparisons (across age, sex, and ethnicity) were conducted using multiple group analysis with the two final models retained from Question 2. Before group comparisons were examined, however, the language and literacy latent variable was tested for measurement invariance across age, sex, and ethnicity. This was done to ensure that the structure of the latent variable was equivalent across groups (three-year-olds vs. four-year-olds; males vs. females; African American/Black vs. Hispanic/Latino) before any further comparisons were made.

Measurement invariance of the language and literacy latent variable. Metric, scalar, and unique invariance (equivalence of factor loadings, variable intercepts, and residual variances across groups, respectively) were examined. Invariance of factor loadings indicates that the factor loadings are equivalent across groups and that the magnitude of the relationships between the observed variables (Learning Express scales) and the latent variable (language and literacy) are the same across groups (Brown, 2006). Invariance of intercepts indicates that the intercepts of the regression equations of the observed variables on the latent factor are equivalent across groups (Schmitt & Kuljanin, 2008). Invariance of residual variances shows that the variance left unexplained by the common factor in each of the three observed variables is the same across groups.

A model with loadings, intercepts, and residual variances constrained to be equal across males and females fit the data well, χ^2 (7, N = 255) = 12.98, p = .07; CFI = .96, RMSEA = .08, SRMR = .17, indicating measurement invariance of the language and literacy latent variable across sex. A model with loadings, intercepts, and residual variances constrained to be equal across three- and four-year-olds indicated somewhat adequate fit to the data, χ^2 (7, N = 255) = 15.815, p = .03; CFI = .89, RMSEA = 0.10, SRMR = .21. After allowing loadings, intercepts, and residual variances to vary one at a time, a model freely estimating the intercept associated with the alphabet scale resulted in good fit, χ^2 (6, N = 255) = 7.69, p = .26; CFI = .98, RMSEA = .05, SRMR = .17. The alphabet intercept was higher for four-year-old children (213.725, SE = 5.04) in comparison to three-year-old children (193.52, SE = 4.45). This model was not significantly worse than the simpler model that constrained all loadings, intercepts, and residual variances to be equal, $\Delta\chi^2$ (1, N = 255) = 12.24, p < .001. Therefore, group comparisons involving age utilized a language and literacy latent variable that had metric and unique invariance but partial scalar invariance (i.e., the alphabet intercept was freely estimated).

A model with loadings, intercepts, and residual variances constrained to be equal across African American/Black and Hispanic/Latino children indicated somewhat adequate fit to the data, χ^2 (7, N = 233) = 15.46, p = .03; CFI = .93, RMSEA = .10, SRMR = .20. After allowing loadings, intercepts, and residual variances to vary one at a time, a model freely estimating the intercept associated with vocabulary resulted in good fit, χ^2 (6, N = 233) = 10.975, p = .10; CFI = .96, RMSEA = .08, SRMR = .18. The vocabulary intercept was higher for African American/Black children (221.72, SE = 5.70) in comparison to Hispanic/Latino children (211.96, SE = 4.69). This model was not significantly worse than the simpler model that constrained all loadings and intercepts to be equal, $\Delta\chi^2$ (1, N = 233) = 9.27, p = .002. Therefore, group comparisons involving ethnicity utilized a language and literacy latent variable that had metric and unique invariance but partial scalar invariance (i.e., the vocabulary intercept was freely estimated).

Group comparisons of the structural models. For each demographic variable (age, sex, and ethnicity), the two final prediction models (language/literacy and science/math) were estimated within each group concurrently. First, the path coefficients between learning behaviors and the outcome(s) were specified to be constrained equal across the groups. If the more parsimonious model with all paths constrained equal across the groups fit the data well, models freely estimating individual parameters were not tested. If the more parsimonious model did not fit the data well, then models that freely estimated individual parameters were tested.

When comparing three-year-olds (n = 125) to four-year-olds (n = 135) in the language and literacy structural model, constraining all path coefficients to be equal across the two age groups fit the data well, χ^2 (66, N = 255) = 67.503, p = .43; CFI = .99, RMSEA = .01, SRMR = .06. Learning behaviors explained approximately 10% of the variance in three-year-olds' language and literacy outcomes and 8% of the variance in four-year-olds' language and literacy outcomes.

When comparing three-year-olds (n = 125) to four-year-olds (n = 135) in the math and science structural model, constraining all path coefficients to be equal across the two age groups fit the data somewhat adequately, χ^2 (24, N = 260) = 40.094, p = .02; CFI = .86, RMSEA = .07, SRMR = .03. Several models freely estimating individual path coefficients one at a time, therefore, were tested and compared using the Satorra-Bentler scaled chi-square difference test (Satorra & Bentler, 2001). The best fitting model allowed the path coefficient between the initiative intercept and science to vary between three- and four-year-olds, χ^2 (23, N = 260) = 27.906, p = .22; CFI = .96, RMSEA = .04, SRMR = .03. Although this model fit the data well, its results were unusual. There was still no evidence of moderation as this path coefficient was nonsignificant for both three-year-olds and four-year-olds; it should be noted that initial initiative scores marginally predicted science outcomes for four-year-olds, B = 13.10, SE = 7.23, p = .07. Whereas in the previous prediction model with the full sample, the initiative intercept, slope, and quadratic, as well as the problem-solving flexibility quadratic, significantly predicted math, none of the learning behaviors' initial scores or growth parameters significantly predicted math outcomes for either three- or four-year-olds in this new model. The results remained the same for science outcomes: both the problem-solving flexibility slope and quadratic slope remained significant predictors of science for both three- and four-year-olds. Because this modification (i.e., allowing the one path to vary between age groups) had unusual results and did not demonstrate any evidence of moderation, which was the focus of this analysis, it suggests that it was not a substantive change. Therefore, the original model that constrained all path coefficients to be equal across the two age groups was retained.

When comparing males (n = 127) to females (n = 133) in the language and literacy latent structural model, constraining all path coefficients to be equal across the two groups fit the data well, χ^2 (67, N = 255) = 67.195, p = .47; CFI = 1.00, RMSEA = .01, SRMR = .06. Learning behaviors explained 27% of the variance in male's language and literacy outcomes and 23% of the variance in female's language and literacy outcomes. When comparing males (n = 127) to females (n = 132) in the math and science model, constraining all path coefficients to be equal across the two age groups fit the data well, χ^2 (24, N = 259) = 18.834, p = .76; CFI = 1.00, RMSEA = 0.00, SRMR = .03. Learning behaviors explained 22% and 20% of the variance in male's math and science outcomes, respectively, and 22% and 16% of the variance in female's math and science outcomes, respectively.

When comparing African American/Black children (n = 169) to Hispanic children (n = 64) in the language and literacy latent structural model, constraining all path coefficients to be equal across the two age groups fit the data well, χ^2 (66, N = 233) = 70.577 p = .97; CFI = .97, RMSEA = .02, SRMR = .06. Learning behaviors explained 42% of the variance in Hispanic children's language and literacy outcomes and 27% of the variance in African American/Black children's language and literacy outcomes. When comparing African American/Black children (n = 172) to Hispanic children (n = 65) in the math and science structural model, constraining all path coefficients and scale intercepts to be equal across the two age groups fit the data well, χ^2 (24, N = 233) = 25.445 p = .38; CFI = .99, RMSEA = .02, SRMR = .03. Learning behaviors explained 37% and 26% of the variance in Hispanic children's math and science outcomes, respectively, and 19% and 16% of the variance in African American/Black children's math and science outcomes, respectively.

Question 4: Classes of Differential Developmental Patterns

To examine whether distinct classes of preschoolers could be empirically identified based on their initial scores and growth trajectories for each learning behavior, growth mixture models were conducted. First, a 2-class solution that allowed the mean intercept, slope, and quadratic parameters to be freely estimated between two groups was conducted for each learning behavior. The 2-class solutions seemed reasonable; for each learning behavior, there were no problems with estimation, each class had an adequate number of children, and entropy values were .85 or higher. Further, the specifics of the class solutions seemed realistic and practical: the two classes differed in their intercept, slope, and quadratic estimates, with one class beginning the school year with a higher average learning behavior baseline score than the other class.

The model fit indices of the 2-class solutions were compared to the model fit indices of their respective 1-class, baseline models (i.e., conventional latent growth models from Question 1) in order to see whether the 2-class solutions were appropriate (see columns one and two [labeled "1-Class Baseline" and "2-Class Means"] in Tables 6-9 for the initiative, persistence, planning, and problem-solving flexibility models, respectively). Model fit comparisons showed inconsistent results. Both the chi-square difference test using the loglikelihood and the relative fit information criteria indicated that 2-class solutions fit the data better than 1-class solutions. The loglikelihood differences results were $\Delta\chi^2$ (4, N = 260) = 28.99, $p < .001$, $\Delta\chi^2$ (4, N = 260) = 43.10, $p < .001$, $\Delta\chi^2$ (4, N = 260) = 62.84, $p < .001$, and $\Delta\chi^2$ (4, N = 260) = 37.69, $p < .001$ for the initiative, persistence, planning, and problem-solving flexibility models, respectively. Additionally, the AIC, BIC, and Adjusted BIC for the 2-class solutions were all lower than the values for the 1-class solutions by at least 20; differences of 10 have been considered important (Raftery, 1995). In contrast, the Adjusted Lo-Mendell-Rubin likelihood ratio test (LMR-LRT), which compares the current model to a model with one fewer class, indicated that the 2-class solutions did not fit significantly better than the 1-class solutions: the *p*-values were non-significant for all four learning behaviors (the *p*-

value associated with the 2-Class Means model for planning was marginally nonsignificant, $p = .07$).

Due to lack of previous learning behavior research using child-centered analyses, additional growth mixture models were conducted despite the inconsistent results provided by fit indices. Furthermore, the results for the 2-class solutions seemed theoretically sensible and, therefore, have the potential to further our limited understanding of learning behaviors' developmental trajectories. For these reasons, different models were specified that allowed for class differences in: (1) the intercept, slope, and quadratic *means*, (2) intercept, slope, and quadratic *means* + *variances*, (3) intercept, slope, and quadratic *means* + *variances* + *latent variable covariances*, and (4) intercept, slope, and quadratic *means* + *variances* + *latent variable covariances* + *residual variances*. These models were conducted for 2-, 3-, and 4-class solutions. See Tables 5-8 for the estimated class counts for the classes based on the posterior probabilities and the model fit statistics for the 2- and 3-class solutions for initiative, persistence, planning, and problem-solving flexibility, respectively. Due to persistent convergence issues encountered when running 4-class solutions for each learning behavior, model fit results for 4-class models are not reported as those models were deemed inappropriate for these data.

In order to determine the model that best represented the observed data for each learning behavior, parameter estimates and output details were first examined for each model. Several models encountered convergence issues, including singularity and negative variance estimates (the negative variance was fixed at zero and the model was re-estimated [e.g., Ram & Grimm, 2009]; see notes in Tables 6-9). Models with estimation issues should be interpreted cautiously (Ram & Grimm, 2009). Next, model fit statistics and entropy were examined.

Initiative growth mixture models. For initiative, all 3-class solutions had problems with estimation, especially the 3-Class$_{\text{Means+Var+LatCov}}$ model (its Class 1 did not have any children in it). Therefore, it was decided that the 3-class models were inappropriate for the initiative data. There were two models that had clear improvements in terms of information criteria over the 1-Class$_{\text{baseline}}$ model: 2-Class$_{\text{Means}}$ and 2-Class$_{\text{Means+Var+LatCov+ResVar}}$. Neither of these models had significant *p*-values for the Adjusted LMR-LRT, however, suggesting that a 1-class model could be a better fit. The 2-Class$_{\text{Means}}$ model had no problems with estimation, decent entropy (.85), and AIC, BIC, and Adjusted BIC values that were lower than the 1-Class$_{\text{baseline}}$ model. The 2-Class$_{\text{Means+Var+LatCov+ResVar}}$ model, whose intercept variance in Class 1 was fixed to zero, had a similar entropy value (.82) and had the smallest information criteria out of all the models, thus indicating it was the more appropriate model. The estimated parameters for the 2-Class$_{\text{Means+Var+LatCov+ResVar}}$ initiative growth mixture model can be found in Table 10.

