ACADEMIC PERFORMANCE OF CHIDREN WITH SOCIAL-EMOTIONAL DIFFICULTIES: EXAMINING THE ROLE OF SELF-REGULATION

Cristin Montalbano

A dissertation submitted to the faculty at the University of North Carolina at Chapel Hill in partial fulfillment for the degree of Doctor of Philosophy in School Psychology in the School of Education

Chapel Hill
2018

Approved by:

Desiree W. Murray

Steven Knotek

Sandra Evarrs

Jeffrey A. Greene

Rune Simeonsson

ABSTRACT

Cristin Montalbano: Academic Performance of Children with Social-Emotional Difficulties: Examining the Role of Self-Regulation
(Under the direction of Desiree W. Murray, PhD)

Student with social-emotional difficulties are at increased risk for many adverse outcomes, including school dropout, serious mental health concerns, justice-involved behavior, and decreased quality of life. Thus, considerable attention needs to be directed toward identifying ways to bolster resilience and mitigate these risks for these students. Research suggests that self-regulation skills, including attention, inhibitory control and emotion regulation, are critical for success across a variety of areas including academic performance; however, there are many questions about which specific facets of self-regulation are most critical for academic performance more broadly as well as in specific areas like reading and mathematics. Moreover, most of the prior literature has focused on early childhood, overlooking the critical learning opportunities in early elementary school. Little is also known about the impact of these factors for higher risk students with clear social-emotional difficulties. As such, this study utilized an integrative theoretical framework of self-regulation to examine how self-regulation factors influence academic performance, specifically for early elementary students with social-emotional difficulties. The student sample consisted of 129 first and second grade students nominated by 68 teachers for a self-regulation intervention. Using baseline data collected as part of a federally-funded study, multilevel modeling was used to determine the extent to which various cognitive and emotional mechanisms of self-regulation were associated with teacher-rated academic performance, reading proficiency, and mathematics proficiency, after controlling for gender and socioeconomic status. Results indicated that attention, inhibitory control, and emotion regulation were significant predictors of teacher-rated academic performance. Attention was the only significant predictor of reading proficiency and inhibitory control was the only significant predictor of mathematics proficiency. Results also indicated that attention was the strongest predictor of teacher-rated academic performance and reading proficiency, whereas inhibitory control was the strongest predictor of mathematics performance. Socioeconomic status, one of the control variables, also accounted for significant variance in reading and mathematics proficiency as indicated by report card grades but not teacher-rated academic performance. These results add to the evidence that self-regulation is important for school success, and functions in a manner expected for early elementary students with social-emotional difficulties. Results suggest that both self-regulation and academic performance should be considered in interventions to help foster positive outcomes for students, particularly those with social-emotional difficulties who are most in need.

This work is dedicated to my extraordinary family, friends, mentors, and students.

Thank you for inspiring and supporting me on this journey.

ACKNOWLEDGEMENTS

This dissertation was indeed a great journey, one which I could not have traveled without the support of so many wonderful and caring people who remind me daily of all the goodness in the world.

First, I would like to extend my deepest gratitude to the exceptional faculty members and researchers who have inspired and supported me. To my amazing advisor, Dr. Desiree Murray, thank you for your unwavering support, encouragement, and expertise. Over the past three years you have provided me with phenomenal mentorship not only in research and clinical endeavors, but also in life, as I truly admire the person you are and the work you do to enhance the lives of those around you, including the children who need extra support. The experience and insights I have gained from working with you have been invaluable and will continue to inspire me throughout my life and career. Thank you for being patient, thorough, and dedicated to my dissertation and graduate school journey. I could not have done this without you and I am forever grateful to you for believing in me. To my dissertation chair, Dr. Steve Knotek, thank you for always being so caring, positive, and encouraging. I will never forget our meaningful discussions that undoubtedly helped me persist through many obstacles. To Dr. Jeff Greene, thank you for all of your support, guidance, and mentorship. I greatly appreciate your dedication to student growth and I would not be where I am today without your encouragement and everything I have learned from working with you. To Dr. Rune Simeonsson, thank you for being such a positive role model and for your unwavering efforts geared toward helping children with special needs around the world. I am inspired by your kindness and dedication. To Dr. Sandra Evarrs, thank you so

much for always being so kind, helpful, and thoughtful. I am a better clinician due to the example you have set and all the ways in which you supported my growth as a clinician and a person. To Dr. Cathy Zimmer, thank you for all of your guidance and support through my dissertation process. I am so grateful for all the time you spent helping me learn what I never thought I could. To Dr. Laura Kuhn, thank you so much for all of your expertise and assistance. I am grateful for your kindness, patience, and willingness to help. To the Self-Regulation Skills for Success research team, thank you for being such a supportive and knowledgeable team. This work would not have been possible without you all and your ceaseless dedication to children in need and the research process.

Next, I would like to thank my wonderful family and friends, as I could not have done this without their unwavering support, encouragement, love, and senses of humor. To my Mom and Dad, thank you for showing me what it truly means to put others before yourself and for being an inspiration every day. I am the person I am today because of your support, kindness, and unconditional love each step of the way. To my life partner, Roman, thank you for being you and for always being caring and encouraging throughout my graduate school journey. I am humbled by your quiet strength and unwavering support. To my brothers and sisters, Gina, Nevio, Lisa, Paul, VJ, Jen, Brian, Gina, Robert, and Koren, thank you for being constant sources of support and laughter. I am grateful for each of you. To my nieces and nephews, Evan, Lucas, Erik, Vincent, Olivia, Marissa, Alicia, Brian, Logan, and Kayla, thank you for brightening my life in so many ways and for being constant sources of inspiration. To the Fox-Peck Family, thank you for always being so kind, caring, positive, and supportive. I am so grateful for each of you and for the ways in which you show unconditional love, acceptance, and intolerance of injustice. To my dear friends from all walks of life, thank you for being beautiful, inspiring, and supportive people. I could not have done this without you by my side. Finally, to all the students, clients, and families I have had the privilege of working with throughout my career thus far, thank you for the opportunity to work with and learn from each of you.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1: INTRODUCTION

In the United States, approximately 15% to 25% of children and adolescents struggle with social-emotional difficulties (McLaughlin et al., 2012; Merikangas et al., 2010; Perou et al., 2013), which include disruptive behaviors, poor peer interactions, hyperactivity, impulsivity, and withdrawn behavior (Cole, Daniels, & Visser, 2012; Cooper & Cefai, 2013). Students presenting with these challenges often experience learning, achievement, and social concerns (Blair, 2002; Calkins, Blandon, Williford, & Keane, 2007; Lambert, 1988), and are often at increased risk for truancy (Henry & Huizinga, 2007) and school dropout (Henry, Knight, & Thornberry, 2012), as well as more serious mental health concerns (Darke, Ross, & Lynskey, 2003; Lambert, 1988) and justice-involved behavior (Fergusson & Horwood, 2003; Moffitt et al., 2011). Thus, considerable attention needs to be dedicated toward identifying ways to bolster resilience factors and mitigate risk for students with social-emotional difficulties in order to promote more favorable and positive outcomes.

One way to promote more positive outcomes for students with social-emotional difficulties is to enhance academic performance in early elementary school (Oldfield, Hebron, & Humphrey, 2016). Academic performance in early elementary school is foundational for positive educational and life outcomes (Valiente, Lemery-Chalfant, Swanson, & Reiser, 2008). The relationship between social-emotional difficulties and academic performance is well documented in research, such that poor achievement has been found to be a predictor of challenging behaviors (Tremblay, Masse, Leblanc, Schwartzman, & Ledingham, 1992) and difficult behaviors have been shown to be a predictor of poor school success (Fleming et al., 2005;

Hinshaw, 1992; Valiente et al., 2013; Valiente, Lemery-Chalfant, Swanson, & Reiser, 2008). However, research has shown that bolstering students' academic performance may mitigate the risks associated social-emotional difficulties (Oldfield et al., 2016). As such, focusing on specific factors that influence academic outcomes may suggest ways to strengthen interventions for students with social-emotional difficulties.

Self-regulation is one area that researchers have focused on extensively to better understand the connection between social-emotional functioning and school readiness and success (i.e., Blair & Razza, 2007; Bull & Lee, 2014; Monette, Bigras, & Guay, 2011; Ng, Tamis-Lemonda, Yoshikawa, & Sze, 2015; Ponitz, McClelland, Matthews, & Morrison, 2009; Shaul & Schwartz, 2014; Ursache, Blair, & Raver, 2012). Self-regulation is defined as the ability to initiate and sustain goal-directed actions through managing cognition, emotion, and behavior for the purposes of adapting to various social and cognitive demands of situations (Berger, Kofman, Livneh, & Henik, 2007; Berger, 2011; Murray, Rosanbalm, Christopolous, & Hamoudi, 2015; Schunk & Zimmerman, 1997). Self-regulation has been studied extensively across various disciplines of psychology, including, but not limited to, developmental, cognitive, and educational psychology (Greene, 2018; Nigg, 2017). For example, developmental psychologists typically examine self-regulation in terms of effortful control defined as the ability to inhibit a dominant response in order to engage in a subdominant response, detect errors, and plan (Rothbart & Bates, 2006), which has been studied in relation to emotion regulation (Eisenberg, Smith, Sadovsky, & Spinrad, 2004). On the other hand, cognitive psychologists typically focus on self-regulation and various executive functions, including working memory, inhibitory control, and task switching, and how they influence attention, cognition, and behaviors (Blair, Zelazo, & Greenberg, 2005). Educational psychologists focus on similar constructs; however, emphasis is on self-regulated learning, which encompasses the processes utilized to sustain goal-oriented cognitions, motivation, affect, and behaviors in the context of learning (Greene, 2018; Schunk & Greene, 2018; Zimmerman & Schunk, 2011).

Due to the various ways in which researchers have investigated self-regulation, there is considerable variation in how it is conceptualized and how particular mechanisms are believed to relate and interact to influence behavior (Eisenberg & Zhou, 2016; Greene, 2018; Zhou, Chen, & Main, 2012). When self-regulation is investigated in the context of academic performance, factors such as executive functions, attention, and emotion regulation are often examined. As such, research on academic performance and self-regulation should incorporate both cognitive and emotional constructs.

Given this recommendation, my study employed an integrative theoretical framework of self-regulation proposed by Murray and colleagues (2015). Drawing from developmental and cognitive models of self-regulation, this framework describes core self-regulatory mechanisms in three main domains: (1) cognitive (i.e., attention and executive functions), (2) emotional (i.e., emotion regulation), and (3) behavioral. Within this framework, cognitive and emotional domains influence behavioral self-regulation. Behavioral self-regulation encompasses various actions that can be regulated by an individual, including goal-setting, utilization of coping strategies, motivation, and various learning behaviors (Murray, Rosanbalm, Chistopolous, Hamoudi, 2015). This framework is useful in investigating how self-regulatory mechanisms relate to academic performance, as it identifies specific domains that can be examined and targeted through interventions.

There is a wealth of research on how various self-regulatory mechanisms influence academic performance. For example, several researchers found that attention, a cognitive mechanism, made unique contributions to the prediction of students' academic performance in reading and mathematics (Welsh, Nix, Blair, Bierman, & Nelson, 2010; Fuchs et al., 2005). Similarly, another study indicated that attention predicted school success in reading and mathematics, above and beyond other cognitive factors (Lan, Legare, Ponitz, Li, & Morrison, 2011). Other studies have highlighted that inhibitory control was the only executive function that predicted unique variance in academic performance (Blair & Razza, 2007; Espy et al., 2004). Although research is unclear on how inhibitory control impacts mathematics performance versus reading performance (Lan et al., 2011; Ponitz et al., 2009), there is considerable support linking cognitive mechanisms of self-regulation to academic performance.

Researchers have also found positive correlations between students' emotion regulation skills and overall academic performance as well as functioning in mathematics and reading (Graziano, Reavis, Keane, & Calkins, 2007; Howse, Calkins, Anastopoulos, Keane, & Shelton, 2003; Trentacosta & Izard, 2007). For example, Howse et al. (2003) found positive correlations between parent reports of children's emotion regulation skills and children's scores on standardized achievement measures of reading and mathematics. In another study, Graziano and colleagues (2007) found that emotion regulation was positively associated with teacher reports of academic performance and with standardized early reading and mathematics achievement scores. These studies highlight that emotional mechanisms of self-regulation are associated with academic performance.

Overall, it appears that both cognitive and emotional mechanisms of self-regulation are related to academic performance, and likely interact to influence learning and behavior (Bell & Wolfe, 2004; Blair, 2016; Calkins & Marcovitch, 2010; Carlson & Wang; Raver et al., 2012; Ursache et al., 2012). What is not clear from extant literature, however, is what these conceptual relationships among and between self-regulatory constructs look like in early elementary school for students with social-emotional difficulties, as most studies were conducted with preschool aged children from a more general population of students. Thus, my research examined how various cognitive and emotional mechanisms of self-regulation predicted academic performance for students with social-emotional difficulties in first and second grade.

Early elementary school (i.e., ages 6 to 8) is a critical time for self-regulation development, as self-regulation capacities and skills are undergoing rapid changes and development (Berger, 2011). Students of this age are developing more sophisticated cognitive strategies, including cognitive flexibility, attentional control, and problem-solving skills, which contribute to improvements in their abilities to self-regulate their cognitions, emotions, and behavior (Berger, 2011). Students with atypical or immature development in these areas, however, may exhibit social-emotional difficulties as well as academic challenges. Thus, it is important to understand self-regulation processes in these children in order to identify how to help before struggles are exacerbated over time. A more comprehensive understanding of how self-regulation and academic performance are related may provide additional insight into specific mechanisms that can be targeted through intervention and prevention efforts in schools for students with social-emotional difficulties.

In summary, in order to achieve school success, students need to effectively utilize cognitive and emotional self-regulatory mechanisms that enable them to successfully regulate their behavior and navigate academic demands within a classroom setting (Raver et al., 2012). While there is a wealth of research on various self-regulatory mechanisms and academic performance, little research exists on how these mechanisms influence academic performance, particularly for early elementary students with social-emotional difficulties who are at increased risk for adverse outcomes. Research in this area has the potential to identify ways that students with social-emotional difficulties can be supported in order to change potential adverse trajectories. Thus, my study focused on better understanding how attention, inhibitory control, and emotion regulation interact to influence the academic performance of young students with social-emotional difficulties.

My study examined academic performance and the influence of attention, inhibitory control, and emotion regulation for first and second grade students with social-emotional difficulties, addressing three main research questions: (1) What are the associations between key cognitive and emotional self-regulation mechanisms (e.g., attention, inhibitory control, and emotion regulation) and teacher-rated academic performance, when controlling for gender and free/reduced lunch status?, (2) What are the associations between key cognitive and emotional self-regulation mechanisms and academic performance as measured by proficiency in reading, when controlling for gender and free/reduced lunch status?, and (3) What are the associations between key cognitive and emotional self-regulation mechanisms and proficiency in mathematics, when controlling for gender and free/reduced lunch status? In order to examine these research questions, baseline data from a large intervention study with multi-method measures of self-regulation and academic performance were analyzed.

