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LATENT PROFILE ANALYSIS OF FIRST GRADE STUDENTS' SOCIAL SKILLS AND PROBLEM BEHAVIOR

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ABSTRACT

Given the well-established importance of promoting students' social skills and reducing problem behavior for school success and social development, a body of intervention programs have been designed and implemented for children and adolescents in the U.S. To provide appropriate targeted intervention programs for students of various needs and better allocate resources, educators and school psychologists need to understand different patterns of social skills and problem behaviors. However, relatively little research has adopted a person-centered approach to identify first-grade students' distinct profiles of social skills and problem behavior together and to pinpoint the associated behavioral and academic needs of children with different behavioral profiles. The purpose of this study was to identify the first-grade students' profiles of social skills and problem behaviors in classroom settings via teacher ratings, to analyze the association between student demographic variables and behavior profiles, and to explore the relationship between student behavior profiles and academic outcomes five months later. We fitted five latent profile models based on eleven indicators of social skills and problem behavior. Results revealed three different latent profiles from 566 first-grade students: Prosocial, Moderate, and Vulnerable. Male students were more likely to be in the Vulnerable group than in other two groups. White students were more likely to be in the Prosocial group. Students whose primary language was English most often tended to be in the Vulnerable group rather than in the other two groups. Students not receiving special education services (i.e., Title 1, instructional support, tutoring, response to intervention) or supplemental services (i.e., speech/language impairment, learning disability, emotional behavior disorder, ADHD, intellectual/cognitive disability) were more likely to be in the Prosocial group. While controlling for early academic achievement and the covariates (i.e., gender, race, primary language, supplemental services, special education services), no significant predictive relationships between profile membership and academic outcomes a year later were found. Implications for designing targeted interventions for different profiles of students, limitations of the current study, and future research direction were discussed.

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Chapter 1

Introduction

The importance of promoting students' social skills and reducing problem behavior for school success and social development has been well-established. As two separate yet related aspects of the overarching concept of social functioning, social skills and problem behavior are linked with both self-regulation and academic achievement (Eisenberg et al., 2000; Eisenberg et al., 2001; Montroy et al,. 2014). Children who fail to master necessary social skills tend to be involved in inappropriate social interactions and develop problem behavior (Coie & Dodge, 1983).

Social skills have been characterized as learning behavior that enable an individual to interact appropriately with others in ways that evoke positive reactions and help avoid negative reactions (Gresham & Elliot, 1984). For example, in general education classrooms, teachers expect students to appropriately express the need for help, abide regulations, remain focused while being distracted, and handle disagreement (Hersh & Walker, 1983; Kerr & Zigmond, 1986; Lane et al., 2003). Research has revealed the critical role that social skills play in maintaining students' successful academic performance, relationships with others, and school readiness (Lodder et al., 2016; Powless & Elliot, 1993; Whitted, 2011). Social skills also have long-term effects over an individual's life as studies have found that teacher ratings of children's prosocial skills at school entry may predict key adolescent and adult outcomes (Jones et al., 2015). To be more specific, kindergarten children who are more inclined to exhibit social skills such as sharing, cooperating, or helping other kids, may be more likely to attain higher education and well-paying jobs. In contrast, children with weaker social skills may be more likely to experience drug abuse, high school dropout, and unemployment (Jones et al., 2015).

Problem behavior that children and adolescents exhibit in general education classrooms may be rooted in emotional and behavior disorders that prevent them from effectively negotiating with peers and teachers and further encumbering their academic success (Gresham et al., 2004). Among these deficits of social skills, behavior associated with anxiety, externalizing behaviors, and not following directions were the most common problem behaviors among children between 6 and 11 (Harrison et al., 2012). Studies found that problem behaviors were related to lower achievement (Wentzel & Caldwell, 1997). Poor social skills also predicted worse performance on achievement tests (Malecki & Elliot, 2002). More importantly, the negative relationship between academic achievement and problem behavior was likely to endure over time (Kremer et al., 2016) and it affects both populations with disabilities (e.g., emotional disturbance, learning disabilities; Lane et al., 2008) and students not receiving special educational services (Ansary & Luthar, 2009).

Research has suggested that teacher ratings are a highly reliable approach to understanding children's social and academic behavior (e.g., Gerber & Semmel, 1984; Gresham & Elliott, 2008). Kindergarten and primary school settings play a crucial role in helping children develop meaningful social relationships. Since children spend most of their time in the classroom, teachers are often the most frequent assessors of children's social, emotional, and academic behavior. Although elementary teachers' perspectives on the most important social skills were found to differ across grades (Gresham et al., 2000), the overall importance placed on particular kinds of social skills by teachers remained stable over time, especially ratings of self-control and cooperation (Lane et al., 2003; Meier et al., 2006). Students who fail to fulfill teachers' expectations of social behavior are more likely to have negative school outcomes, such as poor relationships with peers and teachers, poor academic achievement, and problem behaviors (Coie & Jacobs, 1993).

Conceptual Overview

The association between motivation, interpersonal skills (i.e., social skills), engagement, study skills, and academic achievement was described through DiPerna et al.'s (2002; 2005) model of academic enablers and elementary reading/mathematics achievement. Through structural equation modeling analysis, the model showed that social skills and prior academic achievement predicted motivation, which then predicted study skills and engagement. Study skills and engagement then predicted current academic achievement. Overall, social skills, motivation, study skills, and engagement were positively associated with current academic achievement (DiPerna et al., 2002; 2005). The model also adopted Elliot and Gresham (2007)'s working definition of social skills, 'learned behaviors that promote positive interactions while simultaneously discouraging negative interactions when applied to appropriate social situations (p. 1)'. In their view, social skills include several domains of behaviors: *Communication*, *Cooperation*, *Assertion*, *Responsibility*, *Empathy*, *Social Engagement*, and *Self-control* (Gresham & Elliott, 2008). Additionally, problem behavior was identified by several prominent researchers as a specific dimension of social-emotional development (e.g., National Research Council, 2008; Raver, 2008). Problem behavior reflects extreme variation of children's development in social competence, self-regulation, and emotional expression (Campbell, 2006). Over-controlled or internalizing problem and under-controlled or externalizing problem are two outward manifestations of young children's problem behavior (Campbell, 2006). The current study examined these social skill deficits and problem behavior: *Internalizing*, *Autistic Behavior*, *Externalizing*, *Bullying*, and *Hyperactive-Inattentive* (Gresham & Elliott, 2008). These social skills and problem behavior were selected because they have been identified as important in children's school success and social competence (e.g., Beebe-Frankenberger et al., 2005; Kern et al., 2004).

Problem Statement

Given the importance of promoting social skills and reducing problem behavior among students, intervention programs that targeted social and emotional skills in school have been designed and implemented for children and adolescents. Though such interventions were found to positively affect the development of social and emotional skills and the reduction of problem behavior (e.g., Corcoran et al., 2018; Durlak et al., 2011; Sklad et al., 2012), the overall magnitude of effectiveness varies across programs and participants. A recent meta-analysis indicated that for preschool students, the overall impact (i.e., improvement of social skills and reduction of problem behavior) of universal social and emotional learning programs (g_1 = .35, CI = [.28, .42]) was smaller than programs targeted for at-risk students in need of additional services (g_2 = .48, CI = [.38, .57]), indicating that students at risk gained more from the intervention programs than their non-at-risk peers (Murano et al., 2020). Although the effect of preschool intervention may differ from the intervention programs for students of other grade levels, the study above highlighted the need to design and implement targeted intervention programs in order to cope with individual differences and to maximize the intervention effect for targeted population given finite resources. To provide suitable targeted intervention programs, educators and school psychologists need an appropriate understanding of differential patterns of social skills and problem behavior and classify students with similar instructional needs on behavior into the same group. Yet, little research has applied a person-centered approach to identify distinct profiles of social skills and problem behavior. Even among the previous studies that adopted such an approach, many use a small amount of indicator variables of social-emotional skills, therefore some fine-grained profiles may not be able to be differentiated in the existing research findings.

Research adopting a variable-centered approach has focused on children and adolescents and provides important knowledge about how behavioral problems, social skills, or social-emotional learning are associated with other primary outcomes such as academic achievement, school dropout, and psychological well-being (e.g., Hawkins et al., 2013; Malecki & Elliot, 2002; Segrin & Taylor, 2007). Although variable-centered analyses are able to reveal latent, multivariate association among key constructs, the person-centered approach assumes there are qualitatively distinct latent profiles within the population (Lanza et al., 2013) and thus provides better prediction of children's outcomes. Latent profile analysis (LPA), or latent class analysis (LCA), is a statistical method used to identify unseen subgroups within a population based on individuals' responses to a chosen set of indicators (Collins & Lanza, 2009). Both LPA and LCA are viewed as "person-centered" approaches driven by individual cases, which is considered superior to the dominant "variable-centered" approaches to reveal homogeneity between and within individuals (Nylund et al., 2007). Individuals classified in the same profile are homogeneous with each other based on their response patterns. Though their modeling processes are similar and the two terms are sometimes interchangeably used by researchers, one of the major differences between LPA and LCA is that LPA uses continuous indicators, whereas LCA uses categorical indicators (Masyn, 2013).

Though social skills and problem behaviors are found to be negatively correlated (Hukkelberg et al., 2019), it is not necessary that all children who show poor social skills exhibit problem behaviors, and not all children who display these problems are socially maladaptive. Studies to date have not provided enough evidence on how multiple types of social skills and problem behaviors simultaneously develop. Thus, it is of great interest to gain a comprehensive picture through a collective examination of social skills and problem behavior. In addition, behavior patterns identified at the elementary level are likely to persist and worsen unless they are timely addressed (Walker et al., 1996). Studies have suggested that early interventions were more effective than interventions conducted on older students (January et al., 2011). Yet, limited studies have focused on the population of primary-grade students and pinpointed the associated academic needs of children assigned to each profile. Thus, there is an urgent need to discover whether there are distinct profiles of social skills and problem behaviors co-occurring together among primary-grade students who may have different service needs so that resources can be better allocated.

Purpose of the Study

Given the problem statement above and as a response to researchers' call for a person-centered approach to identify subgroups within the population (e.g., Denham et al., 2012), the current study explores first-grade students' profiles of social skills and problem behavior using SSIS-RST (Social Skills Improvement System Rating Scales – Teacher; Gresham & Elliott, 2008). SSIS-RST is a research-based assessment instrument of K-12 students' social-emotional skills (Humphrey et al., 2011). It is developed based on national norms and has consistently strong psychometric properties for broader use. Besides, SSIS-RST features easy administration, wide age coverage, application to diverse child groups, and coverages across multiple subdomains (Halle & Darling-Churchill, 2016). Once these profiles are identified, further examination of associated individual demographic characteristics and academic needs of the profiles are conducted to facilitate the match of children in each subgroup to appropriate intervention efforts.

Chapter 2

Literature Review

Chapter 2 presents a review of literature related to the latent profiles extracted by the researchers based on students' prosocial skills and/or problem behaviors, the predictive roles of individual-level predictors on the profiles, and the association between the profile membership and later academic achievement.