Persistence growth mixture models. The quadratic mean had to be fixed to zero in all classes for every persistence model estimated, which was not surprising given that the quadratic estimate in the 1-Class baseline model was very small and non-significant. Similar to initiative, there were also convergence issues with all the 3-class persistence models, and therefore it was decided that these models were inappropriate for the data. There were two models that showed improvements over the 1-Class$_{\text{baseline}}$ model: the 2-Class$_{\text{Means}}$ and the 2-Class$_{\text{Means+Var+LatCov}}$. The 2-Class$_{\text{Means}}$ model did not have any estimation problems, but the slope and quadratic variances for Class 1 were fixed to zero in the 2-Class$_{\text{Means+Var+LatCov}}$. However, the latter model had better entropy (.907 vs. .867) and information criteria smaller than both the 1-Class$_{\text{Baseline}}$ and 2-Class$_{\text{Means}}$ models, suggesting that this model fit the data better. Additionally, this model had a significant *p*-value associated with the Adjusted LMR-LRT, suggesting that the 2-Class$_{\text{Means+Var+LatCov}}$ model fit better than a 1-Class$_{\text{Means+Var+LatCov}}$ model. The estimated parameters for the 2-Class$_{\text{Means+Var+LatCov}}$ persistence growth mixture model can be found in Table 10.

Planning growth mixture models. For planning, some of the 3-class models had the lowest information criteria (e.g., 3-Class$_{\text{Means+Var}}$ and 3-Class$_{\text{Means+Var+LatCov+ResVar}}$) but those models had convergence problems. The 3-Class$_{\text{Means+Var+LatCov}}$ model also had information criteria smaller than all the 2-class models. However, the *p*-value for its LMR-LRT was non-significant. Because the LMR-LRT was significant for almost all the 2-class models, the 2-class solutions were considered more appropriate for the data. With the exception of the 2-Class$_{\text{Means}}$ model, the intercept variance in Class 2 was fixed to zero for all the other 2-class models. Of the 2-class models, the model with the lowest criteria information, a significant *p*-value for LMR-LRT, and adequate entropy (.84) was the 2-Class$_{\text{Means+Var+LatCov+ResVar}}$ model. The residual variance associated with planning at the first time point had to be fixed to zero in this model. The estimated parameters for the 2-Class$_{\text{Means+Var+LatCov+ResVar}}$ planning growth mixture model can be found in Table 11.

Problem-solving flexibility growth mixture models. For the problem-solving flexibility models, some of the variance estimates had to be fixed to zero (see notes in Table 9), suggesting possible unreliability of estimated parameters. Unlike the other learning behavior models, however, there were not as many convergence problems with the 3-class models. Models with the lowest information criteria that did not have problems converging were the 2-Class$_{\text{Means+Var}}$ model and the 3-Class$_{\text{Means+Var}}$ model. When comparing these two models, the 3-Class$_{\text{Means+Var}}$ model had higher information criteria (but the information criteria were still lower than the 1-Class$_{\text{Baseline}}$ model). However, it also had slightly higher entropy (.837 vs. .805) and a significant LMR-LRT, suggesting that the 3-class model fit better than the 2-class. However, when examining the class parameter estimates, the addition of a third class did not seem to provide much practical information as the slope and quadratic mean estimates were non-significant. Therefore, the final model chosen was the 2-Class$_{\text{Means+Var}}$ model; its estimated parameters can be found in Table 11.

Growth mixture models with distal outcomes. Finally, distal outcomes were added to the growth mixture models chosen above for each learning behavior to determine whether the children comprising the classes varied in their academic school readiness outcomes (i.e., latent variable of language and literacy; math; science). Because these three outcomes were significantly correlated with one another, they were allowed to covary in all the models. Adding distal outcomes to the models slightly changed the class specifics, as class membership was also determined by the distal outcomes (Muthén, 2004). However, the changes in the estimates and class sizes were very slight for the persistence, planning, and problem-solving flexibility models, suggesting that these models are good representations of the observed data. The changes in some of the estimates for initiative model were slightly more pronounced, but the overall interpretation of the classes remained the same. Additionally, the class sizes for the problem-solving flexibility model became more evenly distributed between the two classes. See Table 12 for the final parameter estimates for the initiative and persistence growth mixture models with distal outcomes and Table 13 for the final parameter estimates for the planning and problem-solving flexibility growth mixture models with distal outcomes.

Final initiative growth mixture model with distal outcomes. Class 1 was estimated to have approximately half (n_1 = 134.85) the sample. On average, the children in this class had a very high (.976) probability of being assigned to this class (and, accordingly, a very low probability of being assigned to the other class). The average trajectory for this class started at 2.5, increased by 1.6 points every two months and then slowed down over time (plateaued) by 0.18 points (see Table 12). Additionally, there was significant within-class variation in the slope and quadratic (the intercept was fixed to have no variability within this class). The average probability of being assigned to Class 2 was also high (.96). In comparison to Class 1, the average trajectory for the children within Class 2 started off higher, at 5.7, and had a slower increase (.29 points every two months) across the year. The quadratic term for Class 2 was non-significant. There was also significant within-class variation in the intercept, slope, and quadratic. See Figure 3 for the estimated means and observed individual initiative values for both Class 1 and Class 2.

For the final initiative growth mixture model, the class means for math and science were 197.52 (*SD* = 3.36) and 485.88 (*SD* = 5.83), respectively, for Class 1 and 224.61 (*SD* = 4.22) and 510.88 (*SD* = 7.13), respectively, for Class 2. The Class 2 means were significantly higher for both math, $\chi^2(1, N = 260) = 6418.43$, $p < .001$, and science, $\chi^2(1, N = 260) = 15{,}015.94$, $p < .001$. Because the language and literacy outcome was a latent variable, Mplus (by default) provided a language and literacy mean for Class 1 in comparison to Class 2. The mean on the language and literacy latent variable for Class 1 was 16.36 (*SD* = 5.70) points lower than the mean for Class 2, $t(258) = -2.85$, $p < .01$.

Final persistence growth mixture model with distal outcomes. Class 1 was estimated to have 79% ($n_1 = 206.49$) of the sample. On average, these children had a very high (.979) probability of being assigned to this class. The average trajectory for this class started at 1.7 and increased by 0.73 points every two months (see Table 12). The quadratic term for Class 1 was fixed at zero. There was also significant within-class variation in the intercept, slope, and quadratic. The probability of being assigned to Class 2 was also high (.929). In comparison to Class 1, the average trajectory for Class 2 started off higher, at 5.2, but increased at a slower rate (.20 points every two months) across the year. The quadratic term for Class 2 was also fixed at zero. Additionally, there was significant within-class variation in the intercept (the slope and quadratic were fixed to have no variability within Class 2). See Figure 4 for the estimated means and observed individual persistence values for both Class 1 and Class 2.

In the final persistence growth mixture model, the class means on math and science were 204.33 (*SD* = 3.09) and 492.32 (*SD* = 5.04), respectively, for Class 1 and 234.26 (*SD* = 8.22) and 519.11 (*SD* = 9.81), respectively, for Class 2. The Class 2 means were significantly higher for both math, $\chi^2(1, N = 260) = 6418.43$, $p < .001$, and science, $\chi^2(1, N = 260) = 15{,}015.94$, $p < .001$. The mean on the language and literacy latent variable for Class 1 was 20.48 (*SD* = 6.39) points lower than the mean for Class 2, $t(258) = -3.21$, $p < .01$.

Final planning growth mixture model with distal outcomes. Class 1 was estimated to have 69% ($n_1 = 180.09$) of the sample. On average, these children had a very high (.962) probability of being assigned to this class. The average trajectory for this class started at 1.9 and increased by 0.21 points every two months (see Table 13). The quadratic term for Class 1 was non-significant. There was also significant within-class variation in the intercept, slope, and quadratic. The probability of being assigned to Class 2 was also high (.960). In comparison to Class 1, the average trajectory for Class 2 started off lower, at 0.60, but increased at a faster rate (0.83 points every two months) across the year. The quadratic term for Class 2 was non-significant. Additionally, there was significant within-class variation in the slope and quadratic (the intercept was fixed to have no variability within this class). See Figure 5 for the estimated means and observed individual planning values for both Class 1 and Class 2.

In the final planning growth mixture model, the class means on math and science were 208.30 (*SD* = 3.92) and 495.16 (*SD* = 4.58), respectively, for Class 1 and 215.65 (*SD* = 5.29) and 503.79 (*SD* = 8.36), respectively, for Class 2. The Class 2 means were significantly higher for both math, χ^2 (1, N = 260) = 6236.84, $p < .001$, and science, χ^2 (1, N = 260) = 14835.52, $p < .001$. The mean on the language and literacy latent variable for Class 1 was 3.77 (*SD* = 4.62) points lower than the mean for Class 2, but this difference was not significant, $t(258) = -0.82$, $p = .42$.

Final problem-solving flexibility growth mixture model with distal outcomes. Class 1 was estimated to have approximately half (n_1 = 131.62) of the sample. On average, these children had a high (.937) probability of being assigned to this class. The average trajectory for this class began at 0.87. Although the slope was non-significant, meaning there was no significant change in scores across the year, there was a significant quadratic term, indicating a slight change in the continuity of children's scores across the year by 0.07 points (see Table 13). There was also significant within-class variation in the quadratic but none in the intercept (the within class variability in the slope had been fixed at zero). The probability of being assigned to Class 2 was also high (.937). In comparison to Class 1, the average trajectory for Class 2 had a higher baseline score, 2.7, and a faster increase (.63 points every two months) across the year. The quadratic term for Class 2 was non-significant. Additionally, there was significant within-class variation in the intercept, slope, and quadratic. See Figure 6 for the estimated means and observed individual values for both Class 1 and Class 2.

In the final problem-solving flexibility growth mixture model, the class means on math and science were 193.40 (*SD* = 4.40) and 478.99 (*SD* = 6.24), respectively, for Class 1 and 228.13 (*SD* = 9.01) and 517.37 (*SD* = 10.31), respectively, for Class 2. The Class 2 means were significantly higher for both math, $\chi^2 (1, N = 260) = 6418.43$, $p < .001$, and science, $\chi^2 (1, N = 260) = 15{,}015.94$, $p < .001$. The mean on the language and literacy latent variable for Class 1 was 24.82 (*SD* = 10.08) points lower than the mean for Class 2, $t(258) = -2.46$, $p < .05$.

Chapter 4: Discussion

The multi-method approach taken by the current study extends the extant limited research base that has sought to explicitly examine change over time in learning behaviors. By taking a variable-focused approach, this study found that: (1) the learning behaviors of initiative, persistence, planning, and problem-solving flexibility had differential, nonlinear trajectories of change; (2) initiative and problem-solving flexibility were significant predictors of end-of-year academic school readiness skills, controlling for persistence and planning; and (3) there was no evidence for moderation, or differences in the relations between learning behaviors and academic skills based on child demographics. By taking an exploratory, child-focused approach, findings revealed unobserved heterogeneity in the growth trajectories of the four learning behaviors, suggesting that there may be two subgroups of developmental patterns that Head Start preschoolers exhibit for each learning behavior. These findings, if replicated, can broaden our understanding of how learning behaviors change over time and can inform the content and timing of early childhood teaching practices and interventions.

