

DISSERTATION

PROFILES OF SCHOOL READINESS SKILLS AMONG LOW-INCOME PRESCHOOLERS  
IN THE U.S.

Submitted by

Aimée Kleisner Walker

Department of Human Development and Family Studies

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Fort Collins, Colorado

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Doctoral Committee:

Advisor: David MacPhee

Karen Caplovitz Barrett

Kimberly Henry

Erika Lunkenheimer

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## ABSTRACT

### PROFILES OF SCHOOL READINESS SKILLS AMONG LOW-INCOME PRESCHOOLERS IN THE U.S.

The current population-based study employs a person-oriented approach to examine patterns of functioning across school readiness domains (pre-academic competence, self-regulatory abilities, and problematic social behaviors) at kindergarten entry within a national sample of low-income children ( $N = 2,073$ ), utilizing data from the Early Head Start Research and Evaluation Project (EHSREP; 1996-2010). This study is the first to employ factor mixture analyses (FMA), a hybrid of latent transition analysis and factor analysis, to explore at-risk children's school readiness profiles and assess whether these profiles are salient indicators of academic and social functioning in fifth grade. Results from the FMA identified two distinct classes. Specifically, class 1 (poor school readiness profile) exhibited greater weaknesses in their school readiness profiles than class 2 as demonstrated by higher scores on problematic behavioral indicators that thwart early school success, and lower scores on pre-academic competences and regulatory abilities that support early school success. Additionally, class 1 displayed higher within-class correlations among school readiness indicators on each factor than class 2. Evidence for the predictive validity of these classes was found: In fifth grade, class 1 showed significantly lower scores on academic indicators of school success (e.g., reading, math), and significantly higher scores on indicators of maladaptive social functioning. Notably, class 1 demonstrated lower reading scores and higher scores on problematic behaviors (e.g., attention problems, aggressive behavior) than any of the high-risk groups identified in the final report of

the EHSREP). These findings support the putative dynamic connections that exist across readiness domains, suggesting that at-risk children's school readiness is not simply an additive model. These findings point to analytic strategies that better illuminate variations in school readiness within high-risk samples, and also suggest that a significant minority of low-income preschoolers need intensive intervention if they are to succeed in school.

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## LIST OF TABLES

Table 1: School Readiness Latent Profile and Factor Analysis Results .....	33
Table 2: School Readiness FMA Model Comparison Results .....	36
Table 3: School Readiness Unstandardized Factor Loadings .....	39
Table 4: School Readiness Standardized Factor Loadings .....	41
Table 5: Class Differences on Fifth-Grade Academic and Social Outcomes .....	43
Table 6: Class Comparison to Age-level Averages .....	44

## LIST OF FIGURES

Figure 1: School Readiness Standardized Profile Plot .....	40
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## TABLE OF CONTENTS

ABSTRACT.....	ii
ACKNOWLEDGEMENTS.....	iv
LIST OF TABLES.....	v
LIST OF FIGURES.....	vi
CHAPTER 1- BACKGROUND AND LITERATURE REVIEW.....	1
CHAPTER 2- METHOD.....	20
CHAPTER 3- RESULTS.....	32
CHAPTER 4- DISCUSSION.....	46
SUPPLEMENTARIES: REFERENCES.....	57



## CHAPTER 1 – BACKGROUND AND LITERATURE REVIEW

### Profiles of School Readiness Skills among Low-Income Preschoolers in the U.S.

#### **School Readiness and the Achievement Gap**

The marked differences in achievement that exist between children growing up in poverty and their socioeconomically advantaged peers at school entry have remained a central focus of developmental and educational research for several decades. School readiness research focused on cross-group comparisons has consistently identified low-income children as being behind their affluent peers on cognitive and social outcomes before school entry (e.g., Fryer & Levitt, 2006; Halle et al., 2006). This research, coupled with the remarkable stability of educational trajectories that are found after the first few years of formal schooling, highlights the importance of ameliorating achievement disparities early in children's academic careers (Alexander & Entwisle, 1988; Cowen et al., 1996). Consequently, early childhood has been identified as a critical opportunity for interventions that target children at-risk for poor school achievement (Barnett, 2011; Camilli et al., 2010; Duncan & Magnuson 2006; National Institute of Mental Health, 2002; National Research Council, 2001).

According to the National Center for Children in Poverty, in 2011, 25% of children in America lived below the federal poverty line and an additional 23% lived between 100 and 200% of the federal poverty line. In tandem, these statistics establish that 49% of children, approximately 11.5 million, are living in families who are struggling to meet their basic needs. Children being raised in poverty are at greater risk for negative developmental outcomes, including school failure, school dropout, grade retention, suspension or expulsion, learning disabilities and delays, poor academic achievement, and correspondingly poor long-term employment potential (Brooks-Gunn & Duncan, 1997; Campbell & Von Stauffenberg 2008;

Duncan & Brooks-Gunn, 2000; McClelland, Acock, & Morrison, 2006; McLoyd, 1998; Ryan, Fauth, & Brooks-Gunn, 2006). Children who are raised outside of poverty start school with academic competencies (e.g., preliteracy skills, numeracy, etc.) that range from a half to a full standard deviation above their peers living in poverty. Low-income children are also found to struggle with social-emotional competencies and self-regulation (see Raikes, Brooks-Gunn, & Love, 2013). Thus, high-quality early childhood education programs, such as Head Start and Early Head Start, were designed to narrow this achievement gap attributable to poverty by providing comprehensive child development services that support early school success.

Typically, research on early school success has focused on what competencies children need to be prepared for school entry. Essentially, the goal has been to level the playing field by identifying what skills and characteristics children need to ensure that they are *ready* to take full advantage of the learning opportunities presented within our school system. Being ready for school or school readiness at the child level is therefore conceptualized as these competencies that children possess that will in part determine their likelihood of obtaining early school success (National Governor's Association [NGA], 2005). These competencies are representative of children's development across multiple domains, including the social-emotional, physical, academic/cognitive (including language and literacy development and mathematical knowledge), and approaches to learning domains (National Research Council, 2001; Snow 2007).

Early childhood is a dynamic developmental period that influences both immediate and long-term outcomes across school readiness domains. Much research has been dedicated to understanding children's readiness for kindergarten not only because it supports proximal processes that predict a successful transition to school and therefore early school success, but also distal academic achievement (e.g., Boethel, 2004). Patterns of achievement across school

readiness domains that emerge during early childhood are enduring throughout schooling without appropriate interventions (e.g., Alexander & Entwisle, 1998; Duncan et al., 2007; Konald & Pianta, 2005). Essentially, readiness at school entry represents a critical point in the developmental cascade that leads to the school achievement outcomes that are at the forefront of educational policy in the “era of accountability.”

### **Variable-Oriented School Readiness Research**

Much of the extant literature on variability in school readiness has taken a *variable-oriented* approach that explores relations between various school readiness indicators and academic achievement (e.g., Jordan, Snow, & Porche, 2000) or to examine associations across domains. This body of research sought to identify and verify key child-level competencies for each of the school readiness domains that are related to achievement. For example, in the domain of language development, preliteracy skills such as phonological awareness, letter recognition, and print concepts and knowledge have been established as the foundational competencies needed to support the development of reading ability (Compton, 2000; Dickinson & Tabors, 2001; Furnes & Samuelsson, 2009; Jordan et al., 2000; Lonigan, Burgess, & Anthony, 2000). These early literacy skills are concurrently and longitudinally associated with mathematical abilities (Duncan et al., 2007; Hooper, Roberts, Sideris, Burchinal, & Zeisel, 2010; McClelland et al., 2007; Purpura, Hume, Sims, & Lonigan, 2011; Welsh, Nix, Blair, Bierman, & Nelson, 2010). Deficits in language development in childhood have been positively associated with contemporaneous and future behavioral problems, including attention and externalizing problems, and delinquency (Beitchman et al., 2001; Brownlie et al., 2004; Yew & O’Kearney, in press). La Paro and Pianta’s (2000) meta-analysis found that early academic/cognitive competencies predicted later academic functioning with large effect sizes (around  $r = .50$ ).

Together, these findings establish the importance of language and literacy development in school success. Furthermore, these findings indicate a likely developmental interplay between language and literacy development and other school readiness domains.

Similarly, basic mathematical knowledge, such as counting and number concept, has been established as a foundational competency needed to support the development of later math ability (DeSmedt, Verschaffel, & Ghesquiere, 2009; Jordan, Kaplan, Locuniak, & Ramineni, 2007). Math skills also are positively associated with reading ability across time (Duncan et al., 2007; Hecht, Torgesen, Wagner, & Rashotte, 2001). In fact, Duncan and colleagues (2007) found children's math ability at school entry to be the strongest predictor of school achievement. Yet, Blair (2002) suggested that poor regulatory abilities physiologically prevent children from being able to use higher cognitive functions needed to learn academic content within classrooms. Additionally, research has consistently found children's math achievement and early literacy to be positively associated with emotional and behavioral regulation (Graziano, Reavis, Keane, & Calkins, 2006; Howse, Calkins, Anastopoulos, Keane, & Shelton, 2003). A more recent study found that attention abilities at age 4 predicted math and reading abilities at age 21. These age 4 attention abilities were also found to dramatically increase children's odds of graduating from college by age 25 (McClelland, Acock, Piccinin, Rhea, & Stallings, 2013). Together, these findings establish the importance of math ability and regulatory abilities in school success. Additionally, they suggest that development within these school readiness domains does not occur in isolation from competencies in other domains.

The critical importance of these school readiness competencies in long-term academic trajectories is practically evidenced by the Head Start National Reporting system (2003), which mandated high-stakes testing of such competencies for this federally funded preschool program.

However, this public policy highlights that *variables* are the current focus of educational researchers and policy makers. By treating children's performance across domains of readiness as independent metrics, findings fail to capture the profiles of functioning across domains and the probable interactions among domains *within* individuals (Bergman & Magnusson, 1997; McWayne, Green, & Fantuzzo, 2009). The difficulty with treating children's competencies as domain specific is that such an approach ignores the dynamic connections and interactions that exist across domains (Frye, 2005; Hirsh-Pasek et al., 2005). This has led developmental researchers to call for a multidimensional approach that can account for "the complex ontogenic negotiations that occur in the early childhood period" (McWayne, Green, & Fantuzzo 2009, p. 2; see also Cicchetti & Toth, 1997; Mendez, Fantuzzo, & Cicchetti 2002).

Overall, variable-oriented research fails to account for the complex interactions that occur across developmental domains within individuals. By aggregating data across individuals, variable-centered research does not accurately capture the variability within groups (Bergman & Magnusson, 1997; Bergman, von Eye, & Magnusson, 2006; von Eye & Bergman, 2003). It is problematic when results from these aggregate investigations are used to develop "evidence-based curricula" that are then applied to the whole population. As such, these curricula are tailored to none because they are based on research that likely misrepresents all. This problem is labeled the ecological fallacy and is one of the fundamental tenets of person-oriented theory (Freedman, Klein, Ostland, & Roberts, 1998; von Eye & Spiel, 2010). Understanding the developmental interplay of children's functional abilities across school readiness domains is important for guiding needed improvements to interventions that target children at-risk for poor school outcomes and the associated negative consequences (Fantuzzo, Gadsden, & McDermott, 2011).

