A HOLISTIC VIEW ON A TARGETED INTERVENTION ON EXCLUSIONARY DISCIPLINE USING GENERALIZED ADDITIVE MODELS FOR LOCATION, SCALE, AND SHAPE

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by

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The undersigned, appointed by the dean of the Graduate school, have examined the dissertation entitled

A HOLISTIC VIEW ON A TARGETED INTERVENTION ON EXCLUSIONARY DISCIPLINE USING GENERALIZED ADDITIVE MODELS FOR LOCATION, SCALE, AND SHAPE

presented by Anna M. Kim,

a candidate for the degree of doctor of philosophy in social work,

and hereby certify that, in their opinion, it is worthy of acceptance.

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DEDICATION

To my loving family, who have always encouraged me to pursue my dreams and have been my unwavering source of support throughout my academic journey. And to my grandfather, who supported me and inspired in me a love for learning and whose memory, alongside that of my father, continues to motivate me every day. Above all, I dedicate this dissertation to God, who has blessed me with the strength and perseverance to complete this work and who continues to guide me on my path.

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ABSTRACT

The use of Generalized Linear Models (GLMs) to analyze count data has become a common practice in social work research. However, most applications of GLMs to count data fail to test for various distributions, which can result in inaccurate estimates. An alternative approach that provides more flexibility is the Generalized Additive Models for Location, Scale, and Shape (GAMLSS). GAMLSS is an innovative statistical approach that tests over 30 different count distributions by comparing each model and selects the best fitted models for the data. Despite its advantages, a preliminary search of the social work literature yielded no published papers utilizing this approach. This raises questions about the accuracy of current analyses of models using count data. The purpose of this dissertation is to demonstrate the use of GAMLSS in analyzing the effectiveness of the *Self-Monitoring and Regulation Training Strategy* (SMARTS), a school-based behavioral intervention, on in-school suspension (ISS), out-of-school suspension (OSS), and exclusionary discipline (ED) in elementary schools. Overall, this study provides evidence that GAMLSS is a powerful and flexible tool that can be used to analyze social work data. GAMLSS can be applied to important social work areas, such as addiction studies, health disparities, crime, aging-related outcomes, and homelessness, making it a tremendous utility for social work research.

Chapter 1

CHALLENGING BEHAVIORS

Statement of the Problem

Challenging student behaviors are a significant problem for all students in primary school. Students experiencing challenging behaviors represent a population of great concern to their peers, teachers, communities, and their caregivers. In the United States, 53% of students have at least one challenging behavior, and 90% of teachers reported having at least one child with challenging behavior in their classroom (Emerson et al., 2001; Granja et al., 2018). Students with challenging behaviors can have a serious impact on their relationship with peers and teachers, thereby adversely affecting their academic achievement. In turn, those students are more susceptible to experience exclusionary discipline thereby increasing the likelihood of more serious societal problems, such as school dropout and entry to the juvenile justice system (American Psychological Association [APA], 2022; Fenning et al., 2012; Skiba et al., 2014). Children who can manage or regulate their emotions are more likely to have better peer and teacher relationships and academic performance (Zins & Elias, 2006). It is imperative students and school officials utilize evidence-based programs to reduce challenging behaviors and enhance prosocial and positive behaviors in children (Humphries et al., 2018; Thompson et al., 2016).

Definition and Scope of the Problem

In this study, challenging student behaviors are defined as exhibiting two types of behaviors: externalizing behavior and internalizing behavior. Externalizing behaviors incorporate various overt and externally focused behavioral symptoms, including aggression, attentional problems, conduct problems, delinquent behavior, stealing, oppositionality, and hyperactivity (Willner et al., 2016). Externalizing behavior is one of the main factors that significantly impact children's school adjustment (Demirtaş-Zorbaz & Ergene, 2019). More frequently and intensely, primary school children have feelings, such as anger, jealousy, and aggression, which have an adverse effect on school adjustment.

Internalizing behaviors include various covert and internally focused symptoms, such as noncompliance, social withdrawal, stealing, betrayal, anxiety, fear, and depression (Demirtaş-Zorbaz & Ergene, 2019). Internalizing behavior is another variable that significantly influences children's academic achievement as well as maladjustment in peer interaction (Wang & Zhou, 2019). Primary school children exhibiting internalizing behavior can manifest poor self-regulation, which adversely impacts their academic achievement, peers, and teachers in school settings (Demirtaş-Zorbaz & Ergene, 2019). Challenging behaviors are comprised of externalizing and internalizing behaviors that interfere with obtaining a positive learning environment (Blair et al., 2010). Challenging behaviors are repeated patterns of problematic behavior that interfere with children's ability to learn and get along with their peers in classrooms (Granja et al., 2018).

The prevalence rates of children with emotional and behavioral problems are omnipresent, although specific estimates of significant rates vary depending on the study and sample used (Powell et al., 2006). In a review of prevalence studies, Granja et al. (2018) estimated that 90% of teachers reported having at least one child with challenging behavior in their classrooms. Data from the American Academy of Pediatrics (2001) revealed estimates as high as 12% to 16% of the total population ages birth to three years old of young children with challenging behavior. Roughly 3% to 7% of children display aggressive signs, and often, it is in the school setting that these behaviors are manifested (Zahrt & Melzer-Lange, 2011). However, if children with mild and short-term behavior problems are considered, then the prevalence rates for students with challenging behavior may be as high as 40% (Carter et al., 2006).

These challenging behaviors often begin at an early age among children before entering school (Powell et al., 2006). Nonetheless, some children continue to exhibit challenging behaviors when entering school, leading to school maladjustment and poor academic performance (Powell et al., 2006). Among toddlers and preschoolers identified with clinical levels of disruptive disorders, 50% or more have been found to display challenging behaviors and continue to manifest these behaviors into the school years (Powell et al., 2006). For example, data from children enrolled in Head Start revealed that 22% of girls and 39% of boys exhibit both internalizing and externalizing problem behaviors (Conroy et al., 2005).

Unfortunately, if left untreated, children with challenging behaviors will most likely worsen, leading to more severe internalizing and externalizing problems (Conroy et al., 2005). With more severe internalizing and externalizing problems, the more likely students will receive exclusionary discipline (i.e., in-school suspension and out-of-school suspension), which then can lead to more contact with the criminal justice system (American Psychological Association, 2022; Skiba et al., 2008, 2014). Unaddressed challenging behaviors can increase the rate and the severity onto adolescence and adulthood, such as substance abuse, unemployment, criminal behavior, and diagnosis of a psychiatric disorder.

Precursors of Challenging Behavior

Children enter school with different backgrounds and life experiences. These unique contextual and ecological circumstances influence children’s behaviors in school settings. There are many causal factors of challenging behaviors in children. Such exposure to risk factors provokes patterns of internalizing and externalizing behaviors in children. It is important to understand the underlying risk factors and, more specifically, precursors of children with challenging behaviors.

Low income and poverty contribute to uninvolved and unsupportive parenting styles and exacerbate parental stress, thereby leading to more challenging behaviors in children (Kaiser et al., 2017; Mazza et al., 2017). Economic hardship increases the likelihood of parental distress and stress, which indirectly affects children’s behavioral development (Mazza et al., 2017). Familial factors are associated with externalizing and internalizing problems in children, including maternal education, early age parenthood, family income, parental emotional distress (e.g., depression, anxiety, anger, and alienation), marital conflicts, criminal behaviors, and family substance abuse (Hay et al., 2014; Mazza et al., 2017).

For example, Kim et al. (2019) examined the association between neighborhood poverty and behavioral problems among young children. This study used a longitudinal design to investigate the association between neighborhood poverty and greater internalizing and externalizing problems among children aged five years. This study examined the potential mediating role of social environments (i.e., neighborhood social cohesion and safety when the child was three years old) in the relationship between neighborhood poverty and child behavioral problems.

Kim et al. (2019) collected data from the third and fourth waves of the Fragile Families and Child Wellbeing Study (FFCWS). The study interviewed parents about their parenting, sociodemographic status, employment, health, social support, and relationship status with the child’s biological mother or father shortly after the birth of their child. Follow-up surveys were also conducted, such as child health and well-being when the child was 1, 3, 5, and 9 years old. The sample size in the study included 1,908 respondents. The respondents were primarily non-Hispanic White mothers who were more educated with a higher family income-to-needs ratio at age 3.

Univariate and bivariate analyses were conducted to explain all variables' distribution and family poverty experiences (Kim et al., 2019). Multiple linear regression models were then evaluated to analyze the associations between neighborhood poverty and children’s behavioral problems. The findings showed that children with family poverty living in high poverty neighborhoods presented with a higher level of internalizing (M = 6.24) and externalizing problems (M = 14.42). Among children with family poverty, internalizing (r = -.06, p < .05) and externalizing problems (r = -.10, p < .01) were negatively correlated with low-poverty neighborhoods. Whereas internalizing (r = .07, p < .05) and externalizing problems (r = .08, p < .01) were positively correlated with high poverty neighborhoods. The study has several gaps identified in the literature. The present study examined neighborhood poverty, and because neighborhood economic status changes over time, neighborhood economic histories need to be taken into account. The study also only focused on neighborhood poverty and social environments to examine the effect on children; however, other key neighborhood measures need further attention, such as racial/ethnic composition and employment, to better understand children with behavioral problems.

While the contextual and ecological situations shape children's classroom behaviors, biopsychosocial factors are also related to challenging behaviors in children. Having a better understanding of the biopsychosocial factors would enable a more complex explanation of the determinants of challenging behaviors in children, such as cognitive deficits and impairment and biological and neurological processes (Koritsas & Iacono, 2012). For example, Gunsett et al. (1989) reported that eight out of ten children with severe intellectual disability continued to struggle with their challenging behaviors. Other studies suggest that challenging behaviors are more frequent among children with intellectual, learning, and/or developmental disabilities compared to those without disabilities (Emerson et al., 2014; Simó-Pinatella et al., 2019).

For example, Yu et al. (2006) investigated the comorbidity of verbal and nonverbal learning disability subtypes with behavior problems among eight year old children and sought to determine whether receipt of an early intervention modified the relationship between childhood behavior problems and learning disabilities. The study used a secondary data analysis of the Infant Health and Development Program (IHDP, Yu et al., 2006). The study also collected maternal reporting of children's behavior by conducting an interview. The total sample size included 985 infant participants and their mothers in the initial phase of this. The total sample size of the original cohort by age 8 was a total of 874 participants. The study evaluated the impact of an early intervention to enhance the cognitive, behavioral, and physical development of low-birthweight and premature infants. The analysis of the study used regression models to examine the association between learning disability subtypes and measures of behavior.

Children with a verbal learning disability were approximately twice as likely to display clinical levels of total behavior problems (OR = 2.17, 95% CI: 1.22-3.87) and clinically externalizing behavior problems (OR = 1.89, 95% CI: 1.02-3.48) compared to children with no verbal learning disability. Within the domain of externalizing behavior, children with a verbal learning disability were 3.5 times more likely to display aggressive behavior (95% CI: 1.55-8.19) than children with no disability. Within the domain of internalizing behavior, children with a verbal learning disability were four times more likely to exhibit a clinical level of anxious/depressed behavior (OR = 4.08, 95% CI: 1.67-9.92) and more than three times likely to manifest withdrawn behavior (OR = 3.41, 95% CI: 1.04-11.13).

The findings for the second research revealed a significant association between verbal learning disability and the intervention when predicting clinical internalizing behavior (OR = 4.80, 95% CI: 1.36-15.79, Yu et al., 2006). Among the children with a verbal learning disability who received the intervention were more than four times as likely to display clinical internalizing behavior problems than those who did not receive the intervention (OR = 4.42, 95% CI: 1.38-12.14). There are several gaps found in this literature. The study used maternal reporting of children’s behavior by conducting an interview. This could create biases, such as recall bias and misrepresented information. Unlike a clinician’s observations or a child’s self-report, using maternal reporting could influence the findings and not be as valid. In addition, the total sample size was relatively small, which could create outliers, skewing the results of the study. Lastly, the young age of these participants may misrepresent the general representation of the learning disability cohort in the study's sample.

It is also critical to recognize that African-American and Latino youth are disproportionally exposed to suspension (Cohen et al., 2021; Skiba et al., 2008, 2014). The U.S. Government Accountability Office (2016) states that high poverty schools with high proportions of students of color (75% or greater Black and Latinx) represent 22% of students with suspensions. African American students were three times at risk for suspension compared to White students (Skiba et al., 2011). Disciplinary disproportionality for African American students also increased from the 1970s (Skiba et al., 2011). There are continuous racial and ethnic disparities in education, including achievement gap, disproportionality in special education, dropout, and graduation rates (Wald & Losen, 2007).

The possible precursors to account for rates of disciplinary disparity by race and ethnicity include poverty, differential rates of challenging behaviors in school settings, and racial stereotyping (Skiba et al., 2011). Race and socioeconomic status (SES) are highly connected to racial disparities in school disciplines. Low SES has been found to be a risk factor for school suspension (Skiba et al., 2011).

Ample evidence from numerous studies suggests that challenging behaviors are related to contextual and ecological determinants and biopsychosocial factors. Looking at all facets of the complex interactions a child encounters is the key to finding the appropriate school-based intervention. It is crucial to consider these factors to have a deeper understanding of children who display challenging behaviors in schools. Thus, recognizing the main precursors of challenging behaviors in children is essential to implement feasible school-based interventions for all children in school settings.

Consequences of Challenging Behavior

Students who display challenging behaviors have a negative impact on their relationships and overall academic success in schools. Challenging behaviors interfere with the child's relationships with peers and teachers, academic achievement, and development (Blair et al., 2010). If not addressed, challenging behavior of children is likely to continue to negatively affect the child's social-emotional competence (Blair et al., 2010; Arnold et al., 1999; Dunlap et al., 2006). Challenging behaviors are often associated with poor attention span, noncompliance, elevated activity levels, which restrict children's academic development and social-emotional skills (Arnold et al., 1999). Therefore, a vicious cycle is created in which once a child exhibits a challenging behavior, and it is likely that other negative series of factors build up and reinforce each other, and aggravate the problem.

The home's emotional climate also plays a significant role in a child's social-emotional growth (Aviles et al., 2006; Thompson & Hapold, 2002). When there are conflict, stress, and abuse presented in the home, the child's emotional growth is often impaired (Thompson & Hapold, 2002). Four possible risk factors impair a child's emotional growth: (a) childhood history of early deprivation and trauma; (b) family instability/conflict; (c) involvement in the child welfare system; and (d) Neighborhood danger/limited resources (Aviles et al., 2006). Exposure to violence in the home and community hampers a child's development, placing them at greater risk for developmental or behavioral problems.

Challenging behaviors can lead peers, teachers, and parents to inadvertently contribute to the cycle and exacerbate the situation (Arnold et al., 1999). For example, a child who displays challenging behaviors during class may often disrupt their peers from learning and interrupt teachers from teaching. Thereby, teachers may then remove the child from the classroom as a disciplinary action, which in turn, adversely affects the child by engaging in more challenging and negative behaviors in the future (Blair et al., 2010; Arnold et al., 1999). Exclusionary discipline (i.e., in-school suspension and out-of-school suspensions) can lead to repeated removals from the class, which in turn, will increase the likelihood of class failures and school dropouts (Blair et al., 2010; Arnold et al., 1999; Dunlap et al., 2006; Simó-Pinatella et al., 2019; Skiba et al., 2011). Consequently, students with challenging behaviors often contribute to teacher emotional factors, such as teacher stress, which then negatively impacts the child-teacher relationship as well as the child's learning environment (Eddy et al., 2020).

Eddy et al. (2020) sought to examine the association of teacher emotional exhaustion and teacher efficacy with student office discipline referrals, in-school suspension, and out-of-school suspension using multilevel logistic regression models. This study used an exploratory data analysis by evaluating the relation of both teacher emotional exhaustion and efficacy and mean rates of disciplinary sanctioning related to office discipline referrals, in-school suspension, and out-of-school suspension. Data from the present study were collected as part of a cluster randomized controlled trial investigating the effects of a classroom management program in elementary schools. The sample size of this study included 105 teachers and 1,681 K–3 students from nine elementary schools in St. Louis, Missouri.

For students who experienced disciplinary outcomes at least once during the academic year, 18.4% of students received office discipline referrals, 12.1% received an in-school suspension, and 6.3% received out-of-school suspension (Eddy et al., 2020). Teacher emotional exhaustion were associated with those receiving office discipline referrals (r = .28, p < .001) and an in-school suspension (r = .26, p < .01). The association between teacher emotional exhaustion and out-of-school suspension was not statistically significant (r = .09, p = .33). The relation of teacher efficacy, higher efficacy was associated with lower use of office discipline referrals (r = -.20, p = .04) and out-of-school suspension (r = -.25, p < .01). The association between teacher efficacy and in-school suspension was not statistically significant (r = -.15, p = .14).

The findings suggest that teachers higher on emotional exhaustion are more likely to use office discipline referrals and in-school suspension (Eddy et al., 2020). In contrast, teachers who are higher on teacher efficacy are less likely to use the office of discipline referrals and out-of-school suspensions. The results also showed that teacher emotional exhaustion was associated with increased levels of students receiving office discipline referrals and in-school suspension, which suggests that an emotionally exhausted teacher may have a lower threshold for challenging behaviors in students. Therefore, this study reveals that teacher emotional exhaustion and stress can negatively contribute to the vicious cycle of children exhibiting challenging behaviors in schools.

Herman et al. (2018) also examined how teacher stress, burnout, coping, and self-efficacy are interrelated and determine student outcomes, including disruptive behaviors and academic achievement. The purpose of this study was to investigate the co-occurrence of teacher stress, burnout, coping, and self-efficacy and the association between these patterns or profiles of their co-occurrence with student academic and behavioral outcomes. This study used the latent profile analyses (LPA) to examine patterns of four indicators of teacher adjustment: emotional exhaustion index of burnout, stress, coping, and self-efficacy. By conducting the LPA analyses, the study could identify the smallest number of profiles that accurately report the relationship between the teacher adjustment indicators.

Data from the present study were drawn from a larger ongoing randomized efficacy trial analyzing a teacher classroom-management training program (Herman et al., 2018). The sample size of this study was 121 general education teachers and 1,871 students in kindergarten to fourth grade. The participants for this study were from nine elementary schools in an urban Midwestern school district. The schools in this study were all implementing school-wide PBIS with high fidelity. The findings of this study demonstrated that the Stressed/Low Coping class showed the higher rates of student behavior problems and lowest academic achievement. The Stressed/Low Coping class had significantly lower mean scores on prosocial behavior ($M = 4.24$) than the Well-Adjusted class ($M = 5.41$; $p < .001$), Stressed/High Coping ($M = 4.76$; $\chi^2 = 14.77$, $p < .001$), and the Stressed/Moderate Coping class ($M = 4.58$; $p < .01$). The Well-Adjusted class also had higher mean scores for prosocial behavior compared to the Stressed/Moderate Coping class ($p < .01$). This suggests that even moderately lower levels of teacher coping can impact student prosocial development (Herman et al., 2018). The findings for disruptive behavior ($p < .001$) and concentration problems ($p < .001$) demonstrated overall tests of significance (Herman et al., 2018). The Stressed/Low Coping class ($M = 2.35$) had significantly higher disruptive behavior mean scores than the Well-Adjusted class (*M* = 1.48; $p < .001$), Stressed/High Coping (*M* = 1.93; $p < .001$), and the Stressed/Moderate Coping class (*M* = 2.30; $p < .001$). Stressed/Not Coping class had the highest mean scores for concentration problems (*M* = 3.14) than the Well-Adjusted class (*M* = 2.13; $p < .05$), the Stressed/High Coping class (*M* = 2.83; $p < .001$), and the Stressed/Moderate Coping class (*M* = 2.68; $p < .01$).

In addition, the students of teachers in the Stressed/Not Coping class had lower mean scores (*M* = 93.14) than those in the Stressed/High Coping class (*M* = 98.00; $p < .05$) on math achievement (Herman et al., 2018). For Well-Adjusted class, there was a nonsignificant trend for higher scores (*M* = 97.97; $p < .06$). For reading achievement scores, there were no significant differences between classes. Thus, this study suggests that nearly all teachers experience high stress, and the Stressed/Low Coping teacher profile was associated with lower student behaviors, math achievement, higher disruptive behaviors, and overall worst student outcomes. These findings support prior studies that teacher stress and coping may impact teacher well-being and the students in their classrooms.

In summary, evidence-based interventions in the context of school can help and promote healthy social-emotional development, thereby reducing challenging behaviors in children. As children reach pre-school age, the school becomes an environment in which children spend most of their time, making it a social setting where children acquire academic and social skills simultaneously (Aviles et al., 2006; Ren et al., 2019). Thus, school is a good setting to identify and provide critical services to children with social-emotional difficulties, particularly those with developmental or behavioral problems (Aviles et al., 2006). To enhance children's social-emotional competencies, it is also crucial to train school personnel about social-emotional learning to provide the necessary skillsets to children, which will improve their overall relationships with peers and teachers and academic performance.