CHAPTER 2: LITERATURE REVIEW

This section defines students with social-emotional difficulties, academic performance, and self-regulation. Additionally, the relevant research on self-regulation and academic performance is reviewed in order to establish context for the analysis of various cognitive and emotional mechanisms that may influence academic outcomes. My research is informed by several theories spanning developmental, cognitive, and educational psychology. Thus, pertinent theoretical frameworks of academic performance and self-regulation are reviewed. The literature on the connections between academic performance and self-regulation mechanisms is also presented, concluding with research focused specifically on various mechanisms that have been shown to influence academic performance for students with social-emotional difficulties and the gaps in research my study sought to address.

Students with Social-Emotional Difficulties

Students with social-emotional difficulties are often characterized by externalizing behaviors such as hyperactivity, impulsivity, aggression, and difficulty following directions, internalizing concerns including anxiety or depression, and/or difficulties with social interactions (Cole et al., 2012; Cooper & Cefai, 2013). Although all students with social-emotional difficulties may not exhibit all of these concerns, they often exhibit difficulties in one or more of the aforementioned areas. This conceptualization of students with social-emotional difficulties is broader than typical conceptualizations provided by the law (i.e., IDEA) and by classification systems (i.e., DSM-V) due to the age of participants. Most students in early elementary school have not yet received a more formal diagnosis or classification (Kessler et al., 2007; McLaughlin et al., 2012); however, the indicators noted are often viewed as precursors for the development of psychiatric diagnoses, including attention deficit/hyperactivity disorder (ADHD), conduct disorder (CD), oppositional defiant disorder (ODD), depression, and anxiety. In order to be relevant to a broad group of at-risk students, my study included students with externalizing, internalizing, and/or social deficits, referred to as students with social-emotional difficulties.

Students with social-emotional difficulties often experience both academic and behavioral challenges in the classroom (Bradley, Doolittle, & Bartolotta, 2008; Lane, Wehby, & Barton, 2005). Such concerns often extend from self-regulation issues such as attentional difficulties, poor emotion regulation skills, and difficulties with impulse control. Students with social-emotional difficulties often have academic and social performance difficulties, including lower grades and higher rates of conflicts with peers and teachers (Lane et al., 2005). For example, students with attentional, emotion regulation, and impulse problems demonstrate difficulty engaging effectively in the learning process (Massetti et al., 2008; Morris et al., 2013; Neuenschwander et al., 2012). Additionally, students who have frequent conflicts with teachers and peers often have higher rates of discipline referrals and suspensions that result in missed instructional time (Bradley et al., 2008). Thus, it is evident that students with social-emotional difficulties warrant special consideration, as their dysregulated behavior can have profound effects on their own learning and the learning of others.

Academic Performance

Academic performance in early elementary school is foundational for favorable educational and life outcomes (Valiente, Lemery-Chalfant, Swanson, & Reiser, 2008). Strong academic performance has been linked to positive mental health and academic outcomes (Caspi, Elder, & Bem, 1987; Ensminger & Slusarcick, 1992). On the contrary, poor academic performance is one of the strongest predictors of delinquency (Maguin & Loeber, 1996). Given the relationships between academic performance and critical developmental outcomes, it is imperative to understand the ways in which students' academic performance can be bolstered.

Academic performance is a broad term used in the context of my study to describe students' report card grades and teacher reports of their productivity and success. Academic performance has been comprehensively investigated, including for students with social-emotional difficulties (Lee, 2016). Academic performance can be measured by report card grades or by teacher-rated academic performance. Each of these measures provides related but complimentary types of information regarding student performance. Teacher report captures specific information such as the percentage of work completed, level of independence in work completed, consistency in performance, as well as accuracy of work (DuPaul et al., 1991), while grades reflect the extent to which certain performance standards are met.

Report card grades and teacher-rated academic performance have great utility (DiPerna, 2006; DiPerna & Elliott, 1999; DuPaul et al., 1991). For example, both reflect student performance over a long period of time. Additionally, grades and teacher-rated academic performance generate specific information about performance-related behaviors while simultaneously providing an understanding of how students are performing in comparison to their peers (DuPaul et al., 1991). The specific performance-related information provides useful information regarding areas that can be targeted by interventions to bolster students' academic performance.

Theoretical Underpinnings of Self-Regulation and Academic Performance

Self-regulation is broadly defined as the ability to initiate and sustain goal-directed actions through managing cognition, emotion, and behavior for the purposes of adapting to various social and cognitive demands of situations (Berger et al., 2007; Berger, 2011; McClelland & Cameron, 2011; Murray et al., 2015; Schunk & Zimmerman, 1997). Many researchers have examined the influence of self-regulation on different outcomes including social, emotional, and academic success (Greene, 2018). There are three main areas of psychology that have examined the relationships between self-regulation and academic performance, including cognitive, developmental, and educational psychology. While there is definitely some overlap, each area focuses on different mechanisms or constructs. For example, developmental psychologists typically examine effortful control, defined as the ability to inhibit a dominant response, in their investigations of the relationships between self-regulation and academic performance (Eisenberg, Smith, Sadovsky, & Spinrad, 2004). On the other hand, cognitive psychologists focus on the relationships between executive functions, defined as cognitive mechanisms that help regulate behavior, and performance (Van der Ven, Kroesbergen, Boom, & Leseman, 2012). Educational psychologists incorporate similar constructs; however, researchers in this area typically examine various learning-related concepts, including self-regulated learning and motivation, and how these constructs facilitate and relate to academic performance (Greene, 2018; Zimmerman & Schunk, 2011). Given the pivotal roles each area of psychology has played in the understanding of self-regulation and academic performance, the theoretical underpinnings of each area was reviewed in order to provide a theoretical framework for my study.

Cognitive model of self-regulation. Researchers examining self-regulation from a cognitive perspective have typically focused on cognitive processes, such as attention and executive functions (e.g., inhibitory control, working memory, set shifting, and attention) involved in goal-directed behaviors (Blair & Razza, 2007; Miyake & Friedman, 2012; Miyake et al., 2000; Willoughby et al., 2012). Executive functions are a set of cognitive mechanisms that play an integral role in organizing, planning, and executing attentional control, thoughts, and behaviors (Blair & Ursache, 2011; Blair et al., 2005; Miyake & Friedman, 2012). The most comprehensively understood and investigated executive functions are inhibitory control, working memory, and task switching (Berger, 2011; Blair & Ursache, 2011; Diamond, 2013; Miyake & Friedman, 2012; Miyake et al., 2000). Working memory assists with the process of holding, manipulating, and updating information over a relatively short period of time (Blair & Ursache, 2011; Berger, 2011). Task switching, sometimes referred to as set shifting, is the ability to switch from one cognitive task or operation to another (Berger, 2011; Miyake et al., 2000). Inhibitory control is defined as the ability to constrain a dominant or automatic response in favor of a subdominant response (Blair & Ursache, 2011; Chung, Weyandt, & Swentosky, 2014; Miyake et. al., 2000; Rothbart & Bates, 2006). Attention, defined in various ways, is believed to undergird executive functions (Garon, Bryson, & Smith, 2008). Attention is also often viewed as a relatively fast process and executive functions are believed to be more deliberate (Blair & Ursache, 2011).

Developmental model of self-regulation. Developmental psychologists have focused on effortful control processes (e.g., attentional control, inhibitory control, and activation control) and consider emotional self-regulation processes (Blair & Razza, 2007; Eisenberg et al., 2010; Eisenberg & Zhou, 2016; Raver et al., 2012; Raver, 2004). Attentional control is defined as the "abilities to maintain attentional focus upon task-related channels or to shift one's focus as needed to deal with task demands" (Eisenberg et al., 2010, p. 682). This definition of attention implies a more volitional process than that of the conceptualization of attention by cognitive psychologists. Activation control encompasses "the ability to perform an action when there is a strong tendency to avoid it" (Eisenberg et al., 2010, p.682). Similarly defined in the cognitive literature, inhibitory control is "the capacity to plan and effortfully suppress inappropriate responses under instructions or in novel or uncertain situations" (Eisenberg et al., 2010, p. 682). Finally, emotional self-regulation includes mechanisms geared toward preventing, initiating, or changing an emotional experience (Eisenberg et al., 2010).

Educational model of self-regulation. Educational psychologists who study self-regulation often focus on self-regulated learning, which is defined as the "active, thoughtful pursuit of desired learning goals through planning, enacting, monitoring, controlling, and reflecting upon internal (i.e., cognition, metacognition, motivation, behavior, affect) and external factors (i.e., environment) before, during, and after learning" (Greene, 2018; p. 137). Greene (2018) described a model of self-regulated learning that provides "an amalgamation of numerous predominant models" (p.22) and includes various targets, phases, and processes of self-regulated learning. Targets of self-regulated learning include cognition (i.e., thoughts directed towards learning tasks), metacognition (i.e., thoughts focused on cognition), motivation (i.e., processes that influence the initiating and sustaining of goals), behavior (i.e., learning-facilitating actions), affect (i.e., emotions and emotion regulation), and external environment (i.e., aspects of environment that support or impede the learning process). Phases of self-regulated learning include "before" learning, which includes task-identification, goal-setting, and planning, "during" learning, which encompasses learning engagement and strategy use, and "after" learning, which includes self-reflecting and evaluating results and processes. Lastly, processes of self-regulated learning include monitoring and control, such as assessing the effectiveness of strategies and outcomes and modifying accordingly, and metacognitive experiences, including awareness of cognitions while engaged in learning (Greene, 2018). This model provides important information regarding learning behaviors that can be self-regulated in order to foster more positive academic outcomes.

Linking cognitive, developmental, and educational models of self-regulation. As evidenced by the three different frameworks described, cognitive, developmental, and educational conceptualizations of self-regulation overlap. For example, cognitive and developmental psychologists both identify inhibitory control as a central process (Blair & Razza, 2007; Liew, 2012; Zhou et al., 2012). Additionally, these models emphasize attention as an important construct (Zhou et al., 2012; Blair & Razza, 2007). Educational psychologists also acknowledge the central role of attention and executive functions, which are believed to be mechanisms that underlie self-regulated learning and provide the resources that enable individuals to regulate behaviors in the context of learning (Greene, 2018).

The main difference between frameworks is that cognitive psychologists typically examine executive functions that do not consider emotional responses and behaviors (i.e., "cool" tasks), whereas developmental and educational psychologists also often take emotion-related constructs (i.e., emotions, emotion regulation, and "hot" tasks) into consideration (Blair & Razza, 2007; Greene, 2018; Kim et al., 2013; Metcalfe & Mischel, 1999; Neuenschwander et al., 2012). Historically, the self-regulatory processes associated with each framework have been examined separately (Eisenberg & Zhou, 2016; Zhou et al., 2012; Blair & Razza, 2007). However, due to the overlap in constructs, recent literature has encouraged examining these mechanisms in a more integrated manner (Eisenberg & Zhou, 2016; Zhou et al., 2012).

Given this recommendation, Murray and colleagues (2015) proposed an applied, multi-disciplinary model for understanding self-regulation. This model conceptualizes three core areas of self-regulation processes: cognitive, emotional, and behavioral. Cognitive self-regulation includes attention and executive functions which are foundational for academic performance, whereas emotional self-regulation includes regulation of emotions in response to stress and demands such as those encountered in school. These two foundational components support behavioral self-regulation, which includes following rules, controlling impulses, using coping strategies, and engaging in learning-related behaviors (Murray et al., 2015).

Cognitive self-regulation. Cognitive self-regulation can be defined as “the regulation of attention and selective strategy use in the execution of cognitive tasks” (Blair, 2002, p. 112). This definition encompasses both attention and executive functions including inhibitory control. Attention and inhibitory control have been researched extensively in both cognitive and effortful control literature (Blair, 2002; Ponitz et al., 2009; Zhou et al., 2012) and are the two mechanisms of interest in my research given their strong associations with academic performance (Allan et al., 2014; Polderman, Boomsma, Bartels, Verhulst, & Huizink, 2010).

Attention. Many researchers agree that attention is a cognitive process that underlies and drives many other mechanisms of self-regulation (i.e., Fisher & Kloos, 2016; Berger, 2011; Garon et al., 2008). Attention has been conceptualized in various ways across different theoretical perspectives including cognitive, developmental, and behavioral (Tannock, 2003). For example, Posner and Rothbart (2007) described a cognitive model of attention, defining attention as “the regulating of various networks by attentional networks involved in maintaining the alert state, orienting, or regulation of conflict” (p. 2). According to the attention model proposed by Posner and Peterson (2012; 1990), attention encompasses three different, but interrelated systems including orienting, alerting, and executive attention that are activated in response to environmental stimuli (Posner & Peterson, 1990; Peterson & Posner, 2012). The orienting system focuses on “the ability to prioritize sensory input by selecting a modality or location” (Peterson & Posner, 2012, p. 75). The alerting system encompasses the concept of arousal and focuses on maintaining alertness (Peterson & Posner, 2012). Executive attention focuses on error detection and the resolution of conflicting information, and is also related to the control of goal-directed behavior (Berger & Posner, 2000; Berger, 2011; Blair, 2016; Peterson & Posner, 2012). Within the developmental literature, effortful control is believed to be a part of executive attention (Posner & Rothbart, 2007).

Additionally, some theories of attention also include sustained attention, which is defined as “the ability to maintain focus on a single object, task, or sensory channel for an extended period (Fisher & Kloos, 2016, p. 216). Sustained attention is often associated with the alerting system of Posner’s and Peterson’s model of attention (Berger, 2011). Additionally, sustained attention is often synonymous with the attentional control construct of effortful control (Eisenberg et al., 2010).

From a more behavioral standpoint, attention is described in terms of various behaviors, including focus, organization, distractibility, and off-task behaviors (Gray et al., 2015). While cognitive, developmental, and behavioral perspectives on attention have similarities, what is unclear is how the various models of attention relate to one another. One study found that behavioral manifestations of attention map onto cognitive constructs in typically developing children aged three to seven (Rezazadeh, Wilding, & Cornish, 2011). In this study, researchers administered four lab-based measures that assessed various attention-related constructs including selective and sustained attention as well as response inhibition and attentional control, and asked parents to complete a rating scale regarding inattention. Results indicated that parent-rated inattention was significantly correlated with accuracy (i.e., errors) on a task measuring selective attention. No other significant associations were found (Rezazadeh et al., 2011).

Although extant literature is inconclusive regarding the associations between various models of attention, the majority of researchers who have investigated attention as it relates to academic performance have utilized teacher rating scales and observational measures. In fact, attention measured in this manner has been implicated as one of the strongest predictors of academic performance (Garner et al., 2013; Gray, Rogers, Martinussen, & Tannock, 2015; Pingault, Tremblay, & Vitaro, 2011; Zoromsk, Owens, Evans, & Brady, 2005). As such, studies examining academic performance might consider measuring attention in terms of focus, organization, distractibility, and off-task behaviors as measured by teacher ratings as well as observational measures.

Inhibitory Control. As evidenced by the review of literature, inhibitory control is a common component of both executive functions and effortful control. Inhibitory control encompasses the ability to inhibit a dominant or automatic response in favor of a subdominant response in a given situation (Chung et al., 2014; Blair & Ursache, 2013; Miyake et. al., 2000; Rothbart & Bates, 2006). Murray and Kochanska (2002) suggest that inhibitory control is a multidimensional construct that includes the abilities to delay, slow or inhibit, and initiate another response.