Change over Time in the Full Sample

Conventional latent growth modeling revealed differential, quadratic growth trajectories for each of the four learning behaviors, indicating positive change in each learning behavior and then a change in the rate of change. However, where children began the year (intercept), how much they changed across the year (slope), and how much their rate of change changed across the year (quadratic) differed depending on the learning behavior. Although this finding of quadratic change is in contrast with the two previous studies that examined change over time in learning behaviors, methodological and assessment issues appear to account for these differences. Dominguez et al. (2010) found linear growth in learning behaviors, as assessed by the Galileo, across one preschool year, but they examined change over time in *overall* learning behaviors and did not investigate change in *individual* behaviors. McDermott and colleagues (in press) found non-linear growth in individual learning behaviors, but their results suggested cubic growth rather than quadratic. The authors, however, utilized a newly-developed teacher rating scale, the Learning-to-Learn Scales, and examined change across two years of preschool, finding that children's scores in individual learning behaviors increased, plateaued over the summer months, and then increased again during the second preschool year (McDermott et al., in press). Therefore, the discrepancy in growth patterns across the three studies is likely due to the methodological difference in the McDermott study and the assessment differences in both studies. Together, these studies illustrate developmental change in learning behaviors is occurring during the preschool years. Given the dissimilarities in the growth patterns, however, these studies also highlight the importance of examining the trajectories of *specific* learning behaviors across *several* years of schooling.

Change Trajectories of the Four Learning Behaviors

The differential growth trajectories found for each learning behavior suggest that while learning behaviors are developing during the preschool years, they are changing in different ways. Although studies have shown evidence for a general adaptive learning behavior factor (e.g., McDermott et al., in press), the current results suggest that it may not be advantageous to treat learning behaviors as one generic domain. Instead, it may be important to critically study the multiple components that comprise this domain, their developmental trajectories, and their relation to one another.

Because four learning behaviors were examined individually, descriptions of their developmental trajectories can be provided. The preschoolers in this sample began the school year with relatively high initiative scores although there was significant variability in these initial scores. On average, the preschoolers had attained (i.e., “mastered”) four out of the seven items on the subscale, which is 57% of the items. They also showed significant positive change across the year, increasing almost one point (i.e., an additional item) every two months. There was significant variability in this positive change. In addition, there was a significant, negative change in the rates of change by approximately 1/10 of a point every two months. This suggests that, on average, the preschoolers were slowing down in their positive change across the year although there was significant variability across children in this change in the rate of change. If the average preschooler started with a score of four and increased one point every two months, he or she would have achieved the highest initiative score by the fourth time point (and there were five time points). It is, therefore, not surprising that the change in the rate of change was negative, indicating a slowing down of the change. This suggests that there may be a ceiling effect in the initiative subscale.

For persistence, the preschoolers in this sample began the school year with, on average, approximately two out of six items attained on this subscale (33% of the items). They also changed positively across the year, increasing their scores by almost ¾ of a point every two months. Again, there was significant variability in these initial scores and rates of change. The quadratic estimate was not significantly different from zero, indicating that on average there was no change in the rate of change. However, there was significant variability in the quadratic estimate across children, suggesting that some children's rate of change increased over time while others' rate of change slowed down.

Children's change over time in planning was similar to their overall change in persistence. The preschoolers began the year with, on average, approximately 1.5 out of five items (30% of the items). There was positive change across the year: almost half a point every two months. There was significant variability across children in both these initial scores and rates of change. The quadratic estimate was also not significant, but its variance was, suggesting that while some children's rate of change in planning increased over time, others' rate of change slowed down.

Finally, children began the school year, on average, with almost two out of eight items on the problem-solving flexibility subscale (25% of the items). They also showed positive change across the year, gaining about 1/3 of a point every two months. There was significant variability in the baseline scores and rates of change. Additionally, there was a positive change in the rates of change by approximately 1/10 of a point every two months, which suggests that, on average, children's rate of change sped up across the year. It is likely that the preschoolers are showing increases in their rates of change because they began the year with the least amount of skills in problem-solving flexibility (25% of the items, in comparison to 57%, 33%, and 30% of the initiative, persistence, and planning items) and changed the slowest across the year in this learning behavior (1/3 of a point every two months in comparison to 1 point, ¾ of a point, and ½ of a point for initiative, persistence, and planning, respectively).

Because raw scores were used and each learning behavior differed in the number of items in its respective subscale, caution should be taken when making comparisons across parameter estimates. However, some comparisons are warranted. Children began the school year, on average, with the highest scores on initiative, followed by persistence, planning, and problem-solving flexibility. Similarly, they showed change in learning behaviors across the year at different rates, with the fastest change in initiative, followed by persistence, planning, and problem-solving flexibility. Overall, persistence and planning seem to develop in similar ways, with similar average initial scores and rates of change. In contrast, initiative and problem-solving flexibility seem to have unique trajectories, with change in the former slowing down over time and the latter speeding up.

The differences found in the four dimensions of learning behavior trajectories may reflect true dissimilarities in the development of these skills. It may be that planning and problem-solving flexibility are more difficult skills to attain during the preschool years, and this was why children began the year with the lowest scores and changed more slowly across the year in these two competencies. Both planning and problem-solving flexibility are complex skills. For example, planning involves several components such as the selection and organization of goals and subgoals, the selection of appropriate activities to achieve the goal(s), and an evaluation of whether the planning efforts and outcome were successful (Patterson & Roberts, 1982). In addition, children need more explicit instruction from an adult to fully develop these types of skills, and therefore these learning behaviors will increase as children spend more time receiving instruction from teachers in a classroom setting. Research provides support for this theory; five-year-old, as well as 9- to 10-year-old, children are able to produce more efficient plans for performing an errand (e.g., grocery shopping) when working with an adult than when working alone or with a peer; adult guidance may be an effective way to promote planning skills in children (Gauvain & Rogoff, 1989; Radziszewska & Rogoff, 1988). More research using other samples of preschoolers and other measures of learning behaviors is necessary, however, to substantiate these learning behavior trajectories.

Prediction to Academic School Readiness Outcomes

When examining the relations between change in each learning behavior and academic school readiness in language and literacy, math, and science, differential relations were found. In general, findings indicated that initiative and problem-solving flexibility were significant predictors of academic skills. These results, if replicated, could help determine which learning behaviors would be most beneficial for teachers to explicitly promote. The addition of all four learning behaviors in the models accounted for 18-26% of the variance in academic outcomes. This proportion of variance explained is similar to that found in another study that examined the associations between specific learning behaviors (using another learning behaviors measure) and academic skills in math, language, and literacy (using the Learning Express, which was used in the current study; McDermott et al., in press).

For language and literacy, as well as math, outcomes, children who began the school year with higher initiative scores and who changed more quickly in initiative across the year had higher scores in these domains at the end of the year. Additionally, the change in the children's rates of change for both initiative and problem-solving flexibility was also positively associated with language and literacy and math scores at the end of the year. Because the initiative quadratic was negative, this relation suggests that a faster slowing down in initiative scores was related to better language, literacy, and math. Conversely, because the problem-solving flexibility quadratic was positive, this suggests that a faster increase in the change in problem-solving flexibility scores was related to outcomes. For science outcomes, preschoolers who had faster rates of change in problem-solving flexibility, as well as faster changes in this rate of change, also had better scores at the end of the year.

Initiative and academic skills. The association between a faster *slowing* down of initiative scores and higher end-of-year academic scores seems counterintuitive. However, this may be a result of the potential ceiling effect in the initiative subscale on the Galileo and the strong, negative correlation between the initiative slope and initiative quadratic ($r = -.91$, $p < .001$). This negative correlation indicates that children who changed faster across the year tended to have a faster change in their rate of change (more slowing down), probably due to the fact that these children were receiving the highest possible scores in initiative during the last few months of the school year. Therefore, the positive prediction of the initiative quadratic to academic skills may simply be a reflection of the overall positive association between higher initiative scores and better skills in language, literacy, and math.

These results provide further confirmation for a link between preschoolers' initiative and their skills in language, literacy, and math, a finding that has been shown in other studies of preschool and school-age children. For example, Head Start preschoolers' initiative has been shown to be positively related to their general cognitive, verbal, and quantitative abilities (Schweinhart, McNair, Barnes, & Larner, 1993) as well as their math skills (Dobbs, Doctoroff, Fisher & Arnold, 2006). Kindergarteners rated by their teachers as self-starters and as able to interest themselves without direction from others (i.e., demonstrating initiative), tend to have marginally higher reading test scores (Howse, Lange, Farran, & Boyles, 2003). Additionally, third graders' initiative was found to be predictive of a composite grade index of their reading, language arts, written language, and math grades (Cohen, Bronson, & Casey, 1995). The current study extends existing research on initiative as it reveals that change over time in initiative skills, rather than just a single time point, predicts better academic outcomes.

Problem-solving flexibility and academic skills. Previous research has also found an association between problem solving skills and academic outcomes. Teacher practices targeting low-income four-year-old children's problem solving skills have been shown to be related to greater gains in their receptive vocabulary (Pagani, Jalbert, Lapointe, & Hébert, 2006). Being able to utilize effective problem solving skills has also been linked to less anxiety in older children when taking high-stakes tests (Gulek, 2003), theoretically resulting in better test scores. Additionally, problem solving skills tend to be moderately supported by kindergarten teachers as being important skills for school readiness (Lin, Lawrence, & Gorrell, 2003).

One interesting finding in the current study is that children's *change* in the rate of change of problem-solving flexibility (and not initial scores or rates of change) significantly predicted scores on the language and literacy latent variable and in math. This may be because children started the school year with, proportionally, the least number of items in the problem-solving flexibility scale; they also changed the slowest in this scale. Therefore, it makes sense that those children who showed an increase in the relatively slow gain across the year tended to have better language, literacy, and math skills, in comparison to the children who did not show this increase. Perhaps, this finding suggests a link between initiative and problem-solving flexibility whereby having more initiative at the beginning of the year and having positive increases in initiative skills helps to increase the rate of positive change in problem solving skills during the year; all of these increases may contribute positively to academic outcomes. In a preschool classroom, it is likely that child initiative is encouraged by having children select their own activities and be decision makers in that selection process (Schweinhart & Weikart, 1997). Therefore, having more initiative might lead to a willingness to try multiple solutions when solving a problem, resulting in more problem-solving flexibility. This idea is in line with a developmental-ecological perspective of school readiness that examines how children's emerging competencies accumulate and work together to promote development. Previous research has highlighted the cumulative effect of learning-related behaviors, showing that they may not only increase academic skills but also may increase later learning behaviors (Stipek et al., 2010). However, this is speculative, and more research is necessary to determine whether there is a link between initiative and problem-solving flexibility over the course of one year of preschool.

Problem-solving flexibility was also found to be the only learning behavior related to science. The problem-solving flexibility slope and quadratic significant predicted science outcomes at the end of the year, controlling for the other learning behaviors and initial problem-solving flexibility scores. This suggests that children who changed more quickly in problem-solving flexibility across the year and who had faster, positive changes in their rate of change tended to have better science scores. This finding highlights a link between children's problem solving skills and their science process skills and content knowledge. Much national emphasis has recently been placed on the importance of student inquiry, as well as reasoning and problem-solving skills, in becoming proficient in science (National Research Council, 1996, 2007). Further, problem-solving flexibility is inherent in the scientific method, in which children ask questions, plan and conduct investigations, gather data, think critically, and draw conclusions. With an increasing national focus on science learning including the importance of science learning during the preschool (NRC, 2007), this important new findings provides empirical evidence for the role of specific learning behaviors in acquiring early science skills.