Chapter 2

SCHOOL-BASED INTERVENTIONS OF CHALLENGING BEHAVIORS

Intervention Literature Review

Emerging research indicates that students who successfully develop both academic skills and personal traits, such as perseverance, self-control, decision-making, and a positive mindset, have positive peer and teacher relationships and academic performance in school (Thompson et al., 2016; Zins & Elias, 2006; Jennings & Greenberg, 2009; Zin et al., 2004). That is, successful students, develop intrapersonal and interpersonal skills, which is also known as social-emotional learning (SEL, Thompson et al., 2016). Promoting SEL programs for all students—particularly children in primary school—is crucial to succeeding in school (Thompson et al., 2016). Durlak et al. (2011) sought to examine SEL programming on children’s behaviors and academic performance. This meta-analysis study evaluated the effects of 213 school-based, universal social and emotional (SEL) programs involving 270,034 kindergartens through high school students.

Durlak et al. (2011) explored the effects of SEL programming on various outcomes: social and emotional skills, attitudes toward self and others, positive social behavior, conduct problems, emotional distress, and academic performance. This present study focused on interventions for the entire student body (i.e., universal interventions). The hypotheses of this article were the following: (a) SEL programs would have a significant impact on children’s skills, attitudinal, behavioral, and academic areas; (b) teachers would effectively administer the SEL programs; (c) multicomponent programs would be more effective than single-component programs; (d) program outcomes would be moderated by the use of recommended training practices (SAFE practices); and (e) implementation problems.

The main independent variables for this study were intervention format, the use of four recommended practices related to skill development (SAFE practices), and reported implementation problems (Durlak et al., 2011). The intervention formation includes classroom-based interventions administered by classroom teachers and by non-school personnel (i.e., university researchers or outside consultants. Multicomponent strategies were also used to influence students, such as teacher-administered classroom interventions with a parent component or school-wide measures. SAFE practices were used to develop students' skills and were coded dichotomously, which asked about the four recommended practices related to skill development. The program implementation problems were coded as either having no implementation problems or that the program was implemented as intended.

To evaluate how methodological variables might influence outcomes, three variables were coded dichotomously: randomization to conditions, use of a reliable outcome measure, and use of a valid outcome measure (Durlak et al., 2011). The dependent variables used in this study were six different student outcomes: (a) social and emotional skills, (b) attitudes toward self and others, (c) positive social behaviors, (d) conduct problems, (e) emotional distress, and (f) academic performance. The sample consisted of 213 studies that included 270,034 students. 47% of the studies used randomized designs, and more than half the programs (56%) were administered to elementary school students. 31% of middle school students and the rest of high school students were involved. 47% of the studies were employed in urban schools, and the majority of SEL programs were delivered in classroom settings delivered by teachers (53%) or non-school personnel (21%), and multicomponent programs (26%).

The findings from this study showed that SEL programs significantly improved students' skills, attitudes, and behaviors. The grand study-level mean for the 213 interventions was 0.30 (CI = 0.26-0.33), which was statistically significant from zero (Durlak et al., 2011). All six means (range = 0.22 to 0.57) are significantly greater than zero, which confirmed the study's first hypothesis. The results indicated that students demonstrated enhanced skills, attitudes, and positive social behaviors after the intervention and showed reduced conduct problems and less emotional distress. In addition, academic performance was significantly improved following intervention. Thirty-three studies (15%) were used to collect follow-up data at least six months after the intervention took place. The mean follow-up effect sizes remained significant for all outcomes: SEL skills (ES = 0.26; $k = 8$), attitudes (ES = 0.11; $k = 16$), positive social behavior (ES = 0.17; $k = 12$), conduct problems (ES = 0.14; $k = 21$), emotional distress (ES = 0.15; $k = 11$), and academic performance (ES = 0.32; $k = 8$).

The findings also revealed that school staff could conduct successful SEL programs (Durlak et al., 2011). Both the Classroom by Teacher programs (i.e., SEL skills, attitudes, positive social behavior, conduct problems, emotional distress, and academic performance) and Multicomponent programs (i.e., attitudes, conduct problems, emotional distress, and academic performance) were found effective in outcome categories. On the other hand, classroom programs delivered by non-school personnel were only effective in three outcome categories (i.e., improved SEL skills and prosocial attitudes, and reduced conduct problems). Similarly, student academic performance significantly improved only when school personnel administered the intervention.

According to the comparison between current effect sizes to previous meta-analytic findings for school-age populations, SEL programs showed similar to, or even higher than the other types of universal interventions for each outcome category (i.e., skills, attitudes, positive social behaviors, conduct problems, emotional distress, and academic performance). The post mean effect size for academic achievement tests (ES = 0.27) was comparable to the results of 76 meta-analyses of educational interventions. Overall, findings from the current meta-analysis study suggested the benefits of SEL programming. While Durlak et al.'s (2011) study mainly focused on school-based universal interventions, such as SEL programs, Wood et al. (2011) study addressed the challenging behavior of young children through conducting a systematic function-based intervention.

Wood et al. (2011) examined challenging behaviors of three young children (ages 3.75-4.75 years) receiving special education services in inclusive pre-school settings by using systematically construct function-based interventions. The purpose of this study was to examine the effectiveness of function-based intervention using the Decision Model to three exceptional young children within their inclusive pre-school classrooms (Wood et al., 2011). The study was conducted in three phases (Wood et al., 2011). In Part 1, descriptive FBAs (i.e., structured interviews and direct observations) were conducted (Wood et al., 2011). In Part 2, for each participant using the Decision Model, function-based interventions were systematically constructed (Wood et al., 2011). In Part 3, these interventions were implemented within ongoing activities in their pre-school classrooms for an extended period (Wood et al., 2011).

In Part 1, parent/teacher interviews were conducted with each participant's parent/caregiver and teacher using the Functional Assessment Interview Form (Wood et al., 2011). The survey included 27 items that examined ecological factors that might influence the child's behavior, the predictability of the behavior, the child's play skills, the function of the behavior, the methods the child uses to communicate, and the child's preferred and nonpreferred activities (Wood et al., 2011). A-B-C data were collected during at least two sessions in each participant's classroom for approximately 2 to 3 hours (Wood et al., 2011). When the child engaged in the targeted behavior, the researchers recorded the antecedents and consequences (Wood et al., 2011). Observations took place during typical school activities (Wood et al., 2011). Function Matrix was used to analyze data from the interviews and direction observations (Wood et al., 2011). Function Matrix organizes whether the student gains (positive reinforcement) or escapes attention (negative reinforcement) or sensory consequences (Wood et al., 2011). Each of these three intervention methods includes three components: (a) adjustments to the antecedents, (b) appropriate reinforcement for the replace behavior, and (c) an extinction procedure when the targeted behavior occurs (Wood et al., 2011).

The results for the present study were based on the percentages of on-task behavior and treatment integrity during baseline, intervention, and follow-up for the three participants—Mark, Doug, and Paul (Wood et al., 2011). For Mark, the mean of on-task behavior for baseline sessions was 37% (range = 20%–53%). The mean for intervention sessions was 68% (range = 3%–93%), and the mean for follow-up sessions was 84%

([range = 70%–93%], Wood et al., 2011). For Doug, the mean for on-task behavior was 12% (range = 7%–17%). The mean for on-task behavior during intervention sessions was 81% (range = 60%–93%), and the mean for follow-up sessions was 84% ([range = 80%–93%], Wood et al., 2011). Lastly, for Paul, the mean percentage of on-task behavior for baseline sessions was 11% (range = 0%–30%). The mean for on-task behavior during intervention sessions was 99% of intervals (range = 97%– 100%). The mean for on-task behavior decreased during three follow-up sessions to an average of 73% ([range = 50%–97%], Wood et al., 2011).

Thus far, this study examined the effectiveness of interventions developed using the Decision Model (Wood et al., 2011). The interventions effectively increased on-task behavior and decreased the challenging behavior (i.e., disruptive behavior) of three children younger than age five who received special education services in inclusive pre-school settings (Wood et al., 2011). The study that follows moves on to consider a Positive Family Intervention for severe challenging behavior.

Durand et al. (2013) investigated a multisite randomized clinical trial assessing the effects of a cognitive-behavioral intervention to positive behavior support (PBS) with children who displayed challenging behavior, including those with a developmental disability. The current study assessed whether a cognitive-behavioral intervention could improve parents’ ability to implement PBS and help enhance child outcomes (Durand et al., 2013). Durand et al. (2013) adapted the optimism training for parents and sought to compare the effects of PBS on its own as well as PBS plus optimism training (i.e., positive family intervention [PFI]). The current study also evaluated whether a cost-effective approach (clinic-based intervention for parents) could show significant changes in child behavior at home (Durand et al., 2013). The study mainly focused on parents who reported high levels of pessimism and had a child with a developmental disability and exhibited severe challenging behavior (Durand et al., 2013).

The main hypothesis of the present study is in the following: (a) the group receiving the PFI intervention would demonstrate a significant decrease in pessimism, (b) that their children would show more improvements in their severe challenging behaviors, (c) that they would have less attrition from treatment, and (d) a clinic-based intervention would show significant improvements in child behavior at home (Durand et al., 2013). This study used a randomized control design with two conditions: (a) PBS and (b) PBS plus optimism training (PFI). Parents were randomly assigned to the two conditions (Durand et al., 2013). All therapists managed the interventions (Durand et al., 2013). Measures were conducted prior to initiating intervention and within two weeks of completing intervention (Durand et al., 2013).

In the PBS intervention, parents were provided with eight weekly sessions which adhered to the following sequence: (a) Session 1—Introduction and goal setting, (b) Session 2—Gathering information on challenging behavior, (c) Session 3—Analyzing data and plan design, (d) Session 4—Using prevention strategies, (e) Session 5—Using consequences, (f) Session 6—Replacing challenging behavior with appropriate alternatives, (g) Session 7—Implementing the strategies, and (h) Session 8—Monitoring the results (Durand et al., 2013). Throughout the process, the therapists helped the parents to analyze their child’s behavior (functional behavioral assessment) and developed interventions based on the analysis (Durand et al., 2013). In the PFI intervention, each family received eight weekly sessions (Durand et al., 2013). Likewise, the PFI followed the same sessions to the PBS condition to adopt the optimism training (Durand et al., 2013).

While teaching parents how to identify patterns in their child's behavior and develop intervention strategies accordingly, parents also helped identify patterns in their own thoughts and feelings and trained strategies for cognitive restructuring (Durand et al., 2013). In the PFI intervention, parents adhered to the following sequence: (a) Session 1—Identifying situations and associated self-talk, (b) Session 2—Determining consequences of beliefs, (c) Session 3—Disputing current thinking, (d) Session 4—Using distraction to interrupt negative thinking, (e) Session 5—Substituting pessimistic thoughts with positive, productive thoughts, (f) Session 6—Practicing skills to recognize/modify self-talk, (g) Session 7—Practicing skills to recognize/modify self-talk, and (h) Session 8—Maintaining positive changes in self-talk (Durand et al., 2013). These sessions took place individually with the parents (i.e., children were not present) at the university or other professional sites (Durand et al., 2013). Therapists conducted all sessions with master's degrees or PhDs and a background in PBS and/or clinical psychology (Durand et al., 2013).

The findings from the present study were shown in five data: Pessimism Data, GMI Data, Behavioral Observation Data, Attrition Data, and Parental Satisfaction Data (Durand et al., 2013). First, the current study hypothesized that families who completed the eight sessions of PFI would demonstrate a decrease in pessimism as measured by scores on the QRS-SF pessimism scale (Durand et al., 2013). A 2 (treatment condition: PFI vs. PBS) × 2 (measurement occasion: pre- vs. posttreatment) repeated-measure ANOVA with measurement occasion as a within-subject factor was used to test this hypothesis (Durand et al., 2013). The results showed a significant main effect of measurement occasion on the scores of pessimism, $F(1, 33) = 16.41$, $p < .01$, partial η2 = 0.33 (Durand et al., 2013). Compared to the pretreatment pessimism scores ($M = 7.71$, $SD = 1.23$), posttreatment pessimism scores were significantly lower ([$M = 5.77$, $SD = 2.83$], Durand et al., 2013). Both the main effect of treatment condition, $F(1, 33) = 0.88$, $p > .10$, and the interaction effect between treatment condition and measurement occasion, $F(1, 33) = 0.13$, $p > .10$, were not significant on the pessimism scores (Durand et al., 2013).

The current study also hypothesized that the children of families who completed the eight sessions of PFI would show significant behavioral improvements as measured by the GMI score of SIB-R (Durand et al., 2013). This hypothesis was also tested with the same repeated-measure ANOVA (Durand et al., 2013). The findings showed a significant main effect of measurement occasion on the GMI scores, $F(1, 33) = 102.46$, $p < .01$, partial η2 = 0.76 (Durand et al., 2013). For children from families who completed the eight sessions of intervention, their posttreatment GMI scores ($M = -21.51$, $SD = 10.81$) were significantly improved compared to their pretreatment GMI scores ([$M = -38.14$, $SD = 8.22$], Durand et al., 2013). The significant interaction effect between treatment condition and measurement occasion on the GMI scores, $F(1, 33) = 4.67$, $p < .01$, partial η2 = 0.12, and this significant interaction suggests that children from the PFI group significantly improved in their GMI scores compared to those from the PBS group (Durand et al., 2013). More specifically, 13 children in the PFI condition (72.22%) showed reliable improvement in their GMI scores than families in the PBS condition ([35.29%], Durand et al., 2013).

The third hypothesis is that the children of families who completed the eight sessions of PFI would show significant improvements in problem behaviors as measured by behavioral observations (Durand et al., 2013). Likewise, this hypothesis was also tested with the same repeated-measure ANOVA (Durand et al., 2013). This analysis produced a significant main effect of measurement occasion on the observed problem behaviors, $F(1, 33) = 122.91$, $p < .01$, partial $\eta 2 = 0.79$. The posttreatment problem behaviors ($M = 16.46$, $SD = 10.71$) were significantly improved than their pretreatment problem behaviors ([$M = 46.71$, $SD = 16.04$], Durand et al., 2013). It was also expected that families in the PFI group would complete the eight sessions in a shorter time and show less attrition (dropout) compared to the PBS group (Durand et al., 2013). The Cox regression was used to test whether the families in the PFI group would complete the eight sessions in a shorter time (Durand et al., 2013).

The results indicated that the Cox regression coefficient was not significant ($B = 0.10$, $SE = 0.35$, Wald Statistic [1] = .09, $p > .10$), suggesting that there were no differences in the amount of time for PFI ($M = 79.39$ days, $SD = 26.89$) and PBS ($M = 82.00$ days, $SD = 22.08$) groups to complete the treatment sessions (Durand et al., 2013). In addition, logistic regression was used to test whether families in the PFI group would show less attrition (dropout) than in the PBS group (Durand et al., 2013). The result showed that logistic regression coefficient was not significant ($B = 0.16$, $SE = 0.57$, Wald Statistic [1] = .08, $p > .10$), indicating that there were no differences in the attrition rates for PFI (33.33%) and PBS ([37.04%], Durand et al., 2013). Lastly, for parental satisfaction data, parents in both groups rated highly on a PSQ (for PBS condition: $M = 4.43$, $SD = 0.71$; for PFI condition: $M = 4.59$, $SD = 0.71$), indicating that they “slightly agreed" or "strongly agreed" with all questions regarding their satisfaction with the skills taught through the program and their satisfaction with the outcomes (Durand et al., 2013).

This present study has reviewed whether a cognitive-behavioral intervention could improve parents' ability to implement PBS and improve child outcomes. Overall, children whose parents participated in both treatment groups significantly improved their problem behavior problems and behavioral observations (Durand et al., 2013). The next study also describes the use of positive behavior support to address the challenging behavior of young children in a community early childhood program (Blair et al., 2010).

Blair et al. (2010) assessed the effects of an individualized PBS process in an early childhood classroom on the engagement and problem behavior (i.e., challenging behavior) of three young children. The research questions for the current study addressed the following: (a) whether the individualized PBS intervention could be effective in improving child behavior when implemented by classroom staff; (b) teachers would generalize the intervention procedures to non-trained routines, and thereby show collateral effects by improving child behavior during the nontargeted routines; and (c) improved children's behavior during intervention maintained in new settings (Blair et al., 2010).

Three young children in an inclusive community early childhood program participated in the study (Blair et al., 2010). The children were selected based on their display of persistent challenging behavior that interfered with and disrupted classroom activities and routines. All three children were boys, attended the same classroom, and were from families receiving public assistance. A concurrent multiple-baseline design across the three children was used to investigate the impact of the individualized positive behavior support procedures. The intervention included two phases: (a) the first phase in which the intervention was implemented by the lead teacher and (b) the second phase in which the intervention was implemented by the assisting teacher (Blair et al., 2010). A multiple-probe design was also used to evaluate the generalization effects of the intervention to nontargeted routines.

During the first phase of the intervention, the lead teacher implemented the plan with the support of the assistant teacher (Blair et al., 2010). During the second phase of the intervention, the assistant teacher implemented the plan with the support of a substitute teacher while the lead teacher was on extended leave. A multiple-probe design across children was used to evaluate teacher implementation of the intervention and behavioral changes in children during the nontargeted center activity time and transition to outdoor play. For the teacher implementation of the intervention, staff behavior was observed during the baseline and intervention phases to examine the extent to which the staff implemented the PBS intervention strategies during trained and non-trained routines. The implementation of strategies by teachers was evaluated during 40.9% of the sessions by using a 10-s interval recording system. After the intervention, the classroom staff participated in a social validity assessment through a semi-structured interview. The main purpose of the social validity assessment was to identify outcomes of PBS, such as changes in child and teacher behaviors and quality of the program, and to understand better teacher perspectives on the PBS process.

The results from the present study showed that both the lead and assistant teachers rarely demonstrated the use of the intervention strategies during circle time, averaging support strategies in 3.3% of intervals (Blair et al., 2010). Whereas the staff implemented the behavior support plan during intervention 92.2% across teachers (range = 83.1%–96.5%). The findings also indicated that the teachers could generalize the intervention implementation to non-trained routines. Teachers implemented the strategies on average during 99.4% of intervals (range = 97.8%–100%) for center time and 100% for transition time. Teachers also implemented the preventive strategies during most of the intervals (89.9%–100%) across routines while implementing the response and teaching strategies during less than half (30.3%–35.8%) or very few of the intervals (0.0%– 5.5%), respectively.

The mean percentages of problem behavior across children during baseline were 34.2%, 72.5%, and 77.3% for Ike, Wilson, and Alex, respectively (Blair et al., 2010). During the intervention, the mean problem behavior decreased to 4.2%, 14.5%, and 7.3% for Ike, Wilson, and Alex, respectively. The mean percentages of intervals for engagement during baseline were 61.6%, 27.6%, and 20.7% for Ike, Wilson, and Alex, respectively. During the intervention, the engagement increased to 96.1%, 87.5%, and 89.1% for Ike, Wilson, and Alex, respectively. Also, during both center and transition times, all three children showed lower rates of problem behavior and higher engagement rates in the intervention sessions than the baseline sessions (Blair et al., 2010). Social validity interview results also showed strong support for the use of individualized PBS for children with severe problem behavior (i.e., challenging behavior).

This current study has examined the effects of an individualized PBS process in an early childhood classroom on the engagement and problem behavior (i.e., challenging behavior) of three young children (Blair et al., 2010). The findings from this study indicated that the intervention helped the target children interact positively with teachers and peers, engage actively in the classroom, and enjoy classroom routines and activities (Blair et al., 2010). To conclude this chapter, the literatures based on the interventions targeting children with challenging behaviors all focus on the child's social-emotional development and how it is interrelated to the child's academic performance in schools. The key takeaway from this literature is to help children in their social-emotional development, including social-emotional skills, thereby positively impacting their peers and teachers' relationships and academic success.

Chapter 3

THEORY OF CHANGE FOR CHILDREN WITH CHALLENGING BEHAVIORS

Students with challenging behaviors often have a negative impact on their peer- and teacher- relationships and their academic performance in classrooms. Not only do students with challenging behaviors negatively affect their own performance in classrooms, but also interfere with the peers' academic performances and teachers' abilities to teach effectively in classrooms. Peers tend to have significant influence over one another, and if one student is displaying challenging behaviors, it may disrupt other students from focusing on the given tasks and also encourage similar behaviors in other classmates (Feil et al., 2014). When students continue to engage in challenging behaviors, they are more likely to be removed from their classrooms and be faced with more exclusionary discipline, such as in-school suspension and out-of-school suspension. Repeated removals and exposure to exclusionary discipline can lead to more negative outcomes, including poor academic performance, school dropout, and involvement in the juvenile justice system. On top of this, teacher burnout and emotional exhaustion also share a positive association with student challenging behaviors (Eddy et al., 2020).