Profiles of Students' Social Skills and Problem Behavior

An increasing body of research has attempted to identify distinct subgroups, types, or categories of individuals regarding their social skills and problem behavior. Studies have used person-oriented analysis (e.g., cluster analysis, latent profile/class analysis; Collins & Lanza, 2009) to classify children with learning disabilities or generate a typology according to a specific behavior problem (e.g., attention deficit hyperactivity disorder; autism spectrum disorder) for better diagnosis (e.g., Beg et al., 2007; Granziera et al., 2021; Kalichman et al., 1990; Manning & Miller, 2001). Using cluster analysis on a nationally representative sample of first-time kindergarten children, Hair et al. (2006) revealed four profiles based on the five key dimensions of school readiness: physical health, social/emotional development, approaches to learning, language development, and cognitive development. The four profiles were labelled as: Comprehensive positive development, Social/emotional and health strength, Social/emotional risk, and Health risk. Moreover, a handful of latent profile studies examined the variation in students' problem behavior patterns in general education classrooms. For example, Bulotsky-Shearer et al. (2012) identified six distinct latent profiles of emotional and behavioral problems for low-income preschool children based on teacher observations of eight indicators: aggressive, oppositional, inattentive/hyperactive, withdrawn/low energy, socially reticent, structured learning, peer interaction, teacher interaction. The profiles were labelled as Well-adjusted to the preschool classroom, Adjusted with mild disengagement, Moderately socially and academically disengaged, Disruptive with peers, Extremely socially and academically disruptive, and Extremely socially and academically disengaged. Further, McDermott et al. (2022) identified six profiles based on seven indicators of classroom behavior problems: Well-adjusted, Adequately adjusted, Moderately reticent/withdrawn, Underactive in learning and teacher contexts, Aggressive in peer contexts, and Overactive across contexts.

Among multiple subtypes of problem behaviors, externalizing and internalizing are the two behaviors that researchers have mainly investigated. Lee and colleagues (2017) found three latent profiles among Korean kindergarten children based on externalizing and internalizing problem behaviors: Non-problem, Normal, and In-danger group. A following analysis of variance test indicated that students from the Non-problem group showed the highest level of social skills (i.e., collaboration, assertiveness, self-control, responsibility), whereas students from the In-danger group demonstrated the lowest level of social skills. Similarly, Orpinas et al. (2014) yielded seven classes among sixth-grade public school students based on teacher ratings of externalizing behaviors, internalizing problems, academic skills, leadership, and social assets. The seven classes were labelled as Well-adapted, Average, Average-social skills deficit, Internalizing, Externalizing, Disruptive behavior with school problems, and Severe problems. Students' self-reports further validated the seven latent profiles. Students in the Well-adapted profile reported lower aggression, drug use, delinquency, and high life satisfaction, with the Average class reporting more aggression, drug use, delinquency, and lower life satisfaction. The Severe problems profile reported Disruptive behavior and school problems. They also found the children with co-occurring problems had the most detrimental long-term outcomes. Basten and colleagues (2016) used LPA to study profiles of behavior problems of Dutch children at 1.5, 3, and 6 years with a perspective of long-term impact. Four latent profiles emerged based on six subscale indicators of Child Behavior Checklist (Achenbach & Rescorla, 2000) — Co-occurring internalizing and externalizing, Predominately externalizing, Some internalizing, and No problems.

Researchers also conducted LPA Studies on social skills by focusing mainly on a related concept, social and emotional skills. Ma et al. (2022) identified four profiles among Canadian Grade 4 students based on five teacher-reported indicators of social emotional learning (SEL) skills: prosocial, cooperation, self-control, work habits, and emotion regulation. The four emerged profiles were: Relatively low SEL, Moderate-high SEL, Prosocial/self-control, and Cooperation/work habits. Tze et al. (2021) revealed cross-cultural disparities on social behaviors using the data collected by an international large-scale assessment, PISA 2015 (Programme for International Student Assessment; OECD, 2017). They extracted social-emotional skill profiles in the 15-year-old students from four countries based on four indicators via student report: self-awareness, self-management, social awareness, relationship skills. The profiles were labelled as Sociable, Reserved, and Withdrawn in the students from Canada, Singapore, and the United States; whereas they found three profiles labelled as Solitary, Team-oriented, and Reserved among the cohorts from China.

However, relatively little LPA research has revealed finer-grained profiles based on students' social skills and problem behaviors together. Collie and colleagues (2019) applied LPA to identify the social and emotional behavior (SEB) profiles among kindergarten students based on five SEB indicators of both adaptive and maladaptive behaviors: cooperative, socially responsible, helpful, anxious, and aggressive-disruptive behavior. The four SEB profiles were SE-Prosocial, SE-Anxious, SE-Aggressive, and SE-Vulnerable groups. DiStefano and Kamphaus (2006) used LPA to identify groups of child behavioral adjustment for elementary school children with an average age of eight. The three profiles were identified as Optimal adjustment, Average adjustment, and Functionally impaired adjustment. Although they used fourteen indicators, more than most of the studies, DiStefano and Kamphaus put a greater emphasis on problem behaviors given that nine of fourteen indicators they used were about maladaptive behavioral indicators.

The literature cited here provided several important implications for our study. First, although the number of the profiles generated varies across studies, within each study, the profiles may be ordered roughly along a continuum. The profiles were labelled either by “well”, “average”, and “poor” indicating gradual development, or by “prosocial”, “aggressive”, or “vulnerable” indicating the predominant performance of each group. Second, previous research identified subgroups based on teacher rating with focus on either social skills or problem behavior. To date, only two recent studies have identified profiles on social skills and problem behavior together (i.e., Collie et al., 2019; DiStefano & Kamphaus, 2006) and neither of them focused on first-grade students. An empirical question thus arises. How do social skills co-occur with problem behavior among first-grade students? Specifically, do children demonstrating more problem behavior tend to have low social skills?

Individual Demographic Predictors of Social Skills and Problem Behavior Profiles

In addition to identifying social skills and problem behavior profiles, examination of predictors related to the profiles have also been conducted to extend knowledge via a variable-centered approach. Potentially salient individual predictors in variable-centered approach, including gender, primary language, socioeconomic status, and learning disability, have been associated with prosocial behaviors among children. Studies have found that kindergarten girls tend to report greater adaptive social and emotional behaviors compared with boys (Duchesne et al., 2010). Kindergarten students with a non-English speaking background tend to demonstrate lower social skills (Goldfeld et al., 2014). Students living in a higher socioeconomic status household tend to report less problem behaviors (Morgan et al., 2009). Furthermore, students with learning disabilities tend to exhibit problem behavior. A meta-analysis indicated that children with learning disabilities were more likely to be rated as aggressive, immature, suffering personality problems, and having difficulty attending when compared to peers without disabilities (Swanson & Malone, 1992). Though the prior research cited here enhanced our understanding towards the predictive relationship between student-level predictors and prosocial skills and problem behaviors, they were variable-centered in nature.

A handful of LPA studies have examined the association between student demographic characteristics and the profile membership. For example, McDermott et al. (2022) found that child demographic variables were overall more strongly associated with profile membership than familial socio-demographic variables. Children in an Adequately-adjusted group were more likely to be male than female, African American rather than other diverse groups, or receiving special needs services rather than not receiving these services. Among children with overactive behavior problems, those who were male, required special needs services, or had an immigrant mother tended to have a greater risk of membership in the Aggressive in peer contexts profile. Further, Collie et al. (2019) examined the extent to which profile membership was associated with socio-educational characteristics. They found female students were more likely to be in the SE-Prosocial profile than the remaining profiles. Students whose home language was not English were more likely to be in the SE-Anxious and SE-Aggressive profiles than the SE-Prosocial profile (but not the SE-Vulnerable profile). They also found the higher neighborhood SES was associated with membership in the SE-Prosocial profile rather than the other profiles. This is largely consistent with the results in Hair and colleagues (2006)'s study that children assigned to one of the two risk profiles were more likely to originate from families with multiple socioeconomic disadvantages. Additionally, Bulotsky-Shearer et al. (2012) found the child age and sex were the only two predictive variables of profile membership. Younger children were less likely to be classified within the Well-adjusted profile type, as compared to all other profile types. This is largely consistent with the study of Granziera and colleagues (2021). Younger children were more likely to be in the nonaggressive-unregulated profile compared with all other profiles which displayed higher level of self-regulation skills (Granziera et al., 2021). Each month increment in age decreased the likelihood that children would be classified into a problem profile type (Bulotsky-Shearer et al., 2012). Also, being a girl decreased children's risk for classification in these problem profile types, relative to the Well-adjusted profile type (Bulotsky-Shearer et al., 2012). These studies suggest that some demographic variables were associated with students' profile membership, such as gender, race, receiving special need services, primary language, age, socioeconomic status. Research situated in different cultures revealed findings related to gender as well. Lee et al. (2017) found that profile membership of Korean kindergarten children was related to gender, family income, level of activity and sociality, and mother's parenting stress. They found girls tend to exhibit more internalizing behavioral problems than boys, such as passive and shrinking behavior, physical symptoms of mental instability.

From the above discussed research, the dominant individual demographic characteristics studied in the previous variable-centered studies are child gender, race, primary language, age, family or neighborhood socioeconomic status, and learning disabilities. Person-centered approach studies have not included all these dominant characteristics in the study to provide enough evidence on the predictive relationship with the profile membership. Thus, an important question arises: compared with findings from variable-centered approaches, how do these dominant individual demographic characteristics associate with first-grade students' profile membership generated from both social skills and problem behavior?

Association between Behavior Profiles and Academic Outcomes

Academic outcomes are a core aspect of schooling and schools should promote students' progress in academic achievement (U.S. Department of Education, 2001). A growing body of research and policy has focused largely on the importance of cognitive skills and emergent literacy on later academic achievement (e.g., Kauerz, 2002; Snow et al., 1998). In recent years, policymakers have become more conscious of the importance of the social and emotional development on student success in preschool and elementary school (National Association for the Education of Young Children, 2009; National Research Council, 2012; National School Readiness Indicators Initiative, 2005). An increasing number of bills and legislation have also offered opportunity to support students' social and emotional development both in-school and out-of-school (e.g., Every Student Succeed Act, American Rescue Plan Act of 2021). Plentiful variable-centered research has also shown positive association between social skills and academic achievement and children who exhibit poor prosocial skills perform less well academically than children who exhibit good prosocial skills (e.g., Caprara et al., 2000; Feldhusen et al., 1970; Ollendick et al., 1992).

A handful of research has studied the longitudinal links between social emotional behaviors and distal academic functioning at different time points. However, the findings have been mixed. For example, DiPrete and Jennings (2012) found that social and behavioral skills have substantive important effect on academic outcomes from kindergarten through fifth grade. However, Claessens and colleagues (2009) found that the socioemotional skills (i.e., noncognitive skills for paying attention, sitting still, and making friends) at the entry of kindergarten were not predictive of fifth-grade reading and mathematics achievement, whereas school-entry academic skills had a considerable impact. This was validated both for the overall sample and for subgroups categorized by race/ethnicity and socioeconomic status. Similarly, a meta-analysis revisiting six longitudinal datasets found that among the school-entry academic, attention, and socioemotional skills, early math skill was the strongest predictor of later academic achievement, whereas socioemotional behavior combined social skills and problem behaviors were generally insignificantly predictive (Duncan et al., 2007).

