# Trajectories of Early Education Learning Behaviors Among Children at Risk: A Growth Mixture Modeling Approach

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Abstract

This study examined the latent developmental patterns for classroom learning behaviors among children from underresourced families. Based on standardized teacher observations, a large sample (*N* = 2,152) of children was assessed for manifestations of Competence Motivation and Attentional Persistence twice annually through Head Start, kindergarten and 1st grade. For each form of learning behavior, latent growth mixture modeling revealed dominant subpopulations of change that feature quite good learning behaviors during Head Start but marked deterioration in performance upon kindergarten entry. Other change subpopulations showed children arriving in Head Start with noticeably poor learning behaviors and, while experiencing some early improvement, continued to function with relatively limited learning behaviors throughout the transition years, whereas other children entered prekindergarten with somewhat average performance levels and evinced modest losses when exiting Head Start. Membership in less desirable growth subpopulations is linked to preexisting explanatory factors and to subsequent negative outcomes. The general deterioration in learning behaviors that accompanies formal school entry is examined in the context of Head Start performance fade out and teachers' shifting reference standards.

Keywords: approaches to learning

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America's Head Start programs have long been committed to enhancing children's cognitive and social skills through preventive and compensatory curricula. This commitment is motivated primarily by the evidence that the typical Head Start enrollee is functioning in the 15th to 20th percentile in most areas of cognitive readiness (literacy, language, mathematics; Kopack Klein, Aikens, West, Lukashanets, & Tarullo, 2013; U.S. Department of Health and Human Services [USDHHS], 2003b). Further, these children, as partly related to a dearth of strong social-support networks (stemming from impoverishment), face high risk for continued academic and social-emotional difficulty (Isenberg et al, 2016; USDHHS, 2010b). Thus the most popular curricula are designed to build basic cognitive skills and social-emotional adaptation skills. At the same time, Head Start and many other early education programs have found it beneficial to fortify the process of learning such cognitive and adaptation skills by promoting children's more foundational approaches to the learning process itself. These skills are commonly known as *learning behaviors*, although variously referred to as approaches-toward-learning, learning-related behaviors, or learning-to-learn behaviors (Matthews, Kizzie, Rowley, & Cortina, 2010; McDermott et al., 2009; Stott, McDermott, Green, & Francis, 1988).

## Learning Behaviors

Learning behaviors refer to the effortful and goal-directed mechanisms by which children go about classroom learning processes, thus distinguishing them from the cognitive skills and social-emotional adaptations that might flow from those learning processes. They explain *how* children learn rather than *how well* and encompass stylistic behavioral manifestations of competence motivation, sustained focus and endurance in learning, strategic planning, acceptance of novelty and risk, and cooperation in group learning activities (McDermott et al., 2011). As such, learning behaviors are conceptually rooted in key domains of children's development: social, emotional, and cognitive, and are empirically supported by extensive literatures in each domain. Learning behaviors such as cooperation, verbal interaction and interpersonal responsiveness reflect key social competencies for young children (McClelland & Morrison, 2003). Strategic planning and the ability to focus and sustain attention derive from the broader concepts of executive function and self-regulation (Bronson, 2000; Nelson et al., 2017). Risk acceptance (or alternatively, inhibition) and exploratory behavior have been linked to children's emotional development and personality in the literatures on temperament and attachment (Grossman, Grossman, Kindler, & Zimmermann, 2008; Zentner & Bates, 2008). Yet, whereas constructs such as self-regulation and attachment represent largely theoretical internal processes that influence children's development broadly, related learning behaviors are both observable and measurable, and refer specifically to those aspects of social, emotional, and cognitive development that direct classroom engagement.

Because they are observable and essentially behavioral by nature, learning behaviors are regarded as potentially teachable through modeling or programmed instruction. Theoretically and logically, improvements in learning behaviors are expected to lead to improvements in the cognitive and sociobehavioral skill sets that emerge from them (Barnett, Bauer, Ehrhardt, Lentz, & Stollar, 1996; Heckman, 2006; Hyson, 2008; Kagan, Moore, & Bredekamp, 1995; Shure & DiGeronimo, 1996; Stott et al., 1988). Consequently, Head Start has historically fostered the development of learning behaviors (National Education Goals Panel, 1997; USDHHS, 2003a, 2010a). The importance of learning behaviors has also been highlighted in broader policies influencing all early childhood education (National Association for the Education of Young

Children & National Association of Early Childhood Specialists in State Departments of Education, 2003) and the formal standards enacted by most state departments of education (Scott-Little, Kagan, & Frelow, 2005). Recently, a consortium of federal agencies under the USDHHS and the U.S. Department of Education sponsored randomized field trials assessing the impacts of Head Start curricula on cognitive skills where instruction was scaffolded and primed through built-in modules on learning behavior (Fantuzzo, Gadsden, & McDermott, 2011). The cognitive skills curricula that were interwoven with learning behaviors yielded significantly higher gains in language and mathematics than afforded by competing curricula.

Learning behaviors are ordinarily assessed through teachers' ratings on the Preschool Learning Behaviors Scale (PLBS; McDermott, Leigh, & Perry, 2002) for prekindergarten children and the Learning Behaviors Scale (LBS; McDermott, 1999) for students in kindergarten through 12th grade. Both devices are standardized on large U.S. Census-based national samples, with evidence of high internal consistency, temporal stability, and interrater agreement (Buchanan, McDermott, & Schaefer, 1998). They have also been shown to: (a) augment substantially the explanatory power of general intelligence measures in forecasting subsequent academic achievement and social-emotional adjustment (McDermott, Mordell, & Stoltzfus, 2001; Schaefer & McDermott, 1999; Yen, Konold, & McDermott, 2004), (b) signal significant risk reduction for future school failure and learning disabilities in elementary and secondary education (McDermott, Goldberg, Watkins, Stanley, & Glutting, 2006), and (c) produce assessments that are unbiased by child gender or ethnicity (Schaefer & McDermott, 1999). Moreover, the dimensional structures and predictive efficiency of both the PLBS and LBS have been demonstrated through many national and international replication and generalization studies (e.g., Canivez & Beran, 2009; Fantuzzo, Perry, & McDermott, 2004; Hahn, Schaefer, Merino, & Worrell, 2009).

**The Transitional View**

American educators have promoted some rather remarkable avenues of passage for young children as they move from the home environs and prepare for entry into formal schooling (Petriwskyj, Thorpe, & Tayler, 2005). This is particularly true for children who are emerging from households that are economically underresourced (Entwisle & Alexander, 1993; Pianta, Cox, & Snow, 2007). Here, particular attention is given to the nature of the transition from home care through prekindergarten, kindergarten, and ultimately, 1st grade. Originating with the Piagetian and Eriksonian transitions, early childhood educators contend that the child's responses to the movement from preoperational discovery learning to common structured curricula, from individual interests to group initiatives, and from nurturing acceptance to performance grading, will influence substantively the child's attitudes toward and adaptations to long-term academic and interpersonal challenges (Gurin, Day, Hurtado, & Gurin, 2002; Heckman, 2006; Pianta et al., 2007). The transitional nature of the early childhood educational period is such that adaptation can only be understood as a developmental progression, requiring a clear picture of the course of change in any given area of performance. To acquire understanding of the role of learning behaviors, it follows that researchers would need to follow their developmental pathways as children transition through the milestone movements from preschool to formal schooling.