Understanding malleable factors to improve peer- and teacher- relationships and their academic achievement is critical to enhancing learning environments for all students. For example, ecological influences, such as children from low-income families and poor neighborhoods, can lead to more challenging behaviors in children (Kaiser et al., 2017; Mazza et al., 2017). Taken together, the problem and its malleable precursors help frame and identify important theories for intervention development and testing.

This chapter describes the integration of two theories to help explain the importance of social-emotional learning (SEL) on children with challenging behaviors. The first theory, self-determination theory (SDT), is focused on the experiences of underlying autonomous actions and the awareness of one's needs, values, and goals (Ryan & Deci, 2017). The second theory, the social development model (SDM), integrates aspects of individual's qualities and their immediate environmental factors (e.g., parents, schools, peers), and broader social structures (e.g., socioeconomic status [SES]; Sullivan & Hirschfield, 2011). Together, the constructs, concepts and definitions, and propositions will be discussed. Following the overview of the parent theories, the development of the SMARTS intervention model will be summarized.

Self-Determination Theory (SDT)

SDT is concerned with the self-regulated engagement and overall functioning of a person in action (Ryan & Deci, 2017). The capacity to self-regulate and make autonomous choices is dependent upon supportive social conditions. The integration of autonomy and social contexts is the key to self-determination.

Concepts and Definitions of SDT

SDT is composed of three basic psychological needs—autonomy, competence, and relatedness (Ryan & Deci, 2017). Autonomy is the need to self-regulate one's behaviors, experiences, and actions. Competence is the need to feel effectance and mastery (Ryan & Deci, 2017). Relatedness is the need to feel socially connected (Ryan & Deci, 2017). These three basic needs of autonomy, competence, and relatedness are identified functionally whereby these psychological needs integrate with environmental, social, and interpersonal contexts on intrinsic motivation, and the internalization of extrinsic regulations (Ryan & Deci, 2017).

Propositions of SDT

Parental and school support of autonomy or self-governance are crucial for the healthy development of children (Ryan & Deci, 2017). Autonomy support includes actively considering children's perspectives and providing encouragement for self-expression and self-endorsed activities (Ryan et al., 2006; Ryan & Deci, 2017). Autonomy support nurtures self-development in children and is critical during the early stages of life. With more autonomy, children are becoming aware of their emotions and becoming more attuned to others' emotions and feelings. In addition, children are more autonomously motivated and positively engaged in school, perform better academically, and show greater psychological health and well-being (Ryan & Deci, 2017).

Competence is a core element in motivated actions (Deci, 1975; Ryan & Deci, 2017). The need for competence is inherent and manifested in curiosity (Deci & Moller, 2005; Ryan & Deci, 2017). Competence is contingent upon contexts. If the contexts are too difficult or challenging along with negative feedback, then the feelings of effectiveness and mastery will decrease (Ryan & Deci, 2017).

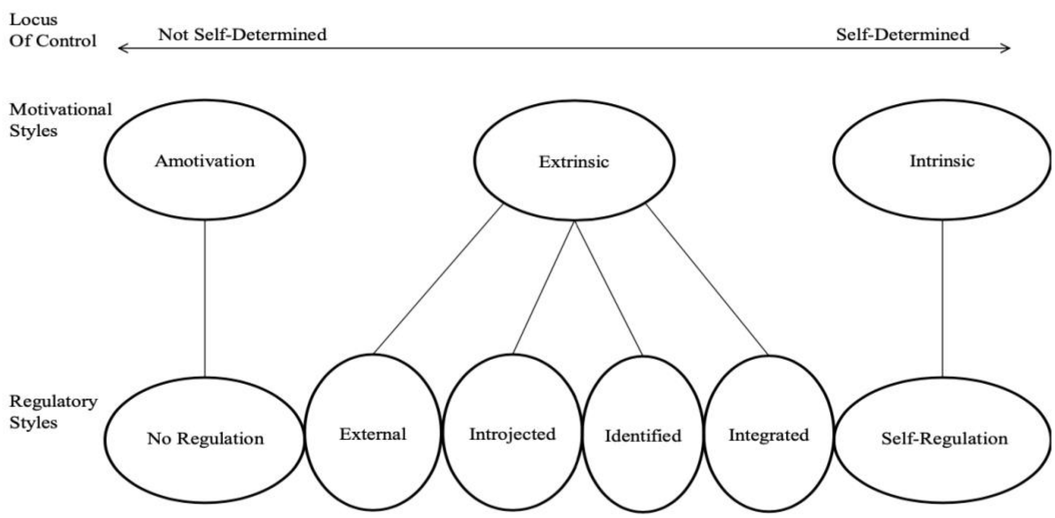
Relatedness is a sense of belonging to a social organization and feeling cared by others. Relatedness mostly occurs when people have a feeling of connectedness with others. By feeling connected to those who are part of their social groups and have a sense of contribution to the group is how people experience relatedness (Ryan & Deci, 2017).

These three basic needs of autonomy, competence, and relatedness are holistically explained by the contextual factors that help to understand human behavior and their motivation (Ryan & Deci, 2000; Ryan & Deci, 2017). When the contexts support the student needs for autonomy, competence, and relatedness, student are more likely to develop motivation. However, when the contexts do not support the student needs for autonomy, competence, and relatedness, student are more likely to continue displaying challenging behaviors (Ryan & Deci, 2000; Ryan & Deci, 2017). Figure 1 is an illustration of self-determination continuum by Deci and Ryan (2000).

Starting from the left of the model, *amotivation* motivational style with *no regulation* regulatory style are shown. In the middle of the model, *extrinsic* motivation is composed of four regulatory styles—*external, introjected, identified,* and *integrated*. Here, the *extrinsic* motivation mechanisms are the intended targets of teacher managed behavioral interventions (Thompson, 2014). On the far-right side, *intrinsic* motivational style is marked with *self-regulation* regulatory style. Contextual factors promote or hinder these behaviors and different types of motivation for the three basic needs of autonomy, competence, and relatedness (Ryan & Deci, 2000).

Figure 1

Self-determination, Motivation, and Regulatory Continuum



Note. Adaptation of self-determination continuum model (Deci & Ryan, 2000, p. 237).

Students who have *no regulation* are *amotivational* styles and are not *self-determined.* Students who are *externally regulated* represents the least autonomous forms of extrinsic motivation (Deci & Ryan, 2000). *Introjected regulation* occurs when students are still quite controlled as their actions are from the feeling of pressure to build self-esteem or to avoid anxiety. *Identified* regulatory styles are defined as more autonomous or self-determined, which is a form of extrinsic motivation. For example, students complete their reading assignments because they believe the assignments are relevant to writing. *Integrated* regulation is the most autonomous form of extrinsic motivation. Students in this stage are fully assimilated to the self and congruent to their internal values; however, the task is still supported by extrinsic motivation. Lastly, students who have *self-regulation* are aligned with *intrinsic* motivation in which students are fully self-determined and their behaviors are entirely for one’s authentic interest and self-satisfaction (Deci & Ryan, 2000).

In summary, SDT posits that when school personnel provide students with autonomy students maintain intrinsic motivation for learning and develop more fully internalized extrinsic motivation for their academic tasks (Deci & Ryan, 2017). The three basic needs of autonomy, competence, and relatedness from the SDT model and their contextual supports are integrated into the SMARTS model to provide students with positive social behaviors, such as self-managed and self-regulated (Thompson, 2014). In addition, the Social Development Model (SDM) contributes to the structuring of the contextual supports that encourage self-managed and self-regulated behaviors among students exhibiting challenging behaviors.

The Social Development Model (SDM)

The SDM is a framework that describes challenging and disruptive behaviors in students in the context of peers, family, and school (Brown et al., 2005). Both risk factors and protective factors are taking into account when predicting whether children will develop prosocial behavior or challenging behaviors as they age. These influences can shape students' behaviors into prosocial behavior or challenging behaviors in schools. SDM is based on an integration of three theoretical approaches—social control theory (SCT), social learning theory (SLT), and differential association theory (DAT).

Concepts and definitions of the SDM

The SDM combines three theoretical approaches as causal linkages formed in the context of social domains (e.g., family, peers, school) as children and adolescents transition through different developmental stages (Brown et al., 2005). Social control theory (SCT) posits that challenging behavior occurs as a result of a having a weak bond with peers, classmates, or teachers (Agnew, 1985; Hirschi, 1969). Social learning theory

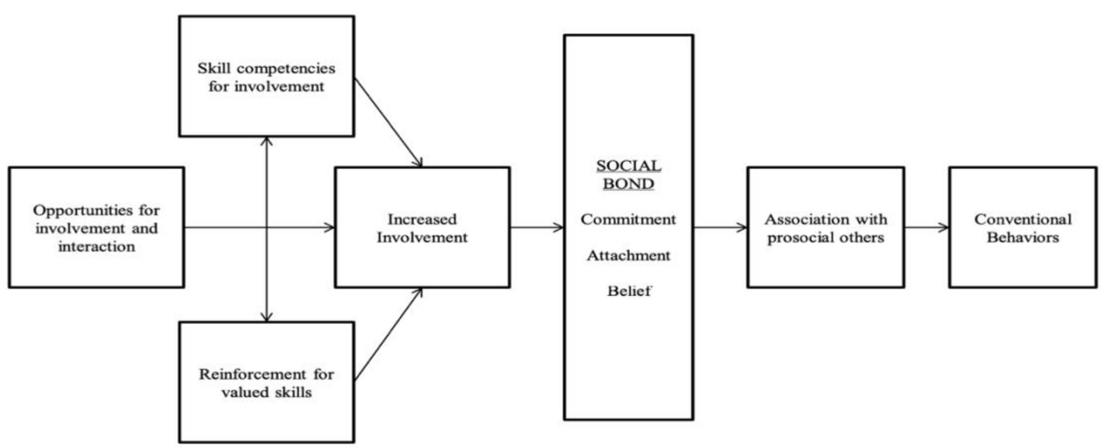
(SLT) asserts that patterns of behavior are learned through interaction with various socializing agents, such as family, peers, and teachers (Brown et al., 2005; Bandura, 1973, 1977). Differential association theory (DAT) asserts that behavior is also learned through interactions with others (Matsueda, 1988).

Propositions of the SDM

There are four main propositions of the SDM (Hawkins & Weis, 1985). First, a student has an opportunity for involvement and interaction with others. Second, a student must have skills for involvement and interactions with others. Third, a student those behaviors are reinforced for valued skills. Fourth, all of these factors will then increase involvement in a student. Figure 2 demonstrates the three central processes (i.e., opportunities for involvement, skills, and reinforcements for valued skills) that lead to increased involvement and social bond with others in schools.

Figure 2

The Social Development Model



Note. Adaptation of the social development model (Hawkins & Weis, 1985, p. 79)

The SDM assumes that after a student has gone through the three central processes and obtained increased involvement, then the individual will develop a bond or attachment to the unit (Hawkins & Weis, 1985). By having association with peers with prosocial behaviors, a student will have reduction in the overall risk of displaying challenging or disruptive behaviors (Hawkins & Weis, 1985). The association with prosocial others will then lead the student to develop conventional behaviors and improve outcomes for the student.

Therefore, the SDM suggests that early prevention that provides students with various supports targeting integration and involvement of prosocial behaviors and skill competencies for those involvement will help reduce challenging behaviors in students. These key contributions of the SDM to the integrated SMARTS model will help address these challenging behaviors and improve overall outcomes in students.

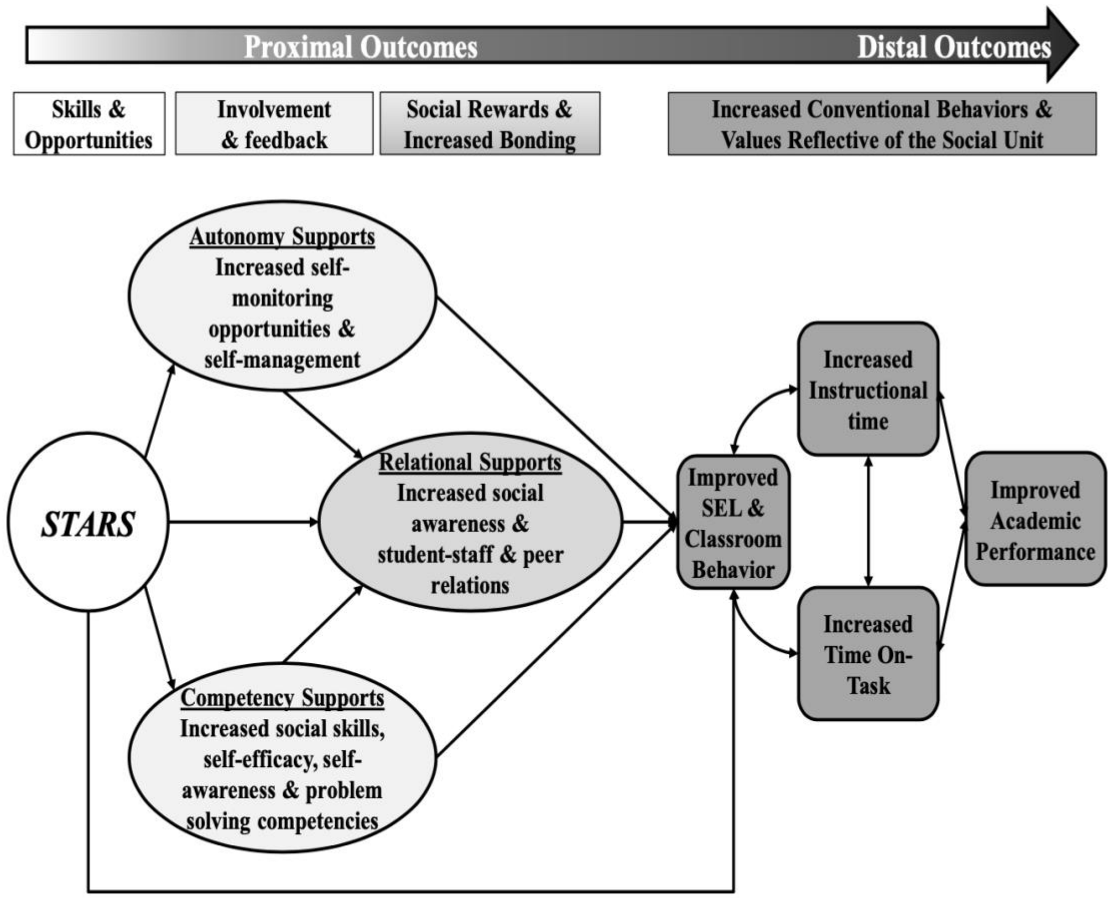
Theory of Change: Integrating Effective Concepts of SDT and SDM to Impact SEL, Behavioral, and Academic Performance

An integration of the concepts from SDT and SDM, the SMARTS model predicts that increased opportunities and ongoing feedback from autonomy, competency, and relational supports lead to improved SEL, increased conventional behaviors, decreased in challenging behaviors, and overall reduction in in-school suspension (ISS), out-of-school suspension (OSS), and exclusionary discipline (ED; Thompson, 2014; Thompson et al., 2021). Figure 3 shows an intervention model integrating the concepts of SDT with the processes of the SDM to guide the development of the SMARTS self-monitoring intervention model.

The SMARTS model suggests that autonomy supports, competency supports, and relational supports lead to proximal outcomes or immediate outcomes in which students will acquire skills and opportunities, involvement and feedback, and social rewards and increased bonding (Thompson, 2014; Thompson et al., 2021). With these three supports, students will have improved SEL and classroom behavior. Increased instructional time and time on-task are interrelated with improved SEL and classroom behavior and improved academic performance. Thus, these improved outcomes are results of increased conventional behaviors and values reflective of the social unit, which lead to the overall distal outcomes or long-term outcomes. These distal outcomes also reflect reduction in overall suspension rates in students with challenging behaviors (i.e., in-school suspension, out-of-school suspension, exclusionary discipline). The more students achieve these proximal and distal outcomes, the less likely students will have in-school suspension (ISS), out-of-school suspension (OSS), and exclusionary discipline (ED).

Figure 3

Integrated Theory of Change Combining SDT and SDM Impacting SEL, Behavioral, and Academic Performance



Note. Adaptation of the SMARTS model (Thompson, 2014; Thompson et al., 2021)

In summary, increase motivation will improve classroom engagement, which will lead to reduction in challenging or disruptive behaviors, thereby reducing negative problem behaviors. Increase competencies will help students to cope better in classrooms and when students have fewer behavioral problems then students will have reduction in suspensions. Students with improved SEL and classroom behavior will lead to reduction in exclusionary discipline. With autonomy supports, competency supports, and relational supports, the SMARTS model posits a student can self-manage and self-regulate one's behavior by self-monitoring one's own progress, thereby producing proximal outcomes and distal outcomes (Thompson 2014; Thompson et al., 2021). By developing these skills, a student will have better social-emotional outcomes, academic outcomes, and reduction in suspension rates. The next chapter will describe the method used to test the effects of SMARTS on challenging student behaviors on ISS, OSS, and ED using a randomized control design.

Chapter 4

METHOD

This dissertation study uses primary data collected from a randomized controlled trial (IES Grant number: R305A150517) to examine the effects of SMARTS (Self-Monitoring And Regulation Training Strategy; formerly called STARS), a school-based self-monitoring intervention for upper elementary youth with challenging or disruptive behavior (Thompson, 2014). The present study hopes to shed light on the significance of social-emotional learning and prosocial behaviors and how these influences can help guide students to perform better in school (i.e., less in-school suspension, out-of-school suspension, and exclusionary discipline) and to promote positive peer and teacher relationships. Building on previous literature, the current study extends the link between social-emotional learning and challenging behaviors and explores the impact of SMARTS on number of in-school suspension (ISS), out-of-school suspension (OSS), and overall exclusionary discipline (ED). The purpose of this study is to examine the effect of SMARTS on ISS, OSS, and ED among fifth grade elementary school students experiencing challenging behaviors. This section will present research questions, study hypotheses, research design, participants, procedures, measures, and data analytic strategy.

Research Questions

The study addresses the following research questions:

1. Do SMARTS students, compared to control students, have a lower number of in-school suspension (ISS), out-of-school suspension (OSS), and overall exclusionary discipline (ED)?

2. Is the SMARTS intervention effect moderated by baseline prosocial behaviors, emotion regulation, and academic competence?

Study Hypotheses

The research is guided by two hypotheses. First, related to the intervention on ISS, OSS, and ED, it is hypothesized that students in the SMARTS condition will have a reduction in ISS, OSS, and ED compared to the students in the control condition. Second, it is hypothesized that the interaction effects, specifically evaluating SMARTS treatment with baseline prosocial behaviors, SMARTS treatment with baseline emotion regulation, and SMARTS treatment with baseline academic competence as well as socio-demographic characteristics (i.e., sex, race, free-reduced lunch, special education status), will have an impact on ISS, OSS, and ED.

Research Design

The study is a longitudinal cohort study that took place from the year 2015 to 2019 to capture the long-term effect of SMARTS from elementary to middle school. As shown in Table 1, the study uses a randomized control trial design (RCT) to compare SMARTS students to control students receiving Check-In Check-Out (CICO; Thompson et al., 2021). The school district implemented CICO for students with challenging behaviors if they were not receiving the SMARTS treatment. Following parent consent, fifth grade students falling at or within the 20% of students exhibiting challenging classroom behaviors during Gate I screening procedures are evaluated by teachers in Gate II. Students who did not meet Gate II externalizing T scores at or above 60 on the Child Behavior Checklist (CBCL) externalizing scale are exempted from the study while students with T scores at or above 60 are retained and randomized into either the SMARTS or the control condition.

SMARTS is a selective intervention; thus, randomization took place at the student level (Thompson et al., 2021). Randomization at the student level are used to provide flexibility for school personnel to deliver the SMARTS intervention. Taking school dynamic contexts into consideration, randomization at the student level help to adhere to an intervention with fidelity. Randomization at the student level also supports power estimates.