A growing body of LPA research has attempted to explore the association between profile classification and academic outcomes longitudinally and the findings have largely demonstrated that profiles featured higher social and emotional behavior tend to be associated with greater subsequent academic achievement. Hair and colleagues (2006) found that school-readiness profile membership in children at kindergarten entry predicted academic and social adjustment at the end of first grade, controlling for child, familial, and kindergarten classroom characteristics. Their profiles were generated based on five dimensions: physical health, social and emotional development, approaches to learning, language development, and cognitive development. Children assigned to an at-risk profile performed the worst on all academic outcomes; on the contrary, children assigned to a comprehensive positive development profile performed the best (Hair et al., 2006). Similarly, Bulotsky-Shearer et al. (2012) found that preschool children who were assigned to the extremely socially and academically disengaged profile started and ended the preschool year with the lowest academic skills, maintaining their disadvantage relative to all other profiles with less negative behavioral and academic outcomes. These children exhibited the second slowest growth rate in both mathematics and literacy scores across 3 assessment time points, and their gap with other profiles at time 3 almost remained the same as the time 1. Collie et al. (2019) examined the association between profile membership and gains in the academic achievement from preschool to middle childhood. Preschool SE-Prosocial profile was associated with the highest achievement in both Grade 3 and Grade 5 (Collie et al., 2019). Though using a longitudinal dataset (Australian Early Development Census), their study was correlational in nature and was not able to make judgements about causality.

Studies have also extended the existent literature by noting that students in a positive profile of social and emotional skills may also struggle with differential learning outcomes when approaching adolescence. Ma and colleagues (2022) examined middle childhood (i.e., Grade 4) students' social-emotional learning profiles and their longitudinal relations to academic and social function in early adolescence (i.e., Grade 6). When controlling for baseline skills, they found that youth who demonstrated a moderate-high level social and emotional learning profile had more positive social and academic outcomes in early adolescence. In contrast, youth with a relatively low level social and emotional learning skills were at the greatest risk for low academic achievement, low peer competence, and high aggression. Moreover, youth who have strengths on some of the social and emotional skills but not all skills had area-specific weakness, either on academic outcomes or social functioning. Specifically, children in the prosocial/self-control profile demonstrated the fewest aggressive behaviors, but demonstrated middle-level academic outcomes and peer competence. However, children in the cooperation/work habits group suffered from significantly more problematic peer relationships in early adolescence, but demonstrated very high-level academic performance.

The mixed longitudinal findings cited here again suggest the value of answering the empirical questions of how profile membership based on social skills and problem behavior together are associated with academic achievement. And, whether there are any profiles for which the findings on associations are more nuanced? In addition, given the limited studies conducted with primary-grade children, there is a need to replicate the current findings of LPA studies to determine their generalization across other samples of students.

Latent Profile Analysis

Latent profile analysis (LPA) and latent class analysis (LCA) are two prominent types of latent variable mixture modeling (Berlin et al., 2014; Williams & Kibowski, 2015) or finite mixture models (Masyn, 2013). Mixture modeling is a family of models that aim to classify a heterogenous population into homogeneous subgroups (Berlin et al., 2014; Muthén, 2001). They allow researchers to discover patterns among a large number of individuals and to further examine how these patterns are related to variables of interest (Berlin et al., 2014). The assumption of mixture modeling is that the heterogeneity of the dataset can be explained by the homogeneity of underlying subgroups that are mixed together (Williams & Kibowski, 2015). LPA is similar to LCA except that LPA reveals underlying subgroups from a population based on the means of continuous observed variables, while LCA is conducted based on the categorical observed variables (Williams & Kibowski, 2015). LPA and LCA are useful in their potential to influence policies and practice-based interventions which focus on a particular latent subgroup that has emerged from the analysis, since each individual is assigned to a profile membership with respect to their patterns of responses or behavior.

As the name implies, LPA and LCA deal with latent variables. Unlike observed variables, latent variables are not measured directly. Figure **2-1** depicts a hypothetical LPA or LCA model. The latent variable is the class or profile membership, often represented by oval labeled c. The observed variables are the indicator variables measuring the latent variables, represented by squares labeled X_1, X_2, X_3. Error associated with the indicator variables is represented by circles labeled e_1, e_2, e_3. The arrows point from the latent variable to each observed indicator variable, and the arrows point from each error to its corresponding indicator variable. This means that the latent variable and the error cause the observed indicator variables, but the observed indicator variables do not cause the latent variables (Collins & Lanza, 2009).

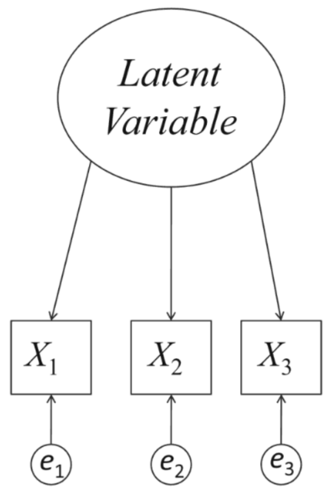

Figure **2-1**: Latent variable with three observed variables as indicators

LPA and LCA set apart from other popular subgroup analytical techniques, such as factor analysis and cluster analysis. LPA and LCA focus on extracting subgroups from the population, whereas factor analysis focuses on dimension reduction of items or variables. Compared with factor analysis as well as many other traditional analytical techniques (e.g., multiple regression), LPA emphasizes more focus on the individual than variables. Cluster analysis is similar to LPA as they both classify large populations into small subgroups. However, the two methods work in different ways. In cluster analysis, individuals are categorized into the same subgroup on the basis of the distance (e.g., Euclidean distance) as measure of the proximity of each pair. The more closely associated with each other, subjects are more likely to be assigned into the same subgroup. LPA and LCA use a probabilistic modeling approach to provide each individual with a probability value of being assigned to each latent class (Collins & Lanza, 2009). Researchers draw inferences to decide possible mixture of several subgroups within the population. The larger the probability value is, subjects are more likely to be assigned to a certain subgroup.

One key issue when conducting LPA and LCA is to select the best fitting solution and determine the number of profiles. Usually, researchers determine the best fit solution after comparing up to four or five solutions statistically and theoretically (Masyn, 2013; Tein et al., 2013). One profile is added to the model solution each time, starting with the hypothesis that the solution with only one profile can fit the data best. Each model solution is compared with the previous one based on a combination of goodness of fit indices to increase the credibility of the ultimate decision on the number of profiles. These goodness of fit indices should be recorded every time when a new model is fitted. The commonly-used criteria in LPA studies within the educational psychology field are information criteria, entropy, and LMR value (e.g., Collie et al., 2019; Marsh et al., 2009; Pastor et al., 2007). Information criteria include Akaike Information Criterion (AIC; Akaike, 1987), Bayesian Information Criterion (BIC; Schwarz, 1978), and Sample-size Adjusted BIC (SABIC; Sclove, 1987). BIC is a conservative criterion with parsimony constraints which perform better in models with more continuous indicator variables (Morgan, 2015; Nylund et al., 2007). Alternatively, SABIC is more liberal on the parsimony constraints as it takes sample size into consideration. Several simulation studies have supported that SABIC provided accurate estimates in small sample with low class separation (Kim, 2014; Morgan, 2015). In contrast to BIC and SABIC, AIC is an inconsistent measure of the model-fit and allows more variation among AIC values across models (Ferguson et al., 2020). Lower values of the information criteria above generally suggest better-fitting models (Masyn, 2013). However, lower is relative and magnitude of differences should be considered (Ferguson et al., 2020). Another useful index is entropy. Entropy measures the general classification accuracy across all the latent classes in the entire sample (Ramasway et al., 1993). Entropy ranges from 0 to 1 and a value closer to 0 indicates poor separation among the classes that have been estimated (Ramasway et al., 1993). Whereas, higher value of entropy indicates higher classification cleanness and lower uncertainty (Celeux & Soromenho, 1996). Entropy values close to 1 indicate high accuracy in classification (Collins & Lanza, 2009). Additionally, Lo-Mendell Ruben Likelihood Ratio Test (LMR; Lo et al., 2001) resembles the χ^2 difference test. However, a χ^2 distribution is not achievable when comparing a K-profile to a (K −1)-profile finite mixture model (Masyn, 2013). LMR tests the likelihood ratio of one model with an adjusted asymptotic distribution (Lo et al., 2001). It provides a *p*-value assessing whether the current model fit gained significant improvement than a more parsimonious model with one fewer profile. A non-significant *p*-value for a K-profile solution indicates that a K-profile solution did not improve model fit significantly over the (K-1)-profile.

It is very likely that more than one "optimal" model will be retained across the evaluation of the statistical indices above. For these candidates, parsimony principle and substantive evaluation (e.g., interpretability of the profiles, theoretical considerations) may be considered in concert with the above statistical indices (Bauer & Curran, 2003). Parsimony principle means that if the candidate models are statistically and theoretically appropriate to use, the one with the fewest number of profiles should be retained (Masyn, 2013). The profiles generated need to be well discriminated from each other and an additional profile needs to add new information to the prior solution (Berlin et al., 2014). Apart from the number of the profiles as a whole, sample size of each profile should be examined and compared. Lubke and Neale (2006) suggested that if the additional profile contains only a small number of cases, it is suspicious whether the profile should be adopted given the possible lower power, less representativeness, and less parsimony. They also recommended that the additional profile includes less than 1.0% of the total sample size or less than 25 cases, the profile should be rejected (Lubke and Neale, 2006). Finally, researchers need to label substantive meanings to each profile to gain interpretability of the optimal solution by referring to theory, previous research, and the research question. Labels of each profile are determined by the average score across the indicator variables (i.e., class 1 -

Average activity, Moderate screen, Above average Diet; class 2 - Average risk/resource; class 3 - Mixed risk/resource). Profiles are clearly distinguishable from each other.

After decision of the optimal model through the above procedures, researchers also use different strategies to validate these profiles, including to test the mean differences across all the profiles, to examine the predictors of the profile membership, and to compare the LPA results with the results of traditional linear regression analysis (Spurk et al., 2020). Marsh et al. (2009) also related profiles with external validity criteria and applied discriminant function analysis, canonical analysis, and auxiliary variable analysis to validate generated profiles. In the end, individuals were assigned to subgroups based on the conditional probabilities. Final profile membership represents the profile to which each individual most likely belongs to.

The Current Study: Research Questions and Hypotheses

Our first research question is “How can we describe the latent profiles of first-grade students’ social skills and problem behavior?” We use a person-centered approach to uncover groups of individuals who have similar social skills and problem behaviors. Rather than placing the emphasis on the interaction between prosocial skills, problem behavior, demographic variables, and later academic achievement, the current study shifts the focus towards the natural differences within a population and uncovering the unique characteristics of each group. By identifying profile types based on a comprehensive assessment of both prosocial skills and problem behavior using eleven indicator variables, the current study may bring more nuanced understanding for teachers and researchers toward how the prosocial skills and problem behaviors may co-occur within one profile type and co-develop across different groups of individuals. Also, early detection of social skills deficit and problem behavior patterns for first-grade students is crucial. We hypothesize that at least three profiles reflecting different levels of student social skills and problem behavior will emerge from this research. Individual characteristics (i.e., student gender, race, primary language, receipt of special education services or supplemental services) will have different distribution across three profiles.

Given the mixed findings on to what extent the sociodemographic characteristics play a role in predicting person-centered profiles, the present study further evaluates the role of demographic variables in relation to prosocial skills and problem behavior profiles. Thus, our second research question is “Can individual demographic characteristics (i.e., student gender, race, primary language, receipt of special education services, receipt of supplemental services) predict first-grade students’ profile membership?” We hypothesize that child gender, race, primary language, receipt of special education services, and receipt of supplemental services will predict the membership of students’ behavior outcome profiles. Findings on how the individual-level demographic variables (i.e., child gender, race/ethnicity, primary language, receipt of supplemental service, receipt of special education service) are associated with profile membership in the current study may be helpful in ensuring intervention efforts are targeted appropriately to different groups of students.