Considerable research has been conducted on whether cognitive self-regulatory mechanisms (i.e., inhibitory control, working memory, and set shifting) are a unitary construct or unique and dissociable constructs (Davidson, Amso, Anderson, & Diamond, 2006; Garon et al., 2008; Miyake & Friedman, 2012; Miyake et al., 2000). Research on younger children ages two through five suggests that executive functions may be unitary (Wiebe et al., 2011; Wiebe, Espy, & Charak, 2008; Willoughby, Blair, Wirth, Greenberg, & Investigators, 2010; Willoughby et al., 2012). Starting around the age of six or seven, however, a multiple factor structure of executive functions begins to emerge (McAuley & White, 2011;Lee et al., 2012; Miller, Giesbrecht, Müller, McInerney, & McInerney, 2012). For instance, in a study conducted by McAuley and White (2011) with 147 participants between the ages of 6 to 24, cognitive self-regulatory mechanisms were separable across all age levels. Additionally, in a cross-sectional study of 7-, 11-, 15-, and 21-year-olds, Huizinga et al. (2006) found that various executive functions were dissociable yet correlated regardless of age. Thus, research suggests that cognitive self-regulatory mechanisms become more dissociable with age (Lee, Bull, & Ho, 2013), and begin to appear as separate constructs as early as the age of six (McAuley et al., 2011; Lee et al., 2012). Distinct yet correlated constructs have been identified for older children and young adults (McCauley & White, 2011; Miyake et al., 2000).

Given this support for the dissociability of executive functions around the age of six and the age of participants in my study, I conceptualized inhibitory control as a unique and dissociable construct from other executive functions. Inhibitory control is a particularly relevant construct for understanding young children's social-emotional difficulties. Inhibitory control enables children with social-emotional difficulties to exhibit control over impulses and to engage in more desirable academic and social behaviors. The ability to engage in more desirable, positive behaviors supports positive outcomes, including academic performance (Eisenberg, Valiente, Eggum, 2010).

Researchers across different areas of psychology have examined inhibitory control extensively (Zhou et al., 2012; Miyake et al., 2000; Murray & Kochanska, 2002). As Zhou and colleagues (2012) emphasize, there is little difference in the conceptualization of inhibitory control; however, there are differences in the ways in which inhibitory control is measured. For example, cognitive psychologists typically employ lab-based procedures, whereas developmental psychologists often use questionnaires and behavioral tasks to measure inhibitory control (Zhou et al., 2012). Further research is warranted, however, on how these different measures are related. Given this lack of consensus, a multi-method approach to investigate inhibitory control, including child performance tasks and teacher reports, has been recommended.

Emotional self-regulation. Emotional self-regulation, synonymous with emotion regulation, is another construct that has been extensively investigated. Perhaps related to the prevalence of research, emotional self-regulation is also differentially defined and conceptualized within the field (Cole, Martin, & Dennis, 2004; Djambazova-Popordanoska, 2016; Eisenberg & Spinrad, 2004; Gross, 2014). Using a definition provided by Eisenberg and colleagues, emotional self-regulation is "the process of initiating, avoiding, inhibiting, maintaining, or modulating the occurrence, form, intensity, or duration of internal feeling states, emotion-related physiological, attentional processes, motivational states, and/or the behavioral concomitants of emotion in the service of accomplishing affect-related biological or social adaptation or achieving individual goals" (Eisenberg & Spinrad, 2004, p. 338). This definition acknowledges that emotional self-regulation stems from internal experiences and includes various processes used to "manage and change whether, when, and how one experiences emotions and emotion-related motivational and physiological states, as well as how emotions are expressed behaviorally" (Eisenberg, Hofer, Sulik, & Spinrad, 2014, p. 157). This includes processes used to assess and modify a situation, deploy attention, and engage in various strategies that modulate the expression of emotion (Eisenberg et al., 2014). Stated from a more applied perspective, emotional self-regulation involves understanding feelings and managing strong feelings in situations of frustration and distress, including accepting unpleasant emotions and utilizing feelings to guide prosocial behaviors (Murray et al., 2015).

Several researchers have developed models to describe the processes of emotional self-regulation. For example, Gross (2014) presented the *Process Model of Emotion Regulation.* Gross asserts that emotions involve "person-situation transactions that compel attention, have meaning to an individual in light of currently active goals, and give rise to coordinated yet flexible multisystem responses that modify the ongoing person-situation transaction in crucial ways" (Gross, 2014, p. 5). According to this model, the person-situation transactions can be modified using five strategies of emotion regulation: situation selection, situation modification, attentional deployment, cognitive change, and response modulation. Situation selection involves taking action to avoid or participate in situations, situation modification encompasses modifying a circumstance to change the emotional experience, attentional deployment includes carefully utilizing attention in a specific situation to influence one's emotional response, cognitive changes is modifying one's cognitive appraisal of a situation, and response modulation includes engaging in various behaviors to alter one's emotional response (Gross, 2014).

In another conceptualization by Hoeksma and colleagues (2004), emotion regulation is described as a dynamic system with three defining components. The first component includes identifying when emotion regulation is needed. The second component includes understanding the goal(s) emotion regulation appears to serve, and the third component is understanding how such goals are achieved. Researchers assert that this system is warranted when there is a conflict between the desired emotional state and the one currently being experienced. Awareness of this discrepancy activates the system and assists with emotion regulation (Hoeksma et al., 2004).

These models highlight the dynamic, multifaceted nature of emotional self-regulation and the complexity of processes that comprise one's ability to regulate emotions. Researchers have investigated emotional self-regulation by assessing emotion knowledge and awareness as well as management of strong emotions in different situations or tasks (i.e., emotion regulation). In most cases, emotion regulation as reported by teachers was the most significant predictor of academic performance (Garner & Waajid, 2012; Howse et al., 2003; Trentacosta & Izard, 2007).

Behavioral self-regulation. Behavioral self-regulation is defined as the conscious management of behaviors for the purposes of achieving goals (Blair & Ursache; 2011). Many researchers agree that cognitive and emotional self-regulatory mechanisms intersect and provide the basis for behavioral regulation (e.g., Murray et al., 2015; Wanless et al., 2011). The intersection between cognitive and emotional self-regulation is best highlighted by the bidirectional developmental model described by Blair and Ursache (2011). In this model, cognitive mechanisms are described as effortful and deliberate aspects of self-regulation (i.e., top-down), whereas emotional self-regulatory mechanisms are described as more automatic (i.e., bottom-up). The top-down and bottom-up mechanisms interact in an "adaptive feedback loop" as a response to environmental stimuli and influence behavioral self-regulation (Blair & Ursache, 2011, p. 300). Given the associations between cognitive and emotional mechanisms of self-regulation and their influence on behavior, including learning behaviors, it is essential for researchers to assess aspects of both.

Summary. Together, research in cognitive, developmental, and educational psychology provides a strong foundation for understanding cognitive, emotional, and behavioral self-regulation in the context of learning. Research extending from cognitive and developmental models of self-regulation has advanced understanding of various cognitive and emotional self-regulatory mechanisms. Self-regulation researchers within education have investigated similar constructs and have focused on specific targets, phases, and processes that can be self-regulated in order to foster learning. Given the overlap in constructs across models of self-regulation, my study was guided by the broadest framework with relevance for academic performance described by Murray and colleagues (2015). This framework includes several self-regulatory mechanisms including attention, inhibitory control, and emotion regulation. These are constructs that have been investigated across disciplines in self-regulation research.

As highlighted in the theoretical model for my study (see Figure 1), both cognitive and emotional self-regulatory mechanisms are believed to be related to academic performance. The theoretical strength of the association is indicated by the size of the arrows. Researchers have shown that attention is consistently the strongest predictor of academic performance (e.g., Lan et al., 2011; Razza et al., 2012). Inhibitory control and emotion regulation have also been found to be significant predictors of academic performance; however, the magnitudes of such associations have been unclear and inconsistent in previous research studies (e.g., Graziano et al., 2007; Howse et al, 2003; Lan et al., 2011; Razza et al., 2012).

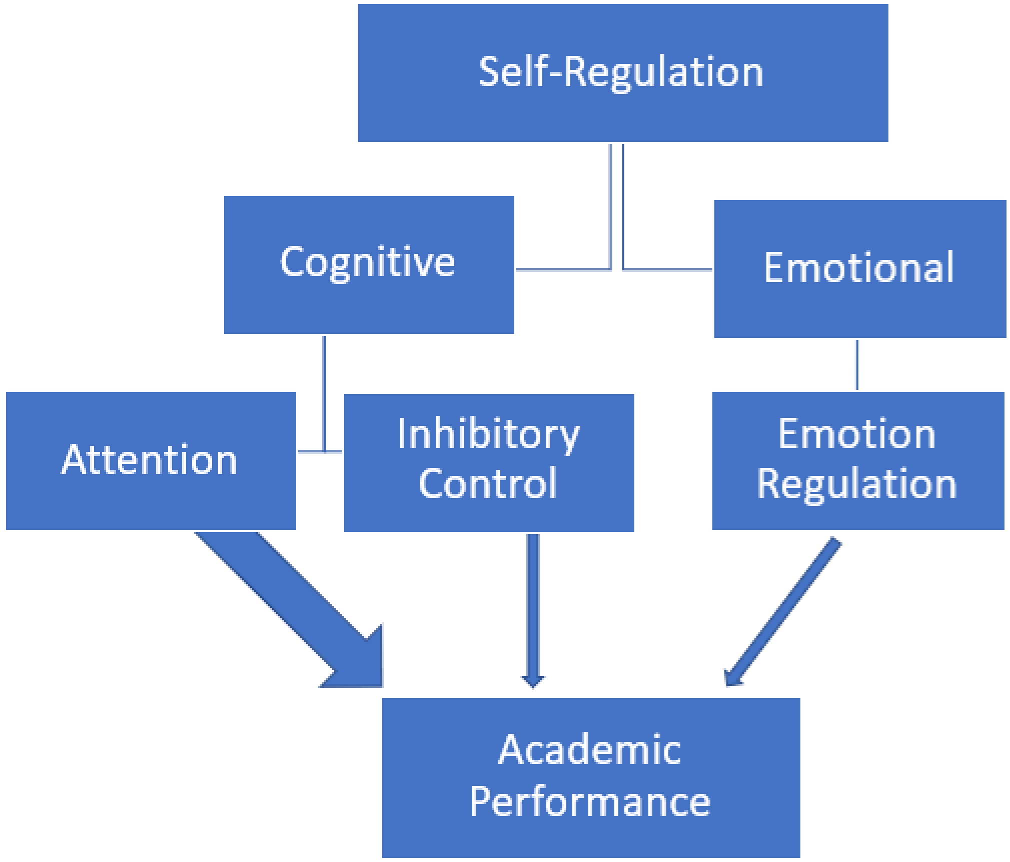

Figure 1: Integrative Theoretical Framework

Linking Cognitive and Emotional Self-Regulation and Academic Performance

Evidence suggests that various cognitive and emotional self-regulatory mechanisms work in an integrative, bidirectional manner to influence learning and behavior (Bell & Wolfe, 2004; Blair, 2016; Calkins & Marcovitch, 2010; Carlson & Wang, 2007; Ursache et al., 2012). For example, previous researchers have found that children's emotional self-regulation skills can support or impair processing of cognitive tasks (Lench & Levine, 2005; Schimmack 2005). Researchers have also shown that cognitive self-regulation plays a pivotal role in helping manage emotions, as it facilitates children's abilities to recall and utilize various rules and strategies (i.e., inhibitory control and emotion regulation skills), which subsequently decreases emotional responses that may impede performance (Schmeichel & Demaree, 2010; Wolfe &

Bell, 2007). Furthermore, cognitive neuroscientists suggest that areas of the prefrontal cortex (PFC) that influence cognitive self-regulation also influence emotional self-regulation (Calkins & Marcovitch, 2010). Essentially, cognitive and emotional self-regulation provide the foundation for behavioral self-regulation (Murray et al., 2015). As such, cognitive and emotional mechanisms of self-regulation need to be examined in an integrative manner.

An integrated examination is essential, especially in the context of academic performance in reading and mathematics performance, given that success in academic areas requires students to pay attention and avoid distractions, inhibit predominant responses or cognitions, and regulate emotions (Blair & Raver, 2015; Schmitt, Geldhof, Purpura, Duncan, & McClelland, 2017). For example, attentional skills support students' abilities to focus on lessons, reading materials, and many other activities, including written work (Willner, Gatzke-Kopp, Bierman, Greenberg, & Segalowitz, 2015). Inhibitory control supports students' abilities to inhibit preconceived notions or understandings in order to learn new materials and rules in both mathematics and reading (Borella, Carretti, & Pelegrina, 2010; Dekker, Ziermans, & Swaab, 2016). Inhibitory control also helps students refrain from behaviors that can impede learning (e.g., talking with peers during lessons, searching through belongings instead of engaging in a learning task, etc.). Emotion regulation also helps students maintain appropriate affective states that support motivation and initiative in the learning process (Garner, 2010; Schutz & Davis, 2010; Tyson, Linnenbrink-Garcia, & Hill, 2009). Together, these mechanisms help students persist and participate when faced with academic demands such as varying learning structures (i.e., whole group, small group, partner, and individual work), difficult content, fatigue, distraction, frustration and other factors associated with classroom learning. In the next section, empirical studies that have examined the associations between self-regulation and academic performance are reviewed in order to provide support for the hypotheses of my study.

Empirical Studies: The Influence of Cognitive and Emotional Self-Regulation on Academic Performance

It is important to understand the mechanisms by which cognitive and emotional self-regulation influence academic performance, as extant literature suggests that self-regulation is more critical for school success than is intelligence (Blair & Raver, 2015; Clark et al., 2010; Duckworth & Seligman, 2005; Espy et al., 2004). Many researchers have investigated the association between self-regulation and academic performance by grouping regulatory processes, such as attention, inhibitory control, and emotion regulation, under the general umbrella of self-regulation (Brock, Rimm-Kaufman, Nathanson, & Grimm., 2009; Gestsdottir et al., 2014; Guimard, Hubert, Crusson-Pondeville, & Nocus, 2012; Hubert et al., 2015; Ponitz et al., 2009). Other researchers have investigated individual self-regulation constructs and academic performance (e.g., Allan et al., 2014; Graziano et al., 2007; Lan et al., 2011; Rabiner et al., 2004). The literature from both types of research is reviewed next.

Self-regulation and academic performance. Several researchers have investigated the association between self-regulation more broadly defined and academic performance, likely due to an overarching conception that various mechanisms of self-regulation are not dissociable for younger children (Brock et al., 2009; Gestsdottir et al., 2014; Guimard et al., 2012; Hubert et al., 2015; Ponitz et al., 2009). Hubert and colleagues (2015) examined associations between self-regulation and academic achievement in mathematics and reading in a sample of 138 French children between the ages of five and seven years old. Using a measure of self-regulation that requires attention, cognitive flexibility, working memory, and inhibitory control, researchers found that self-regulation was significantly associated with mathematics, but not with reading performance (Hubert et al., 2015). Ponitz and colleagues (2009) examined similar constructs with 343 kindergarten students in the United States and found comparable results, such that self-regulation predicted improvements in mathematics performance, but not reading.