Table 1

Randomized Control Trial Design

Group	Randomization	Pretest	Intervention	Posttest
SMARTS Treatment	R	O_1	SMARTS Treatment	O_2
Control/CICO	R	O_1	X	O_2

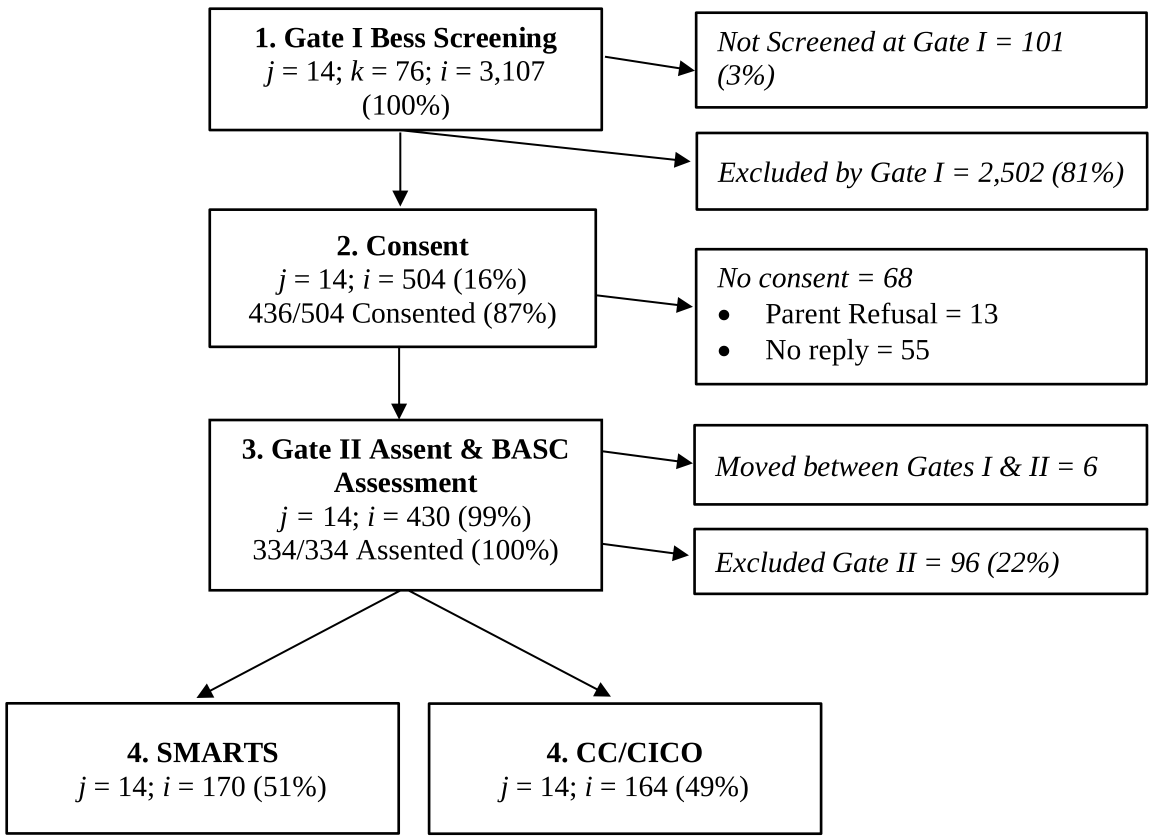
Participants

The sample of the study recruited and consented 334 fifth grade students and 77 teachers from 14 separate school sites located in a Midwestern district in a suburban-sized community (Thompson et al., 2021). Out of the 334 students in the study sample, 170 students were assigned to the SMARTS treatment group and 164 were assigned to the control group/Check-In Check-Out (CICO; Thompson et al., 2021). The total study sample size is collected from four different sequential cohorts in 2015-2016 (*n* = 84), 2016-2017 (*n* = 106), 2017-2018 (*n* = 89), and 2018-2019 (*n* = 55; Thompson et al., 2021). As shown in Figure 4, the flow chart of the 334 participants is illustrated including

Gate I screenings, consents, Gate II assessments, and randomization of participants into either the SMARTS or control condition (Thompson et al., 2021).

Figure 4

Participant Flow Chart



Note. j = school levels, k = teachers, i = individual students.

Procedures

The study was funded by the US department of education (Grant number: R305A150517). Study sample recruitment, assent, and consent procedures were implemented at the student level.

Intervention Procedures

The SMARTS intervention consisted of three phases conducted by school personnel (e.g., social workers, school psychologists, school counselors; Holmes et al., 2021). In Phase I, school personnel trained students in small (4-6) groups using ten scripted lessons: (1) Group Expectations; (2) Assessing & Defining Problems; (3) Generating & Weighing Alternative Solutions; (4) Writing Goals to Implement Solutions; (5) Recording Goal Progress; (6) Evaluating Goal Progress; (7) Perspective Taking; (8) Reframing Mistakes; (9) Managing Internal Responses to Problems; and (10) Managing External Responses to Problems (Holmes et al., 2021). The first lesson was to review the overall purpose, behavioral expectations of SMARTS group meetings, and to introduce the “SMARTS jar” (Holmes et al., 2021; Thompson, 2014; Thompson et al., 2021). The SMARTS jar is a large glass jar with students dropping a marble each time a student participated, engaged in a socially acceptable exchange with peers, and once the jar was filled up, students were given with a small group reward, such as a pizza, lunch in the counselor’s office, etc. (Holmes et al., 2021; Thompson, 2014; Thompson et al., 2021).

In Phase II, students entered SMARTS Phase II self-monitoring and teachers monitored student performance on a goal the student created during Phase I for 7 intervals per school day for 8 weeks total (Holmes et al., 2021; Thompson, 2014; Thompson et al., 2021). The students completed their self-monitoring using the SMARTS app and entered a “yes,” “sometimes,” or “no” reflecting on the student’s goal performance. Every day, each SMARTS student responded to four prompts: (1) How ready they were to follow their goal; (2) How confident they felt they could successfully achieve their goal; (3) How good they felt; and (4) How good they felt and how well they slept the night before. The classroom teachers also rated student performance using the same app where both students and teachers can view their performance as a percentage on a chart (Holmes et al., 2021; Thompson, 2014; Thompson et al., 2021).

Following Phase II, a week of daily ratings, SMARTS students were ready for Phase III Data Review meetings (Holmes et al., 2021; Thompson, 2014; Thompson et al., 2021). SMARTS students met with their group and counselor to review their weekly data and examine differences between student's data and teacher's data. Using motivational prompts, school personnel reviewed the data with students and helped students to reflect on behaviors contributing to discrepancies and revised their goals or continued with the same goals. With the revised goal, Phases II and III were repeated and posttest assessments were then collected from students, teachers, and counselors (Holmes et al., 2021; Thompson, 2014; Thompson et al., 2021).

Data Collection Procedures

All data of the study were collected from the year 2015 to 2019 (Thompson et al., 2021). The data were provided by the schools and collected school records regarding the attendance, educational status, lunch status, disciplinary records, and record of suspensions and expulsion as well as performance scores for all study students on state-wide assessments (Thompson et al., 2021). For each cohort, the following gate and baseline data were collected in the Fall prior to the intervention (T1). For each cohort, the following follow-up data were collected, and these data were collected in the Spring (T3), with another follow-up collected in the Winter of the following year (T4).

Finally, for the extension study, a final time point of data was collected for Cohort 1 and Cohort 3 in the Spring of the 2019 – 2020 school year (T5). Again, for the extension study, a final point time of data was collected for Cohort 2 and Cohort 4 in the Spring of 2020 – 2021 school year (T5). All study measures were collected in fifth grade were repeated in sixth grade with the exception of the Child version of the BASC (Thompson et al., 2021). Instead, youth entering sixth grade used the adolescent version of the tool (Thompson et al., 2021). Observations were conducted in classroom settings during math instruction (Thompson et al., 2021).

Measures

Following multi-gated screenings (gate one and gate two pretests) and consent/assent, students were randomly assigned to SMARTS or a control condition (Holmes et al., 2021; Thompson et al., 2021). After SMARTS training and 8 weeks of self and teacher monitoring, posttest surveys were completed (Holmes et al., 2021; Thompson et al., 2021).

In the analysis, the study used the number of incidents for in-school suspension (ISS), number of incidents for out-of-school suspension (OSS), the total suspensions or the overall exclusionary discipline (ED) as outcomes. Baseline prosocial behaviors, baseline emotion regulation, and baseline academic competence, as well as socio-demographic characteristics (i.e., sex, race, free-reduced lunch, special education status), were used as potential moderators.

Suspensions

The dependent variables of the current study are the suspension variables: in-school suspension (ISS), out-of-school suspension (OSS), and exclusionary discipline (ED). These variables are count data, which counts the number of days students were suspended. Table 2, 3, and 4 demonstrate the descriptive statistics for ISS, OSS, and ED for the overall sample and by treatment status.

Table 2

Descriptive Statistics for In-School Suspension (*ISS*)

	SMARTS Treatment (Frequency)	% (Percentage)	Control Condition/CICO (Frequency)	% (Percentage)	Total
Zero Suspension	129	83.2%	123	82.6%	252
Non-Zero Suspension	26	16.8%	26	17.4%	52
Total	155	100%	149	100%	304

In-school suspension (ISS). The number of ISS is a count variable that was measured as an administrative record after the year of the study (Thompson et al., 2021). ISS is counted as number of days where students were temporarily excluded from their regular classrooms away from peers. Per ISS occasion, for all the students that participated in the study, if a student was temporarily removed from his or her classroom then the measure was counted as counting numbers, which are non-negative integer values (i.e., 0, 1, 2, 3, etc.).

Out-of-school suspension (OSS). The number of OSS is a count variable that was measured as an administrative record after the year of the study (Thompson et al., 2021). OSS is counted as number of days where students were removed from school grounds. Per OSS occasion, for all the students that participated in the study, if a student was excluded from school then the measure was counted as counting numbers, which are non-negative integer values (i.e., 0, 1, 2, 3, etc.).

Table 3

Descriptive Statistics for Out-of-School Suspension (*OSS*)

	SMARTS Treatment (Frequency)	% (Percentage)	Control Condition/CICO (Frequency)	% (Percentage)	Total
Zero Suspension	101	65.2%	96	64.4%	197
Non-Zero Suspension	54	34.8%	53	35.6%	107
Total	155	100%	149	100%	304

Exclusionary discipline (ED). The number of ED is a count variable counted as the total number of suspensions. By adding the number of ISS and OSS, the total sums of the exclusionary discipline were measured.

Table 4

Descriptive Statistics for Exclusionary Discipline (*ED*)

	SMARTS Treatment (Frequency)	% (Percentage)	Control Condition/CICO (Frequency)	% (Percentage)	Total
Zero Suspension	95	61.3%	90	60.4%	185
Non-Zero Suspension	60	38.7%	59	39.6%	119
Total	155	100%	149	100%	304

Covariates

Sex. Student sex was categorized into female and male. Female was coded as 1 and male was coded as 0.

Race. Student race was categorized into five groups: White, Hispanic, Biracial, Black, Asian, and Other. White was coded as 0, Hispanic was coded as 1, Biracial was coded as 2, Black was coded as 3, Asian was coded as 4, and Other was coded as 5. For the analysis, the race was collapsed into a binary variable where white students were coded as 0 and students of color were coded as 1.

Free-reduced lunch (FRL). Student status in free-reduced lunch (FRL) was coded into two categories. If a student received FRL, then they were coded as 1. If a student did not receive FRL, then they were coded as 0.

Special Education Status (SPED). Student special education status was categorized into two groups. If a student did receive special education, then they were coded as 1. If a student did not receive special education, then they were coded as 0.

Moderators

The moderators were measured using the Social Competence Scale, which is a Likert-type scale. Table 5 shows the descriptive statistics for prosocial behaviors, emotion regulation, and academic competence.

Prosocial behaviors. Prosocial behaviors were measured using the Social Competence Scale – Teacher (T – COMP) consisted of five items, which had a high degree of reliability (α = .90). Teachers rated the student's prosocial behaviors, such as "*Show empathy and compassion for others' feelings," "Provide help, share materials, and cooperate well with others,"* and *"Listen carefully to others"* (Thompson et al., 2021).

Emotion regulation. Emotion regulation was measured using the Social Competence Scale – Teacher (T – COMP) consisted of seven items, which had a high degree of reliability (α = .81). Teachers rated the student's emotion regulation that includes questions like "*Stop and calm down when excited or upset" and "Handle disagreements in a positive way"* (Thompson et al., 2021).

Academic competence. Academic competence was measured using the Social Competence Scale – Teacher (T – COMP) consisted of six items, which had a high degree of reliability (α = .80). Teachers rated the student's academic competence that includes questions, such as *"Able to effectively set goals and work toward them"* and "*Able to read grade level material and answer questions about what they have read*" (Thompson et al., 2021).

Table 5

Descriptive Statistics for Moderators by Treatment and Control Groups

	SMARTS Treatment *M*(*SD*)	Control Condition/CICO *M*(*SD*)	Cronbach's Alpha
Prosocial Behaviors	2.02(0.94)	2.08(0.99)	α = .90
Emotion Regulation	1.99(0.85)	2.12(0.81)	α = .81
Academic Competence	1.89(1.09)	2.05(1.17)	α = .80

Analysis

The Generalized Additive Models for Location, Scale, and Shape was used (GAMLSS; Rigby & Stasinopoulos, 2005) to evaluate the impact of SMARTS on ISS, OSS, and ED, and the impact of SMARTS and moderation effects on ISS, OSS, and ED. The analysis of the data was all conducted using R studio, an open-source program for statistical computing and scientific research (RStudio, 2022). GAMLSS is a distributional regression approach which evaluates not only means of outcome variables, but any distributional parameter (i.e., variances, skewness, and kurtosis) (Stasinopoulos et al., 2018). GAMLSS is a general framework for performing a regression using a single response variable and multiple explanatory variables (Stasinopoulos et al., 2018).

GAMLSS is an extension of the classical linear model (LM), generalized linear models (GLMs), and generalized additive models (GAMs). The response variable can have any parametric distribution (Stasinopoulos et al., 2018). All the parameters of the distribution can be modelled either as linear or smooth functions of the explanatory variables. The distribution can be continuous or discrete and does not have to belong to the exponential family. A GAMLSS model assumes that for $i = 1, 2, \ldots n$ independent observations, Y_i has a probability (density) function $f\ (y_i \mid \mu_i, \sigma_i, \nu_i, \tau_i)$ conditional on up to four parameters (i.e., μ_i = location parameter, σ_i = scale parameter, ν_i = skewness parameter, τ_i = shape parameter).

The GAMLSS model can be written as

$$y \sim \mathcal{D}(\mu, \sigma, \nu, \tau) \qquad (1)$$

for $i = 1, ..., n$ where $\mathcal{D}$ is any distribution with up to four parameters (Stasinopoulos et al., 2018). Further, Figure 5 shows the equation for parametric GAMLSS, whereby X_k is a known design matrix and β_k is a parameter vector (Stasinopoulos et al., 2018). Each parameter of $\mathcal{D}$ (i.e., mean, variance, skewness, and kurtosis) is modelled using explanatory variables. The explanatory variables for this study are SMARTS treatment, student race, student sex, free reduced lunch status, and special education status. Moderation models additionally included students' prosocial behaviors, emotion regulation, and academic competence at study baseline.

Figure 5

Parametric GAMLSS equation

$$g_1(\mu) = \eta_1 = X_1\beta_1$$

$$g_2(\sigma) = \eta_2 = X_2\beta_2$$

$$g_3(\nu) = \eta_3 = X_3\beta_3$$

$$g_4(\tau) = \eta_4 = X_4\beta_4$$

For this study, within the GAMLSS family, discrete distributions were examined to answer the research questions. Discrete distributions are defined on $y = 0, 1, 2, \ldots, m$ finite numbers (Stasinopoulos et al., 2018). In-school suspension (ISS), out-of-school suspension (OSS), and exclusionary discipline (ED) are discrete or count variables, which are our dependent variables (Thompson et al., 2021). Model selection is performed using the GAMLSS deviance, which denotes the global deviance (Stasinopoulos et al., 2018). The global deviance is defined as

$$D_{\text{GAMLSS}} = -2 \log L_c$$

and is used to select the best fitting model, the Generalized Akaike Information Criterion (GAIC) is computed with k being the penalty for each degree of freedom used (Stasinopoulos et al., 2018). The model with the lowest value is selected as the best fitting model. Worm plots of residuals are used to identify regions of an explanatory variable in which the model does not fit the data well (Buuren & Fredriks, 2001).

Count Data Distributions

When using discrete distributions for count data, mixed distributions account for overdispersion (Rigby et al., 2017). Table 6 shows all 33 count data distributions currently available in **gamlss** package in R. Within the 33 count data distributions, mixed distributions are also included. The corresponding distributions for γ, where $Y \mid \gamma \sim PO(\mu\gamma)$, and their mean $E(Y)$ and variance $Var(Y$; Rigby et al., 2017).

Many of the mixed Poisson distribution in Table 6 have mean equal to parameter μ: the negative binomial type I and type II, Poisson-inverse Gaussian (PIG), Sichel, and Delaporte distributions. The negative binomial type I distribution NBI(μ, σ) is a continuously mixed Poisson distribution obtained as the marginal distribution of Y when $Y \mid \gamma \sim \mathrm{PO}(\mu\,\gamma)$ and $\gamma \sim \mathrm{GA}(1, \sigma^{\frac{1}{2}})$, where γ has a gamma distribution with mean 1 and scale parameter $\sigma^{\frac{1}{2}}$ (Rigby et al., 2017). The negative binomial type II distribution NBII(μ, σ) is a mixed Poisson distribution obtained as the marginal distribution of Y when $Y \mid \gamma \sim \mathrm{PO}(\mu\,\gamma)$ and $\gamma \sim \mathrm{GA}(1, \sigma^{\frac{1}{2}}\mu^{\frac{1}{2}})$.

The negative binomial family distribution NBF(μ, σ, ν) is obtained by replacing σ by $\sigma\mu^{\nu-2}$ in the NBI distribution. This distribution has mean μ and variance $\sigma\mu^{\nu}$. The Poisson-inverse Gaussian distribution PIG(μ, σ) is a continuously mixed Poisson distribution obtained as the marginal distribution Y when $Y \mid \gamma \sim \mathrm{PO}(\mu\,\gamma)$ and $\gamma \sim \mathrm{IG}(1, \sigma^{\frac{1}{2}})$, which is an inverse Gaussian mixing distribution. The Sichel distribution SICHEL(μ, σ, ν) is a continuously mixed Poisson distribution obtained as the marginal distribution Y when $Y \mid \gamma \sim \mathrm{PO}(\mu\,\gamma)$ and $\gamma \sim \mathrm{GIG}(1, \sigma^{\frac{1}{2}}, \nu)$, which provides three parameters to model over-dispersed Poisson count data displaying high positive skewness. The Delaporte distribution DEL(μ, σ, ν) is a mixed Poisson distribution obtained as the marginal distribution Y when $Y \mid \gamma \sim \mathrm{PO}(\mu\,\gamma)$ and $\gamma \sim \mathrm{SG}(1, \sigma^{\frac{1}{2}}, \nu)$, which is a shifted gamma mixing distribution.

Table 6

Count data distributions

Distribution	**gamlss** name	Range R_Y	Parameter link function μ	σ	ν	τ
Geometric	GEOM	{0, 1, 2, . . .}	log	-	-	-
Geometric (original)	GEOMo	{0, 1, 2, . . .}	logit	-	-	-
Logarithmic	LG	{1, 2, 3, . . .}	logit	-	-	-
Poisson	PO	{0, 1, 2, . . .}	log	-	-	-
Yule (μ the mean)	YULE	{0, 1, 2, . . .}	log	-	-	-
Zipf	ZIPF	{0, 1, 2, . . .}	log	-	-	-
Negative binomial type I	NBI	{0, 1, 2, . . .}	log	log	-	-
Negative binomial type II	NBII	{0, 1, 2, . . .}	log	log	-	-
Poisson inverse Gaussian	PIG	{0, 1, 2, . . .}	log	log	-	-
Waring (μ the mean)	WARING	{0, 1, 2, . . .}	log	log	-	-
Zero alt. logarithmic	ZALG	{0, 1, 2, . . .}	logit	logit	-	-
Zero alt. Poisson	ZAP	{0, 1, 2, . . .}	log	logit	-	-
Zero alt. zipf	ZAZIPF	{0, 1, 2, . . .}	log	logit	-	-
Zero inf. Poisson	ZIP	{0, 1, 2, . . .}	log	logit	-	-
Zero inf. Poisson (μ the mean)	ZIP2	{0, 1, 2, . . .}	log	logit	-	-
Generalised Poisson	GPO	{0, 1, 2, . . .}	log	log	-	-

Double Poisson	DPO	{0, 1, 2, . . .}	log	log	-	-
Beta negative binomial	BNB	{0, 1, 2, . . .}	log	log	log	-
Negative binomial family	NBF	{0, 1, 2, . . .}	log	log	ident.	-
Delaporte	DEL	{0, 1, 2, . . .}	log	log	logit	-
Sichel	SI	{0, 1, 2, . . .}	log	log	ident.	-
Sichel (μ the mean)	SICHEL	{0, 1, 2, . . .}	log	log	ident.	-
Zero. alt. negative binomial	ZANBI	{0, 1, 2, . . .}	log	log	logit	-
Zero alt. PIG	ZAPIG	{0, 1, 2, . . .}	log	log	logit	-
Zero inf. negative binomial	ZINBI	{0, 1, 2, . . .}	log	log	logit	-
Zero inf. PIG	ZIPIG	{0, 1, 2, . . .}	log	log	logit	-
Zero alt. negative binomial fam.	ZANBF	{0, 1, 2, . . .}	log	log	log	logit
Zero alt. beta negative binomial	ZABNB	{0, 1, 2, . . .}	log	log	ident.	logit
Zero alt. Sichel	ZASICHEL	{0, 1, 2, . . .}	log	log	ident.	logit
Zero inf. negative binomial fam.	ZINBF	{0, 1, 2, . . .}	log	log	log	logit
Zero inf. beta negative binomial	ZIBNB	{0, 1, 2, . . .}	log	log	log	logit
Zero inf. Sichel	ZISICHEL	{0, 1, 2, . . .}	log	log	ident.	logit
Poisson shifted GIG	PSGIG	{0, 1, 2, . . .}	log	log	logit	logit

Note. μ = mean; σ = variance; ν = skewness; τ = kurtosis.