Moreover, the current study provides an opportunity to examine the predictive association between person-centered profiles and later academic outcomes in a first-grade sample. Rather than knowing the overall influence of social skills or problem behaviors on academic outcomes via a variable-centered approach, this may extend our knowledge on how multiple combinations of social skills and problem behavior are linked to different levels of academic outcomes. Thus, our third research question is “Can profile membership predict first-grade students' reading and mathematics achievement?” We hypothesize that student behavior profiles will predict reading and mathematics outcomes after controlling for covariates (i.e., student gender, race, primary language, receipt of special education services, receipt of supplemental services). We anticipate that students who are assigned to a more positively-featured profile would attain better academic outcomes. In contrast, we anticipate that students who are assigned to a negatively-featured profile would obtain lower scores in academic achievement than their peers.

Chapter 3

Method

This chapter delineates the research design and methodology of the study. The procedures to collect data, the instrument used to gather data, participants' characteristics, and determination of the analytical strategies are described.

Participants

Data Source and Data Collection

This study used first-grade data of students participating in the *Positive, Engaged, Achieving Kids* Study (The PEAK Project). One of the goals of the PEAK Project is to evaluate the effectiveness and usefulness of the Social Skills Improvement System-Classwide Intervention Program (SSIS-CIP; DiPerna et al., 2018). The SSIS-CIP is a universal program developed for classroom use in the general education context, and it utilizes instructional strategies to facilitate classroom social behaviors of young children in primary grades (DiPerna et al., 2016; Elliot & Gresham, 2007). The whole data set collected for the PEAK project through two years includes multiple kinds of student, teacher, and school administrators survey results. However, the current study merely used part of the dataset and variables to address the research questions.

The sample for the current study was limited to 575 first-grade students recruited in 2018 Fall and 2019 Fall from the Midwest and Northeast regions of the United States. The data used in the current study include survey results of students' baseline behavior outcomes (i.e., social skills, problem behavior), baseline and post-intervention academic outcomes (i.e., reading skills, math skills), and demographic variables (i.e., child gender, race/ethnicity, primary language, receipt of special education services, receipt of supplemental services). These data were collected during November and December before the intervention and April and May after the SSIS-CIP implementation. The interval between two data points was roughly 5 months. Although the academic achievement after the intervention was of research interest, the intervention effectiveness on neither academic nor behavior was the main goal of the current study and thus treatment condition was controlled for when testing the relationship between profile membership and academic outcomes. All procedures of the current study as a secondary data analysis were approved by the Pennsylvania State University Institutional Review Board (IRB).

Missing Data

Two samples were generated from the data for analyses. For the LPA sample used to address the first two research questions, we deleted 9 cases as they were either missing on behavior outcomes or on demographic variables. The LPA sample size was 566. After the deletion, no cases had missing data on all measured LPA indicators. For the reading or mathematics outcomes used to address the third research question, we retained students who had both waves of data for either content domain. For example, if an observation contributed data for both waves of mathematic achievement but not reading achievement (or reading achievement but not the mathematic achievement), it was retained. However, if the student contributed wave 1 data of both mathematics and reading achievement, it was deleted. The analyzed sample size was 347.

Participant Characteristics

The demographic variables included gender, race, primary language, receipt of supplementary services (i.e., Title 1, instructional support, tutoring, response to intervention), and receipt of special education services (i.e., speech/language impairment, learning disability, emotional behavior disorder, ADHD, intellectual/cognitive disability).

In the LPA sample, students' average age was 6.89 years, with a standard deviation of 0.40 and median of 6.59. As shown in Table **3-1**, 50.9% of the students were male. The majority of the students were white only (35.2%), followed by students who were Hispanic only (26.9%) and Black or African American only (25.3%) respectively. 5.3% of the students were Asian only. Most students' primary language was English (86.9%). A substantial portion of children were receiving supplementary services (28.6%) during the data collection, some students were receiving special education services (5.7%), and a few students were receiving both services (2.12%).

In the analyzed sample for academic outcomes, students' average age was 6.90 years, with a standard deviation of 0.42 and median of 6.60. The demographic characteristics of the analyzed sample were consistent with the sample for behavior outcomes. As shown in Table **3-1**, 52% of the students were male. The majority of the students were white only (43.6%), followed by students who were Black or African American only (24.6%) and Hispanic only (23.1%) and respectively. 3.5% of the students were Asian only. The majority of students' primary language was English (93.6%). A substantial portion of children were receiving supplementary services (23.4%) during the data collection, some students were receiving special education services (5.5%), and a few students were receiving both services (2.31%).

Table **3-1**: Participant demographic characteristics

Demographic Characteristic	Behavior outcomes N = 566		Academic outcomes N = 347	
	n	%	n	%
Gender				
Male	288	50.9	180	52.0
Female	278	49.1	167	48.0
Race				
Asian only	30	5.3	12	3.5
Black/African American only	143	25.3	86	24.6
White only	199	35.2	151	43.6
Hispanic only	152	26.9	80	23.1
Other only	14	2.5	3	0.9
Multi-racial	28	4.9	15	4.3
Primary language				
English	492	86.9	325	93.6
Non-English	74	13.1	22	6.4
Special education services	32	5.7	19	5.5
Supplemental services	162	28.6	81	23.4

Measures

Social Skills and Problem Behavior

The SSIS-RST (Social Skills Improvement System Rating Scales – Teacher; Gresham & Elliott, 2008) was used to evaluate students' social skills and problem behaviors in the classroom. Teachers rated each item on the Social Skills and Problem Behavior scales using a 4-point format ranging from never to almost always. The two domains are further divided into subdomains. The SSIS-RST Social Skills Scale includes 46 items across 7 subscales (Communication, Cooperation, Assertion, Responsibility, Empathy, Engagement, Self-control, Externalizing, Hyperactive-Inattentive, Internalizing, and Bullying). The Problem Behavior Scale includes 24 items across five subscales (Externalizing, Bullying, Hyperactive-Inattentive, Internalizing, and Autism Behavior); however, the Autism Behavior subscale was not analyzed in the current study.

The number of items and example items in each scale is in Table **3-2**. Psychometric evidence for SSIS-RST scores is consistent with its intended purpose (Gresham & Elliott, 2008), and reliability indices (α = .88 - .98) in the current sample are strong (see Table **3-2**).

Table **3-2**: Reliability, number of items and examples for SSIS-RST

Variable	Cronbach's alpha	Number of items	Example item
Social skills			
Communication	.91	7	"Says please", "Takes turns in conversations"
Cooperation	.93	6	"Follows your directions", "Pays attention to your instructions"
Assertion	.87	7	"Asks for help from adults", "Says when there is a problem"
Responsibility	.94	6	"Acts responsibly when with others", and "Respects the property of others"
Empathy	.95	6	"Tries to comfort others", and "Forgives others"
Social engagement	.92	7	"Makes friends easily", and "Interacts well with other children"
Self-control	.94	7	"Stays calm when teased", "Uses appropriate language when upset"
Problem Behavior			
Externalizing	.93	12	"Acts without thinking", "Disobey rules or requests"
Bullying	.90	5	"Does things to make others feel scared", "Keeps others out of social circles"
Hyperactive-inattentive	.93	7	"Is inattentive", "Gets distracted easily"
Internalizing	.89	7	"Withdrawn from others", "Gets embarrassed easily"

Reading and Math Skills

Students' academic outcomes were measured by the STAR Math (Renaissance Learning, 2009) and Reading or Early Literacy (Renaissance Learning, 2010) computerized adaptive tests. STAR Math is composed of 34 multiple choice items that assess numeration and operations, algebra, geometry and measurement, and computation abilities. STAR Reading or STAR Early

Literacy assesses students' word knowledge and skills, comprehension strategies and meaning construction, and literary text analysis. Students may be assessed by STAR Early Literacy first before they were ready to take STAR Reading, but they were on difference score scales. The underlying Rasch ability scales obtained from two measures were equated into a unified Rasch scale. Then a reported score scale that extended from 200 to 1400 was developed through anchoring approaches (Renaissance, 2010). In the current study and most of the studies adopted STAR reading achievement measures (e.g., Bulut & Cormier, 2018; DiPerna et al., 2017), the unified STAR Reading score was used. The scoring for the STAR measurement was completed via a proprietary Bayesian-modal item response theory estimation model (Renaissance Learning, 2009). Each STAR assessment requires approximately 10 minutes to complete. The reliability of STAR scores for math is $\alpha = .97$ (Renaissance Learning, 2009) and reading is $\alpha = .98$ (Renaissance Learning, 2010).

Analytic Strategies

Latent Profile Identification and Description

In order to address the first research question "How can we describe the latent profiles of first-grade students' social skills and problem behavior", this study utilized latent profile analysis in Mplus 8 to determine if there were multiple subgroups of students based on teacher-reported behavior outcomes. LPA was run with eleven indicator variables (i.e., Communication, Cooperation, Assertion, Responsibility, Empathy, Engagement, Self-control, Externalizing, Hyperactive-Inattentive, Internalizing, and Bullying). These indicator variables were composite scores created by averaging the item-level scores of each scale.

To determine the optimal number of profiles, the specification for analysis was TYPE = MIXTURE. The estimator used was ESTIMATOR = MLR, maximum likelihood parameter estimates with robust standard errors, which is found to perform better than other estimators when dealing with non-normality and missing data (Muthén & Muthén, 1998-2017). In order to obtain a consistent solution and identify the model, we used the STARTS subcommand under ANALYSIS to specify the number of random sets of starting values generated in the initial stage and the number of optimizations used in the final stage. We started with the default of 20 random sets of starting values in the initial state and 4 optimizations in the final stage by naming STARTS = 20 4. Then we changed the values to STARTS = 100 20 and STARTS = 1000 250 to check whether the model converged at similar estimates and to avoid local maxima in the estimation process (Asparouhov & Muthén, 2019).

LPA was applied as an exploratory process in our investigation because there were no *a priori* assumptions about the number of the latent profiles. We started first by establishing a one-class solution, and then successively added the number by one profile each time until the model was not plausible as indicated by one or more goodness of fit indices. We fitted five models in total. To obtain the optimal model, goodness of fit indices of five models were recorded and compared, including AIC, BIC, SAIC, LMR, and entropy value. If the model with optimal goodness of fit was not interpretable, alternative models would be considered and multiple fit indices would be weighted. The profile size would also be checked to guarantee that an additional profile contributes substantial new information to the prior solution.

When the final number of profiles were determined, we described each profile's sample size, demographic characteristics, and average scores of behavior outcomes on each indicator variable. One-way ANOVA was used to examine the mean differences of indicator variables and academic outcomes among different profiles as a profile validation approach (Spurk et al., 2020).

Latent Profile Predictors

In order to address the second research question "Can individual demographic characteristics (i.e., student gender, race, primary language, receipt of special education services, receipt of supplemental services) predict first-grade students' profile membership?", the study first utilized Chi-square Tests of Independence to examine the associations between the demographic characteristics and profile membership because they are categorical variables with at least two levels. We checked the Chi square statistics and p value. The measure of the strength of the association between variables we used were phi coefficient (symbolized by ϕ) for 2×2 Tables and Cramer's phi coefficient (symbolized by ϕ_c) when at least one of the two categorical variables has more than two levels. The absolute value of ϕ and ϕ_c is between 0 and 1 and they can be interpreted as a Pearson correlation. Larger values indicate stronger association between the two variables. A value of .1 is considered to be small, .3 medium, and .5 large (Welkowitz et al., 2011).