## **A Person-Oriented Resilience Framework**

From a resilience framework, early education interventions, such as Early Head Start, aim to promote children's positive development by reducing risks that are amenable to change and strengthening protective factors that will buffer children against the adversity they face (Raver & Zigler, 1997). In doing so, these interventions promote children's resilience. Resilience is "a construct connoting the maintenance of positive adaptation by individuals despite experiences of significant adversity" (Luthar, Cicchetti, & Becker, 2000, p. 543). However, these efforts are mismatched with variable-oriented research that explores the mean-level of school readiness competencies across children, ignoring the heterogeneity assumed within a resilience framework. Treatments or curricula are likely to be more effective if they are tailored to the specific needs (i.e., individual profiles) of the learner (Cronbach, 1957). In the case of school readiness, some children exhibit educational resilience in the face of adversity attributable to poverty, whereas others do not. In other words, low-income children do not represent a homogeneous group. Indeed, subgroup analyses within low-income samples suggest high variability among low-income children's academic achievement (e.g., Fantuzzo, LeBoeuf, Rouse, & Chen, 2012). This suggests that our understanding of protective factors relevant to educational resilience would be augmented by first identifying group(s) of resilient children. Examining distinct yet homogenous profiles within low-income samples is critical to identifying risk and protective factors that are salient to specific subgroups of children, thereby avoiding interventions based on costly ecological fallacies (Freedman, et al., 1998).

Research guided by a *person-oriented* approach (Bergmen & Magnusson, 1991,1997; Sterba & Bauer, 2010; von Eye & Bergman, 2003; von Eye & Bogart, 2006) informs our understanding of school readiness as a comprehensive and holistic construct within individuals

(Halle et al. 2006; Knold & Pianta, 2005; McWayne, Green, & Fauntuzzo, 2009). This approach acknowledges the complex interactions that occur across domains of development (Sterba & Bauer, 2010). Person-oriented analyses allow researchers to identify patterns of readiness skills within children that put them at risk for negative academic and developmental trajectories or that act to buffer children against the risks presented by poverty. When such research is coupled with a focus on skill-based variables that are amenable to change through early intervention, the practical utility of findings for comprehensive whole-child interventions, like Head Start and Early Head Start, dramatically rises.

### **Person-Oriented School Readiness Research**

There is a small but growing body of population-based research examining children's school readiness profiles (Hair, Halle, Terry-Humen, Lavelle, & Calkins, 2006; Halle, Hair, Wandner, & Chien, 2012; Konold & Pianta, 2005; McWayne, Cheung, Wright, & Hahs-Vaughn, 2012; McWayne, Fantuzzo, & McDermott, 2004; McWayne, Green, & Fantuzzo, 2009; Quirk, Nylund-Gibson, & Furlong, 2012 ; Sabol & Pinata, 2012). Each of these studies used different school readiness indicators that were collected using teacher and parent reports, as well as direct assessment methods. The studies use various analytical strategies to empirically derive patterns of competencies that exhibit meaningful cross-domain interactions. Several of the studies also provided evidence of external validity through the prediction of long-term academic and social outcomes. Below, the strengths and weakness of the studies are examined, highlighting meaningful lessons that inform the current study.

Konold and Pianta (2005) employed multistaged cluster analysis to identify six readiness core profiles among typically developing preschoolers from a normative sample of children. Profiles were estimated using measures of executive functioning (e.g., working memory and

attention) and social functioning (e.g., self-regulation). The cluster solution confirmed that children's school readiness could be viewed holistically to reflect the links between domains within a child. The six profiles were labeled with the most dominant characteristic of the cluster: (1) attention problems, (2) low working memory, (3) low to average social skills and working memory, (4) socializing and externalizing problems, (5) high social competence, and (6) high working memory and mild externalizing problems. The findings also suggested that these core profiles differentially predicted 1<sup>st</sup> grade achievement. However, a limitation of the findings is that the sample was primarily White (83%) and only 25% of the participants were below the poverty level. These limited demographics did not allow for analyses of within-group commonalities and differences among children at risk due to poverty status.

In a recent extension of this research, Sabol and Pianta (2012) explored how the six core profiles predicted fifth-grade social-emotional and achievement outcomes. Additionally, this study examined the extent to which profiles accounted for fifth-grade outcomes after taking into account early skills and demographics. Indeed, the profiles did predict fifth-grade outcomes and supported cross-domain connections across early schooling. Specifically, profiles that were associated with high working memory and social skills seemed to be buffered against the deleterious effects of weaknesses in other domains. Furthermore, school readiness profiles uniquely predicted fifth-grade math achievement after controlling for early skills and demographics. However, the profiles did not predict reading achievement. The conundrum of divergent findings suggests the importance of further research that may offer a solution as to why. It is possible that the profiles were based on restricted manifest variables that may highlight specific strengths that support math achievement (e.g., working memory). Furthermore, it is still unclear if these clusters would remain salient for children living in poverty. Thus, the current



study employs a range of skill-based variables that are amenable to change as the basis for the latent profiles. There are two reasons for this strategy. First, these skill-based variables are more likely to be associated with strengths and weaknesses in functioning *across* domains; and second, they offer a direct translation to curricular goals within early childhood classrooms (McWayne et al., 2012).

Hair and colleagues (2006) used the ECLS-K, a nationally representative data set of first-time kindergarteners, to examine school readiness profiles and the profiles' ability to predict 1<sup>st</sup> grade achievement outcomes. Using school readiness indices from across five domains (physical well-being, social-emotional development, approaches to learning, language development, and cognitive development), the researchers employed cluster analysis to establish four distinct patterns of children's readiness at school entry that differentially predicted 1<sup>st</sup> grade achievement outcomes and social adjustment. The cluster solution revealed two clusters reflecting developmental strengths (positive across domains [30%] and social-emotional and health strengths [34%]) and two clusters reflecting risks (social-emotional risk [13%] and health risks [22.5% of the sample]). The nationally representative demographics of the sample and comprehensive set of readiness indicators used in this study expanded previous understandings of how children's skills and abilities across domains interact to reflect patterns of developmental functioning that predict later achievement. However, in Hair and colleagues' study, the majority of socio-economically disadvantaged children were classified into the profiles characterized by risk, suggesting the need for further exploration of within-group profile variance (McWayne et al., 2012).

In a 2012 study using the Family and Child Experiences Survey (FACES) dataset, Halle and colleagues examined patterns of school readiness within a representative sample of Head

Start children to investigate how school readiness abilities and skills coalesce within at-risk children. Additionally, the authors investigated concurrent demographics that were associated with profile membership. The study employed latent class analysis and truncated all manifest variables into dichotomies representing on- or off-track. The findings provide further evidence of developmental patterns of readiness and suggest that approaches to learning may act as an important protective factor for at-risk children. Gender, race/ethnicity, and home language were associated with profile membership. However, these findings are limited by the loss of likely meaningful variance represented in the dataset's original continuous constructs. Additionally, the authors appear to have ignored the assumption of conditional independence that is a cornerstone of latent class analysis (Lubke & Muthen, 2005). Please see the data analysis section of the current paper for a full discussion.

Two studies presented by McWayne and colleagues (2004, 2009) coupled variable-oriented and person-oriented approaches to examine low income-children's academic and social functioning from preschool to first grade. The first study examined the school readiness competencies (cognitive, social, approaches to learning, physical/motor) across and within a representative sample of 195 Head Start children (McWayne et al., 2004). The variable-oriented findings suggested that general competencies (e.g., literacy and numeracy) and approaches to learning (e.g., attention, motivation) predicted unique variance in concurrent academic success. Person-oriented analyses using clustering techniques revealed seven profiles of children's competence. However, these profiles were classified into three broad groups of profiles based on variable-centered relations with concurrent academic success: (1) at-risk for later learning difficulties, (2) children likely to demonstrate academic competence, and (3) undifferentiated. Children from four different profiles demonstrated concurrent academic competency placing

them in the competent superordinate group. For example, children with high classroom competencies and average approaches to learning and problem behavior performed similarly to children with average classroom competencies and problem behavior and high approaches to learning on a concurrent measure of academic competency. This first study suggests that variable-oriented and person-oriented analyses complement one another with regards to children's readiness. Furthermore, these findings are redolent of the possibility that the addition of a dimensional component to cluster analysis may simplify profile solutions.

Mun, Bates, and Vaschillo (2010) have suggested that variable-oriented and person-oriented approaches may be used complementarily to inform our understanding of developmental functioning. It is possible that the addition of variable-oriented approaches may account for variables that display what von Eye and Bergman (2003) have described as dimensional identity. They suggested that some variables exhibit strict factorial invariance that connotes dimensional identity. For these variables, data analysis at the aggregate level can be justified. It is possible that some of the competencies contributing to school readiness profiles exhibit dimensional identity and therefore the cluster solutions are simplified by integrating variable-oriented analyses. It is also possible that including the variable-oriented analyses accounts for additional covariance among the predictors. The modeling technique used in the current study will compare models with and without variable-oriented components as well as models with various parameterizations of factorial invariance to assess these possibilities.

The second study was a longitudinal design meant as a follow-up to the 2004 investigation (McWayne et al., 2009). The superordinate groupings meaningfully predicted both social and academic outcomes, providing evidence of external validity for the existence of these groups. The findings again reinforce the advantages of coupling variable-oriented and person-

oriented approaches to explore patterns of strengths and needs within low-income children. Together, these studies endorse the meaningful interplay among developmental domains that occur within children and demonstrate that profiles that represent heterogeneity can predict later academic outcomes. Furthermore, the studies corroborate the potential of mixing variable- and person-oriented analytical techniques to illuminate patterns of functioning that predict school success.

Using the FACES data set, McWayne and colleagues (2012) explored school readiness profiles at entry to preschool and their predictive associations with end of kindergarten academic and social outcomes. Additionally, the authors examined how relevant contextual variables from children's family and classroom predicted and/or moderated this relation. Cluster analyses revealed five patterns distinguished by varying levels of social skills, problem behaviors, and academic skills. Of the five profiles, two were characterized by strengths, two by weakness, and one exhibited average functioning. Notably, the findings suggest that readiness skills and abilities within children at preschool entry combine into distinct patterns that predict later achievement. Additionally, concurrent contextual factors within the family (maternal education and parenting style) and in their classroom (teacher experience, teacher education, and adult-child ratio) accounted for additional variance in social and academic outcomes. These findings capture a holistic picture of how early skills coalesce to predict social and academic achievement in children from socially disadvantaged backgrounds. Missing from this study was the inclusion of variable-oriented analyses to complement and possibly reduce the clusters identified.

Quirk et al. (2012) meaningfully added to this research by examining school readiness profiles within Latino/as at entry to kindergarten. The authors used latent class analysis to identify five distinct profiles that meaningfully predicted academic performance in second grade.