In order to account for excess zero values in a discrete distribution zero inflated adjusted (or altered) discrete distributions were applied (Rigby et al., 2017). The zero inflated Poisson distribution ZIP(μ, σ) is a discrete mixture of two components: value 0 with probability σ and a Poisson distribution with mean μ with probability $1 - \sigma$. A different parameterization of the zero inflated Poisson distribution is ZIP2(μ, σ). This zero inflated Poisson type 2 distribution is the marginal distribution for Y where $Y \mid \gamma \sim$ PO($\mu\,\gamma$) and $\gamma \sim (1 - \sigma)^{-1}$BI($1,1 - \sigma$). Thus, γ has mean 1 and Y has mean μ. Lastly, another zero inflated distribution is the zero inflated PIG denoted as ZIPIG(μ, σ, ν).

In summary, GAMLSS will answer the two research questions by providing more flexibility in data modeling, as GAMLSS is an extension of the LM, GLM, and GAM. In other words, GAMLSS assumes that the distribution can be any parametric distribution, which gives more flexibility. GAMLSS provides a very general and flexible system for modelling a response variable. In this current study, our response or dependent variables (ISS, OSS, ED) are discrete/count data, and GAMLSS will effectively be able to provide up to four parameters. These parameters of the dependent variable distribution can be modelled using parametric and/or non-parametric smooth functions of explanatory variables.

Chapter 5

RESULTS

The results section will first summarize the demographic characteristics of students randomized to SMARTS and control conditions. The findings of the study are presented in the order of the research questions stated in the method chapter (i.e., SMARTS main effects and moderating effects).

Selection Bias

As shown in Table 7, after randomization, both study conditions were equivalent on all observable demographic characteristics. Table 8 gives the pretest scores by eight different outcome measures, including prosocial behavior, emotion regulation, autonomy, dependability, externalizing, disruptive behavior, social competence, and reading achievement.

The models used in the study controlled for pretest scores on each dependent variable. The groups were equivalent at baseline. Therefore, the randomization of students into the SMARTS or the CC/CICO condition resulted in statistically balanced groups of fifth-grade youth with high levels of externalizing behavior problems at baseline before they had access to the intervention.

Table 7

Demographic information and descriptive statistics of the analysis sample (N = 334)

Variable	Control n = 164	SMARTS n = 170	Total	χ^2	*df*	*p=.05*
Sex				.11	1	.74
Male	117 (71.3%)	124 (72.9%)	241 (72.2%)			
Female	47 (28.7%)	46 (27.1%)	93 (27.8%)			
Race/Ethnicity				2.62	5	.76
White	73 (44.5%)	72 (42.4%)	145 (43.4%)			
Hispanic	7 (4.3%)	9 (5.3%)	16 (4.8%)			
Biracial	17 (10.4%)	17 (10%)	34 (10.2%)			
Black	63 (38.4%)	69 (40.6%)	132 (39.5%)			
Asian	2 (1.2%)	3 (1.8%)	5 (1.5%)			
Other	2 (1.2%)	0 (0.0%)	2 (0.6%)			
Free-Reduced Lunch (FRL)				.01	1	.93
Yes	118 (72%)	123 (72.4%)	241 (72.2%)			
No	46 (28%)	47 (27.6%)	93 (27.8%)			
Special Education (SPED)				.48	1	.49
Yes	51 (31.1%)	47 (27.6%)	98 (28.1%)			
No	113 (68.9%)	123 (72.4%)	236 (71.9%)			
Cohort				.36	3	.95
2016	42 (25.6%)	42 (24.7%)	84 (25.1%)			
2017	53 (32.3%)	53 (31.2%)	106 (31.7%)			
2018	44 (26.8%)	45 (26.5%)	89 (26.6%)			
2019	25 (15.2%)	30 (17.6%)	55 (16.5%)			

Note. *n* indicates sample size. *%* = frequency of the variable.

Table 8

Pretest Scores by Treatment Assignment (N = 334)

	Control (n = 164)		SMARTS (n = 170)					
	M	(*SD*)	*M*	(SD)	*t*(*df*)	*p* = .05	ICC[1]	ICC[2]
Prosoc Bx	3.50	(0.99)	3.50	(1.00)	-.03(315.5)	.97	.20	0.00
Emo Reg	3.72	(0.97)	3.89	(1.02)	1.51(316)	.13	.17	0.00
Acad Comp	2.03	(1.17)	1.88	(1.09)	-1.18(311.3)	.24	.11	0.00

Note. ICC = percentage of variance attributed to classroom level effects; ICC[1] = Teacher-level; ICC[2] = School-level. Prosoc Bx = Prosocial Behavior; Emo Reg = Emotion Regulation; Acad Comp = Academic Competence.

Main Effects

Before discussing the evaluation of SMARTS on ISS, OSS, and ED using GAMLSS, the distributions for these dependent variables are given in Figure 6. Next, selecting a proper GAMLSS models for this study are examined (refer to Table 6). GAMLSS regression coefficients to test the main effects of SMARTS on all outcomes (i.e., ISS, OSS, ED) are presented in Table 9, 10, 11, 12, 13, and 14. The independent variable, SMARTS Treatment was included in each model. In addition, all models included the following student-level predictors: sex, race, free-reduced lunch, and special education.

GAMLSS Model Selection

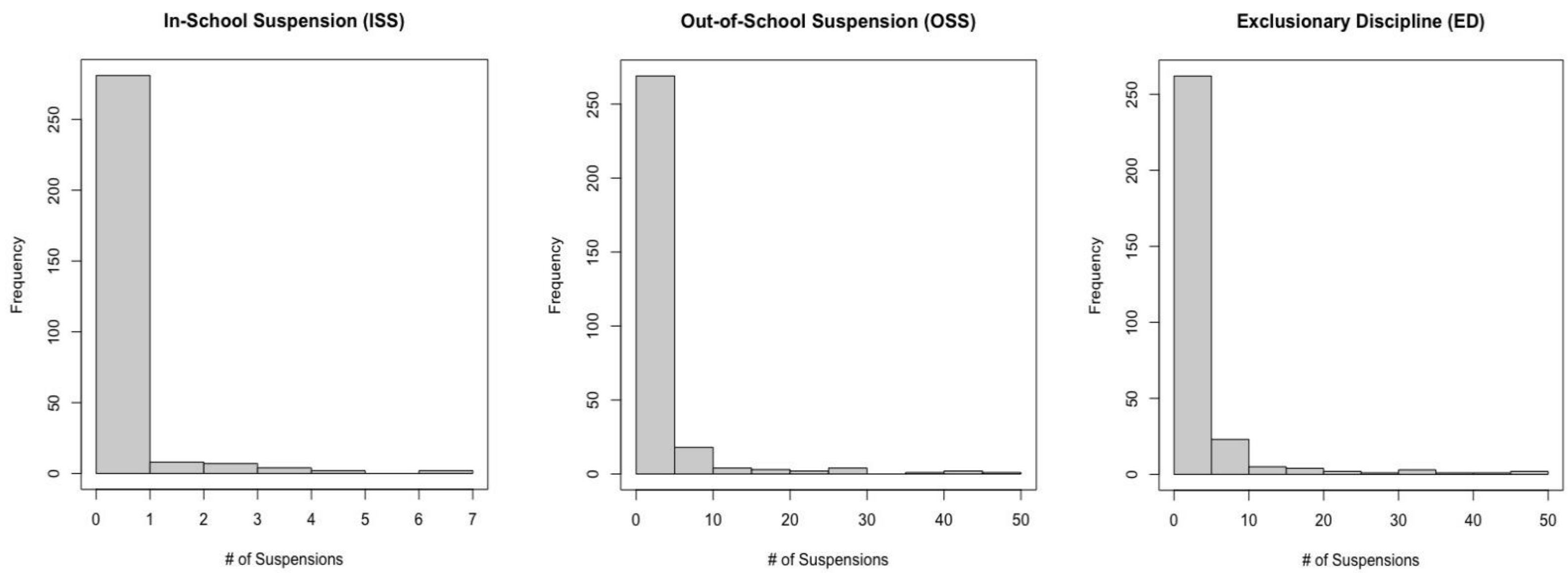
Due to the highly skewed frequency distributions (as shown in Figure 6) of ISS, OSS, and ED, the specific aims of the current study are analyzed using GAMLSS. For this dissertation, GAMLSS offers 33 count distributions including mixed distributions (mixtures of continuous and discrete distributions; Rigby & Stasinopoulos, 2019). Model selection was based on global deviances in the form of generalized Akaike information criterion (GAIC), GAIC(κ) = 2 log L_c + (κ + *df*), with *df* being the total effective degrees of freedom (the effective number of parameters estimated) of the model and κ defines a penalty function (Wiedermann et al., 2022).

The model with the lowest GAIC(κ) value is considered the "best" fitting model to describe the data. Overall, the Zero Altered Logarithmic (ZALG) model showed the best fit (ZALG GAIC = 310.54), and the Negative Binomial Type II (NBII) model showed the second best fit (NBII GAIC = 335.48). Visual model diagnostics were performed using the worm plots, which are used to check local model misspecifications (Wiedermann et al., 2022).

For both, ZALG- and NBII-model, the inspection of the worm plots (see Figure 7) confirmed that, among the 33 count data distributions models, the ZALG-model and NBII-model showed the smallest model-data discrepancies. Therefore, the ZALG-model and NBII-model were selected for the remaining analysis. Given the characteristics of the dependent variables – namely, an excess of zero counts – zero altered logarithmic and negative binomial type II models were selected to address the zero-inflation and explore the mean and variance parameters, respectively. For the ZALG model, the probability of zero suspension parameter quantifies the probability of zero counts.

Figure 6

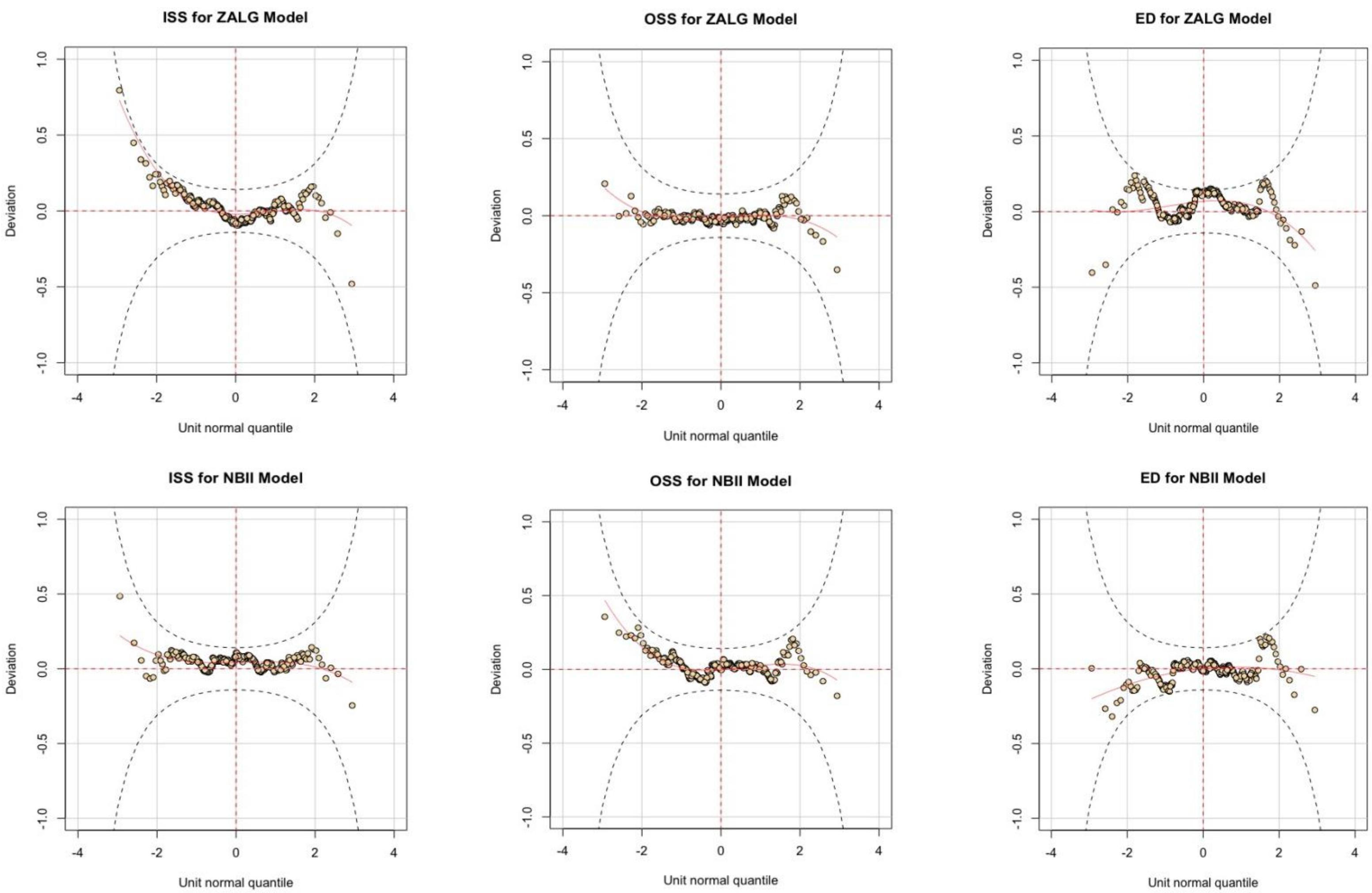
Distributional Features of In-School Suspension (ISS), Out-of-School Suspension (OSS), and Exclusionary Discipline (ED)



Note. Frequency indicates frequency counts of number of suspensions.

Figure 7

Worm Plots for ISS, OSS, and ED for the Zero Altered Logarithmic Model (ZALG; Top Panel) and the Negative Binomial Type II (NBII; Bottom Panel)



Note. Data points along the dashed horizontal line indicate acceptable model fit.

GAMLSS Treatment Effects

In-School Suspension (ISS). First, the SMARTS treatment effects on ISS for the ZALG model were evaluated and the GAMLSS regression coefficients are displayed in Table 9. No significant treatment effects were observed for both the ZALG model and the NBII model of ISS. For other variables in the mean parameter, no significant effects were observed. For the dispersion parameter, female students showed higher variance in ISS compared to male students (*OR* = 1.84), and students receiving free-reduced lunch showed lower variance compared to those not receiving free-reduced lunch (*OR* = 1.11). The coefficients presented in Table 10 are specific to the NBII model. For both the mean and dispersion parameters, no significant treatment effects were observed for ISS. In addition, no significant effects were observed for other variables for ISS.

Out-of-School Suspension (OSS). Table 11 presents the GAMLSS regression coefficients used to evaluate the impact of SMARTS treatment on OSS using the ZALG model. No significant treatment effects were observed on either the ZALG model or NBII model of OSS. For the mean parameter, students receiving free-reduced lunch (*OR* = 5.61) showed higher average suspensions than those not receiving free-reduced lunch. For the dispersion parameter, female students showed higher variance in OSS compared to male students (*OR* = 0.76), and students receiving free-reduced lunch showed lower variance compared to those not receiving free-reduced lunch. Table 12 displays coefficients that are particular to the NBII model.

Table 9

GAMLSS Regression Coefficients of In-School Suspension (ISS) for the Zero Altered Logarithmic (ZALG) model

Variables	Mean parameter μ Mu link function: logit				Probability of Zero Suspension parameter σ Sigma link function: logit			
	Estimate	Standard Error	t-value	p-value	Estimate	Standard Error	t-value	p-value
Intercept	0.94	1.03	0.91	0.36	2.22	0.44	5.01	0.00 ***
SMARTS Treatment	-0.04	0.66	-0.06	0.95	0.06	0.31	0.19	0.85
Sex: Female	0.61	0.95	0.65	0.52	1.15	0.46	2.51	0.01*
Race: Non-White	0.07	0.62	0.11	0.91	-0.36	0.33	-1.07	0.29
Free-reduced lunch	0.11	0.95	0.11	0.91	-0.85	0.42	-1.99	0.04 *
Special education	-0.78	0.69	-1.13	0.26	-0.13	0.34	-0.37	0.71

Note. The racial categories (Hispanic, Biracial, Black, Asian, Other) have been collapsed into the category "Non-White." *p< .05. **p< .01. ***p< .001.

Table 10

GAMLSS Regression Coefficients of In-School Suspension (ISS) for the Negative Binomial Type II (NBII) model

Variables	Mean parameter μ Mu link function: log				Dispersion parameter σ Sigma link function: log			
	Estimate	Standard Error	t-value	p-value	Estimate	Standard Error	t-value	p-value
Intercept	-1.74	0.62	-2.81	0.00 **	0.46	1.52	0.30	0.76
SMARTS Treatment	-0.14	0.48	-0.30	0.77	-0.37	1.18	-0.31	0.76
Sex: Female	-0.61	0.79	-0.77	0.44	1.07	1.37	0.78	0.44
Race: Non-White	0.36	0.39	0.92	0.36	0.13	0.75	0.17	0.86
Free-reduced lunch	0.88	0.63	1.40	0.16	0.35	1.60	0.22	0.83
Special education	-0.16	0.41	-0.38	0.70	-0.70	1.00	-0.70	0.48

Note. The racial categories (Hispanic, Biracial, Black, Asian, Other) have been collapsed into the category "Non-White." *p< .05. **p< .01. ***p< .001.

Table 11

GAMLSS Regression Coefficients of Out-of-School Suspension (OSS) for the Zero Altered Logarithmic (ZALG) model

Variables	Mean parameter μ Mu link function: logit				Probability of Zero Suspension parameter σ Sigma link function: logit			
	Estimate	Standard Error	*t*-value	*p*-value	Estimate	Standard Error	*t*-value	*p*-value
Intercept	1.16	0.48	2.41	0.02 *	1.03	0.32	3.27	0.00 **
SMARTS Treatment	0.31	0.44	0.70	0.49	0.04	0.25	0.16	0.87
Sex: Female	-0.28	0.68	-0.41	0.68	1.11	0.32	3.45	0.00 ***
Race: Non-White	0.38	0.49	0.78	0.44	-0.13	0.26	-0.49	0.63
Free-reduced lunch	1.73	0.60	2.87	0.00 **	-0.83	0.31	-2.70	0.01 **
Special education	-0.45	0.52	-0.85	0.39	-0.04	0.28	-0.13	0.90

Note. The racial categories (Hispanic, Biracial, Black, Asian, Other) have been collapsed into the category "Non-White." **p*< .05. ***p*< .01. ****p*< .001.

Table 12

GAMLSS Regression Coefficients of Out-of-School Suspension (OSS) for the Negative Binomial Type II (NBII) model

Variables	Mean parameter μ Mu link function: log				Dispersion parameter σ Sigma link function: log			
	Estimate	Standard Error	*t*-value	*p*-value	Estimate	Standard Error	*t*-value	*p*-value
Intercept	-0.56	0.33	-1.69	0.09	0.91	0.48	1.90	0.06
SMARTS Treatment	0.19	0.29	0.66	0.51	0.34	0.41	0.83	0.41
Sex: Female	-0.92	0.48	-1.92	0.06	-0.03	0.67	-0.04	0.96
Race: Non-White	0.30	0.32	0.93	0.35	0.26	0.47	0.55	0.58
Free-reduced lunch	1.59	0.38	4.23	0.00 **	1.65	0.62	2.67	0.01 **
Special education	-0.32	0.34	-0.96	0.34	-0.54	0.50	-1.07	0.28

Note. The racial categories (Hispanic, Biracial, Black, Asian, Other) have been collapsed into the category "Non-White." **p*< .05. ***p*< .01. ****p*< .001.