Persistence, planning, and academic skills. The current study did not find any links between persistence or planning and any of the academic school readiness outcomes. This is in contrast to other research findings as well as the current study's hypothesis that persistence would predict math skills. One previous study found that preschoolers who were rated by their teacher as having more persistence had better math scores at the end of the year, controlling for teacher ratings of their initiative (Maier, 2008). Similarly, another study found that children's persistence predicted their growth in reading ability from kindergarten to third grade as well as reading achievement in children with lower intelligence (Newman, Noel, Chen & Matsopoulos, 1996). More research is necessary to clarify these contradicting findings regarding the ability of child persistence to predict academic outcomes.

Although many studies have focused on the development of planning skills in young children and theorize that these competencies are important for learning (e.g., Scholnick & Friedman, 1993), preschoolers' ability to plan has not been examined much in relation to academic school readiness skills. One study indicated a link between teacher ratings of planning ability and school achievement, but this association was found in third graders (Cohen et al., 1995). The current study suggests that initial scores and rates of change in planning, as well as in persistence, was not predictive of academic outcomes when controlling for initiative and problem-solving flexibility. This may be because preschool children are poor planners, in comparison to elementary school children (Hudson & Fivush, 1991), resulting in fewer opportunities for preschoolers to exercise planning skills in the service of learning within the classroom. Therefore, planning skills may be more predictive of academic outcomes in later grades when these skills are more important for completing learning activities. In addition, planning is sometimes conceptualized as part of problem solving (e.g., Zelazo, Carter, Reznick, & Frye, 1997), and it may be that the overlap in the skills needed for these two learning behaviors is one reason why problem-solving flexibility emerged as a significant predictor and planning did not. Additionally, the persistence and planning scales had the least number of items out of the four learning behaviors. It may be that other measures that assess these learning behaviors more comprehensively may find associations to academic outcomes. Future studies using other measures of these competencies are necessary to confirm these findings.

Moderation by Child Demographics

There was no evidence that the effect of learning behaviors on academic outcomes was different depending on the child age, sex, or ethnicity. These results are similar to a previous study that also found no differences in the relation between learning behaviors and academic achievement by sex and ethnicity (Yen et al., 2004). The current study suggests that the influence of learning behaviors on language, literacy, math, and science skills is the same for all children regardless of whether they are three years old or four/five years old, male or female, or African American or Hispanic.

Overall, the non-significant moderation results are surprising given previous studies that have found age-, sex-, and ethnicity-related differences in learning behaviors (e.g., Maier, 2008; McWayne et al., 2004; Schaefer, 2004). In the previous studies, the authors were examining differences in learning behaviors based on demographic characteristics, observing that females, older children, and White children tend to be rated by teachers as exhibiting more adaptive learning behaviors in comparison to boys, younger children, and African American and Hispanic children, respectively. Although this research found mean differences in learning behaviors based on age, sex, and ethnicity, the current findings indicate that the *associations* among the constructs are the same for all children.

Subgroups of Preschoolers with Similar Developmental Patterns

To complement the variable-focused analyses which assumed the children in the sample were from a single population, the final aim of the current study was to utilize growth mixture modeling (GMM) to explore whether there was unobserved heterogeneity in the population. This advanced statistical technique allowed for an examination of whether distinct subgroups could be empirically derived from the data based on individual children’s growth trajectories for a specific learning behavior. One advantage of using GMM was that it permitted greater flexibility by allowing for variation within and between subgroups in terms of growth factors. It also allowed for the examination of subgroup differences on later academic school readiness outcomes.

As is sometimes the case when using this exploratory approach, the results were not straightforward. There was conflicting evidence, in terms of model fit indices, for whether the sample was from a single population or whether there were two (or more) subgroups that differed, in a practical way, in their growth trajectories of individual learning behaviors. However, in GMM there is no standard set of rules for determining the model that best represents the data; selecting a model has been called an "…art – informed by theory, past findings, past experience, and a variety of statistical fit indices" (Ram & Grimm, 2009, p. 571). Additional GMM analyses were therefore conducted and the models then compared for several reasons: most of the fit indices implied that the two-class models fit the data and the subgroup specifics of these models seemed theoretically sensible and practical. Furthermore, this analysis was exploratory as there are no previous studies that have examined heterogeneity in learning behaviors' trajectories. Additionally, because differential growth trajectories have been found for other school readiness skills (literacy and math; Kreisman, 2003), it is likely that similar findings may be found for learning behaviors, which warranted proceeding with the exploratory GMM analyses.

In comparison to the conventional latent growth models previously described, which provided one average trajectory for the whole sample, the final GMMs with distal outcomes provided a more nuanced description of the development of these four learning behaviors across one year. GMM revealed that preschoolers could be classified into two distinct subgroups that differed in terms of their average initial scores, rates of change, and change in the rates of change. For each learning behavior, there was one subgroup of preschoolers that had higher initial scores (of the respective learning behavior) in comparison to the other subgroup. For the subgroup with these higher initial scores, their learning behavior skills changed (increased) at a slower rate across the year. Accordingly, children in the subgroup with lower initial scores changed at a faster rate across the year. This is similar to previous research showing that preschoolers with more adaptive learning behavior scores at the beginning of the year tend to have slower rates of change across the year (Bell, 2010; Dominguez et al., 2010). There was seemingly one exception to this; in the problem-solving flexibility model, the subgroup that had higher initial problem-solving flexibility scores changed more quickly throughout the year in comparison to the other subgroup. Children in the latter subgroup began the school year with lower problem-solving flexibility scores *and* did not show significant increases in their scores across the year. Therefore, given the latter subgroup showed no significant change across the year, any change in the other subgroup would be seen as ‘faster’ change.

Additionally, the GMMs revealed significant differences in the change in the rate of change (quadratic) across the year depending on the subgroup. The conventional initiative growth model indicated negative quadratic growth, but the GMM suggested that this slowing down was exhibited by only some of the children: one subgroup began the year with lower initiative scores, increased more quickly throughout the year, and then plateaued. Meanwhile, the other subgroup exhibited linear growth, beginning the year with higher initiative scores but increasing more slowly throughout the year, without, on average, a significant change in the rate of change. Similarly, the conventional problem-solving flexibility growth model suggested positive quadratic growth across the full sample, but the GMM revealed that only one subgroup showed a change in the rate of change: one subgroup began the year with lower scores, did not have a significant slope (no change across the year), but did have a significant, positive quadratic, meaning the subgroup showed a positive change (increase) in the rate of no-change across the year. The other subgroup, in contrast, exhibited linear growth, beginning the year with higher problem-solving flexibility scores and changing at a faster rate (in comparison to the no-change exhibited by the other class), with on average no significant change in the rate of change. The persistence and planning GMMs, however, had results similar to their conventional growth models: the average quadratic estimates were either fixed to zero or non-significant in both subgroups in the persistence and planning GMMs, respectively. Again, there was significant variation in this average estimate of zero for these subgroups, indicating that some children's rate of change increased while others slowed down.

Finally, whether these identified subgroups differed in their academic readiness outcomes was examined. One practical application of GMM is determining whether children in the different subgroups have actual differences in their academic outcomes. Findings indicated that, for each learning behavior, the subgroup that had higher initial learning behavior scores had significantly better mean academic outcomes; this group also seemed to have higher scores on that learning behavior at the end of the year, according to the graphical representations (see Figures 3-6). Unfortunately, the converse was also true; children who began the school year with lower learning behaviors (despite growing more quickly across the year, in comparison to their peers who began the year with higher scores) had poorer academic school readiness skills at the end of the year. These findings imply that the competencies children bring to the classroom set them on a trajectory that influences their learning during the year; this trajectory is also likely to affect their learning into formal schooling (Alexander et al., 1993). Therefore, the promotion of more adaptive learning behaviors across the year, particularly for those children who start off with less adaptive skills, is critical for helping place children on positive learning trajectories. Intervention research that targets children who begin the school year with poorer learning behaviors is therefore necessary to determine whether learning behaviors can be promoted and encouraged in a way that allow these children to "catch-up" in terms of their learning behaviors *and* academic skills.

The one exception to the pattern of higher initial scores leading to better academic outcomes was the planning model. The growth trajectory for children in the subgroup that had lower initial planning scores surpassed the other subgroup, ending the year with better planning skills as well as significantly better math and science outcomes (but not language and literacy; see Figure 5). This could be a reflection of teachers in the current sample differentiating instruction to children who show poor planning skills at the beginning of the year. Generally, learning behaviors are not an explicit focus of classroom instruction. Teachers in the current study, however, may be promoting planning skills in some children because they use the High/Scope Preschool Curriculum, which emphasizes active learning and is centered around a "plan-do-review" process whereby children are provided with ample opportunities to plan activities, carry them out, and reflect on what they have done (Hohmann, Banet, & Weikart, 1979; Hohmann & Weikart, 1995; Weikart, Rogers, Adcock, & McClelland, 1971). Teachers may have observed some children having difficulty planning and, subsequently, may have guided these children more during planning time. Further examination of these trajectories in other samples of children will help determine whether the two patterns found for planning skills are accurate or whether planning follows the same trends as the other three learning behaviors.

Implications

The current study provides further confirmation that Head Start preschoolers' learning behaviors change across the preschool period and are an important influence on their academic school readiness skills. Results extend our current understanding of learning behaviors as they suggest that the multiple learning behaviors within the Approaches to Learning domain may not develop at the same rate. Furthermore, there is preliminary evidence that there is heterogeneity within trajectories of learning behaviors. These findings provide descriptive information about the developmental trajectories of specific learning behaviors as well as their relation to academic outcomes. Such knowledge can have important implications for designing teacher practices and interventions that aim to improve school readiness by promoting children's learning behaviors. However, more research is clearly needed to substantiate the findings before they can be applied to intervention research. If it is confirmed that Head Start children fall into one of two developmental trajectories for a particular learning behavior based on their initial skill level, teachers may be able to assess children early on and focus on improving learning behaviors specifically in those most at risk for less adaptive learning trajectories.

Perhaps the most interesting, yet also most concerning, finding is the one problem-solving flexibility subgroup that began the year with low problem solving scores and changed very little throughout the year. This may be because these skills are more difficult to master and these children will develop them later. However, the children in the other subgroup made clear gains in their problem solving skills during the preschool year so it is not the case that expecting this learning behavior is developmentally inappropriate. Overall, this developmental pattern is worrisome because approximately *half* the children in the sample were in this subgroup, showing little change in the problem solving abilities *and* lower academic skills at the end of the year.

To the degree that having better problem-solving flexibility influences academic outcomes (which the current study suggests), discovering a subgroup of preschoolers who begin and end the year with less adaptive problem solving skills is a significant finding. If future research finds that this developmental pattern is accurate, then this group of students could clearly be prime candidates for intervention work that focuses on building problem solving abilities. More generally, further longitudinal studies are needed to confirm all the developmental patterns found in the current study, to see if they generalize to other samples, and to further describe change over time in these learning behaviors across several years. Additionally, future research that examines potential predictors of class membership, such as child demographics, classroom instruction, and home and family environment, would be beneficial.

Finally, this study has important implications for the assessment of children's learning behaviors over time. The Galileo is an assessment tool utilized in many Head Start programs, particularly in Miami-Dade County, making it widely available and easy to use. However, there are only a few items in each of the subscales, limiting the ability to examine change across the year. Additionally, there was evidence for a ceiling effect in the initiative subscale, and this occurred without implementation of a specific intervention focused on learning behaviors. The Galileo, in its current form, may not be an ideal assessment tool for evaluating change in children's learning behaviors, especially initiative. For example, to evaluate the effectiveness of a learning behaviors intervention, it would be important to use an instrument that could capture a greater degree of change over time in this population.