McDermott, Rikoon, Waterman, and Fantuzzo (2012) refined the dimensional structure of the PLBS for a large representative Head Start population, and Rikoon, McDermott, and Fantuzzo (2012) did the same for the Head Start alumnae who had moved on into kindergarten and 1st grade. Two dimensions, Competence Motivation and Attentional Persistence, were substantially congruent in behavioral content and relationships with concurrent and future measures of academic achievement and school adjustment. *Competence Motivation* measures phenomena such as acceptance of novelty, interest in learning activities, and voluntary energetic initiative, while *Attentional Persistence* includes paying attention, frustration tolerance, and considering consequences before acting. Each dimension was linked vertically across the PLBS and LBS via multiple-group item response theory (IRT) equating and Bayesian scaling (McDermott, Rikoon, & Fantuzzo, 2014).

## Competing Perspectives on Change

Commensurate with the theme of transitional measurement, McDermott et al. (2014, 2016) assessed a large sample of Head Start children on six occasions across prekindergarten, kindergarten, and 1st grade. Individual growth modeling was used to identify developmental trajectories characteristic of those children who later in 2nd grade manifested adequate versus inadequate proficiency across various academic and sociobehavioral outcomes (e.g., reading, mathematics, classroom behavioral adjustment). While blocking techniques identified two dominant trajectories of learning behavior related to later proficiency, the findings also revealed that transitional learning behaviors were inclined to take on a wide array of longitudinal patterns with almost as many different transitional pathways as there were different outcomes in the future. Although informative, by defining *a priori* a distal outcome (e.g., reading proficiency vs. nonproficiency at the close of 1st grade), this method is at once limited to modeling only the pathways related to those predefined outcomes. This approach not only lacks the parsimony necessary for theoretical development, but more importantly, it precludes identification of the natural unobserved (latent) patterns of change for learning behaviors in the general population.

In the current research, we employ growth mixture modeling (Duncan, Duncan, & Strycker, 2006; Ram & Grimm, 2009) to identify the characteristic trajectories for learning behaviors. This alternative, latent subpopulation perspective is more appropriate if the intent is to discover, irrespective of the many different possible outcomes, the pervasive change patterns that distinguish natural subpopulations of children over the transition years. These discoveries would reveal the relative sizes of those subpopulations and enable researchers to probabilistically associate each latent subpopulation with large swaths of distal outcomes, explore antecedents to children's membership in a specific subpopulation, and to propose a more parsimonious and uniform theory of how changing learning behaviors relate to important precursors and outcomes.

## Research Questions

Within this context, our study seeks to answer three questions. First, are there latent longitudinal subpopulations (distinctive growth trajectories) of Competence Motivation and Attentional Persistence as children transition through Head Start, kindergarten, and 1st grade? Second, do these subpopulations identify with direct assessments of academic skills in 2nd grade (i.e., reading and mathematics) and independent assessments of social-emotional adjustment at the close of 1st grade (contexts involving teachers and learning activities), referred to as distal outcomes? Finally, to what extent do preexisting demographic and education-related variables (child age at Head Start entry, child sex, ethnicity, use of special needs services) associate with child membership in the discovered subpopulations of learning behavior?

# Method

## Participants

The sample included 2,152 children, many having been assessed twice annually over three years beginning in academic year 2000-2001. Assessments transpired at the end of the Fall and

Spring semesters of Head Start (Fall $n$ = 1,665; Spring $n$ = 1,971), kindergarten (Fall $n$ = 910; Spring $n$ = 1,135) and 1st grade (Fall $n$ = 581; Spring $n$ = 698). The sample was constructed through random selection of 49 Head Start centers (including all 119 member classrooms) in the country's fifth largest and most economically impoverished public school district. The children were followed through 378 kindergarten and 314 1st-grade classes of the same school district. Longitudinal sample attrition was attributed mainly to transfers into parochial schools and to national and international emigration. As later discussed, sample accretion and attrition were unrelated to children's measured learning behaviors, the dependent variables of interest.

In the Fall of Head Start, the mean child age was 54.5 months ($SD$ = 6.7, range = 40-76 months). The sample was 50% female and predominantly (82%) African American, with 8% being Latino, 7% Caucasian, and 3% other ethnic groups. The subsamples of children available for follow-up in both kindergarten and 1st grade were essentially identical demographically to Head Start in gender and ethnic composition, varying no more than 1% from Head Start demographic rates. The children lived in 777 different U.S. Census block-group neighborhoods (an average of 2.7 children per neighborhood; U.S. Census Bureau, 2000). All children resided in households whose incomes corresponded with the federal poverty criteria enabling Head Start eligibility (Head Start Act. 2000).

## Measures

**Learning behaviors.** The PLBS and LBS are teacher rating scales each containing 29 items describing a child's typical classroom behavior over the past two months. The PLBS is used by teachers to assess children in prekindergarten and the LBS for students in kindergarten and 1st grade. Relative prevalence of each behavior is indicated by the teacher on a 3-point scale ("Does Not Apply," "Sometimes Applies,", "Most Often Applies"), where higher scores denote greater

Competence Motivation or Attentional Persistence, respectively. Whereas the overall themes of item content are continuous across the two instruments, item phrasing sometimes differs to accommodate the developmental level of children and the context of prekindergarten versus kindergarten and post-kindergarten classrooms. As illustration, a given LBS item states, “Accepts new tasks without fear or resistance,” whereas its PLBS semantic counterpart substitutes the word “activities” for “tasks,” and the LBS item, “Sticks to a task with no more than minor distractions,” has the PLBS counterpart, “Sticks to an activity for as long as can be expected for a child of this age.” Other items are literally identical across instruments, e.g., “Is too lacking in energy to be interested in anything or to make much effort.” Several items have no literal or semantic counterpart, such as the last PLBS item which states “Is dependent on adults for what to do, and takes few initiatives,” whereas the last LBS item states, “Delays answering in the hope of picking up a hint.” Sample Competence Motivation items are, “Accepts new activity without fear or resistance,” and “Depends on adults for what to do,” and Attentional Persistence items include, “Pays attention to what the teacher says,” and “Sticks to activity with only minor distractions.”

McDermott et al. (2012) and Rikoon et al. (2012) independently resolved reliable factor structures for the PLBS based on a large sample of Head Start children and for the LBS based on a large sample of Head Start alumnae in kindergarten and 1st grade. Each dimensional structure featured two factors that were essentially comparable in content and that were similarly named; viz., Competence Motivation and Attentional Persistence. For the Head Start enrollees and alumnae, respectively, extensive evidence is presented for the internal consistency ($\alpha$ = .86-.90 for Competence Motivation and .87-.88 for Attentional Persistence) and concurrent and predictive validity of each dimension.