Then multinomial logistic regression was used in SPSS Statistics 28.0.1 to examine the role of the demographic characteristics in predicting the membership of behavior profiles. Multinomial logistic regression is appropriate to model nominal outcome when the categories in the dependent variable (i.e., profile membership) are truly discrete, nominal, and unordered (Kwak & Clayton-Matthews, 2002). The log odds of the outcomes are modeled as a linear combination of the predictor variables. Profile membership was the predictor variable that was dummy-coded to represent each group. We designated the first identified profile as the reference group. It is noted that the choice of reference group makes no difference in the estimated coefficient, calculated probabilities, and significance of variables if properly transformed (Kwak & Clayton-Matthews, 2002). We regressed behavior profiles on student gender, race, primary language, receipt of special education services, and receipt of supplemental services. The predictors were dummy coded: gender (0 = males, 1 = females), race (five dummy-coded variables were created: Asian, Black, White, Hispanic, and Other. Multi-racial was the reference group), primary language (0 = English, 1 =Non-English), receipt of special education services (0 = no, 1 = yes), and receipt of supplemental services (0 = no, 1 = yes). In the result, we present unstandardized beta coefficients, standard errors, and odds ratios (ORs). ORs greater than 1 indicated the individuals in the current condition group are more likely to be a member in a comparison group, whereas ORs less than 1 suggest increased likelihood of membership in the reference group.

Profile Membership and Later Academic Outcomes

In order to address the third research question "Can profile membership predict first-grade students' reading and mathematics achievement?", hierarchical multiple regression was performed in SPSS Statistics 28.0.1 to determine how behavior profile membership predicted reading and math achievement when the intervention completed. Rather than exploring and maximizing prediction, we were more interested in examining the unique importance of profile membership over and above the demographic variables and baseline scores.

In hierarchical multiple regression, the independent variables were added in steps (or "blocks" in SPSS) to control for the effects of covariates and to better understand how predictors of interest add to the explanation of the variances in outcome variables. It is strongly suggested that researchers generate a theoretically based plan for the selection of predictors and how predictors are entered into the model sequentially (Petrocelli, 2003). As Cohen et al. (2014) argued, demographic variables are suitable choices for the first-step entry. We added covariates in the first block: child gender, race, primary language, treatment condition (0 = control, 1 = treatment), receipt of special education services, receipt of supplemental services, and baseline scores. The reference group was female for gender, multi-racial for race, non-English for primary language, control group for treatment condition, no receipt for special education services or supplemental services. Then, the variable of greatest interest, would be entered for the second step. We added behavior profile membership to the second block. The reference group was the Vulnerable group (i.e., profile 1). We also assumed that the interaction between profile membership and baseline scores, and the interaction between profile membership and treatment condition would predict the post-intervention academic outcome, but perhaps would be less important than the profile membership. Thus, four interaction terms were entered into the regression model in the third block: Baseline reading/math skill * Prosocial group, Baseline reading/math skill * Moderate group, Treatment * Prosocial group, Treatment * Moderate group.

When using hierarchical regression, ΔR^2 (i.e., the change of R^2) and p values are the statistics of greatest interest (Wampold & Freund, 1987). They allow researchers to determine if the ΔR^2 statistics due to profile membership significantly improve the model's ability to predict later academic outcomes over and above that which can be predicted by preexisting variables. A discussion of results should focus primarily on the differences found through comparing progressive steps and not on the overall model (Petrocelli, 2003).

Chapter 4

Result

Research Aim 1: Identify and Describe Optimal Latent Profiles

Model fit summary for 1- to 5-profile solutions are presented in Table **4-1**. The value of AIC, BIC, and SABIC revealed relatively large decreases until the differences between Model 4 and Model 5. Entropy for all models (1-profile model does not provide this index) were above 0.8 and Model 3 had the largest value. Furthermore, the LMR test was only significant for Model 3 ($p = 0.01$), which means the 3-profile model was a better solution than a 2-profile model. The nonsignificant LMR p-value of Model 4 indicated that a 4-profile model was not a better solution than a 3-profile model. In Model 3, 10% of the children from the sample were represented in the smallest profile. The smallest profile in Model 4 comprised only 5% percent of the children and even less children were represented in Model 5. With small frequencies, the model with additional profiles may not be worthwhile (Lubke & Neale, 2006). Ferguson and colleagues (2020) recommended that it may be easier to generalize the findings if retaining a model with a larger proportion of the population in its smallest profile. Finally, a 3-profile model was retained as the optimal model for the data based on the low AIC, BIC, and SABIC values, the highest entropy value, and statistically significant *p* value for LMR test.

Table **4-1**: Model fit summary for 1- to 5-profile solutions

Model	AIC	BIC	SABIC	Entropy	LMR p-value	Smallest class %
1	11184.244	11279.693	11209.853	--	--	--
2	8493.263	8640.775	8532.841	0.922	0.0694	44%
3	7106.391	7305.966	7159.938	0.959	0.0101	10%
4	6572.064	6823.703	6639.580	0.947	0.3894	4%
5	6295.611	6563.312	6341.095	0.932	0.4022	3%

Note. $N = 566$; AIC = Akaike's Information Criterion; BIC = Bayesian Information Criterion; SABIC = Sample-Adjusted BIC; LMR = Lo-Mendell-Ruben adjusted likelihood ratio test.

Figure **4-1** provides a line graph comparing three profiles on all eleven indicator variables. There were 54 (9.5%), 258 (45.6%), and 254 (44.9%) students in the three profiles. Among the three profiles, students in profile 1 had the lowest social skill scores and the highest problem behavior scores, whereas students in profile 2 scored the highest on social skills and the lowest on problem behavior. Students in profile 3 performed moderately on both social skills and problem behavior. As such, we labeled profile 1 as the Vulnerable group and profile 2 as the Prosocial group. As students in profile 3 showed intermediate performance comparing with the first two profiles, we recognized it as the Moderate group. The results of one-way ANOVA in Table **4-2** indicated that all the eleven indicator variables were significantly different across three profiles ($p < .001$).

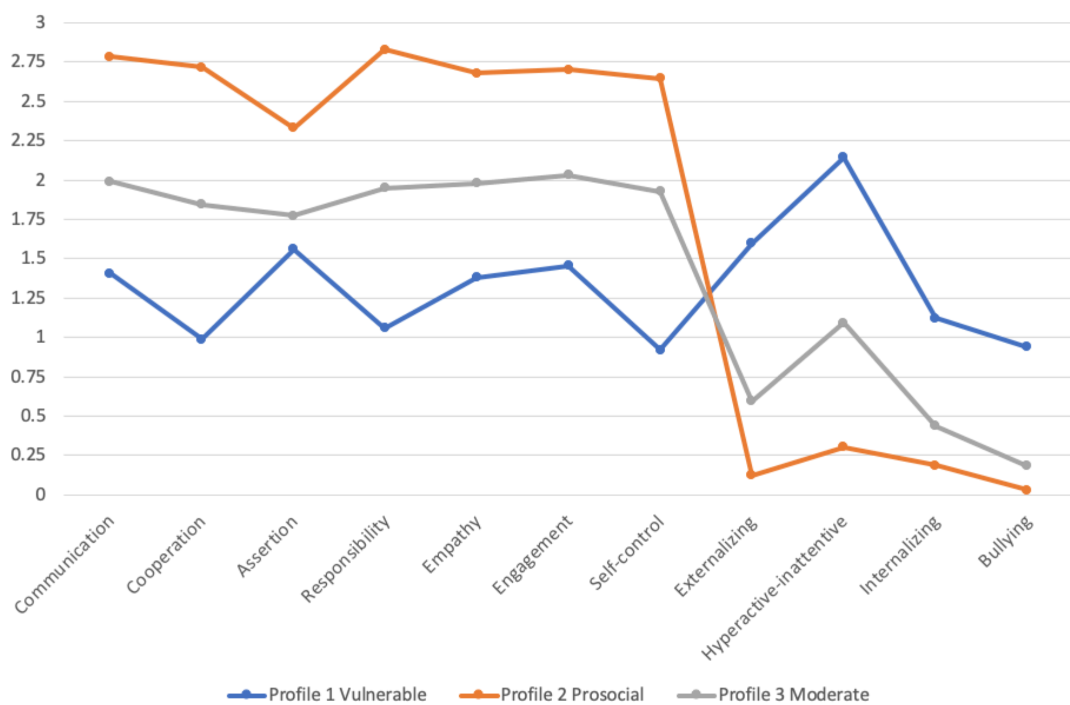

Figure **4-1:** Line graph comparing three profiles on indicators

The first profile generated was the Vulnerable group to which 54 (9.5%) students belonged. This was the smallest membership across all three profiles. As shown in Table **4-2**, students in the Vulnerable group demonstrated below average levels of social skills, but above average levels of problem behavior. Across the three profiles, students in the Vulnerable group demonstrated the lowest social skills scores and the highest problem behavior scores. In fact, students in this group demonstrated notably low level on the cooperation, responsibility, and self-control indicator, and particularly high level on the hyperactive-inattentive indicator.

The second subgroup profile, the Prosocial group, was estimated to contain 258 (45.6%) students in our sample. Out of the three profiles, the Prosocial group had the largest membership. As shown in Table **4-2**, students in the Prosocial group demonstrated above-average levels of social skills and below-average levels of problem behaviors. The Prosocial group demonstrated the highest level of social skills and the lowest level of problem behaviors. Specifically, students in this group had close scores on social skills indicators but with a prominently low level on assertion.

The Moderate group included 254 (44.9%) students. Though students in this group had an intermediate performance compared with the first two profiles, they demonstrated below-average level of social skills and above-average level of problem behaviors, except for a slightly below-average level on bullying indicator.

Table **4-2**: Mean, standard deviation, and one-way ANOVA for indicator variables across profiles

	Profile 1 Vulnerable N = 54 (9.5%)	Profile 2 Prosocial N = 258 (45.6%)	Profile 3 Moderate N = 254 (44.9%)	Average	ANOVA F ratio	η^2
Social Skills						
Communication	1.407(.433)	2.784(.285)	1.992(.354)	2.297(.580)	573.342***	.671
Cooperation	0.988(.427)	2.716(.339)	1.845(.382)	2.160(.672)	663.316***	.702
Assertion	1.561(.543)	2.331(.533)	1.773(.518)	2.007(.607)	92.835***	.248
Responsibility	1.059(.431)	2.828(.253)	1.949(.361)	2.265(.659)	880.319***	.758
Empathy	1.383(.687)	2.679(.407)	1.980(.437)	2.241(.627)	259.079***	.479
Engagement	1.455(.517)	2.703(.360)	2.034(.449)	2.283(.590)	280.935***	.499
Self-control	0.921(.576)	2.644(.373)	1.926(.393)	2.157(.665)	478.865***	.630
Problem Behavior						
Externalizing	1.599(.490)	.125(.178)	.595(.376)	.477(.532)	514.054***	.646
Hyperactive-inattentive	2.143(.509)	.303(.353)	1.094(.533)	.833(.729)	436.417***	.608
Internalizing	1.124(.695)	.187(.292)	.438(.488)	.389(.512)	105.458***	.273
Bullying	.941(.710)	.031(.110)	.183(.347)	.186(.414)	172.904***	.381

Note. Standard deviations are presented in parentheses. ANOVA= analysis of variance
*** $p < .001$

Research Aim 2: Predictors of Profile Membership

In Table **4-3**, the demographic composition of each profile was described based on gender, race, primary language, receipt of special education services, and receipt of supplemental services.