Table 13

GAMLSS Regression Coefficients of Exclusionary Discipline (ED) for the Zero Altered Logarithmic (ZALG) model

Variables	Mean parameter μ Mu link function: logit				Probability of Zero Suspension parameter σ Sigma link function: logit			
	Estimate	Standard Error	*t*-value	*p*-value	Estimate	Standard Error	*t*-value	*p*-value
Intercept	1.59	0.49	3.27	0.001 **	0.99	0.31	3.20	0.001 **
SMARTS Treatment	0.31	0.41	0.75	0.46	0.05	0.25	0.20	0.84
Sex: Female	-0.32	0.60	-0.54	0.59	1.05	0.31	3.44	0.00 ***
Race: Non-White	0.44	0.43	1.04	0.30	-0.23	0.26	0.88	0.38
Free-reduced lunch	1.23	0.54	2.28	0.02 *	-0.95	0.31	-3.15	0.001 **
Special education	-0.30	0.47	-0.65	0.52	-0.01	0.27	-0.02	0.98

Note. The racial categories (Hispanic, Biracial, Black, Asian, Other) have been collapsed into the category "Non-White." *$p < .05$. **$p < .01$. ***$p < .001$.

Table 14

GAMLSS Regression Coefficients of Exclusionary Discipline (ED) for the Negative Binomial Type II (NBII) model

Variables	Mean parameter μ Mu link function: log				Dispersion parameter σ Sigma link function: log			
	Estimate	Standard Error	*t*-value	*p*-value	Estimate	Standard Error	*t*-value	*p*-value
Intercept	-0.30	0.34	-0.90	0.37	1.36	0.47	2.89	0.004 **
SMARTS Treatment	0.19	0.28	0.69	0.49	0.35	0.39	0.90	0.37
Sex: Female	-0.89	0.42	-2.14	0.03 *	-0.10	0.57	-0.18	0.86
Race: Non-White	0.39	0.29	1.38	0.17	0.33	0.40	0.82	0.41
Free-reduced lunch	1.38	0.36	3.82	0.00 ***	1.07	0.54	1.97	0.04 *
Special education	-0.25	0.31	-0.83	0.41	-0.39	0.44	-0.89	0.37

Note. The racial categories (Hispanic, Biracial, Black, Asian, Other) have been collapsed into the category "Non-White." *$p < .05$. **$p < .01$. ***$p < .001$.

Regarding the mean parameter, female students showed lower average suspension rates compared to male students (*RR* = 0.40) and students receiving free-reduced lunch showed higher average suspension rates compared to those not receiving free-reduced lunch (*RR* = 4.92). In relation to the dispersion parameter, students who received free-reduced lunch demonstrated greater variance in comparison to those who did not receive free-reduced lunch.

Exclusionary Discipline (ED). The ZALG model was used to first assess the impact of SMARTS treatment on ED, and Table 13 illustrates the corresponding GAMLSS regression coefficients. There was no significant effect of the SMARTS treatment observed on either the ZALG model or NBII model of ED. In terms of the mean parameter, students who received free-reduced lunch showed higher average suspensions compared to those who did not receive free-reduced lunch (*OR* = 3.43). Regarding the dispersion parameter, female students showed higher values of variance compared to male students (*OR* = 0.72), and those receiving free-reduced lunch showed lower variance compared to those not receiving free-reduced lunch. The coefficients presented in Table 14 are specific to the NBII model. For the mean parameter, female students showed higher average suspensions compared to male students (*RR* = 0.41), and those receiving free-reduced lunch significantly showed higher average suspensions compared to those not receiving free-reduced lunch (*RR* = 3.98). Regarding the dispersion parameter, those receiving free-reduced lunch showed higher variance compared to those not receiving free-reduced lunch. No effects were observed for the other variables.

Moderating Effects

The ZALG model and NBII model did not show any significant moderation effects of prosocial behavior, emotion regulation, and academic competence on the dependent variables (ISS, OSS, and ED) at the $p < .05$ level. Table 15 shows the GAMLSS regression coefficients of prosocial behavior and OSS for the NBII model (see Appendix A for the results of ZALG model). Table 16 displays GAMLSS regression coefficients of prosocial behavior and ED for the NBII model (see Appendix B for the results of ZALG model). The ZALG and NBII regression coefficients for prosocial behavior of ISS are presented in Appendix C and Appendix D, respectively.

Table 17 presents the GAMLSS regression coefficients of emotion regulation and OSS for the NBII model (see Appendix E for the results of ZALG model). Table 18 demonstrates the GAMLSS regression coefficients of emotion regulation and ED for the NBII model (see Appendix F for the results of ZALG model). The ZALG and NBII regression coefficients for emotion regulation of ISS are given in Appendix G and Appendix H, respectively. In addition, Table 19 shows GAMLSS regression coefficients of academic competence and OSS for the NBII model (see Appendix I for the results of ZALG model). Table 20 presents the GAMLSS regression coefficients of academic competence of ED for the NBII model (see Appendix J for the results of ZALG model). Lastly, the ZALG and NBII regression coefficients for academic competence of ISS are displayed in Appendix K and Appendix L, respectively.

Table 15

GAMLSS Coefficients of Prosocial Behavior (Moderation Effects) of Out-of-School Suspension (OSS) for the Negative Binomial Type II (NBII) model

	Mean parameter μ				Dispersion parameter σ			
Variables	Mu link function: log				Sigma link function: log			
	Estimate	Standard Error	*t*-value	*p*-value	Estimate	Standard Error	*t*-value	*p*-value
Intercept	0.77	0.46	1.65	0.09	-1.86	0.70	2.66	0.01 **
SMARTS Treatment	0.45	0.46	0.98	0.33	0.10	0.41	0.25	0.79
Sex: Female	-0.28	0.49	-0.57	0.57	0.77	0.68	1.13	0.26
Race: Non-White	0.35	0.30	1.18	0.24	0.41	0.45	0.92	0.36
Free-reduced lunch	1.48	0.35	4.28	0.00 ***	1.49	0.58	2.55	0.01 **
Special education	-0.44	0.30	-1.48	0.14	-0.85	0.48	-1.76	0.08
Prosocial behavior	-0.75	0.19	-3.98	0.00 ***	-0.63	0.27	-2.38	0.01 **
SMARTS Treatment × Prosocial behavior	-0.25	0.22	-1.16	0.25	N/A	N/A	N/A	N/A

Note. Interaction effect was not tested for the dispersion parameter (i.e., N/A). *p< .05. **p< .01. ***p< .001.

Table 16

GAMLSS Coefficients of Prosocial Behavior (Moderation Effects) of Exclusionary Discipline (ED) for the Negative Binomial Type II (NBII) model

	Mean parameter μ				Dispersion parameter σ			
Variables	Mu link function: log				Sigma link function: log			
	Estimate	Standard Error	*t*-value	*p*-value	Estimate	Standard Error	*t*-value	*p*-value
Intercept	0.96	0.47	2.04	0.04 *	2.31	0.71	3.25	0.01 **
SMARTS Treatment	0.45	0.43	1.05	0.29	0.03	0.39	0.08	0.94
Sex: Female	-0.28	0.44	-0.64	0.52	0.67	0.61	1.10	0.27
Race: Non-White	0.36	0.27	1.34	0.18	0.31	0.39	0.79	0.43
Free-reduced lunch	1.33	0.34	3.93	0.00 ***	0.98	0.52	1.87	0.06
Special education	-0.37	0.28	-1.32	0.19	-0.69	0.43	-1.61	0.11
Prosocial behavior	-0.69	0.18	-3.88	0.00 ***	-0.56	0.26	-2.18	0.03 *
SMARTS Treatment × Prosocial behavior	-0.28	0.20	-1.36	0.17	N/A	N/A	N/A	N/A

Note. Interaction effect was not tested for the dispersion parameter (i.e., N/A). *p< .05. **p< .01. ***p< .001.

Table 17

GAMLSS Coefficients of Emotion Regulation (Moderation Effects) of Out-of-School Suspension (OSS) for the Negative Binomial Type II (NBII) model

Variables	Mean parameter μ Mu link function: log				Dispersion parameter σ Sigma link function: log			
	Estimate	Standard Error	*t*-value	*p*-value	Estimate	Standard Error	*t*-value	*p*-value
Intercept	1.05	0.50	2.12	0.04 *	1.43	0.66	2.16	0.03 *
SMARTS Treatment	0.05	0.51	0.10	0.92	0.22	0.40	0.55	0.59
Sex: Female	-0.45	0.47	-0.97	0.33	0.39	0.64	0.60	0.55
Race: Non-White	0.20	0.30	0.67	0.50	0.27	0.45	0.60	0.55
Free-reduced lunch	1.45	0.35	4.20	0.00 ***	1.67	0.59	2.68	0.005 **
Special education	-0.27	0.31	-0.87	0.39	-0.65	0.48	-1.36	0.17
Emotion regulation	-0.83	0.22	-3.80	0.00 ***	-0.39	0.25	-1.56	0.12
SMARTS Treatment × Emotion regulation	-0.01	0.25	-0.05	0.96	N/A	N/A	N/A	N/A

Note. Interaction effect was not tested for the dispersion parameter (i.e., N/A). $*p< .05$. $**p< .01$. $***p< .001$.

Table 18

GAMLSS Coefficients of Emotion Regulation (Moderation Effects) of Exclusionary Discipline (ED) for the Negative Binomial Type II (NBII) model

Variables	Mean parameter μ Mu link function: log				Dispersion parameter σ Sigma link function: log			
	Estimate	Standard Error	*t*-value	*p*-value	Estimate	Standard Error	*t*-value	*p*-value
Intercept	1.25	0.50	2.45	0.01 *	2.06	0.65	3.17	0.002 **
SMARTS Treatment	0.15	0.48	0.32	0.75	0.12	0.38	0.31	0.75
Sex: Female	-0.44	0.41	-1.08	0.28	0.33	0.57	0.58	0.56
Race: Non-White	0.27	0.27	0.99	0.32	0.26	0.40	0.66	0.51
Free-reduced lunch	1.28	0.33	3.85	0.00 ***	1.13	0.52	2.17	0.03 *
Special education	-0.20	0.29	-0.70	0.48	-0.51	0.44	-1.16	0.25
Emotion regulation	-0.80	0.21	-3.79	0.00 ***	-0.46	0.25	-1.87	0.06
SMARTS Treatment × Emotion regulation	-0.10	0.23	-0.41	0.68	N/A	N/A	N/A	N/A

Note. Interaction effect was not tested for the dispersion parameter (i.e., N/A). $*p< .05$. $**p< .01$. $***p< .001$.

Table 19

GAMLSS Coefficients of Academic Competence (Moderation Effects) of Out-of-School Suspension (OSS) for the NBII model

Variables	Mean parameter μ				Dispersion parameter σ			
	Mu link function: log				Sigma link function: log			
	Estimate	Standard Error	*t*-value	*p*-value	Estimate	Standard Error	*t*-value	*p*-value
Intercept	-0.20	0.53	-0.38	0.70	0.84	0.78	1.07	0.29
SMARTS Treatment	0.57	0.43	1.32	0.19	0.37	0.41	0.90	0.37
Sex: Female	-0.92	0.48	-1.90	0.05 *	-0.05	0.68	-0.08	0.94
Race: Non-White	0.24	0.32	0.76	0.45	0.29	0.47	0.62	0.54
Free-reduced lunch	1.47	0.40	3.63	0.00 ***	1.63	0.68	2.40	0.01 *
Special education	-0.04	0.35	-1.15	0.25	-0.48	0.54	-0.90	0.37
Academic competence	-0.10	0.17	-0.63	0.53	0.02	0.20	0.08	0.94
SMARTS Treatment × Academic competence	-0.24	0.19	-1.29	0.19	N/A	N/A	N/A	N/A

Note. Interaction effect was not tested for the dispersion parameter (i.e., N/A). $^*p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Table 20

GAMLSS Coefficients of Academic Competence (Moderation Effects) of Exclusionary Discipline (ED) for the NBII model

Variables	Mean parameter μ				Dispersion parameter σ			
	Mu link function: log				Sigma link function: log			
	Estimate	Standard Error	*t*-value	*p*-value	Estimate	Standard Error	*t*-value	*p*-value
Intercept	0.13	0.50	0.25	0.80	1.50	0.69	2.17	0.03 *
SMARTS Treatment	0.36	0.40	0.90	0.37	0.35	0.38	0.92	0.36
Sex: Female	-0.85	0.43	-1.99	0.05 *	-0.03	0.59	-0.06	0.95
Race: Non-White	0.34	0.29	1.18	0.24	0.33	0.40	0.82	0.41
Free-reduced lunch	1.27	0.37	3.38	0.00 ***	0.99	0.56	1.76	0.08
Special education	-0.37	0.32	-1.14	0.26	-0.45	0.48	-0.94	0.35
Academic competence	-0.15	0.15	-0.99	0.32	-0.05	0.18	-0.30	0.76
SMARTS Treatment × Academic competence	-0.11	0.17	-0.68	0.49	N/A	N/A	N/A	N/A

Note. Interaction effect was not tested for the dispersion parameter (i.e., N/A). $^*p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Chapter 6

DISCUSSION

The purpose of this dissertation was to examine the effectiveness of SMARTS, a school-based self-monitoring program, by using an innovative analytical approach called, the Generalized Additive Models for Location, Scale, and Shape (GAMLSS). This chapter includes a discussion of major findings as related to the impact of SMARTS on in-school suspension (ISS), out-of-school suspension (OSS), exclusionary discipline (ED), and the SMARTS intervention effect moderated by prosocial behavior, emotion regulation, and academic competence. In addition, the significance and the strengths of the study as well as the implications of the findings are included. The chapter concludes with a discussion of the limitations of the study and areas for future research.

This chapter contains discussion and future research directions to help answer the research questions:

1. Do SMARTS students, compared to control students, have a lower number of in-school suspension (ISS), out-of-school suspension (OSS), and overall exclusionary discipline (ED)?
2. Is the SMARTS intervention effect moderated by baseline prosocial behavior, emotion regulation, and academic competence?

The SMARTS intervention did not show an effect on in-school-suspension (ISS), out-of-school suspension (OSS), and exclusionary discipline (ED) for both the Zero Altered Logarithmic (ZALG) model and the Negative Binomial Type II (NBII) model. However, female students showed higher average suspensions than male students, and students receiving free-reduced lunch showed higher average suspensions than those not receiving free-reduced lunch. No moderation effects (prosocial behavior, emotion regulation, and academic competence) were observed on the dependent variables (ISS, OSS, and ED) for both the ZALG model and the NBII model. Nevertheless, students who exhibited higher levels of prosocial behavior and emotion regulation received lower average suspensions compared to those who exhibited lower levels of these behaviors. All of these investigations were evaluated by using a novel analytical method—GAMLSS.

Interpretation of the Findings

While the SMARTS intervention showed no significant effect, this dissertation shines a critical light on other key factors that lead to students receiving suspensions. For each ISS, OSS, and ED, the ZALG model and the NBII model presented significant underlying implications, which are described in detail in the following sections.

Impact of SMARTS on ISS, OSS, and ED

GAMLSS was used as a distributional regression framework that enables to consider all possible parameters from the four moments, including the mean, variance, skewness, and kurtosis. GAMLSS revealed that the ZALG model and the NBII model are the best-fitted models for the current research data. Both of these models include the two moments—mean (mu [μ]) and variance (sigma [σ]). The results of this study suggest that the SMARTS treatment did not have a significant effect on ISS, OSS, and ED for both the ZALG and NBII models. This suggests that the SMARTS treatment did not have a significant impact on reducing disciplinary actions in the observed schools.

One of the noticeable significances in the findings is that female students showed higher average suspensions and higher values of variance compared to male students. In addition, students receiving free-reduced lunch showed higher average suspensions as well as having both lower and higher values of variance for students receiving free-reduced lunch compared to those not receiving free-reduced lunch. First, these findings indicate that more male students experience suspension than female students. Second, there is more variability or “spread” in the female students’ suspension experiences than male students. This could be due to various factors, such as gender bias, stereotyping, and discrimination, which are consistent with existing research (Skiba et al., 2002; Skiba & Rausch, 2006). Previous literature suggest that male students tend to exhibit more externalizing behaviors, such as aggression and defiance, which are more likely to result in receiving suspension (Skiba et al., 2002; Gregory et al., 2010).

Whereas, female students tend to exhibit more internalizing behaviors, such as anxiety and depression, which may not result in receiving suspension as often as male students (Pike et al., 2005). Another possible explanation could be due to gender biases and stereotypes held by school personnel contributing to these differences in disciplinary actions. For example, if the school personnel have certain biases, such as having lower expectations for female students’ disruptive behaviors and are more likely to excuse or ignore misbehaviors, then these could lead to more variability in disciplinary actions taken against female students (Skiba et al., 2008).

Third, these findings suggest that students from low-income families are more likely to get suspended than higher-income students. Lastly, students from low-income families are more likely to experience consistent disciplinary actions. According to a report from the U.S. Department of Education (2018), low-income students are more likely to experience disciplinary actions (i.e., suspensions and expulsions) than higher-income students. The report also found that students who receive free-reduced lunch, which is often used as an indicator of poverty, are almost twice as likely to be suspended as students who do not receive free-reduced lunch. Additionally, students from low-income families may face challenges, such as hunger, homelessness, and lack of access to healthcare and other essential basic needs, which can all contribute to social, emotional, and behavioral health issues, making it more difficult for those students to succeed in school (Morris & Perry, 2016; U.S. Department of Education, 2018). As such, those who do receive free-reduced lunch may experience more suspension compared to those who do not receive free-reduced lunch.

Overall, the findings indicate that while the SMARTS treatment program may not directly impact ISS, OSS, and ED, there may be underlying socio-economic and gender factors that contribute to suspension. Therefore, the findings highlight the need for schools to take socio-economic and gender disparities into potential consideration that may exist in their disciplinary practices.

SMARTS Intervention and Moderation Effects

In addition to the main treatment effects of ISS, OSS, and ED, the present dissertation evaluated the moderation effects of prosocial behavior, emotion regulation, and academic competence. Here, GAMLSS was also used to determine if the SMARTS intervention effect was moderated by prosocial behavior, emotion regulation, and academic competence. In doing so, both the ZALG and NBII models were employed. The findings showed that neither model (ZALG, NBII) yielded statistically significant moderation effects.

These results suggest that the impact of the SMARTS intervention may be relatively consistent across individuals with different levels of prosocial behavior, emotion regulation, and academic competence. One possible explanation could be simply the fact that the SMARTS treatment itself did not show an effect for both the ZALG and NBII models. Therefore, despite the presence of moderation effects (prosocial behavior, emotion regulation, and academic competence), the SMARTS treatment did not show any significant effect on both the ZALG and NBII models, indicating that these moderators did not enhance the SMARTS treatment's effectiveness. However, it is important to note that prosocial behavior and emotion regulation showed significant effects. In other words, students with higher levels of prosocial behavior had a lower average suspension. Also, students with higher levels of emotion regulation had a lower average suspension.

Prior studies suggest prosocial behavior and emotional regulation are associated with better academic outcomes, including increased academic engagement, higher academic achievement, and greater readiness for academic success (Denham et al., 2014; Durlak et al., 2011; Elias et al., 2003). In addition, research suggest students with higher levels of prosocial behavior were less likely to be suspended or expelled (Skiba et al., 2002). Another study by Bradshaw et al. (2010) found that students with better emotion regulation skills were less likely to engage in externalizing behaviors, such as aggression or challenging behaviors that could lead to suspension or other disciplinary actions. While the current study did not find moderation effects with the SMARTS intervention, it is worth noting that students' prosocial behavior, emotion regulation, and academic competence are important characteristics that should be taken into account for their academic success. Future studies may explore other potential moderating factors to further investigate the impact of the SMARTS intervention.

Implications

The present study provides important insights into the implications of the novel approach used for the analysis, referred to as Generalized Additive Models for Location, Scale, and Shape (GAMLSS). Traditionally, the more common approach for count data is using a Poisson distribution regression or a Negative Binomial regression. Both of these regression models are widely used for count data because they have been extensively studied and their properties are well-understood, which makes them a standard approach for count data analysis in many fields. The common approach of using a Poisson distribution regression or a Negative Binomial regression has a limitation in that it may not accurately capture the properties of the data.