With each dimension, McDermott et al. (2014) conducted multiple-group IRT vertically equating the PLBS and LBS aspects of Competence Motivation and Attentional Persistence. Each vertical scale featured 18 items and was calibrated using expected a posteriori (EAP) Bayesian (Thissen & Wainer, 2001) scaled scores (*SS*s), where the reference group (prekindergarten) *M* = 50, *SD* = 10, and effective range = 1-99. Estimates of internal consistency were .79 for Competence Motivation and .76 for Attentional Persistence. Over the six assessment periods, canonical redundancy indicated that ~ 51.1% of the variability in each dimension was unique and independent. Ample evidence is provided for concurrent and predictive criterion validity of scores (McDermott et al., 2014, 2016).

**Academic achievement.** The TerraNova, Second Edition (CTB/McGraw-Hill, 1997) was used as an external criterion measure. It is a standardized, group-administered, measure of academic achievement. This assessment was completed by students in their 2nd-grade year (Fall, 2003) and has been shown to exhibit acceptable levels of reliability and validity (Cizek, 2005; Johnson, 2005). This study employs Normal Curve Equivalent scores from the Total Reading and Mathematics scales with an effective range of 1-99. Higher scores indicate greater proficiency in Reading or Mathematics, respectively.

**Social-emotional adjustment.** The Adjustment Scales for Children and Adolescents (ASCA; McDermott, Steinberg, & Angelo, 2006) is a teacher-report device containing 97 problem and 24 prosocial behavior items, each presented in 1 of 20 specific situational contexts pertaining to authority, peers, play, learning, or confrontation, scored on a dichotomous scale indicating the presence or absence of a behavior. Low scores denote adjustment and high scores maladjustment. The content is designed to avert the necessity for respondent teachers to draw inferences about children's internal mediating processes (thoughts, feelings) and provides alternative positive variants of behavior so as to reduce teacher response sets or bias. For example, the “Greeting teacher” context includes items, “Greets as most other children do” and “Clings to you or shows tears”.

The 20 situational contexts are assigned to three mutually-exclusive scale factors based on exploratory and confirmatory common factoring. Two of these scale factors are theoretically relevant to classroom learning behavior; Problems in Contexts Involving the Teacher (5 contexts including, “Talking to Teacher,” and “Seeking Teacher Help”) and Problems in Contexts Involving Learning Activities (8 contexts including, “Reaction to Correction,” and “Working with Hands (Art, Shop)”. Coefficient $\alpha$ for the Teacher contexts scale = .76 and for the Learning Activities contexts scale .88. Stratified random national norms are applied to yield scaled scores with a population $M$ = 50, $SD$ =10, and effective range = 1-99. Broad concurrent and criterion-related validity evidence and utility in risk reduction analysis is given by McDermott, Steinberg, et al. (2006), McDermott et al. (2012), and Rikoon et al. (2012).

**Procedure**

Growth mixture modeling (Duncan et al., 2006; Ram & Grimm, 2009) was applied to identify any unobserved subpopulations of longitudinal change in Competence Motivation and Attentional Persistence, the regression of distal outcomes on resultant latent classes of longitudinal change, and the regression of those latent classes on explanatory covariates representing available child demographic and educational factors. We expected there to be multiple trajectories in the Head Start population for each dimension of learning behavior and that certain trajectories would be related to positive academic and socioemotional outcomes and others would be related to negative outcomes (as suggested by McDermott et al., 2014, 2016). We further anticipated that the discovered trajectories would be differentially associated with child sex, age, special needs, and ethnicity (as per Alfaro, Umaña-Taylor, & Bámaca, 2006; McDermott, Goldberg, et al., 2006; Schaefer, Shur, Macri-Summers, & MacDonald, 2004).

**Data analysis.** *Mplus* version 7.3 (Muthen & Muthen, 2015) was used for all analyses, with imputation of missing data under full-information maximum-likelihood estimation. Models were estimated separately for Competence Motivation and Attentional Persistence through series of both fixed (linear and polynomial) and latent basis approaches across the six assessment periods. Models were regarded preferable that produced: (a) lower values for Akaike's Information Criterion (AIC), Schwarz's Bayesian Information Criterion (BIC) and Adjusted BIC (ABIC) than found for less complex models (Nylund, Asparouhov, & Muthen, 2007); (b) minimal values for the Integrated Classification Likelihood with Bayesian-type Approximation (ICL-BIC; McLachlan & Peel, 2000); (c) maximal values for entropy and average posterior classification accuracy (Greenbaum, Del Boca, Darkes, Wang, & Goldman, 2005; Nagin, 1999); (d) statistical significance for contrast with the model featuring one less latent class as per the Vuong-Lo-Mendell-Rubin, Lo-Mendell-Rubin, and parametric bootstrap (using 1000 draws) likelihood ratio tests (Nylund et al., 2007); and (e) theoretically meaningful results (Ram & Grimm, 2009).

Given the preferred growth model for Competence Motivation and Attentional Persistence, respectively, binary distal outcomes were generated and regressed on the latent class variables formed by the most likely posterior classifications. Binary outcomes were appropriate because: (a) the alternative TerraNova and ASCA scaled scores were significantly abnormally distributed and differentially skewed; (b) the TerraNova item-domain representation was relatively sparse below the 25$^{th}$ percentile with punctuated rather than graduated changes in item difficulty (a problem common to commercial tests; see McDermott et al., 2009); and (c) they would yield relative probabilities of desirable versus undesirable outcomes in late 1st-grade and early 2ndgrade as a function of membership in each derived latent growth class. Thus, an outcome reflecting Reading Proficiency versus Nonproficiency was formed from TerraNova Reading Total scores, where Proficiency comprised performance in the upper three quartiles (scored 0) and Nonproficiency the lowest quartile (scored 1). A comparable Mathematics Proficiency indicator was formed from TerraNova Mathematics and, conversely, Social-Emotional Problems in Contexts Involving Teacher and Social-Emotional Problems in Contexts Involving Learning indicators were formed from the ASCA context factors (upper quartile = 1). Quartiles were preferred because they provided the necessary statistical power for reliable point separation in logistic modeling (Stokes, Davis, & Koch, 2000). Probabilities of better versus poorer outcomes associated with each latent growth class were obtained using the M*plus* DCAT function.

The 3-step method (Asparouhov & Muthen, 2014) was applied to regress resultant latent classes on the explanatory demographic and education-related covariates while accounting for measurement error in posterior classifications. Each model held child age (in months) at entry to Head Start as a continuous covariate and other child covariates (child sex, ethnicity, provision of special needs services) as simultaneous binary explanatory variables in a multinomial logistic regression model using the general logit link function. Final models were constructed through sequential series of pilot models examining collinearity, simple, interactive and additive effects for smaller sets of covariates (per Hosmer & Lemeshow, 2000) as guided to the extent possible by prior research (McDermott et al., 2014, 2016). The objective was to ascertain the relative risk increment or reduction for latent growth class membership (estimated through the odds ratio) associated with each explanatory covariate.