Gender

The sample was nearly equally represented by males and females. The majority of students in the Prosocial group were girls (n = 141, 54.7%). However, more boys than girls were assigned to the Vulnerable group (n = 35, 64.8%) and the Moderate group (n = 136, 53.5%). The ratio of boys to girls was almost 2 to 1 in the Vulnerable group. Chi-square analysis indicated that there was a statistically significant association between gender and profile membership ($df = 2$, χ^2=8.075, $p < .05$). The strength of the association between gender and profile membership was small (ϕ = .119, $p < .05$).

Race

In the entire sample, most students reported as White only, followed by Hispanic only, and then Black or African American only. The Moderate group membership was highly similar to the entire sample in their racial composition. Most of the students in the Moderate group identified as White only (n = 85, 33.5%), followed by Black or African American only (n = 76, 29.9%), and Hispanic only (n = 67, 26.4%). Most students in the Prosocial group reported as White only (n = 102, 39.5%), followed by Hispanic only (n = 73, 28.3%), and Black or African American only (n = 45, 17.4%). Students in the Prosocial group and Moderate group predominantly were White only. More Hispanic only students, more Asian only students, and less Black or African American only students were assigned to the Prosocial group than to the Moderate group. However, the majority of students in the Vulnerable group were Black or African American only, which accounted for 40.7% students of the profile. White only and Hispanic only students had equal proportion (n = 12, 22.2%) of the Vulnerable group. There was a statistically significant association between race and profile membership ($df = 10$, χ^2 = 30.121, $p < .05$). The strength of the association between race and profile membership was small (ϕ = .231, $p < .001$).

Primary language

Overall, the sample was represented by students using English as their primary language. No significant association was found between primary language and profile membership ($df = 2$,

$\chi^2 = 3.433$, $p > .05$). The strength of the association between primary language and profile membership was small ($\phi = .078$, $p > .05$).

Receipt of other services

A substantial proportion of students in the sample were receiving special education services or supplemental services when they participated in the study. Notably, the Vulnerable group contained the largest proportion of students who received special education services or supplemental services across three profiles. 40.7% of the students reported the receipt of supplemental services and 14.8% reported the receipt of special education services in this group. The Prosocial group has the smallest percentage of students receiving special education services (n = 5, 1.9%) or supplemental services (n = 63, 24.4%), followed by the Moderate group (n = 19, 7.5%; n = 77, 30.3%). Chi-square test indicated that there was a statistically significant association between profile membership and whether students received special education services ($df = 2$, $\chi^2 = 16.763$, $p < .001$) or supplemental services ($df = 2$, $\chi^2 = 6.47$, $p < .05$). The strength of the association between receipt of special education services and profile membership was small ($\phi = .172$, $p < .001$). The strength of the association between receipt of supplemental services and profile membership was medium ($\phi = .107$, $p < .05$).

Table **4-3**: Demographic characteristics across profiles and Chi-square test

Variables	Profile 1 Vulnerable N = 54 (9.5%)		Profile 2 Prosocial N = 258 (45.6%)		Profile 3 Moderate N = 254 (44.9%)		χ^2	Whole sample	
	n	%	n	%	n	%		N	%
Gender							8.075^{*}		
Male	35	64.8	117	45.3	136	53.5		288	50.9
Female	19	35.2	141	54.7	118	46.5		278	49.1
Race							30.121^{***}		
Asian only	1	1.9	21	8.1	8	3.1		30	5.3
Black/African American only	22	40.7	45	17.4	76	29.9		143	25.3
White only	12	22.2	102	39.5	85	33.5		199	35.2
Hispanic only	12	22.2	73	28.3	67	26.4		152	26.9
Other only	3	5.6	7	2.7	4	1.6		14	2.5
Multi-racial	4	7.4	10	3.9	14	5.5		28	4.9
Primary language							3.433		
English	49	90.7	217	84.1	226	89.0		492	86.9
Non-English	5	9.3	41	15.9	28	11.0		74	13.1
Special education services	8	14.8	5	1.9	19	7.5	16.763^{***}	32	5.7
Supplemental services	22	40.7	63	24.4	77	30.3	6.47^{*}	162	28.6

Table **4-4** reported the result of multinomial logistic regression investigating relationships between demographic information and the likelihood of memberships of each behavior profile. Analyses indicated that these demographic factors significantly differentiated Prosocial group and Vulnerable group (i.e., reference group). Male students were less likely to be in Prosocial group (b = -.876, p < .01, OR = .417). Students who identified themselves as White only were more likely to be in the Prosocial group (b = 1.416, p < .05, OR = 4.121). Students whose primary language was English were less likely to be in the Prosocial group (b = -1.456, p < .05, OR = .233). Students without special education services were more likely to be in the Prosocial group (b = 1.926, p < .01, OR = 6.864). Similarly, students without supplemental services were more likely to be in the Prosocial group (b = .927, p < .01, OR = 2.527).

Table **4-4**: Role of Demographic Variables in Predicting Profile Membership

Variables	Prosocial group[1]			Moderate group[1]		
	b	SE	*ORs*	*b*	SE	*ORs*
Male	-.876**	.331	.417	-.507	.324	.602
Asian only	1.940	1.218	6.961	.713	1.223	2.041
Black/African American only	-.133	.681	.875	-.006	.633	.994
White only	1.416*	.700	4.121	.784	.660	2.190
Hispanic only	.967	.714	2.630	.499	.674	1.647
Other race only	-.553	1.040	.575	-1.281	1.046	.278
English as primary language	-1.456*	.626	.233	-.892	.621	.410
No special education services	1.926**	.619	6.864	.658	.471	1.930
No supplemental services	.927**	.354	2.527	.515	.336	1.673

Note. * $p < .05$, ** $p < .01$

[1] The reference group is Vulnerable group.

Research Aim 3: Profile Membership and Academic Outcomes

The results in Table **4-5** indicated significant differences of math and reading scores across three profiles ($p < .001$). We used hierarchical linear regression to further examine the relation between profile membership and post-intervention math and reading achievement, controlling the covariates (i.e., gender, race, primary language, receipt of special education services, receipt of supplemental services). The predictor of interest, the profile membership, and the covariates were added to separate blocks of the model.

Table **4-5**: Mean, Standard Deviation, and One-way ANOVA for Academic Outcomes across Profiles

	Profile 1 Vulnerable N = 54	Profile 2 Prosocial N = 258	Profile 3 Moderate N = 254	Average	ANOVA		
					F ratio	df	η^2
Reading	852.60 (87.25)	853.56 (86.82)	853.52 (86.78)	853.62 (86.70)	16.396***	2,342	.146
Math	858.95 (58.68)	859.69 (58.72)	860.01 (58.69)	859.65 (58.64)	17.506***	2,344	.152

Note. Standard deviations are presented in parentheses. ANOVA= analysis of variance.
*** $p < .001$

As shown in Table **4-6**, when predicting post-intervention reading skill, the model with all the covariates in step 1 contributed the most in predicting the outcome. 52.6% of the variance was explained by step 1 including baseline reading score, treatment condition, race, gender, receipt of special education services, and receipt of supplemental services ($p < .001$). Comparing to model 1, step 2 adding profile membership and model 3 adding both profile membership and interaction terms did not significantly improve the model ($\Delta R_1^2 = .003$, $p > .05$; $\Delta R_2^2 = .003$, $p > .05$). Across three models, Asian only ($p < .05$) and reading baseline scores ($p < .001$) were the only two predictors that significantly predicted reading skill.

Table **4-6**: Multiple regression predicting reading skill from control variables, behavior profiles, and interactions

Variable	*B*	95% CI for B		*SE B*	β	R^2	ΔR^2
		LL	*UL*				
Step 1						.526	.526***
Intercept	265.933***	178.482	353.384	44.454			
Treatment	-11.692	-25.932	2.547	7.238	-.067		
Male	10.284	-3.048	23.616	6.777	.059		
Asian only	61.120*	10.32	111.608	25.664	.125		
Black/African American	-2.500	-36.180	31.180	17.120	-.012		
White only	13.008	-19.699	45.715	16.626	.075		
Hispanic only	-10.908	-45.190	23.374	17.427	-.053		
Other race	58.488	-18.344	135.320	39.056	.063		
English	-8.724	-38.604	21.156	15.189	-.025		
Special education services	-6.109	-36.361	24.144	15.378	-.016		

Supplemental services	-.803	-17.146	15.540	8.308	-.004		
Baseline	.727***	.626	.828	.051	.623		
Step 2						.529	.003
Intercept	275.868***	186.659	365.077	45.346			
Treatment	-9.936	-24.432	4.560	7.368	-.057		
Male	8.647	-4.897	22.191	6.885	.050		
Asian only	58.926*	8.367	109.486	25.700	.120		
Black/African American	-1.476	-35.294	32.341	17.190	-.007		
White only	13.824	-18.892	46.540	16.630	.079		
Hispanic only	-11.301	-45.596	22.995	17.433	-.055		
Other race	55.011	-21.945	131.967	39.118	.059		
English	-8.332	-38.209	21.545	15.187	-.024		
Special education services	-5.026	-35.357	25.305	15.418	-.013		
Supplemental services	-.037	-16.443	16.368	8.339	.000		
Baseline	.716***	.613	.820	.053	.613		
Prosocial group	3.681	-25.364	32.726	14.764	.021		
Moderate group	-7.094	-34.552	20.365	13.958	-.041		
Step 3						.533	.003
Intercept	29.149	-320.866	379.164	177.909			
Treatment	7.939	-45.702	61.579	27.265	.046		
Male	8.970	-4.634	22.574	6.915	.052		
Asian only	60.227*	8.897	111.557	26.091	.123		
Black/African American	-.501	-34.649	33.647	17.357	-.002		
White only	14.399	-18.555	47.352	16.750	.083		
Hispanic only	-9.967	-44.611	24.676	17.609	-.048		
Other race	56.939	-20.654	134.532	39.440	.062		
English	-7.055	-37.283	23.172	15.364	-.020		
Special education services	-2.083	-32.875	28.709	15.651	-.005		
Supplemental services	1.043	-15.560	17.646	8.439	.005		
Baseline	1.030***	.570	1.490	.234	.882		
Prosocial group	273.011	-87.536	633.559	183.263	1.569		
Moderate group	226.790	-135.074	588.654	183.932	1.307		
Baseline*Prosocial group	-.342	-.816	.132	.241	-1.641		
Baseline*Moderate group	-.299	-.778	.179	.243	-1.370		
Treatment*Prosocial group	-19.868	-77.436	37.700	29.261	-.087		
Treatment*Moderate group	-18.345	-75.529	38.839	29.066	-.093		

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit

* $p < .05$, ** $p < .01$, *** $p < .001$

As shown in Table **4-7**, when predicting post-intervention math skill, the model with all the covariates in step 1 contributed the most in predicting the outcome. 58.8% of the variance was explained by step 1 with baseline reading skill, treatment condition, race, gender, receipt of special education services, and receipt of supplemental services ($p < .001$). Similar to reading skill, step 2 adding profile membership and step 3 adding both profile membership and interaction terms did not significantly improve the model ($\Delta R_1^2 = .003$, $p > .05$; $\Delta R_2^2 = .003$, $p > .05$). Asian only ($p < .05$) and math baseline skill ($p < .001$) were the only two predictors that significantly predicted math skill in step 2. In step 3 adding both profile membership and interaction term, only math baseline skill significantly predicted math achievement ($p < .001$).