As outlined in the Method section, I located 33 count data distributions, including a Poisson distribution; however, Poisson distribution was not the best fitted model. Traditionally, the Poisson distribution model has been commonly used under the assumption that the data is accurate. However, this assumption may not always hold true, and the use of this model could introduce errors into the calculation and lead to false conclusions about statistical significance. Unlike traditional methods, GAMLSS enabled me to evaluate all 33 count distributions using a statistically rigorous measure, the GAIC, to identify the model that best fit the data. This approach reduced errors and facilitated the detection of signals and important features in the data.

In addition to the advantages outlined earlier, GAMLSS offers even more benefits over traditional methods (Rigby et al., 2017; Wiedermann, 2022). First, GAMLSS can model complex relationships between variables and responses, which goes beyond simple linear or polynomial models. Second, GAMLSS can model non-normal distributions, such as skewed or heavy-tailed distributions. Third, GAMLSS can also model different types of variability, such as over-dispersion, under-dispersion, and heteroscedasticity. Ultimately, GAMLSS is an invaluable tool for social work researchers seeking to better understand an important phenomenon by analyzing and modeling complex data.

Limitations and Recommendations for Future Research

To begin, the implementation of the current study was an issue, in which the control condition was in fact an active control condition. As described in the Method section, the schools were implementing a targeted intervention called the Check-In Check-Out (CICO). The students assigned to the control condition were already receiving the CICO intervention, as it was being implemented by the schools. The fact that the schools were already implementing the CICO intervention is a contributing factor to the lack of effect observed in the SMARTS treatment.

A second limitation of the study is that there were no baselines collected for in-school suspension (ISS), out-of-school suspension (OSS), and exclusionary discipline (ED). Without baselines for these dependent variables, it becomes challenging to determine if any changes in these variables are a result of the intervention or simply due to pre-existing trends or random variation. In other words, the absence of baseline data makes it difficult to establish a causal relationship between the intervention and any observed changes in the dependent variables. Future studies may consider collecting baseline data for ISS, OSS, and ED prior to the implementation of the intervention.

The third limitation of the current study is that it employed an Intent-To-Treat Analysis (ITT) in which students who were assigned to the SMARTS treatment were considered to have received the same treatment as everyone in the treatment group, regardless of whether they actually completed the program. Similarly, those who did not receive the SMARTS treatment were given an alternative intervention (CICO), which may have also impacted the results. Future research can benefit by using an alternative analysis called the Treatment On the Treated (TOT). For example, the TOT analysis focuses on students who actually participate in the SMARTS intervention program. The TOT analysis can provide a more accurate understanding of the treatment effect since it only includes students who take part in the SMARTS intervention program, rather than including all students who were assigned to the treatment group regardless of their actual participation. Therefore, the TOT analysis can help reduce the potential confounding effects of non-compliance or partial compliance with the treatment (Huang, 2018).

The fourth limitation is to be aware of other risk factors that can contribute to students receiving suspensions. For example, risk factors can include racial bias, low socio-economic status, gender, disability status, and the school level-factors that do not account for the daily experiences of students (Okonofua et al., 2016; Losen & Skiba, 2010; Skiba et al., 2014; Shifrer, 2013). It is important to note that these risk factors often intersect each other, leading to even higher rates of suspensions and adverse outcomes for certain groups of students. Future interventions should address these risk factors that can help reduce the likelihood of students receiving suspensions and overall negative outcomes.

Lastly, while the GAMLSS framework offers flexibility to evaluate a complex data, it also presents several potential pitfalls. The first step of selecting an appropriate model can be a challenging task (Wiedermann et al., 2022). For the present study, due to the structure of the data, I did not account for the nested data. Since the intraclass correlation (ICC) was fairly low for the dependent variables (ISS, OSS, and ED), the nested data was not taken into consideration.

Additionally, I attempted to compute bootstrapping initially, but found the data to be not feasible due to the inherent structure of the data. Due to its complexity, GAMLSS models can encounter convergence problems, which was the case for the current study. According to Wiedermann et al. (2022), convergence problems are common issues in complex regression models, such as mixed effects and structural equation models. Several factors can lead to nonconvergence, including inadequate number of iterations, excessive model parameters, insufficient sample size, and misspecification of additive terms, such as random effects (Wiedermann et al., 2022). To address nonconvergence issues in the present study, I was able to resolve the problem by increasing the number of iterations and reducing the number of model parameters. Future research may consider accounting for the nested data and performing a bootstrap analysis to build more accurate models.

Significance of the Current Study

A central strength of the current study is its use of an innovative analytic method known as the Generalized Additive Models for Location, Scale, and Shape (GAMLSS). GAMLSS is a statistical modeling technique that can be applied to a wide range of social sciences and beyond. Its flexibility allows it to model any distribution from the four moments: mean, variance, skewness, and kurtosis. Its flexibility also allows the distribution to be continuous, binary, count, and categorical outcomes, making it versatile tool for analyzing complex data.

GAMLSS can be applied to other social science fields, such as education research, health and medical research, psychology research, sociology research, environmental and ecological research, political science research, and social work research. GAMLSS has several potential applications in the field of social work. For example, GAMLSS can be used to model outcomes, such as mental health symptoms, substance use, and quality of life, to evaluate the impact of social work interventions on various outcomes, to model student achievement data and the impact of school interventions on academic outcomes, to examine child abuse or domestic violence, and to explore patterns of service use among different groups of clients (Rigby et al., 2017; Wiedermann, 2022). However, the applications of GAMLSS are not limited to these fields, and it could be used in any area where there is a need for flexible and robust statistical modeling of complex data.

Therefore, the use of GAMLSS offers a new perspective in examining the data and brings in unique and creative analytic strategies to understand the data. GAMLSS is a novel approach to examine how a targeted intervention has an impact on exclusionary discipline among children with challenging behaviors. To my knowledge, GAMLSS has not been widely used in social work research. GAMLSS has the potential to bring novel ideas to social work research. This innovative statistical approach aligns with the social work research and practice.

Conclusion

Although the SMARTS intervention did not show an effect for the current study, the treatment has shown effect in previous studies (Thompson, 2014; Thompson et al., 2020; Thompson et al., 2012). Therefore, it is still important for school personnel to help students develop self-managed and self-regulated positive and prosocial behaviors through strategies, such as promoting student autonomy, direct instruction in relevant skills, and opportunities to practice their goals. More importantly, approaches that highlight self-monitoring and providing supportive feedback can have long-lasting benefits for students both in school and beyond.

In order to effectively examine these intervention programs, applying a novel, robust, and pioneering analytic approach, such as GAMLSS, would introduce innovative ideas to social work research and practice. To conclude, the findings of this dissertation suggest that by applying GAMLSS, researchers and practitioners can gain new insights into the effectiveness of school-based interventions or social work interventions and improve their ability to develop evidence-based policies and programs to address complex social problems.

References

American Academy of Pediatrics Committee on Children with Disabilities. (2001). Policy statement: Developmental surveillance and screening of infants and young children. *Pediatrics, 108*(1), 192–196.

Agnew, R. (1985). Social Control Theory And Delinquency: A Longitudinal Test. *Criminology*, *23*(1), 47–62.

American Psychological Association. (2022). *The Pathway from Exclusionary Discipline to the School to Prison Pipeline*. American Psychological Association.

Arnold, D. H., Ortiz, C., Curry, J. C., Stowe, R. M., Goldstein, N. E., Fisher, P. H., Zeljo, A., & Yershova, K. (1999). *Promoting academic success and preventing disruptive behavior disorders through community partnership*. 10.

Bandura, A. (1973). *Aggression: A social learning analysis.* (pp. ix, 390). Prentice-Hall.

Bandura, A. (1977). Self-efficacy: Toward a Unifying Theory of Behavioral Change. *Psychological Review*, *84*, 25.

Blair, K.-S. C., Fox, L., & Lentini, R. (2010). Use of Positive Behavior Support to Address the Challenging Behavior of Young Children Within a Community Early Childhood Program. *Topics in Early Childhood Special Education*, *30*(2), 68–79. https://doi.org/10.1177/0271121410372676

Bradshaw, C. P., Mitchell, M. M., & Leaf, P. J. (2010). Examining the effects of schoolwide positive behavioral interventions and supports on student outcomes: Results from a randomized controlled effectiveness trial in elementary schools. *Journal of Positive Behavior Interventions*, *12*(3), 133-148.

Brown, E. C., Catalano, R. F., Fleming, C. B., Haggerty, K. P., Abbott, R. D., Cortes, R. R., & Park, J. (2005). Mediator effects in the social development model: An examination of constituent theories. *Criminal Behaviour and Mental Health*, *15*(4), 221–235. https://doi.org/10.1002/cbm.27

Buuren, S. van, & Fredriks, M. (2001). Worm plot: A simple diagnostic device for modelling growth reference curves. *Statistics in Medicine*, *20*(8), 1259–1277. https://doi.org/10.1002/sim.746

Carter, M., Clayton, M., & Stephenson, J. (2006). Students With Severe Challenging Behaviour in Regular Classrooms: Prevalence and Characteristics. *Australian Journal of Guidance and Counselling*, *16*(2), 189–209. https://doi.org/10.1375/ajgc.16.2.189

Cohen, D. R., Lewis, C., Eddy, C. L., Henry, L., Hodgson, C., Huang, F. L., Reinke, W. M., & Herman, K. C. (2021). In-School and Out-of-School Suspension: Behavioral and Psychological Outcomes in a Predominately Black Sample of Middle School Students. *School Psychology Review*, 1–14. https://doi.org/10.1080/2372966X.2020.1856628

Conroy, M. A., Dunlap, G., Clarke, S., & Alter, P. J. (2005). A Descriptive Analysis of Positive Behavioral Intervention Research With Young Children With Challenging Behavior. *Topics in Early Childhood Special Education, 25*(3), 157–166. https://doi.org/10.1177/02711214050250030301

Demirtaş-Zorbaz, S., & Ergene, T. (2019). School adjustment of first-grade primary school students: Effects of family involvement, externalizing behavior, teacher and peer relations. *Children and Youth Services Review*, *101*, 307–316. https://doi.org/10.1016/j.childyouth.2019.04.019

Denham, S. A., Bassett, H. H., & Wyatt, T. M. (2014). The socialization of emotional competence. In *Handbook of socialization: Theory and research* (pp. 208-241). Guilford Press.

Dunlap, G., Strain, P. S., Fox, L., Carta, J. J., Conroy, M., Smith, B. J., Kern, L., Hemmeter, M. L., Timm, M. A., Mccart, A., Sailor, W., Markey, U., Markey, D. J., Lardieri, S., & Sowell, C. (2006). Prevention and Intervention with Young Children's Challenging Behavior: Perspectives regarding Current Knowledge. *Behavioral Disorders*, *32*(1), 29–45. https://doi.org/10.1177/019874290603200103

Durand, V. M., Hieneman, M., Clarke, S., Wang, M., & Rinaldi, M. L. (2013). Positive Family Intervention for Severe Challenging Behavior I: A Multisite Randomized Clinical Trial. *Journal of Positive Behavior Interventions*, *15*(3), 133–143. https://doi.org/10.1177/1098300712458324

Durlak, J. A., Weissberg, R. P., Dymnicki, A. B., Taylor, R. D., & Schellinger, K. B. (2011). The Impact of Enhancing Students' Social and Emotional Learning: A Meta-Analysis of School-Based Universal Interventions: Social and Emotional Learning. *Child Development, 82*(1), 405–432. https://doi.org/10.1111/j.1467-8624.2010.01564.x

Durlak, J. A., Weissberg, R. P., Dymnicki, A. B., Taylor, R. D., & Schellinger, K. B. (2011). The impact of enhancing students' social and emotional learning: A meta-analysis of school-based universal interventions. *Child development*, *82*(1), 405-432

Eddy, C. L., Huang, F. L., Cohen, D. R., Baker, K. M., Edwards, K. D., Herman, K. C., & Reinke, W. M. (2020). Does Teacher Emotional Exhaustion and Efficacy Predict Student Discipline Sanctions? *School Psychology Review*, *49*(3), 239–255. https://doi.org/10.1080/2372966X.2020.1733340

Elias, M. J., Zins, J. E., Graczyk, P. A., & Weissberg, R. P. (2003). Implementation, sustainability, and scaling up of social-emotional and academic innovations in public schools. *School psychology review*, *32*(3), 303-319.

Emerson, E., Blacher, J., Einfeld, S., Hatton, C., Robertson, J., & Stancliffe, R. J. (2014). Environmental risk factors associated with the persistence of conduct difficulties in children with intellectual disabilities and autistic spectrum disorders. *Research in Developmental Disabilities*, *35*(12), 3508–3517. https://doi.org/10.1016/j.ridd.2014.08.039

Emerson, E., Kiernan, C., Alborz, A., Reeves, D., Mason, H., Swarbrick, R., Mason, L., & Hatton, C. (2001). The prevalence of challenging behaviors: A total population study. *Research in Developmental Disabilities*, *22*(1), 77–93. https://doi.org/10.1016/S0891-4222(00)00061-5

Feil, E. G., Frey, A., Walker, H. M., Small, J. W., Seeley, J. R., Golly, A., & Forness, S. R. (2014). The Efficacy of a Home-School Intervention for Preschoolers With Challenging Behaviors: A Randomized Controlled Trial of Preschool First Step to Success. *Journal of Early Intervention*, *36*(3), 151–170. https://doi.org/10.1177/1053815114566090

Fenning, P. A., Pulaski, S., Gomez, M., Morello, M., Maciel, L., Maroney, E., Schmidt, A., Dahlvig, K., McArdle, L., Morello, T., Wilson, R., Horwitz, A., & Maltese, R. (2012). Call to Action: A Critical Need for Designing Alternatives to Suspension and Expulsion. *Journal of School Violence*, *11*(2), 105–117. https://doi.org/10.1080/15388220.2011.646643

Granja, M. R., Smith, S., Nguyen, U. S., & Grifa, B. (2018). *Learning about Young Children's Challenging Behavior and Impacts on Programs and Families: A State-wide Survey of Virginia's Early Care and Education Teachers*. 18.

Gregory, A., Skiba, R. J., & Noguera, P. A. (2010). The achievement gap and the discipline gap: Two sides of the same coin? *Educational Researcher*, 39(1), 59-68.

Hawkins, J. D., & Weis, J. G. (1985). The social development model: An integrated approach to delinquency prevention. *Journal of Primary Prevention*, *6*(2), 73–97. https://doi.org/10.1007/BF01325432

Hay, D. F., Waters, C. S., Perra, O., Swift, N., Kairis, V., Phillips, R., Jones, R., Goodyer, I., Harold, G., Thapar, A., & van Goozen, S. (2014). Precursors to aggression are evident by 6 months of age. *Developmental Science*, *17*(3), 471–480. https://doi.org/10.1111/desc.12133

Herman, K. C., Hickmon-Rosa, J., & Reinke, W. M. (2018). Empirically Derived Profiles of Teacher Stress, Burnout, Self-Efficacy, and Coping and Associated Student Outcomes. *Journal of Positive Behavior Interventions*, *20*(2), 90–100. https://doi.org/10.1177/1098300717732066

Hirschi, T. (1969). Causes of delinquency. *Berkeley: University of California Press*.

Holmes, S. R., Thompson, A. M., Herman, K. C., & Reinke, W. M. (2021). Designing Interventions for Implementation in Schools: A Multimethod Investigation of Fidelity of a Self-Monitoring Intervention. *School Psychology Review*, *50*(1), 42–51. https://doi.org/10.1080/2372966X.2020.1870868

Huang, F. L. (2018). Using Instrumental Variable Estimation to Evaluate Randomized Experiments with Imperfect Compliance. *Practical Assessment, Research, and Evaluation: 23*(2). https://doi.org/10.7275/k0p6-yj16

Humphries, M. L., Williams, B. V., & May, T. (2018). Early Childhood Teachers' Perspectives on Social-Emotional Competence and Learning in Urban Classrooms. *Journal of Applied School Psychology*, *34*(2), 157–179. https://doi.org/10.1080/15377903.2018.1425790

Kaiser, T., Li, J., Pollmann-Schult, M., & Song, A. (2017). Poverty and Child Behavioral Problems: The Mediating Role of Parenting and Parental Well-Being. *International Journal of Environmental Research and Public Health*, *14*(9), 981. https://doi.org/10.3390/ijerph14090981

Kim, Y., Lee, S., Jung, H., Jaime, J., & Cubbin, C. (2019). Is neighborhood poverty harmful to every child? Neighborhood poverty, family poverty, and behavioral problems among young children. *Journal of Community Psychology*, *47*(3), 594–610. https://doi.org/10.1002/jcop.22140

Koritsas, S., & Iacono, T. (2012). Challenging behaviour: The causes (part II). *Advances in Mental Health and Intellectual Disabilities*, *6*(5), 236–248. https://doi.org/10.1108/20441281211261122

Losen, D. J., & Skiba, R. J. (2010). Suspended education: Urban middle schools in crisis.

Matsueda, R. L. (1988). *The Current State of Differential Association Theory*. 31.

Mazza, J. R., Pingault, J.-B., Booij, L., Boivin, M., Tremblay, R., Lambert, J., Zunzunegui, M. V., & Côté, S. (2017). Poverty and behavior problems during early childhood: The mediating role of maternal depression symptoms and parenting. *International Journal of Behavioral Development*, *41*(6), 670–680. https://doi.org/10.1177/0165025416657615

Morris, E. W., & Perry, B. L. (2016). The punishment gap: School suspension and racial disparities in achievement. *Social Problems*, *63*(1), 68-86.

Okonofua, J. A., Walton, G. M., & Eberhardt, J. L. (2016). A vicious cycle: A social–psychological account of extreme racial disparities in school discipline. *Perspectives on Psychological Science*, *11*(3), 381-398.

Pike, A., Coldwell, J., & Dunn, J. F. (2005). Sibling relationships in early/middle childhood: links with individual adjustment. *Journal of Family Psychology*, *19*(4), 523.

Powell, D., Dunlap, G., & Fox, L. (2006). Prevention and Intervention for the Challenging Behaviors of Toddlers and Preschoolers: *Infants & Young Children*, *19*(1), 25–35. https://doi.org/10.1097/00001163-200601000-00004

Ren, L., Hu, B. Y., & Song, Z. (2019). Child routines mediate the relationship between parenting and social-emotional development in Chinese children. *Children and Youth Services Review*, *98*, 1–9. https://doi.org/10.1016/j.childyouth.2018.12.016

Rigby, R., Stasinopoulos, M., Heller, G., & Bastiani, F. D. (2017). *Distributions for Modelling Location, Scale and Shape: Using GAMLSS in R*. 378.

Ryan, R. M., & Deci, E. L. (2000). Intrinsic and Extrinsic Motivations: Classic Definitions and New Directions. *Contemporary Educational Psychology*, *25*(1), 54–67. https://doi.org/10.1006/ceps.1999.1020

Ryan, R. M., & Deci, E. L. (2017). *Self-Determination Theory: Basic Psychological Needs in Motivation, Development, and Wellness*. The Guilford Press; eBook Collection (EBSCOhost). http://proxy.mul.missouri.edu/login?url=https://search.ebscohost.com/login.aspx?direct=true&db=nlebk&AN=1443574&site=eds-live&scope=site

Shifrer, D. (2013). Stigma of a label: Educational expectations for high school students labeled with learning disabilities. *Journal of health and social behavior*, *54*(4), 462-480.

Simó-Pinatella, D., Mumbardó-Adam, C., Alomar-Kurz, E., Sugai, G., & Simonsen, B. (2019). Prevalence of Challenging Behaviors Exhibited by Children with Disabilities: Mapping the Literature. *Journal of Behavioral Education*, *28*(3), 323–343. https://doi.org/10.1007/s10864-019-09326-9

Skiba, R. J., Michael, R. S., Nardo, A. C., & Peterson, R. L. (2002). The color of discipline: Sources of racial and gender disproportionality in school punishment. *The Urban Review*, 34(4), 317-342.

Skiba, R. J., & Rausch, M. K. (2006). Zero tolerance, suspension, and expulsion: Questions of equity and effectiveness. *Institute for Educational Leadership*, 20, 1-15.

Skiba, R. J., Reynolds, C. R., Graham, S., Sheras, P. L., Conoley, J. C., & Garcia-Vazquez, E. (2006). Are zero tolerance policies effective in the schools?: An evidentiary review and recommendations. *American Psychologist*, 61(9), 852-862.