## Results

### Latent Growth Models

Models derived through latent basis growth estimates were uniformly better fitting than those through fixed basis estimation. Parameters of the basis vector $A_1$ were fixed as model identification constraints to 0.0 for the initial Fall Head Start assessment and to 1.0 for the culminating Spring First Grade assessment. Estimates of residual variance were allowed to vary across academic years, producing better model fit as partly related to the differing amounts of available data over time. For Competence Motivation, the 2-class model was preferable and for Attentional Persistence the 3-class model, having met all of the stated criteria including minimal ICL-BIC, which is known to correctly identify the best solution even when covariances are misspecified (Fruhwirth-Schnatter, 2006, pp. 214-215; McLachlan & Peel, 2000, pp. 217-220).

Figure 1 displays the estimated mean trajectories for the 2-class Competence Motivation model and Figure 2 for the 3-class Attentional Persistence model (exact estimated and observed means are posted in Supplementary Table A). For convenience, the highest classes (in terms of *SS*s) are named Higher Motivation or Higher Persistence, respectively, and the lowest classes Lower Motivation or Lower Persistence, reflecting the *SS* levels over time. The middle class for Attentional Persistence is named Marginal Persistence because mean *SS* values range consistently below the population mean (50) but never reach ½ *SD* below the mean. Based on posterior membership estimates for the Competence Motivation classes, 63.2% of children were classified with Higher Motivation and 36.8% with Lower Motivation, while for Attentional Persistence, 45.0% were classified with Higher Persistence, 32.0% Marginal Persistence, and 23.0% Lower Persistence. Thus, membership for Higher performance classes is about 1.4-1.7 times the size of Lower performance classes. Additionally, the figures reveal characteristic negative slope trends for the Higher performance classes (children manifesting markedly decreasing motivation and persistence after leaving Head Start), whereas the Lower performance classes manifest positive slope trends (modestly increasing motivation and persistence with kindergarten entry). In contrast, the Marginal Persistence class shows a modest decrement in performance as associated with kindergarten entry.

Ancillary analyses were conducted to assess the sensitivity of models to sample accretion and attrition. Growth mixture models were tested for subsamples of children who were first enrolled in Fall of Head Start and children enrolled at all time points. The resultant mean growth levels and patterns were essentially the same as those for the full imputed sample. Resulting random effects were likewise similar. This supports the assumption that the children in the full sample were observed at random with some data missing at random and unrelated to levels of or changes in the dependent variables (Little & Rubin, 2002; Marini, Olsen, & Rubin, 1979).

**External Validity Evidence**

Figures 3 and 4 illustrate the relative probabilities of each distal outcome associated with each latent growth class for Competence Motivation and Attentional Persistence, respectively. Thus, Figure 3(a) shows that the mean probability of reading nonproficiency in the Fall of 2nd grade increases significantly and nearly triples from .12 for members of the Higher Motivation class to .34 for the Lower Motivation class, and in Figure 3(b), such findings are essentially duplicated for the probability of mathematics nonproficiency. In Figure 3(c) the probability of social-emotional problems in contexts involving teachers at the close of 1st grade increases dramatically from .03 for Higher Motivation members to .47 for Lower Motivation members, the trend echoed in Figure 3(d) where the probability of social-emotional problems in contexts involving learning activities increases from .02 for Higher Motivation members to .52 for Lower Motivation members. The probabilistic separations displayed in Figure 4 for Attentional Persistence are somewhat more complicated because they involve three growth classes, but overall reveal a uniform trend wherewith each undesirable outcome (reading and mathematics nonproficiency and social-emotional problems in both teacher and learning contexts) is markedly more likely for children in the Lower Persistence class than either the Higher or Marginal Persistence classes, but the Higher and Marginal classes show no separation between themselves. In general, it is evident that a child's membership in either the Lower Motivation or Lower Persistence growth classes is associated with discernibly greater risk for subsequent academic deficiencies and social-emotional difficulties.

**Explanatory Evidence**

Table 1 presents results of the generalized multinomial logistic regression of the Competence Motivation latent growth classes on preexisting explanatory variables and Table 2 presents similar information for the Attentional Persistence growth classes. Only statistically significant main effects remain in final models (no interactions were significant) as reported in the tables and each explanatory variable appearing in a given table is controlled for all other variables appearing in that table. For Competence Motivation classes (Table 1), the risk of child membership in the Lower Motivation class decreases on the average with every additional month of age, whereas male children and those receiving special needs services are far more likely (i.e., 107.3% and 204.0% risk increments, respectively) to be members of the Lower rather than Higher Motivation latent growth class. In contrast, Latino children are afforded a 46.8% reduction in the risk for inclusion in the Lower Motivation class. In similar fashion for Attentional Persistence (Table 2), increasing age at Head Start entry and Latino ethnicity are found as protective agents against inclusion in the Lower Persistence class as compared to the Higher Persistence reference class, while being a male or recipient of special needs services greatly increases the risk of Lower Persistence versus Higher Persistence membership. The male child and special needs risk factors also separate the Marginal from Higher Persistence growth classes, with Marginal Persistence more likely. As a rule, maleness and special needs involvement operate as risk factors for inclusion in the least desirable latent growth classes of both Competence Motivation and Attentional Persistence, and Latino ethnicity and increased age act as protective factors from those same classes.

## Discussion

This research sought to discover the latent developmental patterns for early education learning behaviors among children from economically disadvantaged families. The focus was on competence motivation and attentional persistence because those are the specific forms of classroom learning behaviors that manifest continually over the focal early education transition years. Each form of learning behavior is earmarked by two classes. One is a dominant high performance class evincing appreciably lower probability of negative academic and sociobehavioral outcomes at the end of the transition period. The other is a relatively rarer class (~ ¼ to ⅓ of children) associated with significantly higher probability of serious deficits in future reading and mathematics skills, with a substantial likelihood of subsequent sociobehavioral problems. A third rather medial developmental class is discovered for attentional persistence, one that essentially hovers just below the population mean (hence marginal performance representing **~ ⅓** of children) which portends risks for negative outcomes that are effectively indistinguishable from those associated with the higher levels of attentiveness and persistence.

Interpretations of the roles of preexisting explanatory factors regarding children are rather straightforward. Although the growth patterns for most children do suffer a marked downturn with kindergarten entry, those higher competence and persistence classes nevertheless maintain functional superiority relative to other growth classes throughout the transition years, with all of the attendant probabilities for better academic and behavioral outcomes. Even those children in the least desirable growth classes demonstrate noticeable improvements in motivation and persistence during Head Start and their better performances tend to sustain thereafter. Thus, it makes sense that children's relative maturity (as reflected in their ages) at prekindergarten entry should comport with increasingly better learning behavior as time passes. Male children and those receiving services for special needs are at particularly high risk for membership in the least fortunate growth classes of learning behavior, both findings which correspond to research on the emergence of disengaged classroom behavior among Head Start-eligible children from the national Head Start Impact Study (McDermott et al., in press). Interestingly, Latino children find a general protective advantage in averting membership in the least desirable growth classes of learning behavior and this makes sense in view of research showing that Latino children exhibit generally high motivation toward educational success as encouraged by teachers and families (Alfaro et al., 2006), a phenomenon echoed in research studying those from recently immigrated families (Cardoso & Thompson, 2010; Greenman, 2013).