One newly-developed, IRT-based measure of learning behaviors that is designed to track change over time is the Learning-to-Learn Scales (LTLS; McDermott et al., in press). This instrument distinguishes seven dimensions, or learning behaviors, and has been shown to be sensitive to growth in Head Start children's skills across two years of preschool (McDermott et al., in press). Using this measure in future studies may alleviate any issues with ceiling effects. However, some of the learning behavior dimensions in the LTLS also have few items. Furthermore, although there is an overlap in item content between the Galileo and LTLS, there does not seem to be a consensus within the field regarding the components of learning behaviors. Further work in this domain is warranted: theoretical work is needed to determine the critical facets of the Approaches to Learning domain, and the development of appropriate measures that assess change in these components with a reasonable number of items is also essential.

Limitations and Future Directions

This study advances the current limited understanding of change in specific learning behaviors across one year of preschool, but several limitations must be recognized. Learning behaviors were measured using the Galileo, a teacher rating scale. The differences found in the trajectories of each learning behavior may reflect genuine developmental differences in these competencies. The differences in trajectories, however, could also reflect discrepancies in how teachers observe individual learning behaviors and interpret the meaning of the items on the Galileo. Future studies should incorporate a multi-method, multi-informant approach by using observational and direct measures of learning behaviors. Additionally, although the Galileo differentiates the items on its Approaches to Learning scale into separate subscales, there are only a few items in each subscale. It is likely that this contributed to the ceiling effect found for the initiative subscale.

In the variable-focused analyses, a two-step approach was used: the intercept and growth parameters were obtained from the conventional growth modeling and then used as predictors of academic outcomes. While this is one valid way of examining the effect of the four learning behaviors on academic skills, taking a one-step approach whereby the four growth models and prediction to outcomes were conducted simultaneously is another way to answer that question. Future studies should incorporate a one-step approach when examining the links between different learning behavior trajectories and academic outcomes.

The language and literacy latent had metric and unique invariance but partial scalar invariance across age and ethnicity. This indicates that this latent factor was measuring something slightly different for these two groups. Future research using other measures of language and literacy that are invariant across age, sex, and ethnicity would be beneficial.

Finally, there are a number of potentially key variables that were left out in these analyses. For example, in the prediction models, although evidence of moderation of child demographics was not found, future research should examine the effect of learning behaviors baseline scores and growth on academic skills while controlling for child demographics. Similarly, in the GMMs, covariates can and should be incorporated into the models in future work. Just as adding distal outcomes changed class membership and class specifics, covariates can, as well. To the degree that child demographic variables are significantly related to change over time in learning behaviors (and to the distal outcomes), leaving out key variables can lead to model misspecification. Therefore, it is imperative for future research to conduct GMMs using covariates and distal outcomes on other samples of Head Start preschoolers to confirm the developmental patterns found in the current study. GMM is a relatively new and underutilized, but potentially powerful, technique for examining unobserved heterogeneity in children's growth trajectories. Within a GMM context, it would also be interesting to determine whether different variables predict different subgroups of developmental trajectories and to examine class-level influences, such as specific teacher practices or the quality of classroom interactions, on the different developmental trajectories.

Conclusions

The current study corroborates previous research indicating that learning behaviors help set a foundation for learning. Findings indicate that Head Start preschoolers' learning behaviors change across the preschool period and are an important influence on their academic school readiness skills. Findings suggest that individual learning behaviors do not develop at the same rate and may differentially predict outcomes. As the first study to incorporate a child-centered approach when examining individual learning behaviors, results also provide preliminary evidence for different subgroups of developmental trajectories for dimensions of learning behavior. Because learning behaviors are competencies that can be assessed and taught, these findings may have important implications for designing and implementing classroom practices that promote learning behaviors and overall school readiness. Furthermore, results suggest the importance of critically studying different learning behaviors over time and in relation to one another. Given limited time and resources in preschool classrooms, research seeking to determine which learning behaviors are important for which academic outcomes and for specific subgroups of children is particularly crucial.

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Table 1

Galileo Items for the Four Subscales

Subscale	Items
Initiative	
	Explores most areas of the classroom.
	Participates in an increasing variety of experiences independently.
	Selects activities or objects from a choice of at least two in a daily routine.
	Initiates preferred purposeful activities when playing in interest centers.
	Selects activities that are within her/his capabilities, most of the time.
	Combines materials, objects, equipment in new ways to produce multiple uses.
	Experiments with a variety of strategies to solve a problem or complete a task.
Persistence	
	Maintains interest in an activity for an appropriate period of time.
	Completes a simple self-selected activity or task.
	Maintains concentration in an activity despite distractions or interruptions.
	Persists with a difficult or non-preferred activity.
	Corrects her/his own mistakes, some of the time.
	Checks to see if a simple task has been completed, without being asked.
Planning	
	While playing, says what s/he wants to accomplish, when asked.
	Sets a goal prior to beginning of an activity or a project.
	Says, signs, or gestures whether or not a simple task has been completed.
	Sets a goal, and with adult help, plans a small number of steps to achieve it.
	Revises, with adult help, a plan that has not produced the intended result.
Problem-solving flexibility	
	Seeks assistance from an adult when attempting to solve a problem.
	Seeks assistance from peers when attempting to solve a problem.
	Uses concrete materials to solve a problem (e.g., blocks to count).
	Reorganizes objects to solve a problem (e.g., stacking so blocks don't fall).
	Suggests an alternative solution to solve a problem, without assistance.
	Tries out new ideas to see if they will work.
	Predicts the effects of an action.
	Applies general rules or strategies from one experience to another.

Table 2

Descriptive Statistics

	N	Mean	*SD*	Skewness	*SE*	Kurtosis	*SE*
Age	260	48.07	6.49	.01	.15	-1.03	.30
Vocabulary (LE)	255	213.83	41.76	-.41	.15	-.02	.30
Listening Comprehension (LE)	255	209.37	37.35	-1.10	.15	1.43	.30
Alphabet (LE)	255	215.02	45.32	-.46	.15	-.13	.30
Math (LE)	255	210.55	41.28	-.12	.15	-.32	.30
Science	251	498.29	50.29	.38	.15	.55	.31

Note. Child age is in months. The Learning Express (LE) subscales (M = 200, SD = 50) and Science assessment (M = 500, SD = 50) represent IRT-based scores.

Table 3

Bivariate Correlations

	1.	2.	3.	4.	5.	6.	7.	8.
1. Age	1							
2. Gender	-.07	1						
3. Ethnicity	.06	-.01	1					
4. Vocabulary	.40***	.00	.03	1				
5. Listening Comprehension	.38***	.08	-.08	.52***	1			
6. Alphabet	.43***	.06	-.05	.44***	.43***	1		
7. Math	.54***	-.02	.01	.55***	.55***	.67***	1	
8. Science	.52***	.00	-.15*	.74***	.60***	.46***	.65***	1

Note. Age is in months. Gender (1 = female, 0 = male) and ethnicity (1 = African American/Black, 0 = Hispanic/Latino) are dummy-coded.
* $p < .05$. *** $p < .001$.

Table 4

Model Fit Results for the Latent Growth Models of the Four Learning Behaviors

	χ^2	df	*p* value	CFI	TLI	RMSEA	SRMR
Initiative							
No growth	505.951	17	$p < .001$	.342	.613	.333	.951
Linear growth 1	139.282	14	$p < .001$	.832	.880	.186	.219
Linear growth 2	64.114	10	$p < .001$	.927	.927	.144	.088
Latent Basis 1	108.302	11	$p < .001$	.869	.881	.184	.250
Latent Basis 2	41.826	7	$p < .001$	.953	.933	.138	.162
Quadratic 1	44.858	10	$p < .001$	.953	.953	.116	.091
Quadratic 2	15.711	10	$p = .015$	.987	.978	.079	.033
Persistence							
No growth	564.796	17	$p < .001$	.491	.701	.352	.445
Linear growth 1	56.925	14	$p < .001$	.96	.972	.109	.129
Linear growth 2	65.853	10	$p < .001$	.948	.948	.147	.100
Latent Basis 1	55.879	11	$p < .001$	.958	.962	.125	.126
Latent Basis 2	134.688	7	$p < .001$	.881	.831	.265	.116
Quadratic 1	29.768	10	$p < .001$	.982	.982	.087	.045
Cubic 1	8.816	5	$p = .117$	.996	.993	.054	.015

Note. 1 = error variances constrained; 2 = error variances unconstrained; var = variance

	χ^2	df	p value	CFI	TLI	RMSEA	SRMR
Planning							
No growth	449.004	17	$p < .001$	.183	.519	.313	.311
Linear growth 1	41.193	14	$p < .001$	.949	.963	.086	.089
Linear growth 2	52.064	10	$p < .001$	.92	.92	.127	.117
Latent Basis 1	45.854	11	$p < .001$	.934	.940	.110	.079
Latent Basis 2	113.364	7	$p < .001$	.799	.712	.242	.111
Quadratic 1	12.362	10	$p = .262$	.996	.996	.030	.027
Cubic 1	1.754	5	$p = .882$	1.00	1.01	0.00	.007
Problem-solving flexibility							
No growth	304.818	17	$p < .001$	.314	.596	.255	.230
Linear growth 1	55.456	14	$p < .001$	.901	.929	.107	.083
Linear growth 2	49.208	10	$p < .001$	.907	.907	.123	.119
Latent Basis 1	58.071	11	$p < .001$	.888	.898	.128	.094
Latent Basis 2	89.989	7	$p < .001$	.802	.717	.214	.125
Quadratic 1	15.285	10	$p = .122$	.987	.987	.045	.022
Cubic 1	3.192	5	$p = .670$	1.00	1.01	0.00	.010

Note. 1 = error variances constrained; 2 = error variances unconstrained; var = variance

Table 5

Parameter Estimates for the Final Multilevel Latent Growth Models

Parameter	Initiative[a]		Persistence		Planning		Problem Solving Flexibility	
	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*
Intercept	4.029***	*.227*	2.421***	*.226*	1.486***	*.187*	1.796***	*.237*
Slope	0.932***	*.103*	0.700***	*.097*	0.409***	*.089*	0.326*	*.129*
Quadratic	-0.100***	*.019*	-0.021	*.023*	0.028	*.022*	0.080**	*.029*
Random effect								
	Variance	*SE*	Variance	*SE*	Variance	*SE*	Variance	*SE*
Intercept	3.051***	*.350*	2.986***	*.292*	2.123***	*.247*	3.116***	*.522*
Slope	0.523***	*.134*	0.484***	*.117*	0.357**	*.112*	0.782***	*.192*
Quadratic	0.016**	*.006*	0.017**	*.006*	0.019**	*.006*	0.047*	*.019*

Note. [a]Error variances freely estimated across time in this model.
* $p < .05$. ** $p < .01$. *** $p < .001$.