Academic achievement in second grade was assessed using the California Standards Test of Math and English Language Arts. By using a standardized assessment, the authors were able to not only compare average performance among profiles but also compare profiles to grade-level expectations. In the current study, children who were unable to complete the assessments in English were excluded (please see the Methodology section for a complete discussion). This makes it difficult to generalize the findings of Quirk and colleagues' study to the present study. However, Quirk and colleagues' use of standardized outcomes to explore the implications of profiles memberships for children's future school achievement in the context of national expectations informs the choice of long-term outcomes in the present study.

Together, these population-based studies of children's school readiness profiles demonstrate that a person-oriented approach can illuminate meaningful patterns of cross-domain strengths and needs that predict future academic and social outcomes. More importantly, the most recent studies (Halle et al., 2012; McWayne et al., 2012) highlight specific profiles of functioning within at-risk children who exhibit resilience in the face of significant adversity associated with chronic poverty. By exploring these patterns of heterogeneity within groups of children at risk for poor educational outcomes, researchers are able to examine possible sources of resilience that can be used to guide interventions. Sabol and Pianta's (2012) study was the only study that looked at prediction of academic and social indicators of school success beyond early elementary school. The remaining studies explored more proximal predictions of outcomes at the end of kindergarten and first grade. This presents a significant gap in our understanding, given that Sabol and Pianta's (2012) sample did not represent low-income children and that the impacts of Head Start dissipate across time (Administration for Children and Families, 2010).

## **The Current Study**

Guided by a resilience framework, the present investigation uses a hybrid of variable- and person-oriented approaches to explore patterns of heterogeneity within a nationally representative sample of low-income children. This study meets the three criteria for person-oriented research proposed by von Eye and Bogart (2006). Namely, it uses a heterogeneous sample to identify subgroups that are externally validated and substantively interpreted using the extant literature. Three research questions are explored: First, what patterns of school readiness skills are found in at-risk prekindergarten children? Second, do these school readiness profiles exhibit differential functioning in fifth grade on social and academic competence? Third, does participation in early childhood care and education predict class membership? By identifying diverse profiles among low-income children, the current study strives to “move beyond the cross-group comparisons that consistently portray low-income children as irrevocably behind their middle class peers” (McWayne et al., 2012, p. 863) to identify those children who exhibit resilience in the face of adversity attributable to poverty. To my knowledge, this is the first study to employ factor mixture analysis (FMA), an amalgam of factor analysis and latent class analysis, to estimate models of children’s school readiness.

### **Factor Analysis**

Classic factor models (Lubke & Muthen, 2005; Thurston, 1947) are variable-oriented analyses that model commonalities of observed variable content by grouping variables together on continuous latent variable(s), or factor(s). The participants from whom the observed data are collected are assumed to be part of a homogenous group whose differences are a matter of degree or location on the latent factor continuum(s). These differences can be represented by the variance-covariance matrix of the continuous latent variable(s). In context, if the underlying

structure of the school readiness data was best represented by a factor model, then school readiness could be described as a fully dimensional characteristic and individual differences would be represented by children's level of functioning on the latent factor. These differences in degree of functioning on the factor produce the covariances of the observed variables.

Regression associations between the observed variables and the continuous latent factors are specified to model the covariances of the observed variables. It is assumed that all shared variability in observed variables is accounted for by the latent factor(s). As such, factor models are variable-oriented analyses because their purpose is to group variables, not individuals. If the underlying structure of the school readiness data is best represented with a factor model, then school readiness is a multidimensional construct. Within this model, children's readiness is determined by levels of functioning on continuous latent factors.

### **Latent Class Analysis**

Lazarsfeld and Henry (1968) first introduced latent class analysis (LCA) as a person-oriented approach to identify subpopulations or classes within populations of individuals. As opposed to factor models, latent class models group individuals, not variables. The underlying latent structure of the observed variables is represented by a latent categorical variable. However, a critical assumption of LCA is the assumption of conditional independence. This assumption means that the correlation among observed variables within class is zero. In the current example, if the underlying structure of school readiness data was best represented by a latent class model, then the construct of school readiness would be interpreted as a discrete categorical construct where individuals within a class are sufficiently similar on the observed variables.

There are two inherent problems associated with this structure. First, we would need to add classes until we satisfied the assumption of conditional independence. This would result in

classes that do not actually reflect meaningful population heterogeneity but simply serve to model residual correlations between small sets of observed variables. Second, we expect there to be variation of functioning on observed variables within each class of school readiness. For example, a subgroup of resilient children may exhibit a range of abilities on items related to the academic/cognitive domain but they would still be classified as having successful adaptive functioning with the domain. Specifically, a child can do extremely well on indicators of math ability but average on indicators of reading and still be identified as achieving school success. The assumption of LCA models does not allow for this type of differential functioning.

### **Factor Mixture Analysis**

FMA (Clark et al., in press; Lubke & Muthen, 2005; Muthen, 2008) combines the models described above so that the underlying structure of the data can be explored as simultaneously dimensional and categorical. FMA uses both categorical latent variable(s) and continuous latent variables to model the underlying structure of the observed variables. The categorical latent variable classifies individuals into groups and the dimensional latent factor models the correlation structure of the observed variables for each class. FMA relaxes the assumption of conditional independence within class to allow for differential functioning within class. In context, if the underlying structure of the school readiness data were best described with an FMA, the latent class(es) could be interpreted as distinct subgroups of children based on qualitative differences on school readiness indicators. The parameters of FMA can be specified in different ways that reflect variations in restrictiveness. Models without strict factorial invariance prevent the interpretation of factor metrics (Lubke & Dolan, 2003; Meredith, 1993;). However, Clark and colleagues (in press) suggested that FMA model variations that do not free



all factor parameters allow for partial exploration of factor metrics. A full discussion is provided in the method section of this paper.

FMA was chosen as the analytical strategy for the current investigation for two reasons. First, although classic latent class models (Lazarsfeld & Henry, 1968) can be used to model population heterogeneity, given the strong associations among readiness skills found in the extant literature reviewed above, the data being modeled would likely violate the assumption of conditional independence. The second reason is that by coupling both person-oriented and variable-oriented analytic procedures, FMA will likely provide the most parsimonious solution for modeling children's school readiness (McWayne et al., 2004). The achievement gap represents a social injustice that is being faced by children in poverty. It reflects differential developmental affordances that are based on poverty status. School readiness has the potential to create equal opportunity within our public school system by ensuring that children have the competencies they need to take advantage of learning opportunities, enabling them to experience school success. As such, from a resilience framework, the goal of the current study is to identify subgroups of low-income children. The current study will identify profiles of resilient functioning that lead to resilience in the face of adversity and profiles of poor functioning that reflect susceptibility to the adversity of poverty. By adding factors to the model structure, FMA allows for differential functioning within classes on various latent factors, therefore accommodating ranges of abilities. This allows class distinctions to represent dichotomies of resilient versus poor school readiness functioning while also accounting for differential functioning on indicators of school readiness.

## Hypotheses

The current study is believed to be the first to assess children's school readiness profiles using FMA and is therefore exploratory. The extant literature reviewed above varies greatly in terms of analytical methods, readiness indicators, and sample demographics, making it difficult to apply their insights to the present investigation. However, some consistent findings lend credence to basic hypotheses for the three research questions being investigated. The first goal of the current study is to identify patterns of school readiness skills found in at-risk prekindergarten children. All of the studies reviewed above identified profiles that are characterized as reflecting either adequate/competent or poor school readiness functioning. Cluster analysis and LCA have been found to offer similar, stable solutions, but LCA's inclusion of error structure into the analyses typically *reduces* the number of profiles (DiStefano & Kamphaus, 2006). Furthermore, McWayne and colleagues' (McWayne, Fantuzzo, & McDermott, 2004; McWayne, Green, & Fantuzzo, 2009) incorporation of variable-oriented analyses to synthesize their cluster profiles into superordinate groups (e.g., at-risk, competent, and overlapping) suggests that FMA's inclusion of a factor structure to capture the dimensional aspects of readiness will reduce redundancies among profiles further to lead to the most parsimonious solution. Therefore, it is hypothesized that analyses will reveal a small number of classes that either represent resilient or poor school readiness functioning.

The second goal of the current study is to examine if school readiness profiles exhibit differential functioning in fifth grade on indicators of social and academic competence. Several of the reviewed school readiness profiles were able to successfully predict future academic and social functioning (McWayne, et al., 2009; McWayne et al., 2012; Sabol & Pianta, 2012). Namely, profile membership that represented resilient school readiness functioning was

predictive of academic and social competence, whereas profile membership that represented poor school readiness functioning was predictive of lower academic achievement and poor social behaviors. Therefore, it is hypothesized that profile membership is associated with differential performance on fifth grade indicators of academic and social competence. Specifically, children in classes that represent resilient school readiness functioning have higher levels of academic functioning, whereas children in classes that represent poor school readiness functioning demonstrate lower academic achievement and social behaviors.

Finally, the current study uses data collected during the Early Head Start Research and Evaluation Project (EHSREP; Administration for Children and Families, 2002; Love, et al, 2005; Love, Chazan-Cohen, Raikes, & Brooks-Gunn, 2013). As such, the children were randomized into either an Early Head Start (EHS) or control group. The final goal of the current study is to examine if participation in these various early childhood care and education conditions predict class membership. Given the putative importance of early childhood education (Heckman, 2006), it is hypothesized that profiles that represent resilient school readiness functioning include greater proportions of EHS children.

## CHAPTER 2 – METHOD

### **Dataset**

The present study is a secondary data analysis of the Early Head Start Research and Evaluation Project (EHSREP) archived by Research Connections. The EHSREP is a large-scale evaluation of Early Head Start (EHS) (Administration for Children and Families, 2002; Love, et al, 2005; Love, Chazan-Cohen, Raikes, & Brooks-Gunn, 2013). This rigorous evaluation employed random assignment from 17 sites across the United States. Eligible families represented three qualifications: 1. Their income was below or near the federal poverty line; 2. They had a child under the age of 12 months (including pregnant mothers); and 3. They had not participated in any programming similar to EHS. In this prospective longitudinal study ( $N=3001$ ), half of the participants were randomly assigned into the EHS intervention group and received EHS services from birth to age 3. Participants in the control were allowed to access any available childcare services other than EHS, including center-based care. Between the ages of 3 and 5, children were not formally assigned to any preschools. However, the vast majority of the children (89%) participated in some form of formal early childhood education. Of this 89%, more than half were enrolled in Head Start programs (Love et al., 2013). Details of the sampling plan are presented in the Final Technical Report (Administration for Children and Families, 2002).

Prekindergarten data were collected from 71% (2,142) of the original 3001 participants. Response bias analyses suggest that there were no significant differences between responders and nonresponders. The modeling in the current study required consistent measures to be used across all children. As such, the English versions of assessments were chosen in instances where the EHSREP variables included both English and Spanish versions (e.g., Woodcock Johnson-III

and the Woodcock Munoz). Of the 2,142 children, 69 were excluded from the current study because they were missing data on measures used. Prekindergarten data collection included direct child assessments, structured parent interviews, and observations within participants' homes and childcare centers (see Love et al., 2005 and Faldowski, Chazan-Cohen, Love, & Vogel, 2013 for full descriptions of methods).