Arguably the most stunning aspect of the growth curves displayed in Figures 1 and 2 are the precipitous declines that occur for most children as they exit Head Start and enter kindergarten. What could explain such losses with Head Start exodus? We entertain two principal mechanisms that are grounded in empirical research and which probably operate synergistically to diminish measured motivation and persistence—fade out and shifting reference standards. The first proposition holds that the losses are real and likely parallel or even perhaps lend momentum to many other losses that appear in the wake of Head Start exit. The second proposition hypothesizes that the losses are somewhat illusory as related to observational bias and measurement error.

**Fade Out**

The Head Start Impact Study was a nationwide randomized control trial based on a probability sample representative of children eligible for Head Start enrollment (USDHHS, 2010a). Children were randomly permitted to enter Head Start or a comparable non-Head Start prekindergarten program as a means to assess relative Head Start gains in cognitive skills and social adjustment skills. With fair consistency, results showed that Head Start enrollees had improved significantly in their cognitive skills as they finished Head Start, but these gains began to fade noticeably in first grade (USDHHS, 2010a) and had essentially disappeared by the end of third grade (Puma et al., 2012). Measurable gains in the sociobehavioral domains were absent throughout the years. A randomized trial under the Chicago School Readiness Project (Zhai, Raver, & Jones, 2012) also found Head Start gains in cognitive skill areas, as well as in behavioral outcomes, only to discover that they often did not carry over into formal schooling. And still more remarkable, the Tennessee Voluntary Prekindergarten Program (Lipsey, Hofer, Dong, Farran, & Bilbrey, 2013) had orchestrated a comprehensive statewide preschool intervention where prekindergarten teachers had assessed children as being better prepared for kindergarten as well as demonstrating better social behaviors at the opening of kindergarten. But by the end of first grade the control group had caught up to the focal treatment group on achievement measures, and behavioral outcomes had deteriorated to the point where they underperformed children in the control condition. Reflecting on the Tennessee study, Lipsey et al. (2013) and Haskins and Brooks-Gunn (2016) have noted the overly optimistic estimations held by prekindergarten teachers for children’s preparedness for later schooling, where after children’s classroom work habits and attitudes toward the learning process (what we refer to as learning behaviors) gradually soured.

It should not go unnoticed that the striking losses in post-Head Start competence motivation and attentional persistence appear antecedent and concomitant to the performance fade outs observed in the major controlled studies. To the extent that good learning behaviors are foundational to learning-how-to-learn basic academic and behavioral adjustment skills, the timing of the precipitous losses in learning behavior skills associated with kindergarten and first grade entry may be more than a coincidence.

Apart from the notion that declines in good learning behaviors correspond with declines in mastery of academic and sociobehavioral outcomes, two strong lines of empirical inquiry have addressed the fade out phenomenon. First, there exists substantial evidence that Head Start alumnae are more inclined to move into kindergarten and elementary school settings that are qualitatively inferior to those attended by non-Head Start alumnae (Currie & Thomas, 2000; Isenberg et al., 2016; Lee & Loeb, 1995; Zhai et al., 2012). The evidence indicates that recipient schools are often staffed by lower quality teachers and often feature relatively deteriorated infrastructure and sometimes locations in more socially stressed neighborhoods. Promising evidence is also forthcoming from meta-analytic studies (te Nijenhuis, Jongeneel-Grimen, & Kirkegaard, 2014) showing that the fade out phenomena may be linked to the specific kinds of skills that Head Start teachers choose to promote through curricula. That is, as pertains to the types of cognitive content taught, the preponderance of skills are not the type that will tend to sustain over time or generalize to other more advanced domains of cognitive mastery. Rather, the skills are more often the kinds associated with teaching-to-the-test and are thus short-lived. Again, these revelations remind why other researchers advocate instruction in fundamental learning behaviors to scaffold academic content instruction (Hyson, 2008). The purpose of the learning behavior preparation is to fortify ordinary content instruction and to ease its generalization to more advanced content material.

**Shifting Reference Standards**

Head Start teachers devote expertise to nearly one million learners. Because the focal child population is ordinarily comprised of struggling learners (Kopack Klein et al., 2013; USDHHS, 2003b), it is understandable that such teachers would accommodate in terms of judgments and pacing to the instructional capacities of their child constituents. This accommodation will likely influence the observant teacher to calibrate perceptions of child behavior such that child performance levels that might otherwise, in another, more heterogeneous population (such as ordinary kindergarten or first grade) be perceived as mediocre, will not be assessed that way in a more protective and confined context. What appears as good learning behavior to the Head Start teacher may well appear less so to teachers who work in more heterogeneous classroom settings. This proposition finds much support in the literature showing that teacher evaluations will shift with population shifts and classroom structural changes (class size, length of teaching day, use of desks and student performance evaluations versus learning circles and nurtured learning; Finn & Pannozzo, 2004; Hamre, Pianta, Downer, & Mashburn, 2008; Mashburn & Henry, 2004). Similarly, from the prime research on factors influencing teacher grading practices (Bennett, Gottesman, Rock, & Cerullo, 1993; Brookhart, 1993; McMillian, Myran, & Workman, 2002), it is common for teachers to evaluate children, not just on the basis of observed competence in a given area of cognitive skills or behavioral adjustment, but also on the basis of a teacher’s intention to promote or protect a child, to cultivate child or family cooperation, to recognize unsuccessful effort, and to provide evidence that a teacher is causing improvement even where it does not exist. Such research comports with evidence for what is known as assessor bias variance

(Waterman, McDermott, Fantuzzo, & Gadsden, 2012), whereby substantial proportions of the variability in teacher-provided test scores and observations has nothing to do with the child being assessed, but rather the teachers providing the assessments.

**Future Research and Practice**

These findings show that the declines in children's learning behaviors appear antecedent to the observed fade out of cognitive and sociobehavioral performance in the first grade. Therefore, it is advisable that early education instruction of both academic content and learning behaviors be integrated, with learning behaviors applied to scaffold and prime ordinary curricula (as per Fantuzzo et al., 2011). It is further recommended that instruction in the foundations of early cognitive skills emphasize types of skills that are more inclined to be enduring and generalizable rather than ephemeral (as noted by te Nijenhuis et al., 2014). Future research should focus on the effects of transitional changes that would expectedly flow from such integrated curricula that focus on more generalizable skills. With respect to shifting reference standards, it is important that teachers who are asked to evaluate children be properly sensitized to the target phenomena of the evaluation, and that efforts be made to provide teachers with appropriate professional development prior to evaluation exercises (Waterman et al., 2012). It is imperative that professional development emphasize the importance of objectivity in evaluations and provide teachers with incentives and timely refresher training.