In contrast, another research team investigated associations between self-regulation and mathematics and reading performance for 301 children ages five to seven years old from Germany and Iceland (von Suchodoletz et al., 2013). Results suggested that self-regulation was related to both mathematics and reading performance. Another study with French students ages four to six yielded similar results, with self-regulation being related to both mathematics and reading performance (Guimard et al., 2012). Given that the literature is unclear and inconsistent in terms of whether self-regulation predicts academic performance more in one area than another, research should examine reading and mathematics performance separately.

The aforementioned studies provide a wealth of information regarding self-regulation and academic performance; however, there are notable limitations. While it is understandable that such studies looked at self-regulation in a more unitary manner given the age group of children and the debate on when various mechanisms dissociate (Davidson et al., 2006; Garon et al., 2008; Lerner & Lonigan, 2014; Miyake et al., 2000; Miyake & Friedman, 2012), these studies provide little information about how specific cognitive and emotional self-regulatory mechanisms relate to and influence academic performance. Next, research examining these mechanisms separately is reviewed.

Attention and academic performance. Inattention can impede students' ability to acquire important academic skills, as attention difficulties often make it difficult for students to focus on lessons and retain information (Rabiner, Malone, & Conduct Problems Prevention

Group, 2004). There is a large number of researchers who have investigated the importance of attention for academic performance (Barriga, et al., 2002; Breslau et al., 2009; Fuchs et al., 2005; Lan et al., 2011; Massetti et al., 2008; Preston, Heaton, McCann, Watson, & Selke, 2009; Polderman et al., 2010; Rabiner et al., 2004; Rabiner, Carrig, & Dodge, 2016; Razza, Martin, Brooks-Gunn, 2012; Welsh et al., 2010). These researchers have investigated attentional control and sustained attention and their associations with academic performance across subject areas including reading and mathematics by utilizing lab-based tasks and/or teacher ratings.

Studies on attentional control and sustained attention, as measured by lab-based tasks, suggest that attentional control strongly predicts academic performance (Lan et al., 2011; Preston et al., 2009; Razza et al., 2012; Welsh et al., 2010). According to a study on executive functions and attention by Lan and colleagues (2011), attentional control was the most robust predictor of mathematics and reading performance for 119 Chinese and 139 American preschool children, above and beyond executive functions (Lan et al., 2011). Similarly, in another study with 164 preschool children, researchers found that attentional control predicted growth in both reading and mathematics skills (Welsh et al., 2010). Moreover, in a study of 45 children ages 7 to 15 with attention-deficit/hyperactivity disorder, Preston et al. (2009) found that attentional control accounted for a statistically significant amount of variance across achievement domains including reading, mathematics, and spelling. Razza and colleagues (2012) investigated the longitudinal relationships between students' attention in preschool and success in later elementary school. With a sample of 2,595, results indicated that focused attention, as measured by a sustained attention task that required students to select objects similar to a target object, significantly predicted students' achievement (Razza et al., 2012). These studies contribute to the understanding of the connections between attentional control and reading and mathematics performance for younger students.

While connections between attention and academic performance appear similar for students in early elementary school, the conceptualization and measurement strategies for this age group are different. For instance, many researchers have investigated attention by examining teacher ratings of inattention (Barriga et al., 2002; Breslau et al., 2009; Fuchs et al., 2005; Polderman et al., 2010; Rabiner et al., 2016; 2004). For example, Rabiner and colleagues (2004) found that inattention predicted reduced reading achievement in first grade, even after controlling for IQ and earlier reading ability. Similarly, Fuchs et al. (2005) found that attention, also defined as inattention measured by teacher report, accounted for unique variance in predicting end-of-year mathematics performance.

Other studies have found similar results. In a systematic review of the literature on attention problems researchers found a negative association between attention problems and performance in mathematics and reading (Polderman et al, 2010). Rabiner and colleagues (2004) also examined associations between attention concerns and academic achievement in a sample of 621 first grade students. While this study also considered ethnicity and behavioral concerns (i.e., oppositional behavior, hyperactivity, and anxiety), results suggested that attention problems as measured by teacher ratings were independently related to poor academic achievement (Rabiner et al., 2004).

Similar trends are also seen in students with diagnosable attention problems. In a study of 125 children ages four to six with ADHD, researchers found that children who met criteria for the inattentive subtype of ADHD had lower reading and mathematics performance over time than children who met criteria for the other subtypes of ADHD (Massetti et al., 2008).

Correspondingly, Rabiner and colleagues (2016) examined the long-term effects of attention problems in early elementary school. In a sample of 386 students identified as having attention difficulties by teacher ratings, results suggested that students with attention problems in first and second grades showed declines in mathematics and reading performance throughout elementary school (Rabiner et al., 2016).

With respect to students with social-emotional difficulties, attention is also a significant predictor of academic performance across ages. In one study, attention problems measured by teacher ratings at the age of six significantly predicted mathematics and reading achievement at age 17 for students with social-emotional difficulties, when accounting for socioeconomic status (Breslau et al., 2009). Additionally, in an examination of the associations between social-emotional difficulties and academic performance in a sample of 51 students ages 11 to 17 in an alternative school, Barriga and colleagues (2002) found that teacher ratings of inattention mediated the associations between various difficulties and overall academic functioning, including performance in reading and mathematics.

It appears from the literature that attention skills are the strongest predictor of general academic performance as well as performance in reading and mathematics. Furthermore, the strength of these associations appears to extend beyond factors such as working memory, inhibitory control, and task switching (Lan et al., 2011), other social-emotional difficulties (Rabiner et al., 2004), SES (Breslau et al., 2009), and intelligence (Rabiner et al., 2004). Given the clear association between attention skills and academic performance, studies examining cognitive and emotional predictors of academic performance need to consider attention skills.

Inhibitory control and academic performance. Inhibitory control is another construct that is very important for academic performance. Behavioral and academic expectations in the classroom often require students to inhibit impulsive responses in favor of those desired by teachers and schools. The association between inhibitory control and academic performance has been investigated extensively across both cognitive and developmental literature (Blair & Razza, 2007; Espy et al., 2004). As aforementioned, researchers examining inhibitory control from a cognitive perspective typically measure inhibitory control using lab-based measures. By contrast, researchers examining inhibitory control from a developmental perspective typically utilize questionnaires and lab-based tasks (e.g., Zhou et al.., 2012).

In a meta-analysis of the association between inhibitory control and the development of academic skills in preschool and kindergarten, Allan and colleagues (2014) examined 75 peer-reviewed studies. Results of this analysis yielded an effect size of .27, indicating a statistically significant association between inhibitory control and academic performance. Specifically, inhibitory control was more strongly associated with mathematics performance than with reading skills (Allan et al., 2014). Researchers also found that the association between inhibitory control and academic skills was moderated by the type of measures used to assess this construct. Preferred methods of assessing inhibitory control included behavior tasks and teacher reports, which appear to most strongly predict academic skills (Allan et al., 2014). This meta-analysis suggests that methods from both cognitive and developmental frameworks should be integrated when investigating the associations between inhibitory control and academic performance, an approach my study adopted.

Several studies with a more traditional cognitive focus have investigated inhibitory control and academic performance using lab-based measures (Allan et al., 2014; Espy et al., 2004; Ng et al., 2015; St. Clair-Thompson & Gathercole, 2006; Vuontela et al., 2013). For example, in a study of 66 preschool children, Espy and colleagues (2004) examined whether various executive functions were related to mathematical skills. Researchers used lab-based executive functioning measures as well as a standardized measure of mathematics skills. Results indicated that inhibitory control was the only executive function that accounted for unique variance in mathematical skills (Espy et al., 2004). This study included measures extending primarily from cognitive research; however, the authors noted this as a limitation and recommended using both developmental and cognitive methods to assess various executive functions, including inhibitory control (Espy et al., 2004).

Similarly, in a study of the association between inhibitory control in preschool and mathematics performance in first grade with 255 students, researchers found that inhibitory control at the age of four accounted for an advantage in early mathematics skills (i.e., problem-solving) at ages four and six (Ng et al., 2015). In this study, inhibitory control was measured using a lab-based peg-tapping assessment and early mathematics skills were measured using a standardized test of achievement. These results highlight the importance of inhibitory control for mathematics performance.

Many studies have also investigated the association between inhibitory control and academic performance across content areas including reading and mathematics. For example, Willoughby, Kupersmidt, and Voegler-Lee (2012) conducted an investigation of the causal association between executive function and academic achievement with 926 preschool children. Using lab-based measures of executive function and standardized measures of achievement, they found that students' inhibitory control was positively related to their performance on standardized assessments of reading, writing, and mathematics, even after controlling for previous academic performance (Willoughby et al., 2012). It was noted, however, that different analytic methods resulted in different conclusions, leading to the recommendation that research on executive function and academic achievement should include various measures of constructs.

In a study of 51students aged 11 to 12 years, St. Clair-Thompson and Gathercole (2006) examined the association between specific executive functions and academic performance in reading, mathematics, and science. They used a series of executive function measures including stop signal and Stroop tasks, and standardized test scores were used to measure academic performance. Results indicated that inhibitory control was again the only executive function related to academic performance across content areas (St. Clair-Thompson & Gathercole, 2006). Vuontela and colleagues (2013) conducted a similar study, though academic performance was measured using teacher ratings scales. In this study with 54 students aged eight to twelve years old, researchers found that inhibitory control, as measured by a lab-based task, was significantly correlated with teacher-reported academic performance (Vuontela et al., 2013).

Several studies have also been conducted on inhibitory control and academic performance from a developmental model of self-regulation (Valiente, Lemery-Chalfant, and Swanson, 2010; Hernández et al., 2017). In this literature, effortful control is often synonymous with inhibitory control and the methods for measuring associations with academic performance include teacher and parent ratings as well as lab-based assessments. For example, Valiente, Lemery-Chalfant, and Swanson (2010) examined the associations between academic achievement, effortful control, and emotionality with 291 kindergarten students. Students' effortful control was assessed via teacher and parent reports and by a lab-based measure, and academic achievement was measured using various subtests in reading and mathematics on a standardized achievement test. Results suggested that both parent and teacher reports and lab-based assessments of effortful control were associated with achievement in reading and mathematics (Valiente et al., 2010). Similarly, in a study of 301 kindergarten students conducted by Hernández and colleagues (2017), researchers examined the predictive associations between effortful control in kindergarten and academic achievement in first grade, controlling for prior achievement. Effortful control was measured by teacher and parent ratings and a lab-based task and achievement in reading and mathematics was measured using a standardized achievement test. Results indicated that effortful control in kindergarten positively predicted academic achievement in both mathematics and reading in first grade (Hernández et al., 2017).

Other studies have also examined inhibitory control from both cognitive and developmental perspectives (Allan & Lonigan, 2014; Blair & Raver, 2015; Neuenschwander et al., 2012). Blair and Razza (2007) examined the associations between effortful control, executive function, false belief understanding, and academic performance in reading and mathematics. In a study of 170 children who attended a preschool program for low-income families, these researchers used a peg-tapping measure to assess inhibitory control. Achievement measures were used to assess academic performance in mathematics and reading. Results indicated that various aspects of self-regulation accounted for unique variance in academic performance; however, inhibitory control was the only construct examined that was independently related to all measures of reading and mathematics abilities (Blair & Razza, 2007).

Similarly, Allan and Lonigan (2011) studied the associations between inhibitory control and reading performance with 234 preschool students. Inhibitory control was assessed using various lab-based assessments typically used in effortful control and executive function studies. Academic performance was measured with a standardized measure. Results indicated that effortful control was significantly related to reading skills. Researchers also found no differences between all of the measures used to assess effortful control, suggesting that effortful control and inhibitory control are similar, despite the varying theoretical underpinnings (Allan & Lonigan, 2014).

Neuenschwander and colleagues (2012) studied the predictive associations and interaction of various aspects of self-regulation, including effortful control and executive functions, and grades and performance on standardized tests. This study included 459 students between the ages of four and nine who were part of a longitudinal study conducted in Switzerland. This study included three lab-based measures of executive function, each assessing one of the main components. Measures of effortful control included parent rating scales and grades and standardized tests were used to assess academic performance in reading and mathematics. Results indicated that effortful control and executive functions were not significantly related to each other. Executive functions predicted performance in mathematics and reading and effortful control predicted school grades in reading and mathematics (Neuenschwander et al., 2012). The association between effortful control and school grades should be interpreted with caution, however, as effortful control was measured via parent reports. Teacher reports would have been a more direct manner of assessing effortful control in the context of school performance.

Although the aforementioned studies highlight a link between inhibitory control and performance across content areas, other studies have shown differential associations between inhibitory control and performance in reading and mathematics. For example, Lan and colleagues (2011) investigated the links between various executive functions and academic performance in reading and mathematics. This study was a cross-cultural analysis of 119 preschoolers from China and 139 preschoolers from the United States. Researchers utilized various lab-based measures of executive functions and other standardized tests of academic performance in reading and mathematics. Results showed that inhibitory control uniquely predicted mathematics performance, but not reading performance for students from China and the United States (Lan et al., 2011). In another similar study, Ponitz and colleagues (2009) examined associations between self-regulation, measured by an assessment typically used to capture inhibitory control, and academic performance. This study of 343 kindergarteners showed that gains in self-regulation predicted gains in mathematics, but not in reading skills (Ponitz et al., 2009).

All of the aforementioned studies highlight that, in addition to other aspects of cognitive self-regulation, inhibitory control also plays an important role in academic performance. For example, some literature suggests a strong association between inhibitory control and mathematics performance (Espy et al., 2004; Ng et al., 2015). The associations between inhibitory control and reading performance, however, are less clear (Allen et al., 2014; Lan et al., 2011; Ponitz et al., 2009). As such, further investigation is warranted to help understand how inhibitory control is related to overall academic performance and functioning in reading and mathematics. Additionally, what remains to be further understood is how inhibitory is related to academic performance specifically for students with social-emotional difficulties. No research was found that focused specifically on students with greater self-regulation difficulties, for whom similar mechanisms may or may not be present. More research using cognitive and developmental measures is also needed for students in early elementary school. Thus, I investigated associations between inhibitory control and academic performance for students with social-emotional difficulties.

Emotional self-regulation and academic performance. Emotional self-regulation (i.e., emotion regulation) is an important construct to incorporate into the investigation of academic performance, as a student’s ability to regulate emotions is related to functioning within the school context. For example, children with strong emotion regulation skills often have more positive peer relationships (Ladd, Birch, & Buhs, 1999), better relationships with teachers (Ladd et al., 1999), fewer attention concerns (Trentacosta & Izard, 2007), and fewer behavioral issues in the classroom (Garner & Waajid, 2012). Students with such skills experience less disruption in their learning or socialization when they are able to minimize the impact of intense emotions (Djambazova-Popordanoska, 2016). Emotion regulation also enables students to maintain appropriate affective states that support motivation and initiative in the learning process (Garner, 2010; Schutz & Davis, 2010; Tyson et al., 2009). Thus, children with stronger emotion regulation skills are more likely to be evaluated favorably by teachers (Denham, Bassett, & Zinsser, 2012; Trentacosta & Izard, 2007) and experience school success (Graziano, Reavis, Keane, & Calkins, 2007).