Table 6

Fit Statistics for Initiative Baseline Latent Growth Model, 2-class Growth Mixture Models, and 3-class Growth Mixture Models

	1-Class Baseline	2-Class Means	2-Class Means + Var[b]	2-Class Means + Var + Lat Cov[b]	2-Class Means + Var + Lat Cov + Res Var[c]	3-Class Means[b]	3-Class Means + Var[b]	3-Class Means + Var + Lat Cov[b]	3-Class Means + Var + Lat Cov + Res Var[b,c]
Sample Size[a]									
$N_{c=1}$	260	47.28	74.25	55.85	90.78	140.41	182.57	0.00	128.89
$N_{c=2}$	--	212.72	185.75	204.15	169.22	76.61	73.43	51.49	119.03
$N_{c=3}$	--	--	--	--	--	42.99	4.00	208.51	12.08
Fit statistics									
Loglikelihood	-1552.37	-1527.49	-1498.07	-1487.43	-1448.75	-1502.11	-1484.39	-1487.76	-1399.08
# free parameters	14	18	21	24	26	22	28	34	41
AIC	3132.73	3090.97	3038.13	3022.85	2949.49	3048.21	3024.77	3043.52	2880.16
BIC	3182.58	3155.06	3112.91	3108.31	3042.07	3126.54	3124.47	3164.58	3026.15
ABIC	3138.20	3098.00	3046.33	3032.22	2959.64	3056.80	3035.70	3056.79	2896.17
Entropy	--	.8540	.7010	.8690	.8220	.8080	.8120	.9300	.8980
Adj. LMR-LRT *p*-value	--	.4065	.3115	.1503	.4464	.3989	.7152	.5768	.2640

Note. [a]Estimated class counts for the latent classes based on the posterior probabilities; [b]these models had problems with estimation (e.g., non-positive definite, best loglikelihood not replicated); [c]intercept variance was fixed at zero in Class 1.
Var = variances; Lat Cov = latent covariances; Res Var = residual variances.

Table 7

Fit Statistics for Persistence Baseline Latent Growth Model, 2-class Growth Mixture Models, and 3-class Growth Mixture Models

	1-Class Baseline	2-Class Means[b]	2-Class Means + Var[b,c]	2-Class Means + Var + Lat Cov[b,d]	2-Class Means + Var + Lat Cov + Res Var[b,e]	3-Class Means[b,c]	3-Class Means + Var[b,e]	3-Class Means + Var + Lat Cov[b,c]	3-Class Means + Var + Lat Cov + Res Var[b,e]
Sample Size[a]									
$N_{c=1}$	260	75.23	161.00	52.00	--	74.56	--	84.26	--
$N_{c=2}$	--	184.77	99.00	208.00	--	103.47	--	36.84	--
$N_{c=3}$	--	--	--	--	--	81.97	--	138.90	--
Fit statistics									--
Loglikelihood	-1658.82	-1616.66	-1557.73	-1600.85	--	-1591.86	--	-1479.36	--
# free parameters	10	14	15	13	--	15	--	27	--
AIC	3337.64	3257.32	3145.45	3227.69	--	3213.72	--	3012.71	--
BIC	3373.25	3300.05	3198.86	3273.98	--	3267.13	--	3108.85	--
ABIC	3341.55	3262.00	3151.31	3232.77	--	3219.57	--	3023.25	--
Entropy	--	.8670	.7750	.9070	--	.7870	--	.8260	--
Adj. LMR-LRT *p*-value	--	.2318	.0031	.0314	--	.2410	--	.0000	--

Note. [a]Estimated class counts for the latent classes based on the posterior probabilities; [b]quadratic mean fixed to zero (i.e., freely estimated intercept and slope only); [c]these models had problems with estimation (e.g., non-positive definite, best loglikelihood not replicated); [d]slope and quadratic variances fixed to zero in Class 1; [e]model did not converge.

Var = variances; Lat Cov = latent covariances; Res Var = residual variances.

Table 8

Fit Statistics for Planning Baseline Latent Growth Model, 2-class Growth Mixture Models, and 3-class Growth Mixture Models

	1-Class Baseline	2-Class Means	2-Class Means + Var[b]	2-Class Means + Var + Lat Cov[b]	2-Class Means + Var + Lat Cov + Res Var[b,c]	3-Class Means	3-Class Means + Var[d]	3-Class Means + Var + Lat Cov[e]	3-Class Means + Var + Lat Cov + Res Var[d,c]
Sample Size[a]									
$N_{c=1}$	260	73.49	159.19	174.99	179.78	87.69	142.10	83.40	140.62
$N_{c=2}$	--	186.51	100.81	85.01	80.22	73.86	62.82	19.70	119.38
$N_{c=3}$	--	--	--	--	--	98.46	55.08	156.90	0.00
Fit statistics									
Loglikelihood	-1574.87	-1538.95	-1504.30	-1498.72	-1433.35	-1507.34	-1406.81	-1481.72	-1409.30
# free parameters	10	14	16	17	25	18	24	21	39
AIC	3169.73	3105.90	3040.59	3031.44	2916.71	3050.69	2861.62	3005.44	2896.59
BIC	3205.34	3155.75	3097.56	3091.97	3005.73	3114.78	2947.07	3080.21	3035.46
ABIC	3173.63	3111.37	3046.84	3038.07	2926.47	3057.71	2870.98	3013.63	2911.81
Entropy	--	.8630	.7840	.8670	.8410	.8000	.9090	.8750	.875
Adj. LMR-LRT *p*-value	--	.0653	.0002	.0001	.0068	.3075	.2013	.1202	.3118

Note. [a]Estimated class counts for the latent classes based on the posterior probabilities; [b]intercept variance fixed to zero in Class 2; [c]Residual variance for planning at first time point fixed to zero in Class 1; [d]these models had problems with estimation (e.g., non-positive definite, best loglikelihood not replicated); [e]intercept variance fixed to zero in Class 1 and intercept, slope, quadratic variances fixed to zero in Class 2.

Var = variances; Lat Cov = latent covariances; Res Var = residual variances.

Table 9

Fit Statistics for Problem-solving Flexibility Baseline Latent Growth Model, 2-class Growth Mixture Models, and 3-class Growth Mixture Models

	1-Class Baseline	2-Class Means	2-Class Means + Var[b]	2-Class Means + Var + Lat Cov[c]	2-Class Means + Var + Lat Cov + Res Var[c,d,e]	3-Class Means	3-Class Means + Var[f]	3-Class Means + Var + Lat Cov[g]	3-Class Means + Var + Lat Cov + Res Var[e,h]
Sample Size[a]									
$N_{c=1}$	260	73.94	119.90	154.13	154.10	41.88	172.14	80.54	119.19
$N_{c=2}$	--	186.06	140.10	105.87	105.90	25.26	70.98	54.14	53.29
$N_{c=3}$	--	--	--	--	--	192.86	16.87	125.31	87.52
Fit statistics									
Loglikelihood	-1950.11	-1912.43	-1841.56	-1849.69	-1726.22	-1873.98	-1895.07	-1833.68	-1766.45
# free parameters	10	14	16	15	23	18	15	19	32
AIC	3920.21	3852.86	3715.12	3729.37	3498.44	3783.95	3820.14	3705.36	3596.90
BIC	3955.82	3902.71	3772.09	3782.78	3580.33	3848.04	3873.55	3773.01	3710.84
ABIC	3924.11	3858.32	3721.36	3735.23	3507.41	3790.98	3825.99	3712.78	3609.39
Entropy	--	.8500	.8050	.8120	.9180	.8970	.8370	.7590	.7990
Adj. LMR-LRT *p*-value	--	.3154	.0683	.0107	.1172	.2600	.0146	.1202	.2683

Note. [a]Estimated class counts for the latent classes based on the posterior probabilities; [b]slope variance fixed to zero in Class 1; [c]slope and quadratic variances fixed to zero in Class 2; [d]residual variance for problem-solving flexibility at the fourth time point was fixed to zero in Class 2; [e]these models had problems with estimation (e.g., non-positive definite, best loglikelihood not replicated); [f]slope variance fixed to zero in Class 1, and intercept, slope, and quadratic variances fixed to zero in Class 2 and Class3; [g]slope and quadratic variances fixed to zero in Class 1, and intercept, slope, and quadratic variances fixed to zero in Class2; [h]residual variance for problem-solving flexibility at the first and fifth time points fixed to zero in all classes.

Var = variances; Lat Cov = latent covariances; Res Var = residual variances.

Table 10

Parameter Estimates for the Chosen Initiative and Persistence Growth Mixture Models (No Distal Outcomes)

	Initiative		Persistence	
	2-Class$_{Means+Var+LatCov+ResVar}$		2-Class$_{Means+Var+LatCov}$	
	Class 1	Class 2	Class 1	Class 2
Sample size	90.78	169.22	208.00	52.00
Avg. probability of class membership	.950	.953	.978	.947
Latent variable means				
Intercept mean	1.934 (.53)***	5.145 (.37)***	1.734 (.19)***	5.249 (.21)***
Slope mean	1.554 (.17)***	0.604 (.21)**	0.729 (.04)***	0.185 (.05)***
Quadratic mean	-.160 (.05)***	-.069 (.03)*	0.000 (fixed)	0.000 (fixed)
Latent variable variances				
Intercept variance	0.000 (fixed)	1.226 (.34)***	1.301 (.20)***	0.089 (.06)
Slope variance	1.482 (.44)**	0.481 (.14)**	0.610 (.15)***	0.000 (fixed)
Quadratic variance	0.063 (.02)**	0.015 (.00)***	0.025 (.01)**	0.000 (fixed)
Latent variable covariances				
Intercept-slope covariance	--	-.70***	.01	--
Intercept-quadratic covariance	--	.56***	-.15	--
Slope-quadratic covariance	-.99***	-.97***	-.91***	--
Residual variances				
Initiative1	1.487 (.61)*	0.298 (.26)	0.296 (.03)***	0.296 (.03)***
Initiative2	0.930 (.19)***	0.187 (.07)*	0.296 (.03)***	0.296 (.03)***
Initiative3	0.254 (.17)	0.092 (.08)	0.296 (.03)***	0.296 (.03)***
Initiative4	0.360 (.16)*	0.059 (.03)*	0.296 (.03)***	0.296 (.03)***
Initiative5	0.494 (.35)	0.068 (.07)	0.296 (.03)***	0.296 (.03)***

Note. Var = variances; Lat Cov = latent covariances; Res Var = residual variances
* $p < .05$. ** $p < .01$. *** $p < .001$.

Table 11

Parameter Estimates for the Chosen Planning and Problem-solving Flexibility Growth Mixture Models (No Distal Outcomes)

	Planning $\text{2-Class}_{Means+Var+LatCov+ResVar}$		Problem-solving flexibility $\text{2-Class}_{Means+Var}$	
	Class 1	Class 2	Class 1	Class 2
Sample size	179.78	80.22	119.90	140.10
Avg. probability of class membership	.960	.958	.943	.952
Latent variable means				
Intercept mean	1.893 (.24)***	0.594 (.19)**	0.689 (.22)**	2.740 (.28)***
Slope mean	0.211 (.07)**	0.833 (.19)***	-0.002 (.07)	0.625 (.23)**
Quadratic mean	0.028 (.02)	0.028 (.05)	0.086 (.02)***	0.068 (.05)
Latent variable variances				
Intercept variance	2.614 (.24)***	0.000 (fixed)	0.309 (.23)	3.937 (.53)***
Slope variance	0.168 (.04)***	1.337 (.36)***	0.000 (fixed)	2.132 (.46)***
Quadratic variance	0.008 (.00)*	0.081 (.02)**	0.002 (.00)***	0.120 (.04)**
Latent variable covariances				
Intercept-slope covariance	-.02	--	--	-.25***
Intercept-quadratic covariance	-.20	--	.30	.01
Slope-quadratic covariance	-.83***	-.99***	--	-.92***
Residual variances				
Initiative1	0.000 (fixed)	0.491 (.15)**	0.394 (.07)***	0.394 (.07)***
Initiative2	0.107 (.02)***	0.980 (.22)***	0.394 (.07)***	0.394 (.07)***
Initiative3	0.130 (.05)**	0.277 (.24)	0.394 (.07)***	0.394 (.07)***
Initiative4	0.120 (.06)	0.702 (.17)***	0.394 (.07)***	0.394 (.07)***
Initiative5	0.126 (.13)	0.090 (.20)	0.394 (.07)***	0.394 (.07)***

Note. Var = variances; Lat Cov = latent covariances; Res Var = residual variances
* $p < .05$. ** $p < .01$. *** $p < .001$.