**Limitations**

Our research is limited by the depth and breadth of information collected for a measurement and validation study of learning behaviors. We simply do not know the detailed classroom or family dynamics that earmark membership in different latent classes of learning behavior for economically underresourced children. We also are limited by an absence of a broader array of sociological/ecosystem information that might serve as useful control agents in determining the unique explanatory factors associated with early classroom learning behaviors. Further, it is important to emphasize that our research is designed to reveal salient latent growth trajectories and associated precursors and outcomes; it is not designed to answer questions about causality.

## Conclusion

The aim of this study was to estimate those developmental patterns that defined the subpopulations of change in competence motivation and attentional persistence for the early education population. Growth mixture models revealed dominant trajectory subpopulations earmarked by quite good learning behavior patterns during Head Start that declined precipitously as children departed prekindergarten and proceeded through kindergarten and first grade. In turn, connections were drawn to explanatory precursor variables and to important distal outcomes, in each case accounting for measurement error and probabilistic uncertainty. Perhaps most importantly, the more parsimonious picture of developmental change led to theoretical propositions embracing the roles of performance fade out and shifting reference standards that help explain the emblematic downturns in Head Start children's developmental learning behaviors.

A collection of well-designed randomized field trials has ventured to narrow the looming readiness and achievement gaps affecting at-risk early education populations. These include trials for Early Reading First (Russell et al., 2011, pp. 199-206), Even Start (Judkins et al. 2009), Head Start (USDHHS, 2010b), and the Tennessee Voluntary Prekindergarten Program (Lipsey et al., 2013). Regrettably, these enterprises produced equivocal, ephemeral, and even detrimental effects for focal populations. The relative uniformity of these unfortunate results may well indicate some fundamental misconceptions about the causal mechanisms that motivate and sustain acceptable school outcomes for struggling learners. Whereas myriad factors (including family, poverty, culture, school, curricula) may play central roles in the dilemma, we suggest that there would be reasonable justification to view faulty learning behaviors as prime suspects leading to more pervasive distress and difficulties in schooling.

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Table 1

*Explanatory Relationship between Child Characteristics and Latent Classes of Change in Competence Motivation*

| Explanatory variable | Odds ratio (95% confidence limits) | % Risk increment[a] | % Risk reduction[b] |
|---|---|---|---|
| Odds for classification as Lower Motivation (latent class 2) vs. Higher Motivation (latent class 1) | | | |
| Age in months | 0.97 (0.95/0.98) | | 3.2 |
| Child is male (vs. female) | 2.07 (1.66/2.59) | 107.3 | |
| Child is Latino (vs. other ethnicity) | 0.53 (0.34/0.84) | | 46.8 |
| Child is provided special needs services | 3.04 (2.05/4.51) | 204.0 | |

*Note*. Values are estimated through multinomial logistic regression applying the generalized logit link function, where the latent growth classes are regressed simultaneously on explanatory variables and latent class 1 (Higher Motivation) is the reference group.

[a]Entries equal odds ratio - 1 (100).
[b]Entries equal 1 - odds ratio (100).

Table 2

*Explanatory Relationship between Child Characteristics and Latent Classes of Change in Attentional Persistence*

| Explanatory variable | Odds ratio (95% confidence limits) | % Risk increment[a] | % Risk reduction[b] |
|---|---|---|---|
| Odds for classification as Lower Persistence (latent class 3) vs. Higher Persistence (latent class 1) | | | |
| Age in months | 0.96 (0.94/0.97) | | 4.4 |
| Child is male (vs. female) | 3.79 (2.87/5.02) | 279.2 | |
| Child is Latino (vs, other ethnicity) | 0.54 (0.31/0.94) | | 45.8 |
| Child is provided special needs services | 3.67 (2.22/6.06) | 266.9 | |
| Odds for classification as Marginal Persistence (latent class 2) vs. Higher Persistence (latent class 1) | | | |
| Age in months | 0.88 (0.97/1.00) | | |
| Child is male (vs. female) | 1.67 (1.34/2.08) | 66.7 | |
| Child is Latino (vs, other ethnicity) | 0.97 (0.65/1.43) | | |
| Child is provided special needs services | 1.79 (1.11/2.89) | 79.1 | |

*Note*. Values are estimated through multinomial logistic regression applying the generalized logit link function, where the latent growth classes are regressed simultaneously on explanatory variables and latent class 1 (Higher Motivation) is the reference group.

[a]Entries equal odds ratio - 1 (100).
[b]Entries equal 1 - odds ratio (100).

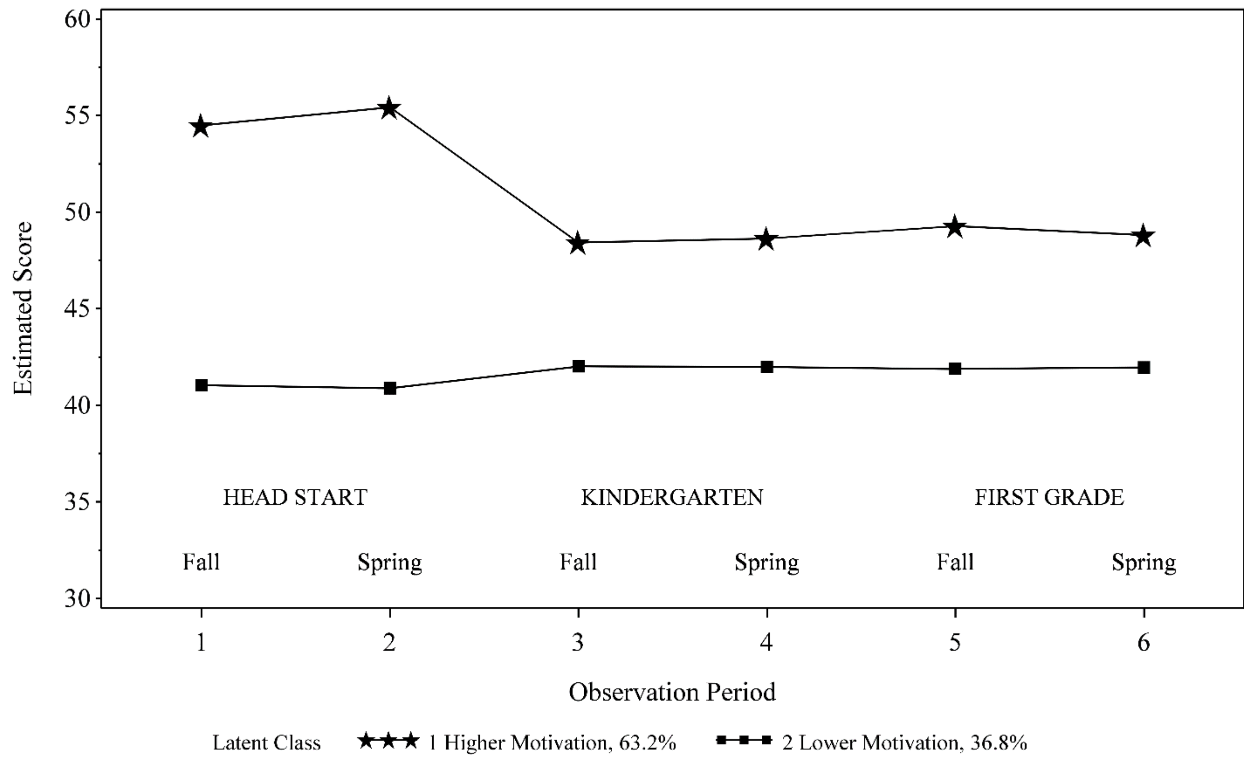


*Figure 1*. Estimated mean latent growth trajectories for Competence Motivation.