In fifth grade, data were collected from 1,632 (66%) of the children who had responded in prekindergarten. Analyses between responders and nonresponders again suggest nonsignificant response bias. All fifth-grade data were collected during home visits that included three components: direct child assessment, child interview, and maternal interview. A complete description of the sample and data collection approach can be found in the final report of the fifth grade follow-up (Mathematic Policy Research, 2010).

### **Sample**

The 2073 participants selected were ethnically diverse: White (41%), African American (35%), Hispanic (20%), and Other (4%). The participants reflect a relatively even gender split, with 49.9% males and 50.1% females. Of the 2073 participants in the sample, 16% were nonnative English speakers and 64% were receiving federal assistance. Although the entire sample represents low-income children, large variability can be seen on self-reported income in relation to the established federal poverty line (FPL): 26% less than 33% of FPL, 24% between 33 and 67% of FPL, 21% between 67 and 99% of FPL, 11% above FPL, and 18% who did not self-identify. A small minority of the sample (7%) were identified as having individual education plans, suggesting the need for special education services.

## Measures

**School readiness variables.** All school readiness indicators used for the identifying profile were collected in the spring or summer before children entered Kindergarten (~age 5). The dimension of pre-academic competence was assessed through direct child assessment using subscales from three norm-referenced tests: Woodcock-Johnson Revised, Peabody Picture Vocabulary Test-III, and Leiter Revised. The social-emotional domain was assessed using two parent-report measures (one designed to assess social and learning skills and the Child Behavior Check List aggression scale), and direct assessment using Leiter-R Examiner Rating scale (both the cognitive social and emotion regulation standard scores).

**Pre-academic.** *Woodcock-Johnson Tests of Achievement (W-J-R)* (Woodcock & Johnson, 1990) is a norm-referenced assessment battery. Two subtests were used to assess pre-academic functioning: Letter-word and Applied problems. The Applied Problems subtest assesses children's ability to analyze and solve practical math problems and was therefore used as the index of math achievement. The estimates of internal consistency for this subtest were acceptable for both the norming sample referenced in the manual ( $\alpha = .91$ ) (Woodcock & Johnson, 1990) and the current sample ( $\alpha = .85$ ). The Letter-Word subtest assesses children's ability letters and words that have been decontextualized and was therefore used as the index of preliteracy skills. The estimates of internal consistency for this subtest were acceptable for both the norming sample referenced in the manual ( $\alpha = .92$ ) (Woodcock & Johnson, 1990) and the current sample ( $\alpha = .84$ ). Construct validity has been established through factor analysis. Additionally, concurrent validity has been established through comparison with similar assessment batteries, such as the Wechsler Intelligence Scale for Children- 3rd edition, and the Das-naglieri Cognitive Assessment System (Hendershott, 2000)

*The Peabody Picture Vocabulary Test–3rd Edition* (PPVT–III; Dunn & Dunn, 1997) is a test of English receptive vocabulary where the child is shown a set of four pictures at a time and asked to select the picture that best represents the word spoken by the examiner. It is appropriate for children and adults over age 2.5. The PPVT-III was normed on a nationally representative sample. This allows raw scores to be converted to standardized scores relevant to chronological age. In the current sample, it demonstrated high internal consistency ( $\alpha = .96$ ), consistent with reliability estimates from the norming sample that range from .92 to .98. Concurrent validity also has been established through comparisons with the OWLS Listening scale and the Wechsler Intelligence Scale for Children- 3rd edition (Dunn & Dunn, 1997). This assessment was given at both prekindergarten and fifth-grade data collection points and is used as an indicator of language development.

*Leiter International Performance Scale Revised- Attention Sustained* (Leiter-R; Roid & Miller, 1997) is a timed cancellation task. Children are given a page full of images and a target image of an item that they have to scan for and cross out. Examiners record how many correct target images they can cross out in a given time frame. Poor performance is considered a representation of difficulty sustaining attention during a detailed task. The manual reports internal consistency coefficients between .88 and .93. The current sample also established acceptable reliability ( $\alpha = .75$ ).

***Social-emotional.*** *FACES parent-report* (Zill et al., 2006) provides parent ratings of children’s social skills and approaches to learning as well as their problem behaviors. On a three-point scale, parents rated how true statements about behavior were for their child: “not true,” “somewhat or sometimes true,” and “very or often true.” Social skills and approaches to learning were assessed with seven statements. Social skill items included statements such as “Makes

friends easily” and “Comforts or helps others.” Approaches to learning items included statements such as, “Enjoys learning” and “Likes to try new things.” These items were aggregated to create the social skills positive approaches to learning scale score. Problem behaviors were assessed in the same way across three categories associated with adjustment problems: aggressive, hyperactive, and withdrawn behaviors. There were 12 statements reflecting problem behaviors, including “Feels worthless or inferior” and “Has a temper tantrums or hot temper.” In the FACES 2000 study, the internal consistency for these scales was acceptable ranging from .76 to .83, which was consistent with reliabilities found in the current sample ( $\alpha = .64-.76$ ).

*The Child Behavior Checklist-aggressive behavior subscale* (CBCL; Achenbach & Rescorla, 2000) is a widely used standardized assessment of children’s behavior for children ages 1.5 to 5. Parents reported on the 19-item aggressive behavior scale, including items that indicate defiance, antisocial behavior, and maladaptive attention seeking (Achenbach & Rescorla, 2000). Parents rate behaviors on a three-point scale: *not true, somewhat or sometime true, or very true or often true*. The scale demonstrated acceptable reliability in the current sample ( $\alpha = .89$ ). Extensive research has been done to establish the reliability and validity of this scale, including establishing internal consistency, cross-informant agreement, test stability, and content and criterion validity (Achenbach & Rescorla, 2001).

*Leiter International Performance Scale Revised- Examiner Rating Scales*. (Leiter-R; Roid & Miller, 1997) was used to assess children’s regulatory functioning. The Leiter-R Examiner Rating Scales were completed by the examiner after observing the children’s behavior during the assessment session. Items were rated on a four-point scale from *rarely/never occurred* to *usually/always occurred*. The scales are used to create two composite scores: social standard score and emotion regulation standard score. The social cognitive standard score reflects



behavioral domain ratings including attention, impulse control, activity level, and sociability. The emotion regulation standard score reflects affective domain ratings, including feelings and energy, mood and regulation, anxiety, and sensory reactivity. Together, the examiner ratings assess children's behavioral and affective regulation that influences their performance on challenging tasks. The behavioral and affective domain ratings demonstrated acceptable internal consistency in the current sample ( $\alpha = .81-.93$ ). Content validity was established using expert examination of items as well as comparison of fit to item response theory models (Carroll, 1993; Wright & Linacre, 1999).

**Fifth-grade social and academic outcomes.** Fifth-grade outcomes were assessed through direct assessment, child interview, and maternal report during a home visit. Fifth graders' academic functioning was assessed using four nationally normed assessments: PPVT-III, Wechsler Intelligence Scale for Children-Matrix reasoning subscale (WISC-MR), ECLS-K Reading, and ECLS-K Mathematics. Social functioning was assessed using the self- and parent report. Youth self-reported delinquent behaviors and mothers completed the CBCL- 6/18, the youth version of the CBCL used in prekindergarten.

***The Wechsler Intelligence Scale for Children-Matrix Reasoning subscale.*** The Wechsler Intelligence Scale for Children (WISC; Wechsler, 2003) is a direct assessment of children's cognitive abilities. The Matrix reasoning subscale is designed to measure children's perceptual reasoning, including visual and spatial processing. Children are shown a matrix of pictures in which one square is missing. They are then given a range of options from which they are asked to select the missing box. Children's scores are highly influenced by concentration, attention, and persistence (Wechsler, 2003). The raw scores are converted to a scaled score based on an American and Canadian standardization sample that has a mean of 10 and a standard

deviation of 3 (Wechsler, 2003). Internal reliability for the subscale is .78. The technical manual provides extensive evidence of the reliability and validity of the instrument including split half reliability, construct validity, and convergent and discriminant validity (Wechsler, 2003).

***Early Childhood Longitudinal Study-Kindergarten Reading Assessment*** (ECLS-K reading; Pollack, Najarian, Attkin-Burnett, & Hausken, 2005) is a fifth grade reading assessment that was designed for the Early Childhood Longitudinal Study. It assesses children's reading comprehension across four content areas: initial understanding, developing interpretation, personal reflection, and critical stance. The test begins with a routing test that is designed to minimize floor and ceiling effects. Based on the results of the routing test, children proceed to one of three second-stage tests that range in difficulty. In the original sample, internal consistency on the reading assessment ranged from .91 to .96. A reliability estimate for the current sample was not provided.

***Early Childhood Longitudinal Study-Kindergarten Math Assessment*** (ECLS-K math; Pollack, Najarian, Attkin-Burnett, & Hausken, 2005) is a fifth grade math assessment that was designed for the Early Childhood Longitudinal Study. In the EHSREP, only the routing test was used. However, in the original sample, the routing test accurately grouped students by ability (low, average, high). This suggests that knowledge of which test students would be routed to gives a general index of math ability (low, average, high). Overall, it assesses children's math ability in the following areas: number and shapes, relative size, ordinarily, sequencing, addition and subtraction, multiplication and division, place values, rate and measurement, fractions, and area and volume. In the original sample, internal consistency on the reading assessment ranged from .89 to .94. Reliability estimates for the current sample were not provided.

*The Child Behavior Checklist for 6 to 18 year olds* (CBCL-6/18; Achenbach & Rescorla, 2001) is a parent-report measure of children's behavior and emotion problems. The CBCL-6/18 is the school-aged version of the CBCL measure used in prekindergarten. However, in fifth grade, data were collected using all syndrome subscales: anxious/depressed, withdrawn/depressed, somatic complaints, rule-breaking, aggressive behavior, thought problems, social problems, and attention problems. Parents rate behaviors on a three-point scale: "not true", "somewhat or sometime true", or "very true or often true". Extensive research has been done to establish the reliability and validity of this scale, including establishing internal consistency, cross-informant agreement, test stability, and content and criterion validity (Achenbach & Rescorla, 2001). Internal consistency estimates for the current sample were not provided.

#### **Data Analyses: Model Building and Comparison**

For the current investigation, model testing was guided in part by Maysn and colleagues' (2009) conceptual framework, the Dimensional-Categorical Spectrum (DCS). DCS suggests that developmental profiles be explored without making an a priori assumption about the categorical vs. continuous distributional nature of the underlying latent construct(s). Rather, the DCS framework recommends the underlying structure be explored simultaneously as categorical and dimensional. Psychometrically, latent class analysis (LCA) exemplifies a purely categorical approach. LCA models unobserved heterogeneity within a sample by categorizing individuals into groups based on patterns of observed variables. In reference to psychological disorders, Maysn and colleagues (2009) suggested that this categorical end of the spectrum is used to identify diagnostic criteria or subtypes. Clearly missing from LCA is the ability to assess differentiated functioning within and across these subgroups, a potential weakness of the LCA approach. Factor analysis (FA) exemplifies the dimensional pole of DCS. FA specifies

continuous latent variables to model correlations among observed variables. FA assumes that individuals are from the same homogenous group and that individual variation is a result of differences in factor scores. FA allows for the examination of differential functioning within a homogenous sample, but individuals cannot easily be classified into subgroups. Masyn and colleagues indicate that factor mixture analysis (FMA) is a hybrid of these two analytical techniques (i.e., LCA and FA) and FMA represents the midpoint of the DCS. .