Table 12

Parameter Estimates for Final Initiative and Persistence Growth Mixture Models with Distal Outcomes

	Initiative $2\text{-Class}_{\text{Means+Var+LatCov+ResVar}}$		Persistence $2\text{-Class}_{\text{Means+Var+LatCov}}$	
	Class 1	Class 2	Class 1	Class 2
Sample size	134.85	125.15	206.49	53.51
Avg. probability of class membership	.976	.960	.979	.929
Latent variable means				
Intercept mean	2.509 (.26)***	5.653 (.18)***	1.718 (.21)***	5.208 (.33)***
Slope mean	1.559 (.12)***	0.293 (.10)**	0.729 (.04)***	0.195 (.07)**
Quadratic mean	-.182 (.03)***	-.020 (.02)	0.000 (fixed)	0.000 (fixed)
Latent variable variances				
Intercept variance	0.000 (fixed)	0.645 (.19)**	1.280 (.27)***	0.105 (.10)
Slope variance	1.548 (.40)***	0.204 (.08)**	0.616 (.15)***	0.000 (fixed)
Quadratic variance	0.069 (.02)**	0.009 (.00)**	0.025 (.01)**	0.000 (fixed)
Latent variable covariances				
Intercept-slope covariance	--	-.35	.01	--
Intercept-quadratic covariance	--	.11	-.16	--
Slope-quadratic covariance	-.99***	-.94***	-.91***	--
Residual variances				
Initiative1	1.888 (.29)***	0.140 (.12)	0.297 (.03)***	0.297 (.03)***
Initiative2	0.895 (.14)***	0.085 (.03)*	0.297 (.03)***	0.297 (.03)***
Initiative3	0.224 (.11)*	0.029 (.02)	0.297 (.03)***	0.297 (.03)***
Initiative4	0.284 (.10)**	0.075 (.02)**	0.297 (.03)***	0.297 (.03)***
Initiative5	0.377 (.24)	0.051 (.06)	0.297 (.03)***	0.297 (.03)***

Note. Var = variances; Lat Cov = latent covariances; Res Var = residual variances
* $p < .05$. ** $p < .01$. *** $p < .001$.

Table 13

Parameter Estimates for Final Planning and Problem-solving Flexibility Growth Mixture Models with Distal Outcomes

	Planning 2-Class$_{\text{Means+Var+LatCov+ResVar}}$		Problem-solving flexibility 2-Class$_{\text{Means+Var}}$	
	Class 1	Class 2	Class 1	Class 2
Sample size	180.09	79.91	131.62	128.37
Avg. probability of class membership	.962	.960	.937	.937
Latent variable means				
Intercept mean	1.889 (.24)***	0.598 (.17)***	0.872 (.47)*	2.738 (.29)***
Slope mean	0.214 (.07)**	0.831 (.19)***	0.056 (.11)	0.630 (.24)**
Quadratic mean	0.027 (.02)	0.028 (.05)	0.071 (.03)**	0.081 (.06)
Latent variable variances				
Intercept variance	2.614 (.23)***	0.000 (fixed)	0.668 (.88)	4.318 (.83)***
Slope variance	0.168 (.04)***	1.335 (.35)***	0.000 (fixed)	2.354 (.50)***
Quadratic variance	0.007 (.00)*	0.081 (.02)***	0.002 (.00)**	0.127 (.05)**
Latent variable covariances				
Intercept-slope covariance	-.02	--	--	-.26***
Intercept-quadratic covariance	-.20	--	.25	.01
Slope-quadratic covariance	-.83***	-.99***	--	-.93***
Residual variances				
Initiative1	0.000 (fixed)	0.498 (.14)***	0.396 (.07)***	0.396 (.07)***
Initiative2	0.108 (.02)***	0.983 (.22)***	0.396 (.07)***	0.396 (.07)***
Initiative3	0.130 (.05)**	0.279 (.24)	0.396 (.07)***	0.396 (.07)***
Initiative4	0.120 (.06)*	0.701 (.17)***	0.396 (.07)***	0.396 (.07)***
Initiative5	0.126 (.12)	0.087 (.20)	0.396 (.07)***	0.396 (.07)***

Note. Var = variances; Lat Cov = latent covariances; Res Var = residual variances
* $p < .05$. ** $p < .01$. *** $p < .001$.

Figure 1. Structural model for language and literacy. Loadings for the latent variable in the measurement model are standardized estimates. Path coefficients and residual variances are unstandardized estimates. Dotted lines represent non-significant paths. Persist = Persistence; Prb Solv = Problem-Solving Flexibility; Vocab = Vocabulary; Listening Comp. = Listening Comprehension; Alphabet Knowl. = Alphabet Knowledge. * $p < .05$. *** $p < .001$.

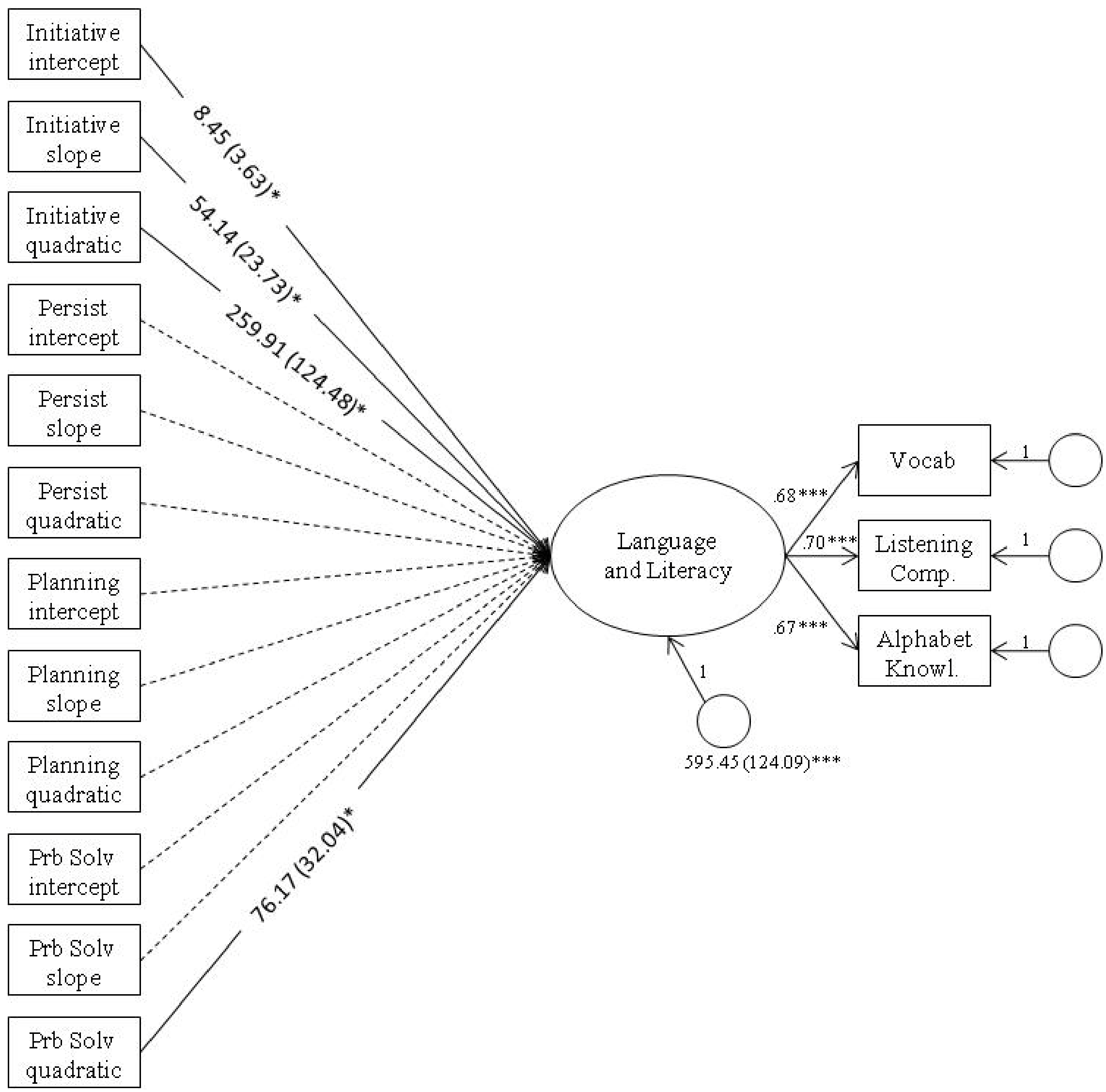

Figure 2. Structural model for math and science. Correlation coefficient is a standardized estimate. Path coefficients and residual variances are unstandardized estimates. Dotted lines represent non-significant paths. Persist = Persistence; Prb Solv = Problem-Solving Flexibility.
* $p < .05$. ** $p < .05$. *** $p < .001$.

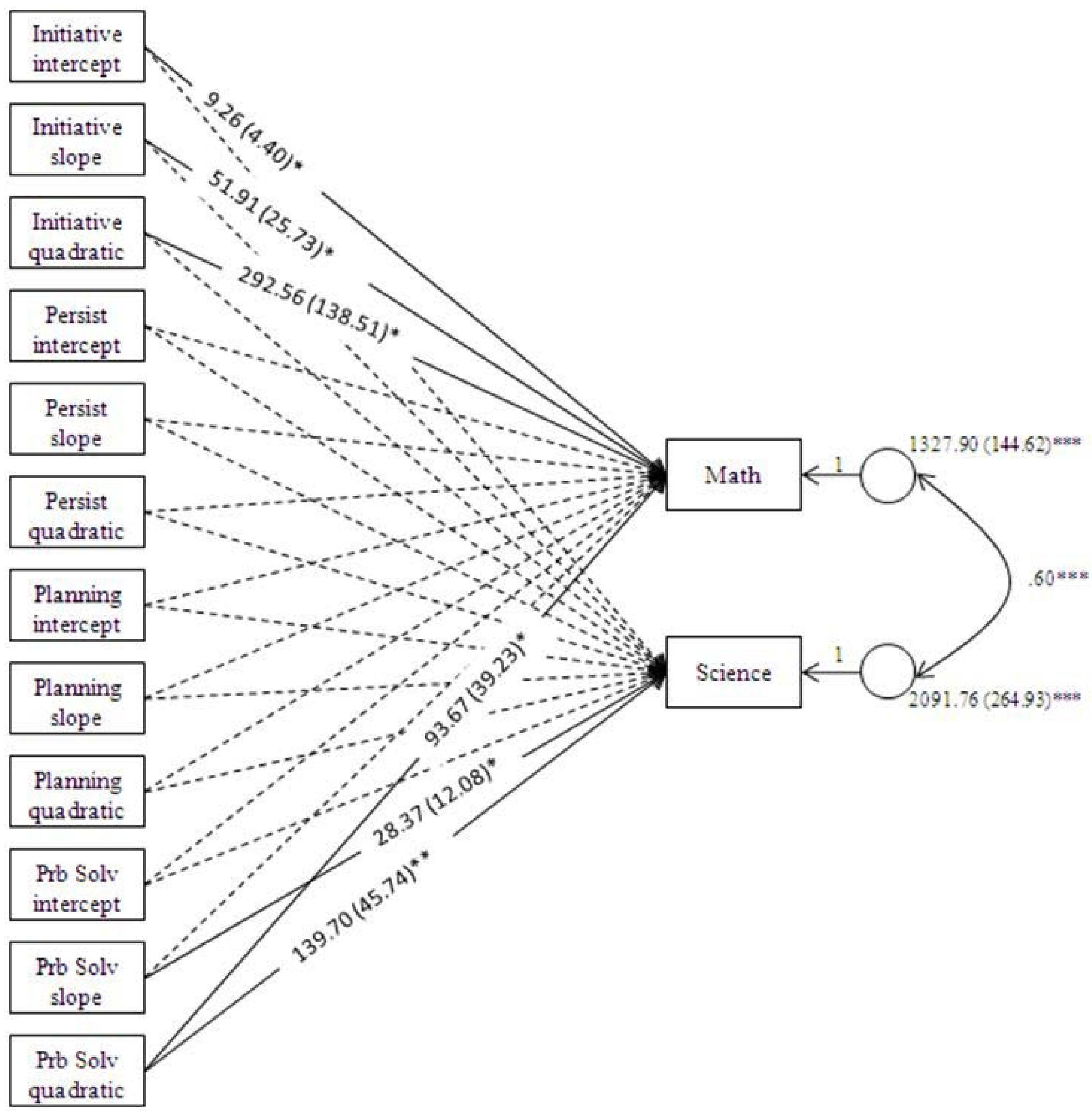

Figure 3. Estimated means and observed individual initiative scores across the school year for both Class 1 and Class 2.