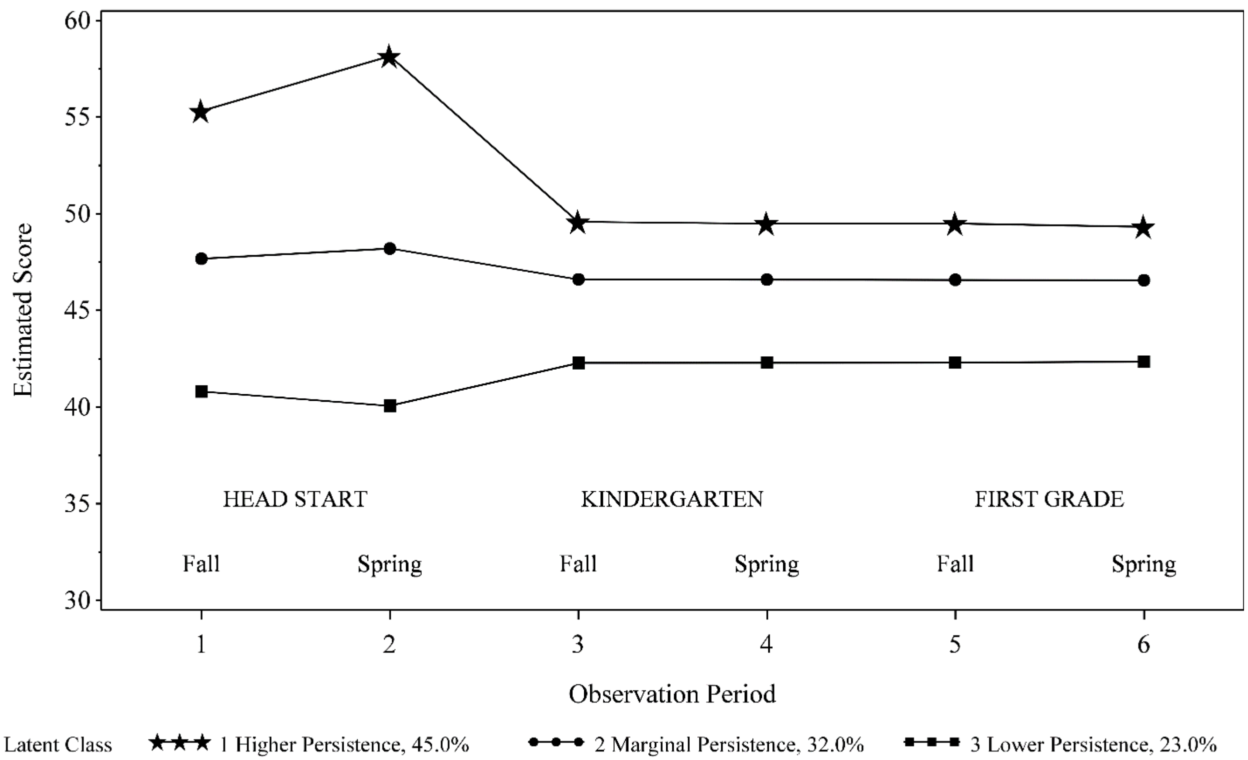


*Figure 2.* Estimated mean latent growth trajectories for Attentional Persistence.

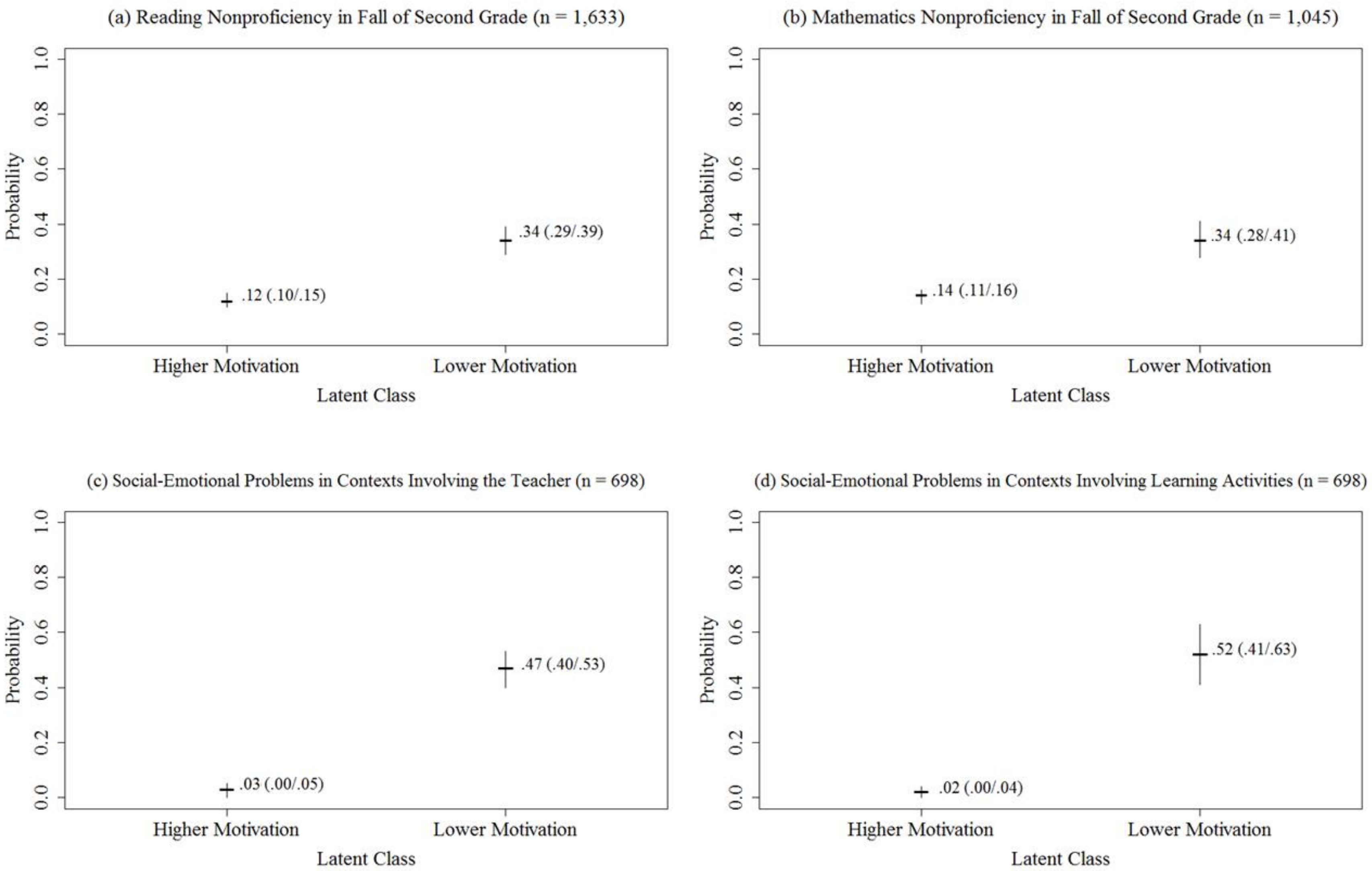


*Figure 3.* Predicted mean probability (and 95% confidence bands) of indicator outcomes associated with membership in latent classes of Competence Motivation.