Skiba, R. J., Arredondo, M. I., & Williams, N. T. (2014). More Than a Metaphor: The Contribution of Exclusionary Discipline to a School-to-Prison Pipeline. *Equity & Excellence in Education*, *47*(4), 546–564. https://doi.org/10.1080/10665684.2014.958965

Skiba, R. J., Horner, R. H., Chung, C.-G., Rausch, M. K., May, S. L., & Tobin, T. (2011). Race Is Not Neutral: A National Investigation of African American and Latino Disproportionality in School Discipline. *School Psychology Review*, *40*(1), 85–107. https://doi.org/10.1080/02796015.2011.12087730

Skiba, R. J., Simmons, A. B., Ritter, S., Gibb, A. C., Rausch, M. K., Cuadrado, J., & Chung, C.-G. (2008). Achieving Equity in Special Education: History, Status, and Current Challenges. *Exceptional Children*, *74*(3), 264–288. https://doi.org/10.1177/001440290807400301

Stasinopoulos, M. D., Rigby, R. A., & Bastiani, F. D. (2018). GAMLSS: A distributional regression approach. *Statistical Modelling*, *18*(3–4), 248–273. https://doi.org/10.1177/1471082X18759144

Sullivan, C. J., & Hirschfield, P. (2011). Problem Behavior in the Middle School Years: An Assessment of the Social Development Model. *Journal of Research in Crime and Delinquency*, *48*(4), 566–593. https://doi.org/10.1177/0022427810395149

Thompson, A. M. (2014). A Randomized Trial of the *Self-Management Training and Regulation Strategy* for Disruptive Students. *Research on Social Work Practice, 24*(4), 414–427. https://doi.org/10.1177/1049731513509691

Thompson, A. M., Wiedermann, W., Herman, K. C., & Reinke, W. M. (2021). Effect of Daily Teacher Feedback on Subsequent Motivation and Mental Health Outcomes in Fifth Grade Students: A Person-Centered Analysis. *Prevention Science*, *22*(6), 775–785. https://doi.org/10.1007/s11121-020-01097-4

U.S. Department of Education. (2018). The role of disciplinary action in schools. Retrieved from https://www.ed.gov/news/press-releases/role-disciplinary-action-schools

Wang, Y., & Zhou, X. (2019). Longitudinal relations between executive function and internalizing problems in grade school: The role of peer difficulty and academic performance. *Developmental Psychology*, *55*(10), 2147–2158. https://doi.org/10.1037/dev0000790

Wiedermann, W., Zhang, B., Reinke, W., Herman, K. C., & Eye, A. von. (2022). Distributional causal effects: Beyond an “averagarian” view of intervention effects. *Psychological Methods*. https://doi.org/10.1037/met0000533

Willner, C. J., Gatzke-Kopp, L. M., & Bray, B. C. (2016). The dynamics of internalizing and externalizing comorbidity across the early school years. *Development and Psychopathology*, *28*(4pt1), 1033–1052. https://doi.org/10.1017/S0954579416000687

Wood, B. K., Ferro, J. B., Umbreit, J., & Liaupsin, C. J. (2011). Addressing the Challenging Behavior of Young Children Through Systematic Function-Based Intervention. *Topics in Early Childhood Special Education*, *30*(4), 221–232. https://doi.org/10.1177/0271121410378759

Yu, J. W., Buka, S. L., McCormick, M. C., Fitzmaurice, G. M., & Indurkhya, A. (2006). Behavioral Problems and the Effects of Early Intervention on Eight-Year-Old Children with Learning Disabilities. *Maternal and Child Health Journal*, *10*(4), 329–338. https://doi.org/10.1007/s10995-005-0066-7

Zahrt, D. M., & Melzer-Lange, M. D. (2011). Aggressive Behavior in Children and Adolescents. *Pediatrics in Review*, *32*(8), 325–332. https://doi.org/10.1542/pir.32-8-325

Zins, J. E., & Elias, M. J. (2006). Social and Emotional Learning. In G. G. Bear & K. M. Minke (Eds.) Children's needs III: Development, prevention, and intervention. *National Association of School Psychologists.*

Zins, J. E., Bloodworth, M. R., Weissberg, R. P., & Walberg H. J. (2004). The Scientific Base Linking Social and Emotional Learning to School Success. *Journal of Educational and Psychological Consultation*, *17*(2), 191-210.

Appendix A

Prosocial Behavior of Out-of-School Suspension

GAMLSS Coefficients of Prosocial Behavior (Moderation Effects) of Out-of-School Suspension (OSS) for the Zero Altered Logarithmic (ZALG) model

Variables	Mean parameter μ Mu link function: logit				Probability of Zero Suspension parameter σ Sigma link function: logit			
	Estimate	Standard Error	*t*-value	*p*-value	Estimate	Standard Error	*t*-value	*p*-value
Intercept	2.16	0.71	3.03	0.002 **	-0.29	0.42	-0.68	0.49
SMARTS Treatment	0.70	1.09	0.64	0.52	0.10	0.26	0.39	0.69
Sex: Female	0.34	0.69	0.49	0.63	0.90	0.33	2.70	0.007 **
Race: Non-White	0.39	0.50	0.79	0.43	-0.08	0.27	-0.28	0.78
Free-reduced lunch	1.53	0.60	2.54	0.01 **	-0.88	0.32	-2.75	0.006 **
Special education	-0.61	0.51	-1.19	0.24	-0.06	0.29	-0.20	0.84
Prosocial behavior	-0.58	0.33	-1.73	0.08	0.69	0.15	4.49	0.00 ***
SMARTS Treatment × Prosocial behavior	-0.35	0.60	-0.58	0.56	N/A	N/A	N/A	N/A

Note. Interaction effect was not tested for the dispersion parameter (i.e., N/A). *p< .05. **p< .01. ***p< .001.

Appendix B

Prosocial Behavior of Exclusionary Discipline

GAMLSS Coefficients of Prosocial Behavior (Moderation Effects) of Exclusionary Discipline (ED) for the Zero Altered Logarithmic (ZALG) model

Variables	Mean parameter μ Mu link function: logit				Probability of Zero Suspension parameter σ Sigma link function: logit			
	Estimate	Standard Error	*t*-value	*p*-value	Estimate	Standard Error	*t*-value	*p*-value
Intercept	2.52	0.72	3.52	0.00 ***	-0.35	0.42	-0.83	0.41
SMARTS Treatment	0.80	1.01	0.79	0.43	0.12	0.26	0.46	0.64
Sex: Female	0.28	0.63	0.45	0.65	0.85	0.32	2.7	0.008 **
Race: Non-White	0.32	0.44	0.72	0.47	-0.18	0.27	-0.68	0.49
Free-reduced lunch	1.05	0.56	1.86	0.06	-1.01	0.32	-3.22	0.001 ***
Special education	-0.43	0.47	-0.92	0.36	-0.03	0.29	-0.09	0.92
Prosocial behavior	-0.47	0.31	-1.51	0.13	0.70	0.15	4.62	0.00 ***
SMARTS Treatment × Prosocial behavior	-0.42	0.55	-0.78	0.44	N/A	N/A	N/A	N/A

Note. Interaction effect was not tested for the dispersion parameter (i.e., N/A). *$p < .05$. **$p < .01$. ***$p < .001$.

Appendix C

Prosocial Behavior of In-School Suspension for the ZALG Model

GAMLSS Coefficients of Prosocial Behavior (Moderation Effects) of In-School Suspension (ISS) for the Zero Altered Logarithmic (ZALG) model

	Mean parameter μ				Probability of Zero Suspension parameter σ			
Variables	Mu link function: logit				Sigma link function: logit			
	Estimate	Standard Error	*t*-value	*p*-value	Estimate	Standard Error	*t*-value	*p*-value
Intercept	0.27	1.34	0.20	0.84	1.15	0.54	2.14	0.03 *
SMARTS Treatment	2.37	1.65	1.43	0.15	0.12	0.32	0.36	0.72
Sex: Female	1.59	1.21	1.31	0.19	0.93	0.47	1.99	0.04 *
Race: Non-White	0.26	0.66	0.39	0.69	-0.33	0.34	-0.97	0.33
Free-reduced lunch	-0.43	1.08	-0.40	0.69	-0.86	0.43	-2.00	0.04 *
Special education	-1.07	0.73	-1.45	0.15	-0.15	0.35	-0.43	0.66
Prosocial behavior	0.57	0.62	0.93	0.35	0.59	0.19	3.14	0.001 **
SMARTS Treatment × Prosocial behavior	-1.69	0.97	-1.75	0.08	N/A	N/A	N/A	N/A

Note. Interaction effect was not tested for the dispersion parameter (i.e., N/A). **p*< .05. ***p*< .01. ****p*< .001.

Appendix D

Prosocial Behavior of In-School Suspension for the NBII Model

GAMLSS Coefficients of Prosocial Behavior (Moderation Effects) of In-School Suspension (ISS) for the Negative Binomial Type II (NBII) model

Variables	Mean parameter μ Mu link function: log				Dispersion parameter σ Sigma link function: log			
	Estimate	Standard Error	*t*-value	*p*-value	Estimate	Standard Error	*t*-value	*p*-value
Intercept	-0.99	0.76	-1.30	0.20	0.41	1.45	0.28	0.78
SMARTS Treatment	0.18	0.81	0.22	0.83	-1.46	1.10	-1.33	0.19
Sex: Female	0.14	0.92	0.15	0.88	2.37	1.60	1.48	0.14
Race: Non-White	0.37	0.36	1.02	0.31	0.14	0.79	0.18	0.86
Free-reduced lunch	1.05	0.47	2.22	0.03 *	1.15	1.21	0.95	0.34
Special education	-0.03	0.36	-0.08	0.94	-0.47	0.93	-0.51	0.61
Prosocial behavior	-0.47	0.35	-1.35	0.18	-0.32	0.68	-0.47	0.64
SMARTS Treatment × Prosocial behavior	-0.40	0.36	-1.11	0.27	N/A	N/A	N/A	N/A

Note. Interaction effect was not tested for the dispersion parameter (i.e., N/A). *p< .05. **p< .01. ***p< .001.

Appendix E

Emotion Regulation of Out-of-School Suspension

GAMLSS Coefficients of Emotion Regulation (Moderation Effects) of Out-of-School Suspension (OSS) for the Zero Altered Logarithmic (ZALG) model

	Mean parameter μ				Probability of Zero Suspension parameter σ			
Variables	Mu link function: logit				Sigma link function: logit			
	Estimate	Standard Error	*t*-value	*p*-value	Estimate	Standard Error	*t*-value	*p*-value
Intercept	1.96	0.77	2.53	0.01 *	-0.74	0.48	-1.54	0.12
SMARTS Treatment	0.37	1.07	0.34	0.73	0.15	0.26	0.57	0.57
Sex: Female	0.06	0.68	0.09	0.93	0.85	0.33	2.52	0.01 *
Race: Non-White	0.30	0.49	0.61	0.54	-0.00	0.28	-0.00	0.99
Free-reduced lunch	1.64	0.61	2.68	0.008 **	-0.70	0.32	-2.16	0.03 *
Special education	-0.46	0.51	-0.90	0.37	-0.17	0.29	-0.58	0.56
Emotion regulation	-0.45	0.41	-1.11	0.27	0.84	0.18	4.76	0.00 ***
SMARTS Treatment × Emotion regulation	-0.09	0.57	-0.16	0.87	N/A	N/A	N/A	N/A

Note. Interaction effect was not tested for the dispersion parameter (i.e., N/A). *p< .05. **p< .01. ***p< .001.

Appendix F

Emotion Regulation of Exclusionary Discipline

GAMLSS Coefficients of Emotion Regulation (Moderation Effects) of Exclusionary Discipline (ED) for the Zero Altered Logarithmic (ZALG) model

Variables	Mean parameter μ Mu link function: logit				Probability of Zero Suspension parameter σ Sigma link function: logit			
	Estimate	Standard Error	*t*-value	*p*-value	Estimate	Standard Error	*t*-value	*p*-value
Intercept	2.49	0.79	3.17	0.002 **	-0.78	0.48	-1.61	0.11
SMARTS Treatment	0.41	1.07	0.39	0.70	0.16	0.26	0.61	0.54
Sex: Female	-0.01	0.60	-0.02	0.99	0.80	0.32	2.48	0.01 *
Race: Non-White	0.30	0.44	0.67	0.49	-0.11	0.27	-0.43	0.67
Free-reduced lunch	1.19	0.56	2.14	0.03 *	-0.83	0.32	-2.60	0.009 **
Special education	-0.30	0.47	-0.63	0.53	-0.13	0.29	-0.46	0.64
Emotion regulation	-0.49	0.40	-1.22	0.23	0.83	0.17	4.78	0.00 ***
SMARTS Treatment × Emotion regulation	-0.16	0.56	-0.28	0.78	N/A	N/A	N/A	N/A

Note. Interaction effect was not tested for the dispersion parameter (i.e., N/A). *$p < .05$. **$p < .01$. ***$p < .001$.

Appendix G

Emotion Regulation of In-School Suspension for the ZALG Model

GAMLSS Coefficients of Emotion Regulation (Moderation Effects) of In-School Suspension (ISS) for the Zero Altered Logarithmic (ZALG) model

Variables	Mean parameter μ Mu link function: logit				Probability of Zero Suspension parameter σ Sigma link function: logit			
	Estimate	Standard Error	*t*-value	*p*-value	Estimate	Standard Error	*t*-value	*p*-value
Intercept	2.07	2.11	0.98	0.33	0.75	0.59	1.26	0.21
SMARTS Treatment	1.66	2.09	0.79	0.43	0.16	0.32	0.49	0.62
Sex: Female	1.81	1.15	1.57	0.12	0.89	0.47	1.91	0.06
Race: Non-White	-0.22	0.72	-0.31	0.76	-0.25	0.35	-0.68	0.47
Free-reduced lunch	-0.13	1.02	-0.13	0.89	-0.73	0.44	-3.22	0.09
Special education	-1.03	0.75	-1.37	0.17	-0.26	0.35	-0.09	0.47
Emotion regulation	-0.42	0.91	-0.46	0.65	0.73	0.21	4.62	0.00 ***
SMARTS Treatment × Emotion regulation	-1.63	1.33	-1.23	0.22	N/A	N/A	N/A	N/A

Note. Interaction effect was not tested for the dispersion parameter (i.e., N/A). *$p < .05$. **$p < .01$. ***$p < .001$.

Appendix H

Emotion Regulation of In-School Suspension for the NBII Model

GAMLSS Coefficients of Emotion Regulation (Moderation Effects) of In-School Suspension (ISS) for the Negative Binomial Type II (NBII) model

Variables	Mean parameter μ Mu link function: log				Dispersion parameter σ Sigma link function: log			
	Estimate	Standard Error	*t*-value	*p*-value	Estimate	Standard Error	*t*-value	*p*-value
Intercept	0.35	1.03	0.34	0.73	3.01	2.17	1.39	0.17
SMARTS Treatment	-0.44	0.91	-0.48	0.63	-1.91	1.16	-1.64	0.10
Sex: Female	0.08	0.69	0.11	0.91	2.48	1.18	2.10	0.04 *
Race: Non-White	0.21	0.41	0.52	0.60	-0.22	0.90	-0.25	0.81
Free-reduced lunch	0.85	0.52	1.64	0.10	0.92	1.36	0.68	0.49
Special education	0.01	0.36	0.03	0.98	-0.60	0.84	-0.72	0.47
Emotion regulation	-1.04	0.42	-2.49	0.01 *	-1.56	0.79	-1.99	0.04 *
SMARTS Treatment × Emotion regulation	-0.13	0.41	-0.32	0.75	N/A	N/A	N/A	N/A

Note. Interaction effect was not tested for the dispersion parameter (i.e., N/A). **p*< .05. ***p*< .01. ****p*< .001.

Appendix I

Academic Competence of Out-of-School Suspension

GAMLSS Coefficients of Academic Competence (Moderation Effects) of Out-of-School Suspension (OSS) for the ZALG model

Variables	Mean parameter μ Mu link function: logit				Probability of Zero Suspension parameter σ Sigma link function: logit			
	Estimate	Standard Error	*t*-value	*p*-value	Estimate	Standard Error	*t*-value	*p*-value
Intercept	1.50	0.85	1.76	0.07	0.34	0.45	0.77	0.44
SMARTS Treatment	-0.02	0.86	-0.02	0.99	0.09	0.25	0.34	0.72
Sex: Female	-0.23	0.70	-0.33	0.75	1.10	0.32	3.41	0.00 ***
Race: Non-White	0.35	0.49	0.72	0.47	-0.04	0.27	-0.14	0.89
Free-reduced lunch	1.64	0.65	2.51	0.01 *	-0.73	0.31	-2.33	0.02 *
Special education	-0.56	0.57	-0.99	0.33	0.09	0.28	0.33	0.74
Academic competence	-0.13	0.25	-0.52	0.60	0.26	0.12	2.13	0.03 *
SMARTS Treatment × Academic competence	0.19	0.44	0.43	0.67	N/A	N/A	N/A	N/A

Note. Interaction effect was not tested for the dispersion parameter (i.e., N/A). *$p < .05$. **$p < .01$. ***$p < .001$.

Appendix J

Academic Competence of Exclusionary Discipline

GAMLSS Coefficients of Academic Competence (Moderation Effects) of Exclusionary Discipline (ED) for the ZALG model

Variables	Mean parameter μ				Probability of Zero Suspension parameter σ			
	Mu link function: logit				Sigma link function: logit			
	Estimate	Standard Error	*t*-value	*p*-value	Estimate	Standard Error	*t*-value	*p*-value
Intercept	1.91	0.79	2.41	0.02 *	0.45	0.44	1.04	0.30
SMARTS Treatment	0.18	0.80	0.22	0.82	0.09	0.25	0.36	0.72
Sex: Female	-0.30	0.62	-0.48	0.63	1.05	0.31	3.41	0.00 ***
Race: Non-White	0.41	0.44	0.94	0.35	-0.16	0.26	-0.60	0.55
Free-reduced lunch	1.15	0.57	2.03	0.04 *	-0.87	0.31	-2.85	0.004 **
Special education	-0.40	0.51	-0.79	0.43	0.10	0.28	0.34	0.73
Academic competence	-0.12	0.23	-0.51	0.61	0.20	0.12	1.72	0.09
SMARTS Treatment × Academic competence	0.06	0.39	0.17	0.87	N/A	N/A	N/A	N/A

Note. Interaction effect was not tested for the dispersion parameter (i.e., N/A). **p*< .05. ***p*< .01. ****p*< .001.

Appendix K

Academic Competence of In-School Suspension for the ZALG Model

GAMLSS Coefficients of Academic Competence (Moderation Effects) of In-School Suspension (ISS) for the Zero Altered Logarithmic (ZALG) model

Variables	Mean parameter μ Mu link function: logit				Probability of Zero Suspension parameter σ Sigma link function: logit			
	Estimate	Standard Error	*t*-value	*p*-value	Estimate	Standard Error	*t*-value	*p*-value
Intercept	0.17	1.38	0.12	0.90	1.92	0.59	3.27	0.001 **
SMARTS Treatment	0.73	1.26	0.57	0.57	0.08	0.31	0.26	0.79
Sex: Female	0.51	1.12	0.46	0.65	1.15	0.46	2.49	0.01 *
Race: Non-White	0.14	0.65	0.21	0.84	-0.32	0.34	-0.94	0.35
Free-reduced lunch	-0.15	1.03	-0.14	0.89	-0.79	0.43	-1.85	0.06
Special education	-0.67	0.70	-0.95	0.34	-0.07	0.35	-0.20	0.84
Academic competence	0.45	0.49	0.91	0.36	0.11	0.15	0.78	0.43
SMARTS Treatment × Academic competence	-0.35	0.62	-0.56	0.58	N/A	N/A	N/A	N/A

Note. Interaction effect was not tested for the dispersion parameter (i.e., N/A). **p*< .05. ***p*< .01. ****p*< .001.

Appendix L

Academic Competence of In-School Suspension for the NBII Model

GAMLSS Coefficients of Academic Competence (Moderation Effects) of In-School Suspension (ISS) for the Negative Binomial Type II (NBII) model

Variables	Mean parameter μ Mu link function: log				Dispersion parameter σ Sigma link function: log			
	Estimate	Standard Error	*t*-value	*p*-value	Estimate	Standard Error	*t*-value	*p*-value
Intercept	-1.51	0.95	-1.59	0.11	0.58	1.70	0.34	0.73
SMARTS Treatment	0.10	0.62	0.17	0.87	0.10	1.44	0.07	0.94
Sex: Female	-0.92	0.85	-1.09	0.28	0.34	1.80	0.19	0.85
Race: Non-White	0.27	0.42	0.65	0.52	-0.01	0.83	-0.01	0.99
Free-reduced lunch	0.62	0.91	0.68	0.49	-0.27	2.02	-0.13	0.89
Special education	-0.24	0.41	-0.58	0.56	-0.87	1.05	-0.82	0.41
Academic competence	0.02	0.19	0.09	0.93	0.21	0.31	0.69	0.49
SMARTS Treatment × Academic competence	-0.06	0.26	-0.22	0.83	N/A	N/A	N/A	N/A

Note. Interaction effect was not tested for the dispersion parameter (i.e., N/A). *p< .05. **p< .01. ***p< .001.

VITA

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