Extant research has linked emotional self-regulation to academic performance in various ways; however, the mechanisms through which poor emotional self-regulation may interfere with the learning process are unclear. From a cognitive resources model, students only have so much cognitive capacity to exert during learning (Schmeichel, Vohs, & Baumeister, 2003). Intense emotions compete for cognitive resources and impact cognitive mechanisms including attention, inhibitory control, working memory, and other higher order processes (Blair, 2002; Caine & Caine, 1991; Fogarty, 2009). Consequently, such intense emotions have the potential to interfere with the learning process (Goleman, 2004).

Several researchers have examined the connections between emotional self-regulation skills and academic performance (Garner & Waajid, 2012; Graziano et al., 2007; Howse et al., 2003; Trentacosta & Izard, 2007), though most have investigated these associations in preschool children. For example, Garner and Waajid (2012) examined 74 preschoolers and found that emotion knowledge incrementally predicted cognitive competence and situation knowledge (i.e., understanding emotions in given situations) was a positive predictor of cognitive competence. Similarly, another study conducted with 122 kindergarten children found positive correlations between parent reports of children's emotion regulation skills and children's scores on standardized achievement measures of reading and mathematics performance (Howse et al., 2003). In a study by Graziano and colleagues (2007), the role of emotion regulation was investigated in 325 kindergarteners' academic performance (e.g., success, productivity, and performance on standardized measures). Results indicated that emotion regulation was positively associated with teacher reports of academic performance and with standardized early reading and mathematics achievement scores.

Each of these studies highlight the importance of emotional self-regulation skills for academic performance in younger children; however, no research was found that investigated the connections between emotional self-regulation and academic performance in these areas for early elementary school students, particularly those with social-emotional difficulties. This population is important to examine because these children may already be behind their same-aged peers academically and are at-risk for long-term negative educational outcomes without intervention.

Summary. Based on the overview of the literature on attention, inhibitory control, and emotion regulation, it is evident that each of these cognitive and emotional mechanisms of self-regulation interact in a complex manner to influence academic performance. Despite the evidenced interconnectedness, no studies were found that examined these specific mechanisms together and how they relate to academic performance, particularly for students with social-emotional difficulties. Within the effortful control literature, variations of each of these constructs have been integrated; however, such studies have often investigated the concept of emotion regulation under the categories of social-emotional skills or emotionality and have looked more indirectly at how these factors influence teacher and peer relationships, which impact school readiness and performance (Morris et al., 2013; Rhoades et al., 2016; Valiente et al., 2011, 2010, 2008). My study sought to investigate a more direct link between cognitive and emotional mechanisms of self-regulation, addressing a gap in research on the interconnectedness of these important constructs for early elementary school students with social-emotional difficulties.

In addition, extant literature suggests that the associations between different self-regulatory mechanisms and performance differ by content area, with the exception of attention. Research has also shown that attention is the most robust predictor of performance in reading and mathematics (Lan et al., 2011; Razza et al., 2012). In terms of inhibitory control, research indicates that inhibitory control is most consistently a significant predictor of mathematics performance, and less often a significant predictor of reading performance (Lan et al., 2011; Razza et al., 2012). Researchers who have investigated emotional regulation and academic performance have found that this predicts both reading and mathematics performance (Graziano et al., 2007; Howse et al, 2003).

Several explanations for these differences in associations between academic areas exist (Schmitt et al., 2017). For instance, one explanation is that mathematics content places more cognitive demands on children than does reading (Bull, Espy, & Wiebe, 2008; Clark et al., 2010). Successful mathematics performance, therefore, may require greater self-regulation (Schmitt et al., 2017). Additionally, literature from cognitive neuroscience suggests an overlap of the brain regions (i.e., prefrontal cortex) that support self-regulation as well as mathematics performance (Klingberg, 2006). Furthermore, methods of assessing mathematics and reading performance may also contribute to differences in associations. For instance, some researchers purport that self-regulatory mechanisms provide “a foundation for the development of reasoning abilities or fluid mental capacities (e.g., problem-solving), which are typically required to do well on math assessments” (Schmitt et al., 2017, p. 1121). On the other hand, many reading assessments place more demands on crystallized mental abilities, as they are more knowledge-based (e.g., word knowledge) (Schmitt et al., 2017).

Given the literature suggesting differences in associations between cognitive and emotional mechanisms of self-regulation and mathematics and reading performance, investigations of academic performance must take such differences into account. Researchers have examined associations between cognitive and emotional mechanisms of self-regulation and mathematics and reading performance (Morris et al., 2013; Rhoades et al., 2016; Valiente et al., 2011, 2010, 2008). Additional research, however, is warranted to further understand how these mechanisms influence academic performance in reading and mathematics, particularly for students with social-emotional difficulties. Thus, my study examined how various cognitive and emotional mechanisms of self-regulation relate to general academic performance as well as performance in reading and mathematics for students with social-emotional difficulties.

Covariates: Socioeconomic Status and Gender

In order to better understand the complex associations between self-regulation and academic performance, researchers often control for other factors that may contribute to variability in these constructs including gender and socioeconomic status (SES) (Gestsdottir et al., 2014; Hubert et al., 2015; McClelland & Cameron, 2011; von Suchodoletz et al., 2013). As such, I have included a brief review of the literature on the associations between gender, SES, self-regulation, and academic performance below. Importantly, however, there was no specific evidence found to suggest that the association between self-regulation and academic performance might vary for boys versus girls or for children from lower versus higher socioeconomic backgrounds.

Socioeconomic status and academic performance. Researchers examining academic performance often control for SES, as literature shows that SES is a well-recognized factor related to academic performance (e.g., Chatterji, 2006; Lee & Otaiba, 2015). For example, several researchers found a strong association between SES and academic performance, such that students from families with higher a SES often performed more favorably academically than students from families with a lower SES (Chatterji, 2006; Lee & Otaiba, 2015; Mulligan, Hastedt, & MCarroll, 2012). The differences in academic performance between students from higher and lower SES backgrounds are noticeable from a young age (Chatterji, 2006; Mulligan et al., 2012), are compounded over time (Chatterji, 2006), and cross various content areas, including reading and mathematics (Mulligan et al., 2012).

There are several factors believed to contribute to the differences in academic performance between students from lower and higher SES backgrounds. First, students from lower SES families are more likely to enter school with fewer academic skills across content areas, as they typically do not have access to a wide variety of activities that promote the acquisition of pre-academic skills (Bradley, Corwyn, McAdoo, & Garcia, 2001; Byrnes & Wasik, 2009; Crosnoe & Cooper, 2010; Galindo & Sonnenschein, 2015; Jordan, Kaplan, Olah, & Locuniak, 2006). Second, research suggests that exposure to language is another differentiating factor between children from lower and higher SES families. For example, students from lower SES families may not have as much exposure to specific language that may prime them for understanding lessons and directions in the classroom setting (Galindo & Sonnenschein, 2015; Hindman, Skibbe, Miller, & Zimmerman, 2010). Furthermore, parents' expectations for achievement may also contribute to differences in academic performance based on SES (Sonnenschein & Galindo, 2015). Lastly, children from lower SES backgrounds experience higher exposure to stress, which can interfere with development in various ways (Hamoudi, Murray, Sorenson, & Fontaine, 2015).

Socioeconomic status and self-regulation. Researchers investigating self-regulation also often control for SES, as lower SES is associated with cognitive and emotional self-regulation difficulties (Blair, 2010; Blair & Ursache, 2011; Wanless, McClelland, Tominey, & Acock, 2011). For instance, in a meta-analysis of 25 studies on children between the ages of 2 and 18, Lawson, Hook, and Farah (2017) found a small, but statistically significant correlation between SES and self-regulatory abilities. However, while some researchers found significant associations between SES and self-regulation, others did not. For instance, Razza and colleagues (2012) found that poverty status did not relate to self-regulation.

Some hypothesized reasons for such differences include environmental factors, such as experiences and stress levels. For example, children from lower SES households are less likely to have experiences and environments that foster strong cognitive and emotional self-regulation skills (Blair & Raver, 2015). Additionally, children from lower SES backgrounds are more prone to negative stress exposure, which negatively impacts the development of self-regulation (Hamoudi et al., 2015).

Gender and academic performance. Gender is another demographic characteristic that is frequently used as a covariate in research on academic performance, as many studies have shown gender differences in this area of research (Below et al., 2010; Lee, Moon, & Hegar, 2011; Lonnemann et al., 2013; Marks, 2008; Robinson & Lubienski, 2011). For example, in a study of gender gaps and reading and mathematics across various countries, Marks (2008) found that gender differences varied by content area, as girls performed better than boys in reading, but boys performed better than girls in mathematics. In another study, Robinson and Lubienski (2011) conducted a longitudinal analysis of gender achievement gaps in mathematics and reading. Results suggested that, over a prolonged period of time, boys outperform girls in mathematics and girls outperform boys in reading. Furthermore, in a study of gender gaps specifically in mathematics, other researchers found that male students consistently displayed significantly higher scores on mathematics than female students from kindergarten through third grade (Lee, Moon, & Hegar, 2011). Another study found that gender differences favoring males in mathematics performance emerges even before kindergarten entry (Lonnemann, Linkersdörfer, Hasselhorn, & Lindberg, 2013). In a study of gender differences specifically in reading, Below and colleagues (2010) found significant gender differences favoring girls in early reading skills.

Many researchers have hypothesized explanations for gender differences in academic performance. Some explanations include differences in behavior, motivation, brain activation, and learning strategies (Logan & Johnston, 2010). Others have attributed differences to sociological issues such as gender-based stereotype threat (Lindberg et al., 2010; Spencer, Steele, & Quinn, 1999). Marks (2008) found that gender gaps were influenced by factors including expectations for students and macro-societal factors, such as the proportion of women in the workplace, societal inequity, and public sector spending.

Gender and self-regulation. Researchers examining self-regulation typically control for gender, as many studies have suggested that girls perform better than boys on measures of both cognitive and emotional mechanisms of self-regulation (Else-Quest, Hyde, Goldsmith, & Hulle, 2006; Matthews, Ponitz, & Morrison, 2009; Matthews, Marulis, & Williford, 2014; Zimmerman & Iwanksi, 2014). For example, in a meta-analysis of gender differences and self-regulation, researchers found significant gender differences favoring females in effortful control, particularly with respect to inhibitory control (Else-Quest et al., 2006). Similarly, Matthews and colleagues (2009) found that girls outperformed boys on both direct and indirect measures of self-regulation (e.g., direct assessment and teacher report). Furthermore, Zimmerman and Iwanksi (2014) found gender differences in emotional self-regulation, particularly with respect to emotion regulation.

Several researchers have generated explanations for gender differences in self-regulation. For example, some researchers attribute gender differences to the types of measurement tools utilized in studies (Matthews et al., 2009; Silverman, 2003). For example, Matthews and colleagues (2009) asserted that bias associated with teacher and parent reports may contribute to observed gender differences in extant literature.

Summary. Based on the review of literature, it is evident that gender and SES may influence both self-regulation and academic performance; however, no specific research was found to suggest that the associations between self-regulatory mechanisms and academic performance vary by gender or SES. As such, in line with previous research, gender and SES were included as covariates in my study to ensure that any potential variance in academic performance resulting from gender and SES were controlled. A more extensive examination of the interrelationships was not possible given sample size limitations.

Purpose of the Current Study

There are two main limitations of the current literature that my study sought to address. First, although many studies have investigated how attention and inhibitory control relate to academic performance and other studies have looked at the relationship between emotion regulation and academic performance, few studies have investigated an integrated model that includes both cognitive and emotional components and examines these in relation to each other. Second, many studies have also examined these constructs in preschool-aged children; however, fewer researchers have looked at the associations in early elementary school children. This is an important developmental period because the capacity to self-regulate continues to develop rapidly until around age seven or eight (Berger, 2011), which is a critical time for the development of foundational academic skills and behaviors. Not only is it important to investigate this developmental period, but it is also important to examine these associations for children with social-emotional difficulties, as they are at significant risk for adverse educational outcomes. To address these limitations, my research investigated the interrelationships among attention, inhibitory control, and emotion regulation in predicting academic performance.

Research Questions and Hypotheses

My study examined predictors of students' academic performance including cognitive and emotional self-regulation in order to better understand the roles each of these constructs play for students exhibiting social-emotional difficulties. The following research questions were investigated:

1. What are the associations between key cognitive and emotional self-regulation mechanisms and teacher-rated academic performance, when controlling for gender and free/reduced lunch status? It was expected that attention skills, inhibitory control, and

emotion regulation would each contribute significantly to teacher-rated academic performance. Attention was expected to be the strongest predictor.

2. What are the associations between key cognitive and emotional self-regulation mechanisms and academic performance, as measured by reading proficiency, when controlling for gender and free/reduced lunch status? It was expected that attention skills and emotion regulation would each contribute significantly to reading proficiency. Attention was expected to be the strongest predictor. Inhibitory control was not expected to be a significant predictor.

   What are the associations between key cognitive and emotional self-regulation mechanisms and academic performance, as measured by mathematics proficiency, when controlling for free/reduced lunch? It was expected that attention skills, inhibitory control, and emotion regulation would each contribute significantly to the variance in outcomes. Attention was expected to be the strongest predictor of proficiency in mathematics.

CHAPTER 3: RESEARCH METHODS

In this study, I examined the extent to which attention, inhibitory control, and emotion regulation contributed to academic performance for students in early elementary school exhibiting social-emotional difficulties. I conducted a secondary analysis of data collected as part of an efficacy investigation of a self-regulation intervention implemented in a school setting. The intervention was not the focus of this research, therefore, only baseline data was used. The original study from which this study extends was funded by the Institute of Education Sciences (IES) and was conducted within multiple school districts (R305A150169). This analysis of secondary data was approved by the University of North Carolina Institutional Review Board (IRB Number: 18-0064). Sources of data for participants included teacher reports, observation, school records, and direct child assessment. Composite scores were generated where appropriate, and multilevel regression and multilevel logistic regression were used to address research questions.

Participants

Participants included students taking part in a federally-funded randomized trial of a self-regulation intervention. Data from the second and third cohorts were utilized for my study as some measures were different for the first cohort. The final sample analyzed included 129 first and second grade students across 79 classrooms (68 teachers) in nine schools and three local school districts. Schools were selected based on principal interest and district recommendation. Teachers volunteered to participate based on information presented at each school via in-person information sessions. Several teachers participated in the study across multiple years, resulting in the difference in the number of teachers and classrooms. Teachers were from schools located in both rural and urban areas of North Carolina within an hour's drive of the university.

Student and teacher characteristics. The student sample consisted of 88 males and 41 females with diverse racial and ethnic backgrounds (see Table 2). There were 58 and 71 first and second grade students, respectively. Students' average age in years was 7.20 (*SD* = 0.69, range: 6.00-9.33). Data for the student sample was collected across two cohorts; there were no statistically significant differences between cohorts one and two on any measures or variables utilized in this study. Sixty-eight teachers provided data for this study, the majority of whom were female with an average of 8.19 years of teaching experience. Demographic information for students and teachers can be seen in Table 1.