The strategies outlined by Clark and colleagues (in print) for building and selecting factor mixture models were employed in this study. All models were assessed using *Mplus 7.1*. In order to avoid local solutions for the mixture models, which can be very different than global solutions (McLachlan & Peel, 2000), each model was estimated three times with 2000 random starts and 500 final stage iterations to ensure that the same best-log likelihood was obtained and replicated. Generally, the number of random starts should be four times the number of final stage iterations (L. Muthen, personal communication, 2013). The extant literature lacks consensus on best practices for class enumeration (Nylund et al., 2007). For the current study, a conservative approach for class enumeration was adopted in order to avoid overextraction (i.e., identification of more classes than is necessary or ideal). The set of models were compared using both statistical and substantive criteria to choose the best-fitting model (Muthen, 2003). Specifically, statistical fit was assessed using the Vuong-Lo-Mendell-Rubin test (LMR-LRT; Lo, Mendell, & Rubin, 2001) and the parametric bootstrapped likelihood ratio test (BLRT; McLachlan, 1987). Both the LMR-LRT and the BLRT compare the likelihood estimates for the proposed model ( $k$  class) against a model with one less class ( $k-1$  class) and assesses if there is an improvement of model fit with the addition of a class. A probability value is provided for each test where a significant test ( $p < .05$ ) indicates that  $k-1$  class model can be rejected in support of the larger

model. Overall, the LMR-LRT and the BLRT safeguard against overextraction by comparing the  $k$  class model to more parsimonious models. To ensure that the  $p$  value of the BLRT was trustworthy for each model, additional model runs that included 1000 bootstrap draws were conducted. Additionally, the Bayesian Information Criterion (BIC; Schwarz, 1978) was compared across models; a lower BIC indicates a better fitting model (Magidson & Vermunt, 2004).

To ensure that the best but most parsimonious solution was chosen, models were tested sequentially by adding classes and factors one at a time. Following the guidelines offered by Masyn and colleagues, model exploration began by accessing the two poles of the DCS to determine an appropriate end point. However, the categorical pole is typically assessed using LCA models based on categorical indicators. The current investigation uses continuous indicators and therefore employs Latent Transition Analysis (LTA), LCA's equivalent analysis for continuous indicators (Vermunt & Magidson, 2005). LTA and FA models were assessed independently with increasing number of classes and factors, respectively, to find the best fitting LTA model and factor structure. As suggested by Clark and colleagues (in press), the number of classes for the best fitting LTA model and the number of factors in the final factor structure will be used to define the end point for model building and comparison. Therefore, model building and comparison will begin with the smallest class/factor combination, 2 latent classes with 1 factor, and finish at the endpoint. In the current investigation, the end point was determined to be a model with three factors and two latent classes (see Table 1).

For each class/factor combination, beginning with two classes and one factor in increasing classes and factors until the end point, three different variations of factor mixture models (FMM) were assessed. These variations began with highly restricted FMM (e.g., FMM1)

and developed progressively to less restrictive variations (e.g., FMM3). It should be noted that Clark and colleagues' (in press) paper presents five variations. The data in their example were categorical, allowing them to test two additional variations where item thresholds were held invariant. Given that the data in the current investigation were continuous, these two variations were not applicable. The following section explicates the three variations of FMM that were used to assess each class factor combination. The model comparison results are presented in Table 1.

It should be noted that the factor mean is fixed at 0 for all three variations for model identification purposes, and the factor distributions are parametric. Additionally, these variations all violate strong factorial invariance by allowing some or all of the measurement parameters to be non-invariant (Meredith, 1993). These violations suggest that the same factor is not applicable to the whole sample, resulting in class-specific factor interpretations. For example, each model variation includes class-varying item means; therefore, class 1 will score differently than class 2, regardless of independent factor scores. The FMM1 variation allows item means to vary across classes. However, factor loadings and factor covariance matrix are held invariant. Therefore, in the FMM1 model, classes are determined by item level data rather than factor because item means are allowed to change across classes.

The FMM2 variation builds on the FMM1 but reduces the model's restrictiveness further by allowing the factor covariance matrix to vary across classes. This factor variation across classes suggests that individuals' differential functioning on the school readiness indicators can be represented within classes. For example, classes that represent resilience across school readiness indicators may exhibit little variance. However, classes that represent felt risks are likely to have more variation due to greater ranges of functioning across indicators.

The final variation, FMM3, is the least restrictive model. All measurement parameters are noninvariant such that item means, factor loadings, and factor covariance matrix are allowed to be estimated freely across classes. Whereas FMM1-3 variations have noninvariant item means, FMM3 also has noninvariant factor loadings. By allowing the factor loadings to vary across classes, FMM3 allows each class to have its own slope in the regression of the items on the factors such that an increase in factor scores will differentially influence the dependent variable depending on class membership. Overall, it is hypothesized that the best fitting model of at-risk children's school readiness profiles will be one of these FMM variations when compared to the traditional LTA and FA candidate models candidates.

### **Missing Data**

Models will be estimated using full information maximum likelihood estimation (FIML; Hancock & Mueller, 2006). This approach assumes that the data are missing at random and uses all available data to estimate missing parameters. FIML has been found to provide less biased estimates (Enders & Bandalos, 2001) and has been used for missing data estimations in similar population-based investigations (e.g., Bulotsky-Shearer et al., 2012; Cook et al., 2012).

## CHAPTER 3 - RESULTS

### Results

All models were estimated using *Mplus* version 7.1 (Muthen & Muthen, 1998-2013). Statistical model fit and comparison indices are presented in Table 1 and 2. To begin, latent profile models were estimated sequentially starting with a one-class model and adding one additional class until the fit indices no longer indicated an admissible model. The BIC continued to decrease from the one-class model through the four-class model, suggesting improvement in model fit. The LMR-LRT was significant ( $p < .05$ ) for the one- and two-class model, indicating that the two-class model had improved model fit. However, the LMR-LRT was no longer significant for the three-class and four-class models. Based on the incongruence between the BIC and LMR-LRT criteria for the three- and four-class models, the BLRT was examined. According to Nylund, Asparouhov, and Muthen's (2007) Monte Carlo simulation study examining class enumeration techniques, the BLRT outperforms both the BIC and LMR-LRT as an indicator of the correct number of classes being selected. The BLRT was significant for the three-class model but could not replicate the best likelihood in the majority of bootstrap pulls for the four-class model, suggesting that the two-class and three-class models were the strongest statistical candidates for the best LTA models. The substantive interpretations of these two solutions were examined to determine the best fitting LTA model.



Table 1

<i>School Readiness Latent Profile and Factor Analysis Results (N= 2073)</i>					
Model	Log-likelihood	Parameters	BIC	LMR <i>p</i> value	BLRT <i>p</i> value
Latent Profile Analysis					
One-class	-67711	26	135538.406		
Two-class	-66063	40	132305.144	0	0
Three-class	-65446	54	131134.521	0.0798	0
Four-class	-64935	68	130173.656	0.0809	1
Confirmatory Factor Analysis					
				RMSEA <i>p</i> value	CFI
One-factor	-65522	39	131219.684	0	0.519
Two-factor	-64246	40	128671.12	0	0.823
Three-factor	-63712	42	127613.175	0.005	0.95

In the two-class LTA model, class 1 represented 29% ( $n = 611$ ) of the sample and was characterized by higher scores for indicators associated with problematic behaviors (e.g., aggression) and lower scores on indicators of pre-academic learning competences (e.g., word-letter identification). Class 2 represented the inverse of class 1 such that children with the highest probability of class 2 membership exhibited lower scores on indicators of problematic behaviors related to poor school readiness and higher scores on indicators of pre-academic learning competences.

In the three-class LTA model, the classes were further distinguished by differentiating pre-academic learning competences into items relating to pre-academic competencies (e.g., applied word problems) and regulatory abilities that influence functional performance (e.g., emotion regulation). It should be noted that this distinction is consistent with the variable-centered extant literature on school readiness (e.g. NRC, 2001; Snow 2007). Class 1 represented 21% ( $n = 438$ ) of the sample and was characterized by lower scores for items associated with

problematic behaviors (e.g., aggression), lower scores on regulatory abilities that influence functional performance, and lower scores on pre-academic readiness skills. Class 2 represented 63% ( $n = 1305$ ) of the sample and was characterized lower scores for items associated with problematic behaviors, higher scores on regulatory abilities that influence functional performance, and higher scores on pre-academic competencies. Finally, Class 3 represented 16% ( $n = 330$ ) of the sample and was characterized by very high scores on indicators related to problematic behaviors, average scores on regulatory abilities that influence functional performance, and average scores on pre-academic competencies. Given the importance of regulatory abilities as a putative protective factor that buffers children at risk for poor school achievement (Denham et al., 2012), the three-class model reflects a substantive meaning that exists in the extant literature. This conceptual argument coupled with the BLRT  $p$  value supported the three-class model as the best-fitting LCA model.

To assess the dimensional end of the DCS, two sets of factor analytic models were estimated. First, an exploratory factor analysis (EFA) was conducted; the possible solutions indicated in these analyses were further examined using confirmatory factor analysis. The EFA suggested three plausible solutions: one-factor, two-factor, and three-factor solutions. The 13 indicators of school readiness all significantly loaded on the one-factor solution. The two-factor solution differentiated one factor that reflected indicators of problematic behaviors (e.g., aggression) and a second factor that reflected pre-academic learning competencies (e.g., word-letter identification). The three-factor solution bifurcated the pre-academic learning competencies into two factors reflecting pre-academic competencies and regulatory abilities. The three potential factor solutions were examined using confirmatory factor analysis (see Table 1) to identify the best fit factor analytic model. In addition to the substantive interpretations

above, model fit statistics that are appropriate for CFA were examined, including the RMSEA and CFI (see Table 1). The model fit statistics for the CFA model suggest that the three factor solution is indeed the strongest model, with a significant RMSEA and CFI closest to 1 (Bentler, 2007; Kline, 2010). Therefore, the three-factor solution was chosen to represent the best factor structure to fit the data both statistically and analytically.

To assess the midpoint of the DSC, a series of FMMs were estimated sequentially beginning with a two-class, one-factor combination and adding classes and factors one at a time until the endpoint of a three-class, three-factor combination (determined by the results of the LTA and FA analyses). As previously explained, three variations of FMM were estimated for each latent class/ factor structure combination. The results of these models are presented in Table 2.