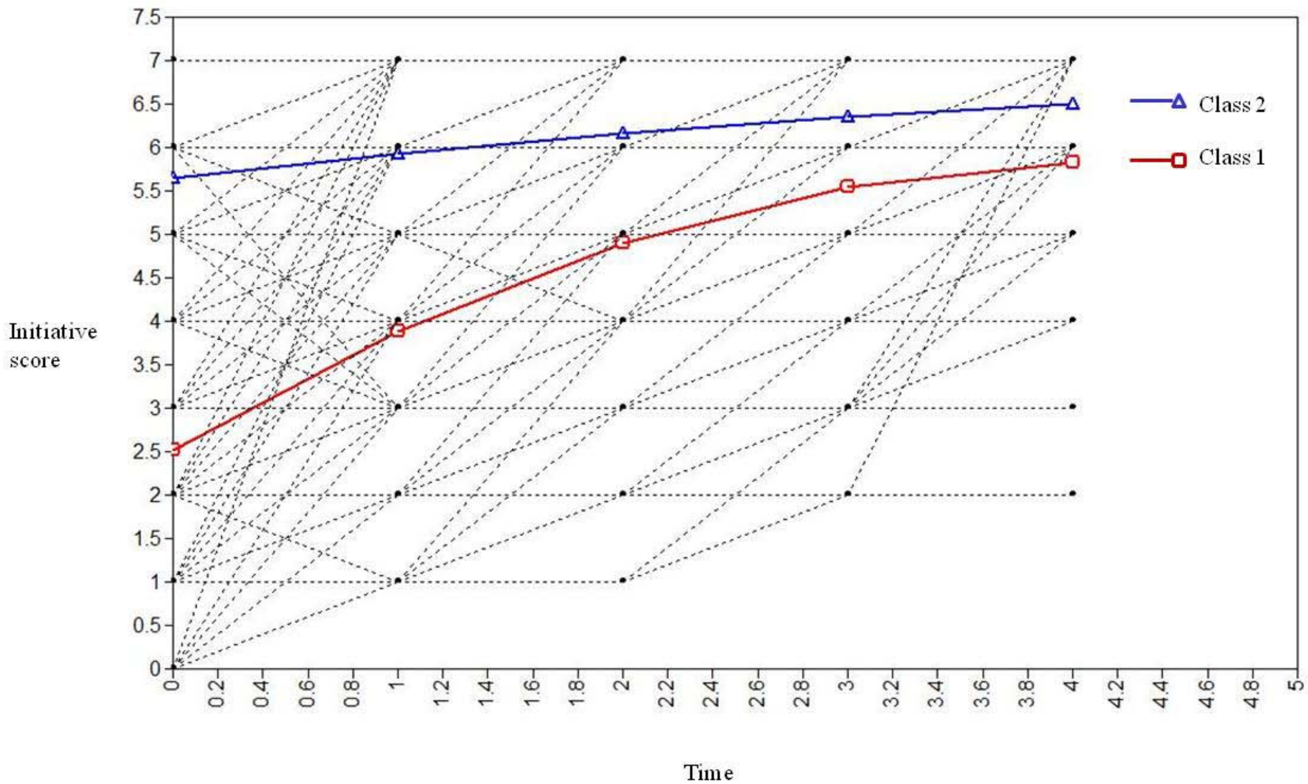

Figure 4. Estimated means and observed individual persistence scores across the school year for both Class 1 and Class 2.

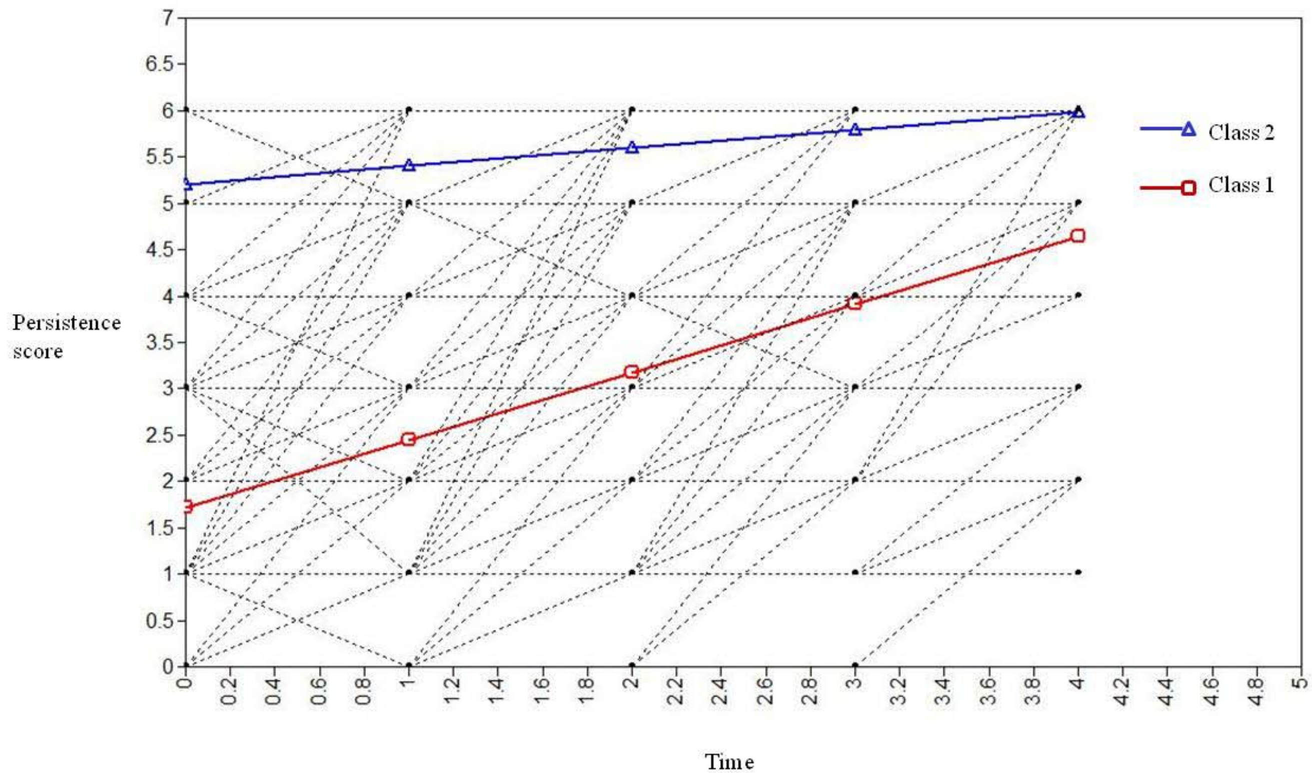

Figure 5. Estimated means and observed individual planning scores across the school year for both Class 1 and Class 2.

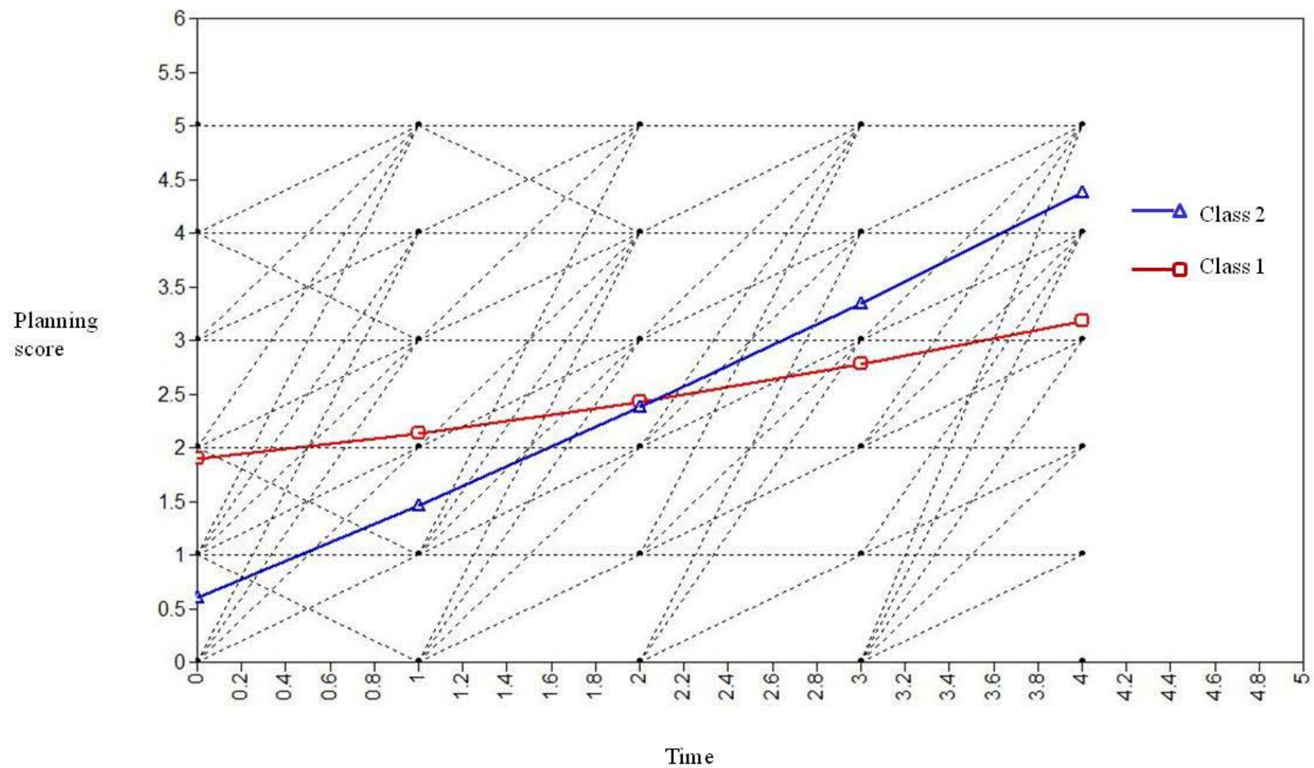

Figure 6. Estimated means and observed individual problem-solving flexibility scores across the school year for both Class 1 and Class 2.