Table 1

Demographic Information

	N	*M* or %	*SD*	Min	Max
Students					
Age in Years	128	7.20	0.69	6.00	9.33
Grade (Grade 1)	129	45%	-	-	-
Gender (Male)	129	68%	-	-	-
SES (Receives Free/Reduced Lunch)	129	76%	-	-	-
Teachers					
Gender (Female)	68	95%	-	-	-
Number of Years Teaching	68	8.19	8.14	0	30

The student sample had a higher than expected number of African Americans and a lower than expected number of Latinx students, given the overall demographics of the schools from which students were recruited (see Table 2). One possible reason for a higher than expected number of African American students is the nature of the recruitment process, which was based partly on teacher nomination. Research has shown that teachers may over-identify discipline problems in children of color in comparison to their white peers (Gregory, Skiba, & Noguera, 2009; Skiba et al., 2014), thus potentially contributing to a higher referral rate in this study. In addition, socio-political factors may have reduced the response rate of Latinx families, as the study was recruiting during a time of heightened concern around immigration. Lastly, some Latinx students may have been excluded because of the study requirement for students to be proficient in English.

Table 2

Sample and Partnering School Demographic Information

Student Race	Overall School Demographics	Sample Demographics
African American	42%	62%
Caucasian	22%	28%
Latinx	30%	10%
American Indian/Alaska Native	0.6%	0.8%
Asian	1%	0%
Native Hawaiian/Other Pacific Islander	0.1%	0%

Procedure

Identification of students. Students were identified using a two-step screening process. First, teachers completed a form providing the names of students in their class “with challenging behaviors or difficulties managing emotions, interacting with peers, and meeting behavioral expectations in the classroom." This form was completed by teachers in the spring of the year prior to the intervention. Once names were provided, parent permission forms were sent home and parent phone calls were made by the counselor. This approach was used to protect students' confidentiality. Teachers during the next school year completed the Strengths and Difficulties Questionnaire (SDQ; Goodman, 1997) after the first three weeks of school. Students were included if they were rated in the "at-risk" range on the Total Difficulties scale ($\geq$12). The mean of students' SDQ scores was 18.56 (*SD* = 5.11, range: 12-34). Students with autism spectrum disorder, full-time placement in special education classrooms, significant intellectual deficits as judged by school staff, and non-proficient in English based upon school staff report were not included, as the intervention for the main study was not designed for students in these categories.

Sources of data. Parent background questionnaires, teacher surveys, direct child assessments, observational assessments, and school report cards were used as sources of data for this study.

Parent background information. Student demographic information including race/ethnicity, free and reduced lunch status, gender, and age was reported by parents and/or guardians on a background questionnaire that was completed at the same time the written consent forms were completed. Any missing information was subsequently gathered via telephone conversations with parents.

Teacher surveys. After students were nominated and parent permission was obtained, teachers were sent electronic surveys including various measures regarding students' social-emotional and academic functioning. These surveys were administered to teachers after approximately three weeks of school to ensure that they knew students well enough to rate them accurately. Teachers were compensated $25 for each survey completed.

Direct child assessments. Direct assessments of self-regulation skills were conducted one-on-one with students for approximately 45 minutes in one session and took place in a private and quiet room in the students' school. All assessments from which data were derived for my study occurred between September and October of the school year. The order of the test administration was held constant across students. Assessments were administered by research assistants, graduate students, and other trained data collectors. Training for the administration of direct assessments included approximately 30 hours of in-person training and administration practice. Each assessor was required to pass predetermined certification standards prior to administering assessments. Additionally, video reviews were conducted and assessor meetings were held to ensure administration procedures were correctly maintained for the duration of the data collection period.

Observational assessments. Observations were also conducted within students' classrooms for approximately 30 minutes on two observation periods during structured learning time (e.g., language arts, mathematics, sciences, and/or social studies). All observations occurred between September and October of the school year. Observations were conducted by research assistants, graduate students, and other experienced data collectors. Training for observational assessments included approximately 40 hours of training which included in-depth examination of all measures, administration procedures, and practice coding. Each observer was required obtain 80% agreement with a master coder for at least two video coding sessions and then two subsequent live coding occasions before conducting any observations of students in the study. Inter-rater reliability was estimated based on 20% of all observations. Furthermore, observers met weekly to prevent coder drift and to address any other field concerns related to observational assessments.

Report card grades. Students' report card grades were obtained from school staff at the end of each school year. To avoid confounding effects of the intervention in the present analysis, only first quarter grades were examined.

Measures

Screening measure. The Strengths and Difficulties Questionnaire (SDQ; Goodman, 1997) was used to determine eligibility as described above. The SDQ has been used extensively in studies to identify students with social-emotional difficulties (e.g., Goodman, Ford, Simmons, Gatward, & Meltzer, 2000; Lavigne, Meyers, & Feldman, 2016). The SDQ is a 25-item teacher rating scale used for assessing social-emotional functioning. It consists of five subscales relating to emotional problems, peer problems, conduct problems, hyperactivity, and prosocial behavior. Each subscale, except the prosocial scale, is summed to generate a total difficulties score, which was used to determine eligibility for the study. Items on the SDQ include "Often loses temper", "Restless, overactive, cannot sit still for long", "Often fights with other children or bullies them", and "Picked on or bullied by other children". Items are rated on a three-point scale, with the following descriptors as anchors: 1 = *Not True*, 2 = *Somewhat True*, and 3 = *Certainly True.*

The SDQ total difficulties score has been found to have strong internal consistency, with average Cronbach's alpha values of .82 with a range of .62 to .85 (Stone, Otten, Engels, Vermulst, & Janssens, 2010). Additionally, according to Stone and colleagues (2010), the total difficulties score has high test-retest reliability (r = .85) and strong concurrent validity (r = .76) with the Child Behavior Checklist (CBCL), another common measure used for identifying social-emotional difficulties. For this study, the Cronbach's alpha value for the total difficulties score was .84, indicating good internal consistency.

Measures by construct. The measures described below were used to assess constructs of interest including attention, inhibitory control, emotion regulation, and academic performance (see Table 3). Composite scores were generated, as appropriate, and as outlined in the data preparation section, for each construct.

Table 3

Measures

Independent Variables	Measures
Attention	• Strengths and Weaknesses of ADHD Symptoms and Normal Behavior – Inattentive Scale • Revised Edition of the School Observation Coding System – Off-Task Behavior
Inhibitory Control	• Academic Performance Rating Scale – Impulse Control Scale • Happy/Sad Stroop • Head-Toes-Knees-Shoulders Task
Emotion Regulation	• Emotion Regulation Checklist • Preschool Self-Regulation Assessment Assessor Report – Positive Emotion Scale
Dependent Variables	**Measures**
Teacher-Rated Academic Performance	• Academic Performance Rating Scale – Academic Success and Productivity Subscales Combined
Reading Proficiency	• Reading Proficiency Level (derived from report card grades)
Mathematics Proficiency	• Mathematics Proficiency Level (derived from report card grades)
Covariates	**Measures**
Gender	• Parent report of child's gender
Socioeconomic Status	• Parent report of free/reduced lunch status

***Attention measures*.** Two measures, the Inattentive scale of the Strengths and Weaknesses of ADHD Symptoms and Normal Behavior (SWAN; Swanson et al., 2012) teacher rating scale and the Revised Edition of the School Observation Coding System (REDSOCS; Bagner, Boggs, & Eyberg, 2010; Jacobs et al., 2000), were used as measures of inattention.

Strengths and Weaknesses of ADHD Symptoms and Normal Behavior Inattentive Scale (SWAN). The SWAN Inattentive Scale (Swanson et al., 2012) is a 9-item teacher rating scale based on the inattentive symptoms of attention deficit/hyperactivity disorder (ADHD) found in the Diagnostic and Statistical Manual of Mental Disorders (DSM-IV-TR). It measures these behaviors on a seven-point scale that includes *far below average, below average, slightly below average, average, slightly above average, above average, and far above average*. Each item on the Inattentive scale is scored from 3 to -3, where zero is considered average and -3 is far above average. Teachers are asked to evaluate the student by comparing them to other children in the classroom. Items on the Inattentive scale include "Sustain attention on tasks or play activities", "Ignore extraneous stimuli", and "Remember daily activities". The Inattentive scale score was generated by calculating an average item score. Higher scores on the SWAN Inattentive scale indicates more inattentive behavior.

The SWAN has been found to have strong reliability and validity (Arnett et al., 2011; Brites, Salgado-Azoni, Ferreira, Lima, & Ciasca, 2015; Young, Levy, Martin, & Hay, 2009). The Inattentive scale has Cronbach's alpha values ranging from .89 to .97 (Gold et al., 2013; Gomez, Vance, & Gomez, 2013). Additionally, correlations with other measures (i.e., the Conners' Teacher Rating Scale-Revised, Short Version) of inattention are high (r = .75), thus demonstrating adequate construct validity (Cornish et al., 2005). Researchers who have used this scale have found predictive validity with respect to achievement (Malone & Fuchs, 2014; Rogers et al., 2011). For this study, the Cronbach's alpha for the Inattentive scale was .93, indicating strong internal consistency.

Revised Edition of the School Observation Coding System (REDSOCS) Off-Task Behavior. The REDSOCS (Bagner et al., 2010; Jacobs et al., 2000) is an interval-based, observational coding system designed to assess behaviors of young children with disruptive behaviors in classrooms settings. This system includes codes for three behavioral categories: (a) Inappropriate Behavior, (b) Noncompliant Behavior, and (c) Off-Task Behavior, the latter of which was used as an indicator of inattention in this study. A child is considered on-task during an interval if he or she is attending to tasks, making appropriate motor responses, asking for assistance, etc. Off-task behavior is coded if the target child does not attend to the expected classroom tasks. Off-task behaviors include behaviors such as staring off, resting head on desk, talking to a classmate, getting out of seat, etc. REDSOCS behaviors are coded in 10 second intervals for a total of 10 minutes per child. In this study, each child was observed twice within a two- to three-week window, with scores averaged for a more reliable score (Ginn, Seib, Boggs, & Eyberg, 2009). Higher scores on Off-task behavior indicate more inattentive behaviors. The REDSOCS has high interrater reliability and convergent validity with teacher rating scales (Jacobs et al., 2000), including significant correlations between off-task behavior and a teacher rating of inattention (r = .29). For my study, the interrater reliability for the REDSOCS Off-Task Behavior was high, as indicated by an intra-class correlation coefficient (ICC) of .96.

Inhibitory control measures. Two direct child assessments and a teacher-rating of impulsivity were used to measure inhibitory control. These measures include the Happy-Sad Stroop Task (Lagattuta, Sayfan, & Monsour, 2011), the Head-Toes-Knees-Shoulders Task (HTKS; McClelland et al., 2007; Ponitz et al., 2009), and the Academic Performance Rating Scale Impulse Control scale (APRS; DuPaul et al., 1991).

Happy-Sad Stroop Task. The Happy-Sad Stroop Task was used to measure children's cognitive inhibitory control (Lagattuta et al., 2011). In particular, this measure assesses children's ability to inhibit a natural response in order to give the correct response. For this task, students were asked to say the opposite of what they saw in a picture. More specifically, students were asked to say ‘happy’ when viewing a sad face and ‘sad’ when viewing a happy face. After an explanation of the task, students were administered four practice trials. If the participant made any errors, he or she was corrected and administered another four practice trial. Data collection associated with this task did not commence until each student completed four consecutive trials correctly. Scores are based on the number of correct responses across 20 consecutive trials. Any incorrect or self-corrected answers are counted as incorrect, as per scoring guidelines from the developer. Higher scores on this measure suggest better inhibitory control.

The Happy-Sad Stroop Task has been used as a measure of executive function, particularly inhibitory control (Fay-Stammbach, Hawes, & Meredith, 2017; Kramer, Hanson Lagattuta, & Sayfan, 2015; Lagattuta et al., 2011). It has shown good validity and reliability in children aged 4-11 years (Lagattuta et al., 2011). For example, test-retest reliability is high for both number of errors and response time (r = .63 and .86, respectively) and scores are significantly correlated with other Stroop versions (Lagattuta et al., 2011).

Head-Toes-Knees-Shoulders Task (HTKS). The HTKS task is a widely used measure of behavioral inhibitory control in young children (McClelland & Cameron, 2012). This task is comprised of up to three parts, which are administered contingent on successful completion of previous parts. Students are initially given an overview of the task and opportunities for corrective feedback, if warranted. In part one, students are asked to touch their head when the examiner prompts them to “touch your toes” and vice versa. If a student scores four or more points on part one, then he or she continues to part two, which includes an additional rule that requires students to touch their knees when the examiner says, “touch your shoulders” and vice versa. If the student scores four or more points on part two, then he or she continues to part three, which includes another change in rules. In this part, students are asked to touch their head when the examiner says “touch your knees” and vice versa, and students are asked to touch their toes when the examiner says, “touch your shoulders” and vice versa.

The HTKS consists of 30 items in total, where scores for each item are either zero (*incorrect*), one (*self-corrected*), or two (*correct*). A total score is calculated by summing the total points students receive in each part. Higher scores on this task reflect higher levels of behavioral inhibition. The HTKS has shown adequate reliability and validity in children aged three to eight and across cultures (McClelland et al., 2007; McClelland et al., 2014; von Suchodoletz et al., 2013; Wanless et al., 2011). McClelland and colleagues (2014) found good test-retest stability with two different populations of students (r = .60 and .74, respectively). Another study found significant, positive correlations between the HTKS and other teacher rating scales of inhibitory control at two different time points (r = .27 and .21; McClelland et al., 2007). Performance on this measure has been shown to predict academic achievement (von Suchodoletz et al., 2013; Wanless et al., 2011).

Academic Performance Rating Scale (APRS), Impulse Control Scale. The APRS is a 19-item teacher rating scale that assesses students’ academic productivity, success, and impulse control (DuPaul et al., 1991). The APRS is made up of three subscales, including Academic Success, Academic Productivity, and Impulse Control. The Impulse Control scale was used as a measure of inhibitory control, as it assesses impulsivity specific to academic tasks. The APRS Impulse Control scale consists of three items, including “What is the quality or neatness of this child’s handwriting?”, “How often does the child complete written work in a hasty fashion?” and “How often does the child begin written work prior to understanding the directions?” (DuPaul et al., 1991). Each item consists of a 5-point Likert scale where teachers are asked to rate students based on their recent performance in school. A total score on this scale was calculated by adding the ratings for each item. Higher scores on this measure indicate better inhibitory control. The Impulse Control scale has demonstrated adequate reliability and validity, with a Cronbach's alpha of .72 and test-retest reliability correlation of .88 (DuPaul et al., 1991). For this study, the Cronbach's alpha value was .45, suggesting poor internal consistency; however, as outlined in the data preparation section, this measure was not used for analyses given the weak correlations between this measure and other measures of inhibitory control.

***Emotion regulation measures*.** Two measures were used to as measures of emotion regulation. These include the Emotion Regulation Checklist (ERC; Shields & Cicchetti, 1997), a teacher report scale, and the Positive Emotion Scale of the Preschool Self-Regulation Assessment Assessor Report (PSRA-AR; Bassett, Denham, Wyatt, & Warren-Khot, 2012; Smith-Donald, Raver, Hayes, & Richardson, 2007), which is based on ratings from the direct child assessor.