Table 2

<i>School Readiness FMA Model Comparison Results (N= 2073)</i>					
Factor Mixture Analysis - Confirmatory					
Model	Log-likelihood	Parameters	BIC	LMR <i>p</i> value	BLRT <i>p</i> value
2-class, 1-factor					
FMM1	-64563	53	129362	0	0
FMM2	-64559	54	129359	0	0
FMM3	-64429	66	129154	0.001	0
2-Class, 2-factor					
FMM1	-63824	54	127890	0	0
FMM2	-63807	57	127870	0	0
FMM3	-63731	68	127766	0.001	0
2-class, 3-factor					
FMM1	-63378	56	127006	0	0
FMM2	-63335	62	126947	0	0
FMM3	did not converge				
3-class, 1-factor					
FMM1	-64166	67	128631	0	0
FMM2	-64160	69	128629	0.1873	0
FMM3	-64008	93	128432	0.004	0
3-class, 2-factor					
FMM1	-63585	68	127473	0.093	0
FMM2	-63543	74	127417	0.037	0
FMM3	-63381	96	127191	0.753	0.5229
3-class, 3-factor					
FMM1	-63199	70	126711	0.213	0
FMM2	-63099	82	126564	0	0
FMM3	did not converge				
Factor Mixture Analysis - Exploratory					
2-class, 1-factor	-65522	39	131219.684		
2-class, 2-factor	-64124	51	128476.795		
2-class, 3-factor	-63579	62	127417.775		
3-class, 1-factor	-63614	119	127758.915		
3-class, 2-factor	did not converge				
3-class, 3-factor	did not converge				

Nylund, Asparouhov, and Muthen (2007) suggested that when assessing model fit, it is best to first examine the BIC and LMR-LRT fit indices of all estimated models. Two variations of the three-class, three-factor combination, FMM1 and FMM2, had the lowest BICs but were excluded from candidacy for best fit because both models had nonpositive definite residual covariance matrices due to negative residual variances on an observed variable. In general, the three-class FMA models demonstrated poor fit that was highlighted by the EFA three-class FMA that did not converge for two- or three-factor combinations (see bottom of Table 2).

The next lowest BIC with a significant LMR LRT was the two-class, three-factor combination with FMM2 variation in model specification. Substantively, this model allowed for class distinction based on relative school readiness strengths and weaknesses that were explicated for the LTA two-class solution. Specifically, class 1 (19%) exhibited greater weaknesses in their school readiness profiles as demonstrated by higher scores on problematic behaviors indicators that thwart early school success, and lower scores on pre-academic competences and regulatory abilities that support early school success (see Figure 1). However, the addition of the three factors with class-varying covariance matrices allowed for different amounts of functionality or severity within class such that class membership could reflect differences in degree of school readiness. In order to better understand the value added by exploring school readiness profiles using categorical and dimensional latent constructs simultaneously, the factor loadings of the dimensional FA were compared with the dimensional-categorical FMA analyses (see Table 3). In both FA and FMA solutions, the factors represent similar interpretations but are nonequivalent. The two-class, three-factor FMM2 variation held factor loadings invariant across classes but allowed the variances to vary across classes. Therefore, the unstandardized loadings for the FMA are the same between classes, but the

standardized loadings that account for differences in variances across classes are not the same (see Table 4). The standardized loadings for class 1 are generally higher than the standardized loadings for the FA solution, whereas the inverse is true for class 2. Therefore, within-class correlations among school readiness indicators on each factor are higher in class 1. This adds further credence to the putative dynamic connections and interactions that exist across readiness domains (Cicchetti & Toth, 1997; Frye, 2005; McWayne, Green, & Fantuzzo, 2009; Mendez, Fantuzzo, & Cicchetti, 2002) suggesting that at-risk children's school readiness is not simply an additive model.

Table 3

*School Readiness Unstandardized Factor Loadings*

Model	FA			2-class, 3-factor FMM2					
				Class 1			Class 2		
	Factor 1	Factor 2	Factor 3	Factor 1	Factor 2	Factor 3	Factor 1	Factor 2	Factor 3
Items									
Leiter-R Attention	1			1			1		
Book Knowledge	.36*			.34*			.34*		
Book Comprehension	.42*			.20*			.20*		
PPVT-III	6.07*			6.20*			6.20*		
WJ Letter-Word	4.18*			4.53*			4.53*		
WJ Applied Problems	8.02*			8.82*			8.82*		
FACES Social Skills and Approaches to Learning		1			1			1	
FACES Aggression		-2.68*			-2.99*			-2.99*	
FACES Hyperactivity		-1.78*			-1.95*			-1.95*	
FACES withdrawn		-.65*			-.72*			-.72*	
CBCL Aggression		-12.25*			-13.76*			-13.76*	
Leiter-R Cognitive Social			1			1			1
Leiter-R Emotion Regulation			.754*			.735*			.73*
Factor Variance	4.02*	.26*	102.68*	5.07*	.239*	146.20*	2.71*	.19*	72.75*

*Note.* Factor analysis (FA); factor mixture model (FMM); Peabody Picture Vocabulary Test - third edition (PPVT-III); Woodcock-Johnson (WJ); Head Start Family and Child Experiences Study (FACES); Child Behavior Checklist - ages 6 to 18 (CBCL)

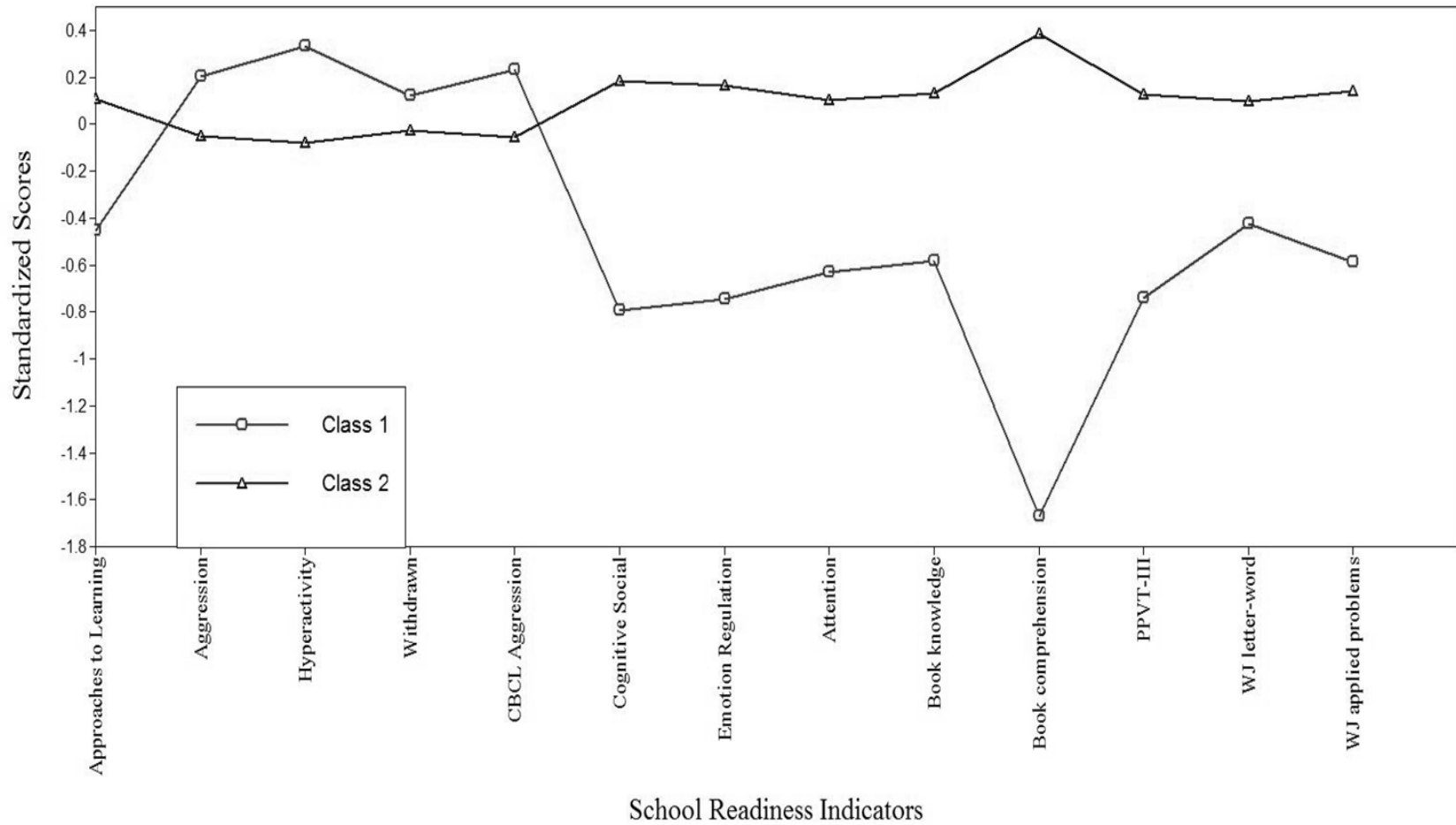


Figure 1

School Readiness Standardized Profile Plot



Table 4  
*School Readiness Standardized Factor Loadings*

Model	FA			2-class, 3-factor FMM2					
				Class 1			Class 2		
Items	Factor 1	Factor 2	Factor 3	Factor 1	Factor 2	Factor 3	Factor 1	Factor 2	Factor 3
Leiter-R Attention	.629*			0.669*			.549*		
Book Knowledge	.570*			0.596*			.477*		
Book Comprehension	.547*			.464*			.358*		
PPVT-III	.785*			.820*			.724*		
WJ Letter-Word	.614*			.690*			.572*		
WJ Applied Problems	.802*			.873*			.794*		
FACES Social Skills and Approaches to Learning		.273*			.266*			.244*	
FACES Aggression		-.821*			-.835*			-.811*	
FACES Hyperactivity		-.622*			-.639*			-.604*	
FACES withdrawn		-.346*			-.362*			-.334*	
CBCL Aggression		-.932*			-.944*			-.934*	
Leiter-R Cognitive Social			.964*			.973*			.949*
Leiter-R Emotion Regulation			.776*			.821*			.713*

*Note.* Factor analysis (FA); factor mixture model (FMM); Peabody Picture Vocabulary Test- third edition (PPVT-III); Woodcock-Johnson (WJ); Head Start Family and Child Experiences Study (FACES); Child Behavior Checklist- ages 6 to 18 (CBCL)

Exploratory FMA was also examined for the two-class factor combinations. However, the confirmatory measurement structure for the two-class, three factor FMM2 variation outperformed all three exploratory measurement structures based on indices of model fit. This is likely due to the *Mplus*' defaults for EFA model specifications that mirror the low restrictions of the FMM3 variation. Therefore, the exploratory models tried to impose an FMM3 structure onto data that has a FMM2 best fit, resulting in estimation of nonsignificant parameters that were likely not needed. Overall, based on fit indices and substantive meaning, the 2-class, 3-factor FMM2 variation was the model deemed to have the best fit.