Table **4-7**: Multiple regression predicting math skill from control variables, behavior profiles, and interactions

Variable	*B*	95% CI for B		*SE B*	β	R^2	ΔR^2
		LL	*UL*				
Step 1						.588	$.588^{***}$
Intercept	132.238^{**}	48.513	215.962	42.561			
Treatment	6.78	-2.03	15.59	4.479	0.058		
Male	0.345	-7.926	8.616	4.204	0.003		
Asian only	34.497^{*}	3.71	65.284	15.651	0.109		
Black/African American	3.059	-17.944	24.062	10.677	0.022		
White only	12.937	-7.442	33.317	10.36	0.111		
Hispanic only	5.638	-15.698	26.974	10.846	0.041		
Other race	1.123	-46.881	49.128	24.403	0.002		
English	4.5	-13.945	22.944	9.376	0.019		
Special education services	0.621	-18.029	19.271	9.481	0.002		
Supplemental services	-7.216	-17.543	3.111	5.25	-0.052		
Baseline	0.868^{***}	0.771	0.965	0.049	0.71		
Step 2						.575	.003
Intercept	135.964^{**}	51.11	220.818	43.134			
Treatment	8.249	-0.755	17.253	4.577	0.071		
Male	-0.981	-9.437	7.475	4.298	-0.008		
Asian only	33.85*	3.051	64.649	15.656	0.107		
Black/African American	4.403	-16.644	25.45	10.699	0.032		
White only	13.172	-7.198	33.542	10.355	0.113		
Hispanic only	4.797	-16.545	26.138	10.848	0.035		
Other race	-0.425	-48.464	47.614	24.42	-0.001		

English	5	-13.441	23.44	9.374	0.021		
Special education services	1.545	-17.142	20.231	9.499	0.006		
Supplemental services	-6.442	-16.802	3.919	5.267	-0.047		
Baseline	0.849***	0.75	0.949	0.051	0.695		
Prosocial group	14.037	-4.577	32.652	9.462	0.121		
Moderate group	8.879	-8.818	26.575	8.996	0.076		
Step 3						.594	.003
Intercept	81.343	-372.95	535.635	230.923			
Treatment	6.649	-30.565	43.863	18.916	0.057		
Male	-1.081	-9.573	7.41	4.316	-0.009		
Asian only	30.88	-0.57	62.329	15.986	0.098		
Black/African American	4.144	-17.024	25.311	10.76	0.03		
White only	13.698	-6.786	34.181	10.412	0.117		
Hispanic only	5.056	-16.4	26.512	10.906	0.037		
Other race	-1.906	-50.363	46.551	24.631	-0.003		
English	5.852	-12.692	24.397	9.426	0.025		
Special education services	2.204	-16.736	21.144	9.628	0.008		
Supplemental services	-6.411	-16.918	4.097	5.341	-0.047		
Baseline	0.92**	0.357	1.482	0.286	0.753		
Prosocial group	46.982	-417.136	511.101	235.918	0.404		
Moderate group	81.518	-378.579	541.614	233.873	0.701		
Baseline*Prosocial group	-4.308	-43.571	34.955	19.958	-0.028		
Baseline*Moderate group	7.568	-31.394	46.53	19.805	0.057		
Treatment*Prosocial group	-0.042	-0.618	0.534	0.293	-0.304		
Treatment*Moderate group	-0.097	-0.67	0.476	0.291	-0.681		

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Chapter 5

Discussion

The current study conducted a latent profile analysis to identify distinct profiles of first-grade U.S students' teacher-reported social skills and problem behavior. To offer targeted information for intervention design and to facilitate children's special academic needs, one-way ANOVA, multinomial regression analysis, and hierarchical multiple regression were also used to further determine the extent to which profile membership was associated with demographic characteristics and academic outcomes. Results revealed the profiles were Prosocial group, Vulnerable group, and Moderate group in first-grade students based on their social skills and problem behavior. The study also found that profile membership was associated with different individual demographic variables, and that the profile membership did not significantly predict later reading or mathematics skills. Key findings, implications for practice, and recommendations for future research are discussed below.

Latent Profile Identification

The study adopted a three-profile solution of latent profile analysis due to its optimal fitness to the data and it generated three distinct profiles with indicators on social skills and problem behavior. Previous studies also found three similar profiles of students based on problem behavior and prosocial skills (e.g., Collie et al., 2019; DiStefano & Kamphaus, 2006). In a norming sample of U.S elementary school children aged between 6 and 11 using the Behavior Assessment System for Children (BASC; Reynolds & Kamphaus, 1992), DiStefano and Kamphaus (2006) identified three profiles: well-adjusted, average adjustment, functionally impaired. At least two profiles in Collie and her colleagues' (2019) study on a national sample of kindergarten children in New South Wales were similar to our findings: Social and emotional behavior-prosocial, Social and emotional behavior-vulnerable.

The profiles in our study can be displayed along a continuum based on the two aspects of social skills and problem behavior. This is consistent with previous research although the profiles generated vary across studies based on the indicators specified (e.g., Collin et al., 2018; Denham et al., 2012; Ma et al., 2022). Prosocial group and Vulnerable group represented two ends of the continuum, while the Moderate group resided in the middle. Students in the Vulnerable group had the lowest social skill scores and the highest problem behavior scores, whereas students in the Prosocial group scored the highest on social skills and the lowest on problem behavior. Students in the Moderate group showed intermediate performance compared with the other two profiles. Mean difference analyses were conducted among the profiles and showed that profile memberships were statistically distinguished from one another. The patterns of social skills and problem behavior in each profile echoed prior research suggesting the negative association between social skills and problem behavior (e.g., Hukkelberg et al., 2019).

As for the proportion of students assigned into each profile, it is encouraging to find that less than 10% of the students in our study were assigned to the Vulnerable group, indicating the studied sample generally demonstrated good social skills and medium-level problem behaviors. This is similar to the findings of Collie and colleagues (2019), in which the "social-emotional Vulnerable" profile contained only 5% of students, which was the smallest proportion of four profiles. Yet, we found that the Prosocial group and Moderate group contained approximately the same number of students (around 45%). Similarly, profiles found in the study of Denham and colleague (2012) also displayed slight difference in the amount of kindergarten children assigned to the "Social-emotional Learning Competent-Social/Expressive" profile (29.3%) and "Social-emotional Restrained" profile (27.8%), though the largest number of children were assigned to the "Social-emotional Learning Risk" profile rather than the most promising group.

Consistent with prior research (e.g., Ma et al., 2022), each of the profiles found in our research presented strengths in some aspects of social skills and problem behavior, but weaknesses on at least one of the remaining aspects. For example, even though the students assigned in the Prosocial group demonstrated the highest level of social skills and the lowest level of problem behavior, they demonstrated low levels of assertion, approximately 0.5 lower than the score they gained on other social skills. Students in the Moderate group displayed only high levels of hyperactive-inattentive behaviors compared with all other indicators, which may signal the potential risk of adopting serious problem behavior. However, students assigned in the Vulnerable group seem to portray an even more complex profile. They demonstrated the highest level on assertion among all the social skills, though hyperactive-inattentive behavior and low self-control were the marked weaknesses. The prominent co-occurrence of these two problem behavior in the Vulnerable group may be explained by an established finding that the major symptom of hyperactive-inattentive disorder is a lack of behavioral and emotional self-control (e.g., Barkley, 1997; 1998).

Predictors of Latent Profiles

Further examination into the demographic components of each profile also revealed important findings. One of the key findings was that male students were less likely to be in the Prosocial group and more likely to be in the Vulnerable group. This is consistent with the findings of previous latent profile studies on kindergarten children (e.g., Collie et al., 2019; Denham et al., 2012). Also, it has been found that girls engage in more prosocial behavior (Fabes & Eisenberg, 1998) and male students are seen demonstrating less empathetic behavior

(Duchesne et al., 2010; Morgan et al., 2009). Such discrepancies in prosocial behaviors and social-emotional development may persist until the end of adolescence (Van der Graaff et al., 2018).

Moreover, a noteworthy finding was that white students were more likely to be in the Prosocial group (4.12 times) than in the Vulnerable group. In contrast, the majority of students in the Vulnerable group identified as Black or African American only. Our result spoke to the previous finding that expressive and aggressive responses to everyday social scenes were significantly more frequently seen with African American adolescents and Hispanic adolescents than their European American peers (Yager & Rotheram-Borus, 2000). A possible reason may be the ethnic discrepancy in understanding the behaviors. The intent of appropriate behavior may be understood differently by the observer or rater than the African American student demonstrating the behavior due to the underlying cultural expectations of proper behavior (Hosp & Hosp, 2001).

The distribution of other races across profiles differed yet not significantly. For example, more Hispanic only students, more Asian only students, and less Black or African American only students were assigned to the Prosocial group than to the Moderate group. White only and Hispanic only students shared equal proportion of the Vulnerable group. Previous study have not yet shed much light on the association between race/ethnicity and profile membership. These findings extended our knowledge of the association between race or ethnicity and profile membership based on first-grade students' teacher-perceived social skills and problem behavior.

Results also showed that students who spoke English as their primary language were less likely to be assigned into the Prosocial group. Similarly, Collie et al. (2019) found kindergarten children who spoke a language other than English at home were less likely to be assigned to the Social-emotional Vulnerable profile. Evidence also indicated that English learners were rated higher on social-emotional skills comparing with their non-English learner peers (Crosnoe, 2007; Halle et al., 2014). For example, using data from the Early Childhood Longitudinal Study —

Kindergarten Cohort (ECLS-K), Crosnoe (2007) found that Spanish-speaking children were rated more positively than their English-only counterparts on the social-emotional skills such as self-control and externalizing and internalizing behaviors. As found in Han's (2010) study using the same database, supportive classroom context might mitigate English learners' problem behavior patterns and children in such environments had slower rates of behavior problems during the K-5 period.

Finally, the Vulnerable group contained the largest proportion of students who received special education services or supplemental services when their behavior outcomes were assessed. The Prosocial group has the smallest amount of students receiving special education services or supplemental services, followed by the Moderate group. This is reasonable because students who had behavioral issues were receiving additional cognitive or behavioral services to better support their adaption to school. As indicated in McDermott and colleague's (2022) study, children who required special needs services had a substantially increased risk of membership to the Overactive Across Contexts profile. Our finding was also consistent with the previous findings that children with a diagnosed learning disability report lower levels of behavioral regulation (McCleland et al., 2007).

Consequences of Latent Profiles

Our findings revealed that the profile membership of first-grade students was not a significant predictor of post-intervention reading and math skills, controlling for the individual demographic variables (i.e., gender, race, primary language, receipt of supplemental services, receipt of special education services) and baseline reading/math skills. This appears to be inconsistent with previous latent profile studies that have revealed significant longitudinal link between profile membership in early childhood and the academic achievement assessed in early adolescence, controlling for key demographics and early academic achievement (Collie et al., 2019; Ma et al., 2022). In other words, students assigned in more prosocial profiles were found to gain more positive academic performance in the long term (Collie et al., 2019; Ma et al., 2022). Our study suggested weak prediction of profile membership on academic achievement gain in the short term (i.e., 5 months). However though significant relationship have been indicated between profile membership and distal outcomes, some of the previous studies did not control for the baseline outcomes. For example, McDermott et al. (2022) found significant relationship between preacademic skills, teacher-student interaction, and several profiles without controlling for baseline scores and key demographics of kindergarten children. Moreover, Tze et al. (2018) found that eighth grade students' profile membership was significantly associated with number of absent days and high GPA in ninth grade without controlling for eighth grade academic outcomes, even though eighth grade GPA itself was tested for relationship with profile membership in their study.