Emotion Regulation Checklist (ERC). The ERC is a 24-item questionnaire completed by teachers to assess children's observed emotion-related responses, including intensity, lability, and regulation (Shields & Cicchetti, 1997). Each item consists of a 4-point Likert scale ranging from 1 (*Rarely/Never*) to 4 (*Almost Always*). The ERC is comprised of two subscales, including the Emotion Regulation and Lability/Negativity subscales. The Lability/Negativity subscale includes items such as "Is easily frustrated" and "Responds negatively to neutral or friendly overtures by peers" and the Emotion Regulation subscale includes items such as "Is a cheerful child" and "Can say when s/he is feeling sad, angry or mad, fearful, or afraid". Previous researchers have generated total scores using all items of this measure, as the two subscales are highly correlated (r = .51) and all items provide an overall measure of emotion regulation (Trentacosta & Izard, 2007).

The ERC has been widely used with children in preschool through middle school and has been shown to relate to academic outcomes (Graziano et al., 2007; Montalbano, Murray, Kuhn, LaForett, & Cavanaugh, 2017; Trentacosta & Izard, 2007). The ERC has also demonstrated strong reliability and validity, with Cronbach's alpha values of .84 and .96 for the Emotion Regulation subscale and .83 and .92 for the Lability/Negativity subscale (Shields & Cicchetti, 1997; Trentacosta & Izard, 2007). In prior research, internal consistency has been high for the overall score generated (Cronbach's alpha = .89; Shields & Cicchetti, 1997). For this study, I generated a total score. Some items were reverse scored so that higher scores reflect better emotion regulation. The Cronbach's alpha value for my study was .81, suggesting adequate internal consistency.

Preschool Self-Regulation Assessment Assessor Report (PSRA-AR) Positive Emotion Scale. The PSRA-AR is a 28-item questionnaire that provides an observer assessment of children's behavior, including their emotion regulation skills, based on a one-on-one assessment. Each item consists of a 4-point Likert scale ranging from 0 to 3, where 0 typically indicates that a particular behavior does not occur and three indicates the behavior occurs more frequently (Smith-Donald et al., 2007). Factor analysis in a previous study (Smith-Donald et al., 2007) identified two factors for the PSRA-AR: (1) the Attention/Impulsivity scale and (2) the Position Emotion scale, which were validated in the present sample with some minor item differences. The Positive Emotion scale was used in this study as a measure of emotion regulation. This scale includes items such as "Modulates and regulates arousal level in self - keeps an 'even keel'" and “shows frequent feelings of anger/irritation”. Each item response on the Positive Emotion scale was averaged in order to calculate a total scale score.

The PSRA-AR has been used in several studies investigating emotion-related self-regulatory mechanisms in young children (Bailey, Denham, Curby, & Bassett, 2016; McCoy & Raver, 2011; Obradović, Portilla, & Ballard, 2016). The PSRA-AR has also demonstrated sufficient reliability. For example, this measure yielded Cronbach’s alpha values of .40 and .88 for the Positive Emotion subscale (Bailey et al., 2016; McCoy & Raver, 2011). The Cronbach’s alpha value for the Positive Emotion Scale in the present study was .83, suggesting adequate internal consistency.

Measures of academic performance. Two measures were examined separately as indicators of student academic performance, including the Academic Performance Rating Scale (APRS; DuPaul et al., 1991) and students’ grades.

Academic Performance Rating Scale (APRS) Academic Success and Productivity Scales. As aforementioned, the APRS consists of three subscales, including Academic Success, Academic Productivity, and Impulse Control. The Academic Success and Academic Productivity subscales were used as measures of teacher-rated academic performance. The Academic Success subscale measures the teachers’ perception of students’ skills in reading, mathematics, and written language and includes items such as “How consistent has the quality of this child’s academic work been over the past week?” and “How frequently does this child have difficulty recalling material from a previous day’s lesson?”. The Academic Productivity Scale assesses the percentage and accuracy of work that is assigned and completed and includes items such as “How frequently does the student accurately follow teacher instructions and/or class discussion during *large-group* (e.g., whole class) instruction?” and “How frequently does the student accurately follow the teacher instructions and/or class discussion during *small-group* (e.g., reading group) instruction?”. Individual item ratings on the Academic Success and Academic Productivity subscales were added together to create a total score. These two subscales were combined to obtain an overall score for teacher-rated academic performance due to high correlations between the subscales in this study (r = .84), consistent with previous research (r = .88; Graziano et al., 2007). Some items were reversed scored so that higher scores on the APRS indicates better academic performance.

The APRS has been used in studies investigating students’ academic performance (Graziano et al., 2007; Power et al., 2012; Rabiner, Murray, Skinner, & Malone, 2010). It has shown strong reliability and validity, with Cronbach’s alpha values of .94 for the Academic Productivity scale and .94 for the Academic Success scale. Cronbach’s alpha values for the overall measure range between .88 and .95 (DuPaul et al., 1991; Merriman, Codding, Tryon, & Minami, 2016). The Cronbach’s alpha value for the combined Academic Success and Productivity subscales in this study was .88, indicating strong internal consistency.

Grades. Students’ first quarter reading and mathematics grades were used as measures of academic performance. Grades have been used extensively in previous research as a measure of students’ academic performance across various content area (Perfect, Levine-Donnerstein, Archbold, Goodwin, & Quan, 2014; Rasmussen & Laumann, 2012; Valiente et al., 2011). Due to differences in grading systems across school districts, grades were dichotomously scored based on level of proficiency, whereby students were either assigned a P (*proficient*) or an N (*not proficient*). Proficiency was determined by whether a student received a “satisfactory” grade or a numerical score at or above 75%, a threshold with ecological validity based on feedback from school partners. Grades in reading and mathematics were analyzed separately to obtain an understanding of how various self-regulatory mechanisms influence functioning in each content area.

Covariates. Free/reduced lunch status and gender were included in analyses as covariates. Subsidized lunch status is typically used in studies of self-regulation (Rouse & Fantuzzo, 2016). In this study, receiving subsidized lunch support was coded as one. This study also included gender, with males coded as one. Including these covariates is typical for this area of research (Garner & Waajid, 2012; Graziano et al., 2007; Howse et al., 2003; Morris et al., 2013; Rhoades et al., 2016; Valiente et al., 2010).

Data Preparation

Missing data. During the data preparation phase, missing data were examined. Only six of twelve measures had any missing values (e.g., HTKS, Happy-Sad Stroop, free/reduced lunch status, reading grades, and mathematics grades). No measure had more than 5% missing data; other measures only had between 0.7 and 4.3% missing data. Patterns of missingness were investigated using various graphs (e.g. dummy code matrix and missing data matrix) and did not display any clear pattern of missingness. Additionally, missing data patterns were examined using Little's MCAR test. Results suggested data was missing at random, as Little's MCAR test did not reach statistical significance [χ^2 (44) = 55.53, p = .11]. Given the low percentage of missing data, no clear pattern of missingness, and a lack of statistical significance in terms of Little's MCAR test, all missing data were determined to be missing at random.

Since composite scores were generated as part of my investigation, only cases that were missing more than one measure of a composite were excluded in analyses. Two cases met this criterion. Six other cases were also excluded due to missing data on other variables including free/reduced lunch status and report card grades. A total of nine subjects were excluded from analyses, which is 6.5% of subjects overall. Subjects included and not included in analyses did not differ significantly on any socio-demographic variables, including age [$t(135) = -.37$, $p > .05$], gender [$t(136) = .10$, $p > .05$], and SES [$t(135) = .06$, $p > .05$].

Composite scores. Composite scores were generated as appropriate to represent constructs of interest. There are various methods that can be utilized for generating composite scores, including formative and reflective measurement strategies (Willoughby, Blair, & The Family Life Project Investigators, 2016; Willoughby, Holochwost, Blanton, & Blair, 2014; Bollen & Bauldry, 2011). Formative measurement generates a standardized mean score, whereas reflective measurement creates factors scores utilizing confirmatory factor analysis (CFA). Within the self-regulation literature, researchers have often utilized confirmatory factor analysis (CFA) to develop factor scores for various constructs (i.e., Miyake et al., 2000; Willoughby et al., 2012). There are advantages of using CFA outlined by Willoughby and colleagues (2014) including reduction of multiple measures into a latent construct, increased statistical power, and addressing the complexities associated with the interconnectedness of various self-regulatory mechanisms (i.e., task impurity problem; Miyake et al., 2000).

Despite some advantages, there are also many concerns related to CFA in the development of composites within the self-regulation literature. According to Willoughby and colleagues (2014), correlations between various measures of self-regulation are often weak, resulting in latent variables that have limited maximal reliability. In addition, CFA represents mechanisms of self-regulation more narrowly than the theoretical conceptualization. As such, using CFA for composite score development can create a mismatch between the conceptualization and measurement of mechanisms of self-regulation (Willoughby et al., 2014).

Willoughby and colleagues (2016) examined whether mechanisms of self-regulation are better characterized as formative or reflective indicators. Using vanishing tetrad tests, they tested the fit of models in which mechanisms of self-regulation were used as formative or reflective indicators of latent constructs. Results indicated that self-regulatory mechanisms are better represented as formative indicators. Thus, Willoughby and colleagues (2016) recommend using formative methods to generate composite scores when examining self-regulatory mechanisms, which is the approach used in my study.

Initially, bivariate correlations were computed to determine if composite scores were possible, as is consistent with prior research using similar measures (e.g., Carlson & Moses, 2001; Fay-Stammbach et al., 2017). All measures that yielded significant correlations ($\geq$ .30) were utilized to generate a composite for constructs of interest, a threshold in line with research in this area (e.g., Carlson & Moses, 2001; Fay-Stammbach et al., 2017). If correlations between measures did not meet this threshold, they were not combined into a composite score. Once bivariate correlations were computed, raw scores from measures that were significantly correlated were then transformed into *z* scores using the overall sample mean and standard deviation. *Z* scores were then averaged to create a composite score for each construct of interest, where appropriate. This process is consistent with other researchers who have utilized formative methods for generating composite scores (e.g., Fay-Stammbach et al., 2017; Willoughby et al., 2016).

It is important to note that two of the three proposed constructs had only two potential measures from which a composite score could be generated (i.e., attention and emotion regulation). In both of these instances, proposed measures did not yield strong enough correlations to create a composite score. As such, decisions had to be made about whether to maintain a measure separately or to forgo use in analyses. This decision-making process was informed by several factors, including the necessity to maintain adequate power and to retain important predictors. Further details regarding the generation of composite scores as well as the rationale for decisions regarding measures, are outlined below.

Attention composite score. As shown in Table 4, the SWAN Inattentive Scale (Swanson et al., 2012) and the REDSOCS Off-Task Behavior measure (Bagner et al., 2010; Jacobs et al., 2000) were significantly correlated (r = .20); however, the correlation did not meet the aforementioned threshold to combine measures into a composite score. Instead, both measures were entered into models as separate measures of attention. Each of these measures capture attentive behavior; however, the SWAN Inattentive Scale is a more global measure and the REDSOCS Off-Task Behavior provides a snapshot of attention functioning during academic activities. Even though these measures were not strongly correlated, both types of attentional functioning are important to include when examining the associations between attention and academic performance (Garner et al., 2013; Gray, Rogers, Martinussen, & Tannock, 2015; Pingault, Tremblay, & Vitaro, 2011; Zoromsk, Owens, Evans, & Brady, 2005). Table 4 also includes descriptive statistics of the attention measures in order to provide an understanding of measures before composites and analyses.

Table 4

Descriptive Statistics and Correlation Matrix for Attention Measures

	M (*SD*)	SWAN Inattentive Scale	REDSOCS Off-Task Behavior Score
SWAN Inattentive Scale	1.48 (0.96)	1	--
REDSOCS Off-Task Behavior Score	31.82 (19.16)	0.20*	1

*p < .05.

Inhibitory control composite score. As seen in Table 5, the Happy-Sad Stroop Task (Lagattuta et al., 2011), the HTKS (McClelland et al., 2007; Ponitz et al., 2009), and the APRS Impulse Control Scale (DuPaul et al., 1991) were all significantly correlated. The correlation between the Happy-Sad Stroop and the HTKS was .36. However, the correlations between the APRS Impulse Control Scale and the Happy-Sad Stroop and the HTKS, which were .28 and .18, respectively, were not strong enough to combine measures into a composite score. Given that the Happy-Sad Stroop and the HTKS have been more frequently used as indicators of inhibitory control (e.g., Fay-Stammbach et al., 2017; Fuhs, Farran, & Nesbitt, 2015; Fuhs, Nesbitt, Farran, & Dong, 2014), these two measures were combined to generate a composite score and the APRS Impulse Control Scale was excluded. Table 5 also includes descriptive statistics of inhibitory control measures in order to provide an understanding of measures before composites and analyses.

Table 5

Descriptive Statistics and Correlation Matrix for Inhibitory Control Measures

	M *(SD)*	APRS – Impulse Control Scale	Happy/Sad Stroop Task	HTKS
APRS – Impulse Control Scale	8.54 (2.15)	1	--	--
Happy-Sad Stroop Task	15.00 (3.21)	0.28**	1	--
HTKS	38.94 (15.34)	0.18*	0.36**	1

*$p < .05$. **$p < .01$.

Emotion regulation composite score. As seen in Table 6, the Emotion Regulation Checklist (Shields & Cicchetti, 1997) and the PSRA-AR Positive Emotion Scale (Bassett et al., 2007) were not significantly correlated ($r = .06$). This likely reflects differences in both the raters and observed behavior, as the Emotion Regulation Checklist is a teacher rating scale based on extensive observations of a child in the classroom whereas the PSRA-AR Positive Emotion Scale is based on a data collector's observation of 45 minutes of interaction with a student during the one-on-one assessments. These measures also have items that may be measuring different areas of functioning in terms of emotional self-regulation. Given that the Emotion Regulation Checklist has been more frequently examined in the literature as a measure of emotion regulation (e.g., Graziano & Hart, 2016; Graziano et al., 2007; Trentacosta & Izard, 2007) and reflects a much broader sample of observed behavior, this measure was used for the emotion regulation variable and the PSRA-AR Positive Emotion Scale was excluded. Table 6 also includes descriptive statistics of emotion regulation measures in order to provide an understanding of measures before composites and analyses.

Table 6

Descriptive Statistics and Correlation Matrix for Emotion Regulation Measures

	M (*SD*)	Emotion Regulation Checklist	PSRA-AR Positive Emotion Scale
Emotion Regulation Checklist	2.66 (0.40)	1	--
PSRA-AR Positive Emotion Scale	1.78 (0.65)	0.06	1

Final measures and variables included in analyses. Table 7 shows the final measures and variables used in analyses. As aforementioned, some measures did not yield strong enough correlations to generate composite scores. Thus, decisions about whether to analyze a measure separately or to forgo its inclusion in analyses were made based power, theoretical considerations, and the extent of use in prior research. Regarding measures of attention, the SWAN Inattentive Scale and REDSOCS Off-Task Behavior were not strongly correlated, but each was entered into the model separately given that they are both considered important and valid measures of attentional functioning. In terms of inhibitory control, only two of the three measures were strongly correlated. As such, the Happy-Sad Stroop and the HTKS were combined to generate a composite score of inhibitory control and the APRS Impulse Control Scale was excluded from analyses. With regard to emotion regulation, the two measures were not significantly correlated. The Emotion Regulation Checklist was added into the model and the PSRA-AR Positive Emotion Scale was excluded from analyses given the Emotion Regulation Checklist is widely used in the literature and presumably represents a much larger sample of child behavior.