### **Class Differences on Fifth-Grade Outcomes**

Additional analyses were employed to assess if classes based on posterior probabilities would exhibit differential functioning on academic and social indicators of school success in fifth grade. Specifically, it is hypothesized that class 1 has lower scores on academic indicators of school success than class 2 based on their relative strengths and weaknesses of their school readiness represented in profile membership. Furthermore, it is also hypothesized that class 2 has lower scores on problematic behaviors based on their relative strengths and weaknesses of their school readiness represented in profile membership. There is lack of agreement in the extant literature about the best method to assess distal outcomes in mixture modeling (for a review, see Asparouhov & Muthen, 2013). One method is the one-step pseudo class approach (PC method; Wang et al., 2005; Clark & Muthen, 2009) that uses the auxiliary function of the variable command in *Mplus 7.1*. This method simply treats the auxiliary variable as a distal outcome without specifying means or variances as in other methods. After the FMA model has been estimated, a latent class variable is multiply imputed for the posterior probability distribution from the FMA model estimation. Then, using Rubin's (1987) technique for multiple imputations,

the distal outcome is analyzed with the imputed class variable to assess for equality of means across classes. Clark and Muthen (2009) found that this method was successful when class separations are large (e.g., when entropy coefficients are high or above .80). Entropy is measured on a scale of zero to one, where one represents perfect identification of individuals' class membership (Clark & Muthen, 2009). The entropy coefficient for the best-fit FMA model in the current investigation is .822, suggesting large class separation (Clark & Muthen, 2009). Therefore, the PC method was employed to assess class differences on fifth-grade outcomes. The results are presented in Table 5.

Table 5

<i>Class Differences on Fifth-Grade Academic and Social Outcomes</i>			
Equality Tests of Means	Class 1 <i>M(SE)</i>	Class 2 <i>M(SE)</i>	$\chi^2$ <i>p</i> value
<b>Academic Indicators</b>			
ECLS-K Math	7.27 (0.33)	8.72 (.14)	0
ECLS-K Language and Literacy	114.18 (2.14)	130.74 (.82)	0
Matrix Reasoning	7.60 (0.22)	8.64 (.10)	0
PPVT-III	88.43 (1.12)	95.45 (.48)	0
<b>Social Indicators</b>			
Delinquent Behaviors	1.81 (.14)	1.45 (.05)	.019
CBCL Anxious/Depressed	3.16(.21)	3.02(.09)	<i>n.s.</i>
CBCL Withdrawn/Depressed	2.06 (.16)	1.57 (.06)	.004
CBCL Somatic Complaints	1.14(.12)	1.05(.05)	<i>n.s.</i>
CBCL Social Problems	3.29 (.22)	2.54 (.08)	.002
CBCL Thought Problems	2.58 (.21)	2.07 (.08)	.022
CBCL Attention Problems	5.11 (.28)	3.89 (.11)	0
CBCL Rule-Breaking Behavior	2.64 (.19)	2.23 (.08)	.050
CBCL Aggressive Behavior	6.50 (.39)	5.63 (.17)	.047
CBCL Internalizing	6.35(.41)	5.64(.16)	<i>n.s.</i>
CBCL Externalizing	9.15 (.55)	7.86 (.24)	.036

*Note.* Early Childhood Longitudinal Study Kindergarten Cohort (ECLS-K); Peabody Picture Vocabulary Test- third edition (PPVT-III); Child Behavior Checklist- ages 6 to 16 (CBCL).

The results from the auxiliary variable analyses support the hypothesis that class 1 would exhibit significantly lower scores on academic indicators of school success, including the ECLS-

K fifth-grade math assessment, the ECLS-K fifth-grade reading assessment, the WISC-IV Matrix Reasoning subscale, and the PPVT-III. Notably, class 1 demonstrated lower average reading scores than the any of the high-risk groups identified in the final report of the EHSREP (Mathematica Policy Research, 2010). Overall, on academic indicators, class 1 had scores below age-level expectations, whereas class 2 had scores that met or exceeded average age-level expectations (see Table 6).

Table 6  
*Class Comparison to Age-level Averages*

Academic Indicators	Class 1 <i>M</i>	Class 2 <i>M</i>	National Comparison <i>M</i>	EHSREP high-risk <sup>d</sup> <i>M</i>
ECLS-K Math	7.27	8.72	> 8 <sup>a</sup>	7.6
ECLS-K Language and Literacy	114.18	130.74	127.35 <sup>b</sup>	118.8
PPVT-III	88.43	95.45	94 <sup>c</sup>	88.6

*Notes.* <sup>a</sup> Of the fifth-grade sample of the ECLS-K, 64% scored higher than 8 which was the lowest cut-off for the math routing test. <sup>b</sup> Average score for children in ECLS-K entering or in fifth grade. <sup>c</sup> The average raw score for a 10 year old. <sup>d</sup> The average score for the highest risk group in the EHSREP final report of the long-term follow-up.

Additionally, class 2 had lower scores on CBCL-6/18 syndrome scale with the exception of three subscales of the CBCL: Anxious/depressed, Somatic Complaints, and Internalizing. The syndrome scales where significant differences were found are associated with problem behaviors, social and thought problems, and attention problems. However, given that class 1 exhibits lower scores on language and literacy indicators, it is not surprising that significant class differences were primarily seen on behavioral indicators that are associated with externalizing behavior problems (Hudziak, Copeland, Stanger, & Wadsworth, 2004). Recent research suggests that children's language ability predicts the development of externalizing behavior problems and attention deficits (Petersen, Bates, D'Onofrio, Coyne, Lansford, Dodge, Pettit, & Van Hulle, 2013). Notably, class 1 demonstrated higher average scores on delinquency, attention problems, social problems, and thought problems than any of the high-risk groups identified in the final report of the EHSREP (Mathematica Policy Research, 2010).

### **Early Head Start Participation as a Predictor Class Membership**

The PC method was employed again to assess if participation in EHS predicted posterior probabilities of latent class membership. It was hypothesized that children who participated in EHS would be more likely to have membership in the resilient school readiness class. Using posterior class probability-based multiple imputations, multinomial logistic regressions were used to assess if EHS was a significant predictor of class membership as a latent categorical variable. The hypothesis was not supported by the regression results that indicated EHS participation did not significantly predict class membership,  $p = .48$ .

## CHAPTER 4 - DISCUSSION

### **Discussion**

Guided by a resilience framework, the present investigation used a hybrid of a variable- and person-oriented approach to explore patterns of heterogeneity within a nationally representative sample of low-income children. The results suggest that at-risk children across our nation enter kindergarten with reliable and identifiable patterns of readiness skills that meaningfully relate to their social and academic performance in fifth grade. Within the study's sample, it is encouraging to see that the majority of at-risk children (~80%) were identified as having the needed skills and abilities to take advantage of the learning opportunities presented within our schools. In fact, this majority group continued to demonstrate academic and social resilience in the face of poverty through fifth grade. However, roughly one fifth of the sample exhibited a profile that was characterized by poor performance on indicators of school readiness. Indeed, children with these poor school readiness profiles proved vulnerable to the putative negative effects of poverty, demonstrating significant weaknesses on academic and social outcomes in fifth grade. Notably, this poor school readiness profile group underperformed all identified risk groups in prekindergarten and fifth grade on almost all cognitive and social-emotional indicators of success. Overall, participation in EHS did not influence class membership. The current study advances our understanding of the developmental interplay among children's pre-academic, social, and regulatory skills that facilitate access to the developmental affordances of education. This understanding has important implications for future research and early childhood practice and policy.

The first hypothesis, that analyses would reveal a small number of classes that either represent adequate or poor school readiness functioning, was confirmed. The results of the FMA

identified two distinct classes: *poor* and *resilient school readiness*. McWayne and colleagues (2009) speculated that using a latent class approach may reveal similar patterns to the superordinate groupings of their clusters, (e.g., at-risk, competent, and overlapping). Additionally, these superordinate groups were the result of coupling variable-oriented and person-oriented methodologies. Therefore, it is not surprising that the FMA methodology, which couples a person-oriented latent class approach with a variable-oriented factor analysis approach, yielded a similar profile solution. For example, McWayne and colleagues (2012) found that two competent profiles (high cognitive-average social skills and average cognitive-high social skills) had different patterns of skills, but both groups demonstrated academic competence and were classified into the superordinate competent group. In the current study, the latent factor structure within the model allowed for differential functioning within domains, or differences in severity. This allowed the children who exhibited different but positive patterns of functioning to be classified into the same class. The absence of an overlapping profile in the current study is likely because individuals are classified into classes based on their estimated posterior probabilities of membership. Therefore, even overlapping cases would be classified based on their greatest probability. It should be noted that in the current investigation the average probabilities for most likely latent class membership were very high for both the poor and adequate classes (.921 and .955 respectively).

Raikes, Vogel, and Love (2013) examined the EHSREP data (the data source for the current investigation) for variability in child outcomes by demographic risk. All children within the sample are at-risk due to poverty status. However, there is a range of risk profiles represented in the data set identified by five additional demographic risk factors: teen parent status, single parent status, parental unemployment/not in school, parent without a high school diploma, and

parent receives government assistance. Children from high-risk families had 4-5 additional demographic risks. At age 5, this high-risk group performed better on all pre-academic, social, and regulatory skills indicators than the poor school readiness group identified in the current study. This suggests that the FMA was able to differentiate a high-need group beyond the demographic risk profiles known to exist in the data.

The poor and resilient school readiness functioning profiles highlight the developmental interplay among children's pre-academic, social, and regulatory skills as representing *developmental coalescence*. Theoretically, domain-specific development is likely augmented by transactional processes within children such that developments across domains likely influence one another as well as concomitant and future experiences across contexts (Sameroff & Fiese, 2000). Findings from the current study support this idea to the extent that profiles are characterized by either predominant strengths or weaknesses across domains. For the resilient functioning group, having skills within these developmental domains likely permits these children access to experiences in which existing skills can be developed and new skills learned (Heckman & Masterov, 2004). Conversely, in the poor functioning group, weaknesses in domains may inhibit learning experiences which likely snowball, making gains less attainable across time. These coalescence effects seem to be amplified in the poor functioning profile where higher interclass correlations are found.

A second set of analyses heeded McWayne and colleagues' (2012) call for research investigating how holistic school readiness profiles relate to later academic and social achievement. An examination of class differences on fifth grade indicators supported the hypothesis that the classes would exhibit differential distal performance on both academic and social indices. Indeed, in fifth grade, the poor school readiness class demonstrated significantly



higher levels of problematic behaviors (e.g., delinquent behaviors, thought problems, attention problems) and lower levels of academic skills (e.g., reading, math) than the resilient school readiness class. Notably, class 1 demonstrated lower average reading scores and higher scores on externalizing behaviors than the high-risk groups identified in the final report of the EHSREP (Mathematica Policy Research, 2010). This again suggests that the FMA in the current study was able to differentiate a meaningful profile that was unique and that could assist in targeting interventions to meet this high-needs group.