In fact, a growing number of longitudinal studies adopted a variable-centered approach have revealed mixed findings on the long-term benefit of social skills and problem behavior on academic outcomes. For example, students' prosocial behavior (i.e., cooperating, helping, sharing, and consoling) at Grade 3 strongly predicted academic achievement at Grade 8 even after controlling for early academic achievement, whereas early antisocial behavior (i.e., verbal and physical aggression) had no predictive effect on Grade 8 academic achievement after controlling for early academic achievement and early prosocialness (Caprara et al., 2000). The above research and the current findings indicate the need to clarify the relationship between profile membership and later academic achievement both in the short and long term controlling for baseline academic achievement and individual demographic characteristics.

Implication for Practice

This investigation provided several noteworthy implications for researchers, educators, school psychologists, and intervention designers. The identification of students at risk and compatible early interventions have increasingly become the primary focus of assessment efforts in school (Glover & Albers, 2007). Thus, researchers are encouraged to use person-oriented approaches to understand patterns of social behaviors among diverse populations. Using latent profile analysis, it is achievable to sort students into homogeneous groups out of a heterogeneous population. In so doing, targeted interventions could be provided more efficiently in groups to address similar social skill deficits and behavior problems. These interventions could be more customized and nuanced than a universal intervention program, yet more practicable and resource-intensive than individualized instructional support for each children.

Moreover, profiles identified in this investigation may provide insight into the direction and amount of resources to allocate when administering the intervention in order to promote social skills and to reduce problem behavior among primary-grade students. Given the low level of prosocial skills and high level of problem behavior displayed by students in the Vulnerable group, such students may be in need of earlier interventions fostering the skills of cooperation, responsibility, and self-control. In contrast, students in the Prosocial group may likely benefit from a focus on assertion strategies, given the noticeable low scores in assertion among all the social skills. Intervention programs may also provide additional strategies for maintaining cooperative and positive behaviors in the long term. Educators and school psychologists may need to provide extra attention and appropriate teaching strategies to help students in the Moderate group, given their significant representation in our study. These students were at the risk of falling into the Vulnerable group as they demonstrated below-average level of social skills and above-average levels of most problem behaviors except for bullying. It appears that a focus on all aspects of social-emotional skills in a timely manner may be needed: reinforcing consistent prosocial behavior and simultaneously rectifying problem behaviors.

The profiles generated in the current study featured a data-informed reference to the intervention designed under the framework of Multi-Tiered System of Support (Brozo, 2009). Tier 1 (universal instruction), which is also the largest tier, encompasses instruction and services available to all students in the classroom level. The high-quality, universal practices of academic and behavioral intervention in Tier 1 may be effective for the vast majority of students assigned to the Prosocial profile in our study as they conformed to socially accepted behaviors in the classroom. Tier 2 (targeted instruction) targets students who need a little extra assistance in meeting academic and behavior goals, for which the interventions and supports are provided in small group settings. Such intervention may be provided for the students assigned to the Moderate or Vulnerable group. Tier 3 (individualized instruction) gives individualized supports to students with intensive needs. Schools may need to provide students classified in the Vulnerable or Moderate profile in our study to these two Tiers if they are not responding to Tier 1 instruction.

Our findings also highlight the urgent need and extra attention to enhance social skills of students categorized by their demographic characteristics, including but not limited to the characteristics in our study (e.g., gender, race/ethnicity, primary language, receipt of special education or supplemental services, socioeconomic status, learning disability status). Such a need is also emphasized in a previous latent profile study (e.g., Granziera et al., 2021). In order to realize this goal, researchers have suggested a culturally-responsive practice to participants' sociocultural and historical contexts (Klingner & Edwards, 2006). Moreover, sociocultural factors (i.e., cultural and linguistic background, trainer characteristics, functional assessment, discourse with family, culturally relevant curriculum, culturally relevant pedagogy) could be included in the design, implementation, and interpretation of social skills intervention program on the part of both trainers and researchers (Olmeda & Kauffman, 2003). Under the sociocultural perspective, researchers and teachers will be able to clearly define the social skills adopted in both cultural minority and majority social norms (Olmeda & Kauffman, 2003). The practice used to be that researchers examine how participants' cultural, racial, and linguistic factors shape the effectiveness of the program. However, given the sociocultural perspective, researchers are encouraged to consider how intervention development, construction, and administration may make a difference with culturally, racially, and linguistically diverse students (Olmeda & Kauffman, 2003). Incorporating a sociocultural framework into the social skills intervention program may be also of great importance to alleviate "Black-escalation Effect[1]" which may extend to other racial minority students (Okonofua & Eberhardt, 2015; Olmeda & Kauffman, 2003).

Limitations and Future Direction

There are several limitations to consider when interpreting the results of the current investigation. First, although this study investigated a sufficient number of primary school students, the sample was selected from the Midwest and Northeast regions of the U.S. To increase the generalizability of this study, a replication study including more regions is necessary.

Another limitation is the potential scoring bias brought by teacher rating, especially the bias on racial minority students. Although teachers often attempt to remain neutral in their evaluations of students' behavior and are considered to be highly valid reporters of students' behaviors (Gerber & Semmel, 1984; Gresham & Elliott, 2008; Oosterlaan et al., 2005), bias can affect teachers' perceptions without their knowledge. Some evidence suggests that teachers are more likely to rate children's behaviors based upon their race than the actual perceived behavior

[1] The escalation of disciplinary treatment that teacher imposes on Black student over the course of interpersonal interaction, usually caused by racial disparity. From *Okonofua, J. A., & Eberhardt, J. L. (2015). Two strikes: Race and the disciplining of young students. Psychological science, 26(5), 617-624.*

problems of children (Wymer et al., 2022). Ratees' race can affect raters' interpretation of particular conduct as well as their ability to detect the conduct across time (Okonofua & Eberhardt, 2015). Further study may adopt different approaches to obtain ratings on students' behavior, such as direct observation and student self-report.

Moreover, although the present study provided an individual-level lens to interpret the behavior profiles, we have not examined the contextual factors of class, school, family, or neighborhood level. According to relevant studies examining classroom and home context factors on students' social skills and problem behavior (e.g., Griffith et al., 2016; Poulou, 2014), these factors may include teacher-student interaction (e.g., Fraser & Walberg, 2005; Wubbels, 2005), classroom goal structure (e.g., Kaplan et al., 2002), classroom experience (Hamre & Pianta, 2005), and parent-child relation (e.g., Clark & Ladd, 2000). Given the commonly-used nested data structure in the educational psychology field, a multilevel latent profile analysis may be adopted to examine how Level 2 unit predictors influence Level 1 indicators that define latent profile membership, as have already been applied in other fields such as organizational research and substance use (e.g., Henry & Muthén, 2010; Makikangas et al., 2018).

Moving forward, it will be meaningful to examine the predictive relationship between the first-grade profile membership and the academic achievement at the end of primary school. Another important next step is to examine whether first-grade children's social skills and problem behavior profiles change over time as they complete primary school, and to test whether the change is related to the academic achievement and if the change may be interpreted by multiple contextual factors. Developmental trajectories will be of great interest for psychologists, researchers, and educational policy-makers to better benefit children of different subpopulations and promote educational equity using person-centered approaches.

Conclusion

The current investigation has provided important knowledge about profiles of social skills and problem behavior in combination among first-grade students based on eleven indicators. The results also revealed that profile membership was predicted by gender, race, primary language, receipt of supplemental services, and receipt of special education services. Most of the predictive relationships were consistent with the previous research findings. Profile membership, however, was not found to be significantly associated with later short-term academic outcomes. The evidence-based profiles provided a data-informed reference for a Multi-Tiered System of Support to better match the social-emotional behavior and academic assessment and instructional resources to students' needs.

Appendix

Latent Profile Analysis Studies Most Relevant to Current study

References	Domain	Sample	Country	Indictors	Profiles	Predictors	Consequences
Bulotsky-Shearer et al., 2012	Emotional and problem behavior	Prekindergarten children	USA	Aggressive, oppositional, hyperactive/inattentive, withdrawn/low energy, socially reticent, problems in structured learning problems in peer interactions, problems in teacher interactions	Well-adjusted, Adjusted with mild disengagement, Moderately socially and academically disengaged, Disruptive with peers, Extremely socially and academically disruptive, Extremely socially and academically disengaged	Gender, age, ethnicity	Literacy and mathematics skills in the preschool year
Collie et al., 2019	Social and emotional behaviors	Kindergarten children	Australia	Cooperative, socially responsible, helpful, anxious, and aggressive-disruptive behavior	Social-emotional prosocial (SE-Prosocial), SE-Anxious, SE-Aggressive, and SE-Vulnerable groups	Gender, age group, language background, neighborhood socioeconomic status, and learning	Reading, writing, and numeracy achievement in Grades 3 and 5

References	Domain	Sample	Country	Indictors	Profiles	Predictors	Consequences
						disability status	
Denham et al., 2012	Social-emotional learning	4-year-old children	USA	Emotion knowledge, emotional and social behaviors, social problem-solving, and self-regulation	SEL Risk, SEL Competent-Social/Expressive, and SEL Competent-Restrained	Gender, center type	Preschoolers' school readiness, and kindergarten adjustment
Granzeira et al., 2021	Behavioral self-regulation	First-year of school children	Australia	Self-regulated learning, socially responsible, aggressive-disruptive	Well-regulated, Moderately-regulated, Aggressive-regulated, Mixed-unregulated, Nonaggressive-unregulated, and Aggressive-unregulated.	Gender, age, language background, neighborhood SES	Subsequent ADHD diagnosis
Ma et al., 2022	Social emotional learning skills	Middle childhood students	USA	Cooperation, prosocial behaviors, work habits, emotion regulation, and self-control	Relatively low SEL, Moderate-high SEL, Prosocial/self-control, and Cooperation/work habits	Prior academic and social functioning at Grade 3, gender, and ethnicity	Academic and social functioning during early adolescence
McDermott et al., 2022		Kindergarten children	USA	Aggression, peer context problems, attention seeking, teacher context problems, reticence/withdrawal,	Adjusted, Underactive, Overactive	Gender, ethnicity, parent education, special needs services	Early academic skills, teacher-student social-emotional interactions, and total

References	Domain	Sample	Country	Indictors	Profiles	Predictors	Consequences
				learning context problems, low energy			problem behaviors
Orphinas et al., 2015	Adaptive and maladaptive behaviors	6 graders	USA	Externalizing behaviors, internalizing problems, academic skills, leadership, and social assets	Well-Adapted, Average, Average-Social Skills Deficit, Internalizing, Externalizing, Disruptive Behavior with School Problems, and Severe Problems	--	Dropout
Tan et al., 2018	Social-emotional learning needs	High school freshmen students	USA	Communication, cooperation, assertion, responsibility, empathy, engagement, self-control, externalizing, hyperactive-inattentive, internalizing, and bullying	Low-all, High-all, Social skills problems only, Assertion, Externalizing, Internalizing problems, and High behavioral needs	--	Eighth and ninth grade academics and behaviors
Tze et al., 2020	Social-emotional skills	15-year-old adolescent	Canada, USA, China, and Singapore	Self-awareness, self-management, social awareness, relationship skills	Sociable, Reserved and Withdrawn in Canada, Singapore, and the United States; Solitary, Team-oriented, and Reserved in students in China	--	Reading, mathematics, collaborative problem-solving skills

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