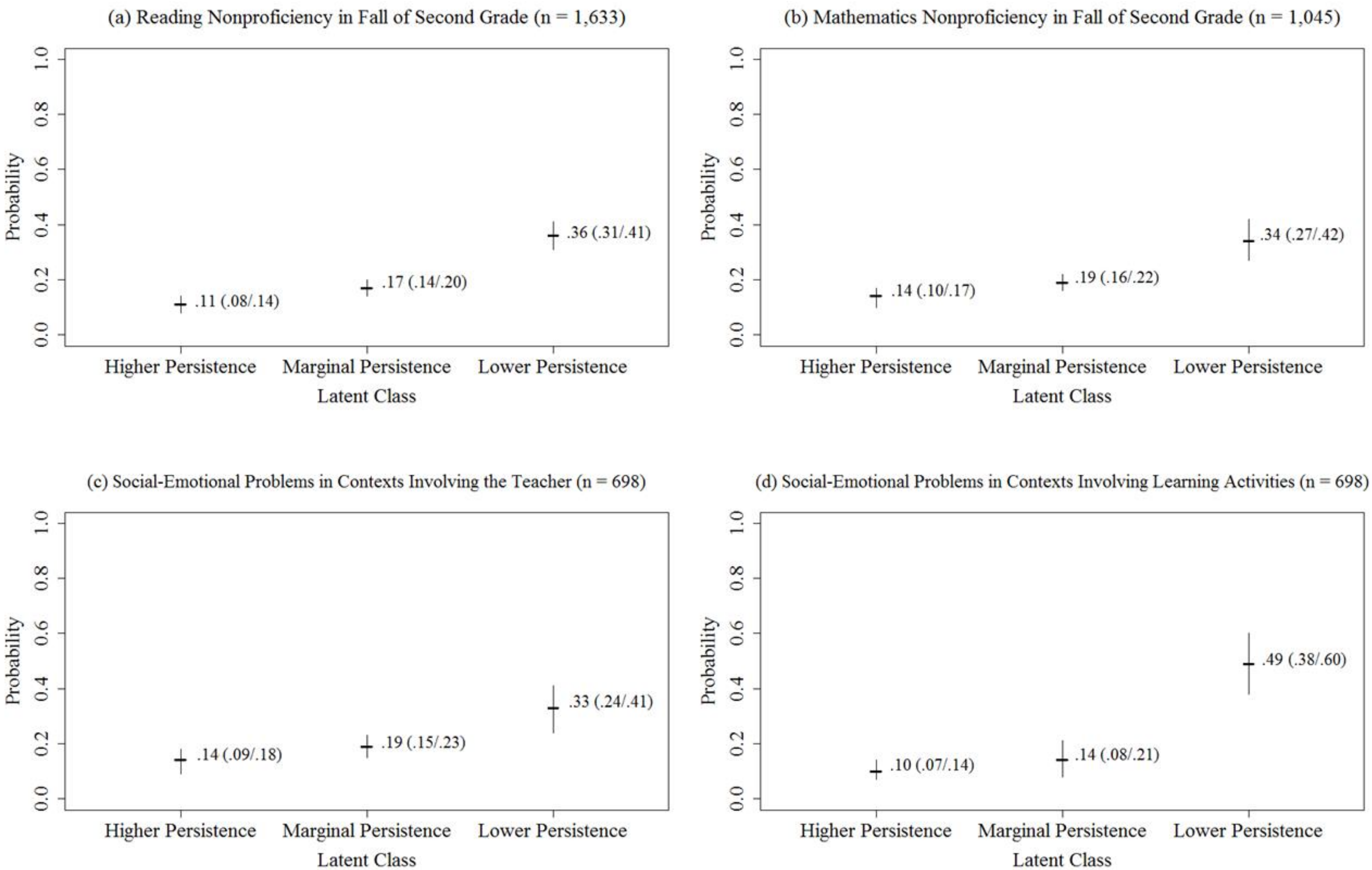


*Figure 4.* Predicted mean probabilities (and 95% confidence bands) of indicator outcomes associated with membership in latent classes of Attentional Persistence

Supplementary Table A

*Latent Class Means Across Observation Periods*

| Observation period | Latent class | Estimated *M* | Observed *M* |
|---|---|---|---|
| | | Competence Motivation | |
| Head Start Fall | 1 | 54.49 | 54.11 |
| Head Start Spring | 1 | 55.43 | 55.58 |
| Kindergarten Fall | 1 | 48.43 | 48.42 |
| Kindergarten Spring | 1 | 48.64 | 49.26 |
| First Grade Fall | 1 | 49.28 | 48.33 |
| First Grade Spring | 1 | 48.82 | 48.24 |
| Head Start Fall | 2 | 41.04 | 41.58 |
| Head Start Spring | 2 | 40.89 | 40.67 |
| Kindergarten Fall | 2 | 42.02 | 42.17 |
| Kindergarten Spring | 2 | 41.99 | 42.64 |
| First Grade Fall | 2 | 41.88 | 41.17 |
| First Grade Spring | 2 | 41.96 | 40.96 |
| | | Attentional Persistence | |
| Head Start Fall | 1 | 55.32 | 54.47 |
| Head Start Spring | 1 | 58.16 | 58.21 |
| Kindergarten Fall | 1 | 49.59 | 49.43 |
| Kindergarten Spring | 1 | 49.50 | 49.99 |

Table A (continued)

| | | | |
|---|---|---|---|
| First Grade Fall | 1 | 49.50 | 49.20 |
| First Grade Spring | 1 | 49.33 | 49.14 |
| Head Start Fall | 2 | 47.68 | 48.66 |
| Head Start Spring | 2 | 48.21 | 48.15 |
| Kindergarten Fall | 2 | 46.61 | 46.37 |
| Kindergarten Spring | 2 | 46.59 | 46.38 |
| First Grade Fall | 2 | 46.59 | 46.40 |
| First Grade Spring | 2 | 46.56 | 46.21 |
| Head Start Fall | 3 | 40.81 | 41.91 |
| Head Start Spring | 3 | 40.07 | 39.39 |
| Kindergarten Fall | 3 | 42.28 | 42.12 |
| Kindergarten Spring | 3 | 42.31 | 42.05 |
| First Grade Fall | 3 | 42.31 | 42.52 |
| First Grade Spring | 3 | 42.35 | 41.74 |

*Note*. Values are based on the full imputed sample, $N$ = 2,152.