Many of the child-level fifth grade outcomes used in the EHSREP are standardized, nationally normed scales or assessments, allowing for the current study's profiles to be compared to national averages. On average, children in the poor school readiness group were reading below grade level expectations and below the average reading level of any risk group in the ECLS-K data set, including English language learners. This group was identified in the 9<sup>th</sup> percentile and performed below chronological age equivalence on receptive language measured by the PPVT-III. Conversely, children from the resilient school readiness group were reading at grade level. This group also performed at chronological age equivalence on receptive language. Overall, it is clear from these comparisons that the poor school readiness profile is associated with significant difficulties in language and literacy development over time.

In mathematics and cognitive ability, children from the resilient school readiness profile continued to outperform their peers from the poor school readiness group. In comparison to the national sample from the ECLS-K, the average math score in the poor school readiness profile was in the low performance group, whereas the score in the resilient school readiness profile was in the middle or average performance group. Additionally, cognitive scores in the poor school readiness profile were between the 7<sup>th</sup> and 16<sup>th</sup> percentile, indicating difficulties in nonverbal

reasoning and processing of visual stimuli. Taken together, these findings indicate that the readiness profiles have important implications for future academic outcomes. Furthermore, they suggest that children from the poor school readiness profile need additional intervention to support their academic success.

Social outcomes in fifth grade were primarily measured using the syndrome scales of the CBCL-6/18 and a self-reported delinquent behavior measure. In comparison to the resilient school readiness profile, the poor school readiness profile exhibited significantly higher levels of syndrome behaviors associated with externalizing problems, including delinquent, aggressive, and rule breaking behaviors; and social, thought, and attention problems. However, all of these problem behavior scores on the CBCL-6/18 were within the normal functioning range and the poor school readiness group scored equal or better than the high-risk group identified in the EHSREP final report, with two notable exceptions: Children in the poor school readiness profile exhibited higher levels of attention and thought problems than any risk group identified in the final report. These findings are consistent with recent research that indicates that children's language ability predicts the development of externalizing behaviors and attention deficits (Petersen, et al., 2013). These findings are particularly concerning given that longitudinal research suggests that early attention predicts short- and long-term reading and math achievement outcomes and influences children's odds of graduating college (Duncan, et al., 2007; McClelland, Acock, Piccinin, Rhea, & Stallings, 2013).

Overall, the differential functioning on distal academic and social indicators found between the poor and resilient school readiness profiles is convergent yet distinct from the existing person-oriented literature. Sabol and Pianta's (2012) analyses revealed that clusters characterized by attention problems without simultaneous social emotional problems

demonstrated positive academic and social competence in fifth grade. They speculated that the attention problems in tandem with problematic social behavior would predict negative distal outcomes (Hinshaw, 1992). This is divergent from Duncan and colleagues' (2007) findings that suggest a linear relationship between attention and later achievement, controlling for early academic skills. The current study confirms Sabol and Pianta's hypothesis that early problems in attention coupled with problem behaviors (accounting for early academic competences) are associated with poor academic and social outcomes in fifth grade. Furthermore, examination of individual trajectories indicates that children with lower attention scores but average-to-high social skills coupled are classified in the resilient school readiness profile. This provides strong evidence for the meaningful cross-domain interactions that are captured by this analytical approach and highlights the critical importance of holistically examining children's functioning.

Finally, the hypothesis that children who had participated in EHS would be more likely to be in the resilient school readiness class was not supported. However, these findings are not surprising given the recently published negative or nonsignificant impacts of EHS for high-risk children found in subgroup analyses of the EHSREP. The majority of children in the EHSREP received some form of preschool care. The profiles identified in the current study are encouraging to the extent that 80% of this low-income sample had been prepared adequately for school and demonstrated long-term educational and social resilience in the face of poverty. Furthermore, there is a rich research base of intensive early interventions that have successfully targeted the needs of children at great risk for poor educational outcomes (Campbell et al., 2012; Reynolds, Temple, Robertson, Mann, 2001; Schweinhart, 2003). By identifying these profiles in preschool, intensive early interventions can be cost-effectively targeted at those most in need of support.

## **Limitations**

Qualifications of the findings are warranted. The participants in the study represent those children who could complete the assessments in English and therefore do not represent children who are not proficient in English. As was previously explained, this decision was made because there is not a one-to-one correspondence between the English and Spanish versions of the normative assessment batteries. From a methodological perspective, this made it impossible to collapse scores into a unitary construct across all children. Furthermore, it is reasonable to question whether having letter-word recognition in Spanish would have the same impact on children's school readiness as having this same skill in English given that the predominant language of our public education system is English. As such, the findings of the current study are not generalizable to linguistically different populations (Bergman & El-Khoury, 2001). Future research should examine school readiness profiles within samples of linguistically diverse children to see if similar patterns exist (for an example, see Quirk et al., 2012). Despite this limitation, the current study fills a recognized gap in literature by identifying patterns of heterogeneity in low-income, English-speaking children and examining how these patterns predict long-term academic and social outcomes (McWayne et al., 2009).

The measures used in the current study present both strengths and limitations. Overall, the measures used as the basis for the school readiness profiles focus on child-level skills and behaviors that are known to be changeable. Based on recommendations in the extant literature, skills amenable to change were chosen to improve the relevance of research finding for early childhood practitioners (McWayne et al., 2009). Additionally, several of the profile indicators and the fifth grade outcomes were measured with standardized assessments (e.g., Woodcock Johnson, PPVT-III, Leiter-R) that allowed for sample comparison to the larger population.

Unfortunately, many of these standardized assessments require trained examiners and are administered individually. This increases the cost and time needed to collect data, which in turn may inhibit the potential replication of these analyses to identify needs in other populations. These child assessments are also limited in that they do not represent assessments that are ecologically valid to a classroom context (Hirsch-Pasek et al., 2005).

Another limitation of the current study is that the profiles modeled did not include an indicator of motor functioning or physical health. Findings from both person-oriented and variable-oriented research suggest that physical health and well-being likely play an influential role in children's school readiness (Halle et al., 2006; Halle et al., 2012; Kagan, Moore, & Bedkamp, 2005). Unfortunately, measures of physical development and health and well-being in the EHSREP did not include measures of key indices of physical health, such as fine and gross motor skills, that likely influence child outcome (Kagan, Moore, & Bedkamp, 2005). Future research should investigate whether the addition of motor skills to the profiles' indicators would improve or expand our holistic understanding of children's school readiness.

### **Future Research**

Future research needs to examine early predictors of these profiles. By examining child-level precursory skills and characteristics that meaningfully predict prekindergarten profile membership, researchers can establish patterns of development for each profile. These developmental patterns could be used to target prevention efforts to promote the development of resilient functioning profiles. Additionally, it is likely that contextual factors moderate these early patterns of profile development, including classroom and family indicators of readiness (Boethel, 2004; Cook, Roggman, & D'Zatko, 2012; Reynolds, Magnuson, & Ou, 2010; Wen, Bulotsky-Shearer, Hahs-Vaughn, & Korfmacher, 2012). Future studies should use ecological

models of readiness to guide investigations that explore how ready families, ready schools, and ready communities influences the development of these child readiness profiles (Early et al., 2001).

In addition to early child and contextual predictors of profiles, future research should explore the stability of these profiles across time (e.g., McWayne, Hahs-Vaughn, Cheung, & Wright, 2012). This research should examine both structural and individual patterns of profile stability using longitudinal data that assesses the same variables with consistent measures across multiple time points (McWayne et al., 2009). Research designs should include contextual variables within families and schools that are likely to predict stability. This future research can inform early childhood practice and policy by highlighting processes that will support the maintenance of intervention impacts across time.

## **Implications**

The current study provides a strong example of how advanced person-oriented methodology can be employed to expand our understanding of the developmental processes of school readiness within children (Bergman & Magnusson, 1997). These patterns of functioning can be used to target early intervention and prevention efforts, as well as early childhood curricula, to meet the specific needs of poor functioning profiles before these patterns are fossilized (Roeser, Eccles, & Sameroff, 1998). Beyond the methodological contribution, the present study makes important strides in our understanding of patterns of heterogeneity within low-income children. Namely, the findings suggest that the majority of low-income children exhibit profiles that are associated with educational and social resilience. However, for the small minority of children who were identified as being vulnerable to the putative effects of poverty, the current strategies being used to boost their protective factors were relatively ineffective. This

highlights the need for the development of targeted interventions that capitalize on the lessons learned from successful intensive early childhood programs (Campbell et al., 2012; Reynolds, Temple, Robertson, Mann, 2001; Schweinhart, 2003).

The profiles identified within the current study offer evidence to support two policy recommendations made by Hirsh-Pasek and colleagues (2005). First, the current study explores dynamic processes of school readiness functioning *within* children, highlighting the developmental interplay that occurs across domains. Second, the FMA in the current study provides a useful example of how to use assessment data to model individual patterns of functioning as a means of identifying subgroups that present distinct strengths and needs. These patterns of strengths and needs provide meaningful information to teachers that enables them to effectively structure instruction.

Overall, the extant literature is plagued with endless debates concerning the relative developmental importance of the cognitive/academic and social-emotional domains (Raver & Zigler, 2004). Inherent in these debates is the belief that a domain-specific “magic bullet” exists that will rectify achievement gaps attributable to poverty. The person-oriented literature to date has found that both domains meaningfully interact within children to create profiles that relate to later outcomes (e.g., McWayne et al., 2004; McWayne et al., 2009; Sabol & Pianta, 2012). Convergent with these findings, in the current study, both the cognitive and social-emotional domains significantly contributed to the class solutions found. When researchers treat domain-specific development as independent metrics, we likely ignore meaningful interactions among domains that highlight the mutually supportive nature of children’s early skills.

This zero-sum debate has been reinforced by educational policy that places a disproportionate emphasis on the cognitive domain. Head Start’s National Reporting System

(2003) introduced the standard of formal academic-only assessments to the realm of early childhood education. Unfortunately, this policy has driven many early childhood practitioners away from the whole-child approach that previously dominated the field's conception of best practices and toward an academic-only curriculum that teaches to the test (Government Accountability Office, 2005). The findings of the present study suggest that this curriculum direction could be detrimental to children's academic trajectories. The cross-domain interactions that are represented in the profiles that were found add credence to calls for comprehensive programming that supports child development holistically (McWayne et al, 2009; Raver & Knitzer, 2002; Zigler & Bishop-Josef, 2006).

Using a policy-relevant sample of low-income children, the current study offers strong empirical support for the critical importance of two primary conclusions. First, early identification of educationally vulnerable subgroups is a critical first step in ameliorating the negative trajectories that are associated with poverty. Second, whole-child comprehensive early childhood programming that capitalizes on cross-domain interactions will likely have greater impact on child outcomes. These conclusions are particularly salient given President Obama's preschool initiative. Given that the vast majority of children in the current study attended preschool, the findings suggest that universal preschool is likely to support low-income children's educational resilience. However, as our plan for universal, high-quality preschool develops, it is critically important that conceptualizations include intensive early childhood education programming that targets the children at greatest risk. Low-income children at greatest risk are children whose readiness profiles reflect patterns observed in the poor school readiness profile of the current investigation.



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