Table 7

Final Measures and Variables Used in Multilevel Models

Independent Variables	**Measures**
Attention	• Strengths and Weaknesses of ADHD Symptoms and Normal Behavior – Inattentive Scale • Revised Edition of the School Observation Coding System – Off-Task Behavior
Inhibitory Control	• Happy/Sad Stroop • Head-Toes-Knees-Shoulders Task
Emotion Regulation	• Emotion Regulation Checklist
Dependent Variables	**Measures**
Teacher-Rated Academic Performance	• Academic Performance Rating Scale – Academic Success and Productivity Subscales Combined
Reading Proficiency	• Reading Proficiency Level (derived from report card grades)
Mathematics Proficiency	• Mathematics Proficiency Level (derived from report card grades)
Covariates	**Measures**
Gender	• Parent report of child's gender
Socioeconomic Status	• Parent report of free/reduced lunch status

Outliers. Data were examined for potential univariate and multivariate outliers. Analysis of frequency distributions, histograms, and box plots did not reveal any significant outliers. In addition, all raw scores for variables were standardized by transforming the data into *z*-scores to further investigate for univariate outliers. No single *z*-scores exceeded ± 4.00, which is an acceptable rule given the sample size was larger than 100 (Stevens, 2001). In terms of multivariate outliers, Mahalanobis distance values were calculated for each variable and tested using chi-square criteria. No outliers were indicated, as no Mahalanobis distance values exceeded the critical value of 18.47 at $p < .001$.

Data Analysis Approach

As previously noted, the 129 students in this study had 68 different teachers, with one to seven students per teacher. Due to the hierarchical nature of the data (i.e., students nested within teachers), multilevel modeling was used. This type of analysis is commonly used to analyze variance in outcomes when predictor variables are nested, as nested data inherently violate the assumption of independence of errors required for other types of analyses, such as the General Linear Model (Tabachnick & Fidell, 2012). Multilevel modeling addresses this issue by permitting intercepts and slopes to vary between levels and/or groups (Tabachnick & Fidell, 2012; Snijders & Bosker, 1999), which accounts for the variance that is shared by children with the same teacher. As such, multilevel modeling was used to examine associations between various self-regulatory mechanisms and academic performance for all analyses. Additionally, different types of multilevel modeling were used for research questions addressing continuous and dichotomous outcome variables, including multilevel regression (i.e., linear mixed) and multilevel logistic regression (i.e., generalized linear mixed).

Analyses related to research questions. In order to establish a common metric for interpretation, all continuous predictors were standardized to have a mean of 0.00 and a standard deviation of 1.00 (Burchinal et al., 2018; Hedges, 2008; Willoughby et al., 2012). I used a top-down multilevel modeling approach to analyze each research question (Kim, Anderson, & Keller, 2014; Ryoo, 2011). First, I fit unconditional means models and calculated intraclass correlation coefficients (ICC) using variance components to determine the amount of variance in the dependent variables explained by grouping structure (i.e., teacher). Next, full models were fit, which included all Level-1 predictor variables and covariates (i.e., two attention measures, the composite score for inhibitory control, and the emotion regulation measure as well as gender and free/reduced lunch status). Since students were nested within teachers, teacher was accounted for at Level-2 of the model, though no Level-2 predictors were included. Predictor variables that were not statistically significant in the full models were trimmed one at a time in order of the smallest statistical significance until models included only statistically significant predictors. Given that gender and free/reduced lunch status were control variables, they remained in the model regardless of significance level. Once statistically significant predictors were obtained, additional analysis included systematically examining the significant predictor variables as random effects. Random effects could not be modeled initially, as this presented issues with model convergence. Analyses specific to each research question are described below. Analyses specific to each research question are described below.

Research question one. The associations between cognitive and emotional indicators of self-regulation (i.e., attention, inhibitory control, and emotion regulation) and academic performance, as measured by teacher ratings of overall academic performance, were analyzed using multilevel regression analysis. Gender and free/reduced lunch were included as covariates. All models were fit using maximum likelihood estimation, as comparisons between successive models using model fit criteria involved both regression coefficients and variance components (Hox, 2010).

First, the unconditional random intercept model was fit to the data with teacher-rated academic performance as the dependent variable and teacher as the Level-2 variable. This model provided an estimated mean teacher-rated academic performance score for all teachers. It also provided a partitioning of variance between Level-1 and Level-2 (Heck, Thomas, & Tabata, 2014). The equations below represent variation at each level:

Level-1 Model

$$Y_{ij} = \beta_{0j} + \varepsilon_{ij}$$

Level-2 Model

$$\beta_{0j} = \gamma_{00} + e_{0j}$$

Combined Model

$$Y_{ij} = \gamma_{00} + e_{0j} + \varepsilon_{ij}$$

Where:

Y_{ij} = teacher-rated academic performance for student i with teacher j

β_{0j} = average teacher-rated academic performance for teacher j

γ_{00} = grand mean of teacher-rated academic performance

e_{0j} = teacher/level-2 error

ε_{ij} = child/level-1 error

This model also provided a measure of dependence of the Level-2 variable through the ICC, which is an estimate of the amount of variance in a dependent variable explained by grouping structure (Hox, 2010). The ICC value was calculated using this formula

$$ICC = \frac{\sigma_B^2}{(\sigma_B^2 + \sigma_W^2)}$$

where σ^2 represents the variance, *B* represents between groups, and *W* represents within groups in the unconditional model.

Second, the full model for research question one was fit, which included all Level-1 predictor variables and covariates (e.g., two attention measures, the composite score for inhibitory control, and the emotion regulation measure as well as gender and free/reduced lunch status). The equations for the full model are shown below. Of note, all Level-1 variables were modeled as fixed effects in the initial examination of the full model in order to ensure model convergence (Heck et al., 2014). The intercept was allowed to vary across teacher groups.

Level-1 Model

$$Y_{ij} = \beta_{0j} + \gamma_{10} X_{1ij} + \gamma_{20} X_{2ij} + \gamma_{30} X_{3ij} + \gamma_{40} X_{4ij} + \gamma_{50} X_{5ij} + \gamma_{60} X_{6ij} + \varepsilon_{ij}$$

Level-2 Model

$$\beta_{0j} = \gamma_{00} + e_{0j}$$

Combined Model

$$Y_{ij} = \gamma_{00} + e_{0j} + \beta_{0j} + \gamma_{10} X_{1ij} + \gamma_{20} X_{2ij} + \gamma_{30} X_{3ij} + \gamma_{40} X_{4ij} + \gamma_{50} X_{5ij} + \gamma_{60} X_{6ij} + \varepsilon_{ij}$$

Where:

Y_{ij} = teacher-rated academic performance for student i with teacher j

β_{0j} = random intercept for teacher j

γ_{00} = fixed intercept for students

$\gamma_{10} - \gamma_{60}$ = fixed slopes for each independent variable

$X_{1ij} - X_{6ij}$ = independent variables (off-task behavior, inattention, inhibitory control, emotion regulation, gender, free/reduced lunch)

e_{0j} = teacher/level-2 error

ε_{ij} = child/level-1 error

Once a model with only statistically significant predictors was obtained (i.e., after trimming non-significant predictors), additional exploratory analysis included systematically examining significant predictor variables as random effects. Due to issues with model convergence and non-significant variance components, all predictors were maintained as fixed. Model deviance statistics were then examined for all models with predictor variables modeled as fixed in order to determine the most parsimonious model.

Research questions two and three. The associations between cognitive and emotional mechanisms of self-regulation (i.e., attention, inhibitory control, and emotion regulation) and academic performance, as measured by proficiency in reading and mathematics, were analyzed using multilevel logistic regression. Gender and free/reduced lunch were included as covariates. Given the similarities between outcome variables for research questions two and three (e.g., both dichotomously scored measures of proficiency), this summary encompasses the use of multilevel logistic regression for both research questions, as the only difference is that research question two included reading proficiency as the outcome measure and research question three examined mathematics proficiency. All models for research questions two and three were fit using robust estimation. Deviance statistics were not utilized for these research questions to assess model fit, as they are misleading and inaccurate for multilevel logistic regression (Hox, 2010).

First, unconditional random intercept models were fit to the data with reading and mathematics proficiency as the dependent variables and teacher as the Level-2 variable. These models provided a partitioning of variance between Level-1 and Level-2 (Heck et al., 2014). The equations below represent variation at each level for both research questions:

Level-1 Model

$$\text{logit}_{ij} = \beta_{0j}$$

Level-2 Model

$$\beta_{0j} = \gamma_{00} + e_{0j}$$

Combined Model

$\text{logit}_{ij} = \gamma_{00} + e_{0j}$

Where:

logit_{ij} = log odds of proficiency versus non-proficiency for student i with teacher j

β_{0j} = average teacher-rated academic performance for teacher j

γ_{00} = grand mean of teacher-rated academic performance

e_{0j} = teacher/level-2 error

These models also provided a measure of dependence of the Level-2 variable through the ICC. The ICC values for both research questions were examined using this formula

$$\rho = \frac{\sigma^2_{Between}}{(\sigma^2_{Between} + 3.29_{Within})}$$

where $\sigma^2_{Between}$ is the proportion of variance between units relative to $\sigma^2_{Between} + 3.29_{Within}$, which represents the total variance (Heck et al., 2012).

Next, the full models for each research question were fit, which included all Level-1 predictor variables and covariates (e.g., two attention measures, the composite score for inhibitory control, and the emotion regulation measure as well as gender and free/reduced lunch status). The equations for the full models are shown in the equations below. Similar to research question one, all Level-1 predictor variables were modeled as fixed effects in the initial examination of the full models in order to ensure model convergence (Heck et al., 2012). The intercepts were allowed to vary across teachers.

Level-1 Model

$\text{logit}_{ij} = \beta_{0j} + \gamma_{10} X_{1ij} + \gamma_{20} X_{2ij} + \gamma_{30} X_{3ij} + \gamma_{40} X_{4ij} + \gamma_{50} X_{5ij} + \gamma_{60} X_{6ij}$

Level-2 Model

$\beta_{0j} = \gamma_{00} + e_{0j}$

Combined Model

$$\text{logit}_{ij} = \gamma_{00} + e_{0j} + \beta_{0j} + \gamma_{10}\, X_{1ij} + \gamma_{20}\, X_{2ij} + \gamma_{30}\, X_{3ij} + \gamma_{40}\, X_{4ij} + \gamma_{50}\, X_{5ij} + \gamma_{60}\, X_{6ij}$$

Where:

logit_{ij} = log odds of proficiency versus non-proficiency for student i with teacher j

β_{0j} = random intercept for teacher j

γ_{00} = fixed intercept for students

$\gamma_{10} – \gamma_{60}$ = fixed slopes for each independent variable

$X_{1ij} – X_{6ij}$ = independent variables (off-task behavior, inattention, inhibitory control, emotion regulation, gender, free/reduced lunch)

e_{0j} = teacher/level-2 error

Once a model with only statistically significant predictor variables was obtained (i.e., after trimming non-significant predictors), additional exploratory analysis included systematically examining significant predictors as random effects. Due to issues with model convergence and non-significant variance components, all predictors were maintained as fixed. Model deviance statistics were not calculated, as variance components cannot be used to compare regression coefficients across models or to examine reduction in variance in the same way as other models with continuous outcome variable. Each time a predictor is added to a model the variance at Level-1 is rescaled, which ultimately impacts the variance estimate at Level-2. As such, regression coefficients or any calculations of reduction in variance can be misleading and should not be interpreted (Hox, 2010).

Assumptions of multilevel linear modeling. Multilevel linear modeling, which was used to analyze research question one, has various assumptions that must be met, including normality, linearity, and homoscedasticity. Similar assumptions are not required to be met for multilevel logistic regression, which was used to analyze research questions two and three, as dependent variables are dichotomous for this type of analysis (Hox, 2010). Teacher-rated academic performance, the outcome variable for research question one, was the only dependent variable examined for deviations from normality, as it was the only continuous dependent variable in my study. As seen in Table 8, skewness and kurtosis values for this variable did not suggest departures from normality. Additionally, analysis of a histogram did not suggest a skewed distribution. Furthermore, results of a Shapiro-Wilk test indicated that the distribution of teacher-rated academic performance was normal (p > .05).

Linearity was examined using bivariate scatterplots and partial regression plots. Based on these plots, associations between predictor variables and teacher-rated academic performance, the only continuous outcome measures, appeared linear. No issues related to multicollinearity were revealed through examination of predictor variable correlations (see Table 10) or through examination of values for the variance inflation factor (VIF) for each predictor. Homoscedasticity was examined using a scatterplot matrix and no concerns were revealed.

Software. All data were analyzed using SPSS Version 24.0. There are several other programs that can be used for multilevel modeling (R, Stata, SAS, HLM, Mplus, etc.). Decisions regarding which program to use for multilevel modeling typically involve consideration of the level of complexity of analyses. Although other programs have advantages for more complex analyses, SPSS Version 24.0 generates the same results as other programs for multilevel regression and multilevel logistic regression, which are the analyses I utilized for my study (Hox, 2010).

Summary

Using baseline data from 129 first and second graders enrolled in the parent study's self-regulation intervention study, I examined how indicators of self-regulatory mechanisms contribute to academic performance for students in early elementary school with social-emotional difficulties. Sources of data included teacher reports, observation, school records, and direct assessment. After screening for missing data and analytic assumptions, creating composites, and generating descriptive statistics, I used multilevel regression to examine research question one, which examined the associations between key cognitive and emotional indicators of self-regulation and academic performance, as measured by a teacher-rating scale of performance, after controlling for gender and free/reduced lunch. I used multilevel logistic regression to examine research questions two and three, which examined the associations between key cognitive and emotional self-regulation indicators and proficiency in reading and mathematics after controlling for gender and free/reduced lunch. The results of analyses are reviewed in detail in the following chapter.

CHAPTER 4: RESULTS

In this study, I examined the influence of attention, inhibitory control, and emotion regulation on academic performance for first and second grade students with social-emotional difficulties, addressing three main research questions: (1) What are the associations between key cognitive and emotional self-regulation mechanisms (e.g., attention, inhibitory control, and emotion regulation) and teacher-rated academic performance, when controlling for gender and free/reduced lunch status?, (2) What are the associations between key cognitive and emotional self-regulation mechanisms and academic performance as measured by proficiency in reading, when controlling for gender and free/reduced lunch status?, and (3) What are the associations between key cognitive and emotional self-regulation mechanisms and proficiency in mathematics, when controlling for gender and free/reduced lunch status? In order to examine these research questions, baseline data from a large intervention study with multi-method measures of self-regulation and academic performance were analyzed. This chapter presents the results of my examination of research questions, which includes descriptive statistics, a correlation matrix, and analytic models for each research questions.

Descriptive Statistics and Correlation Matrix

Table 8 shows descriptive statistics for each of the three outcome variables including teacher-rated academic performance, reading proficiency, and mathematics proficiency, respectively. Since proficiency levels in reading and mathematics were coded dichotomously, the values presented represent the percent of students coded as proficient in each content area. Thus, of the 129 participants, 22% were proficient in reading and 34% were proficient in mathematics.

Given that scores on teacher-rated academic performance can fall within a range of 16-80 with higher scores reflecting better performance, the descriptive statistics below indicate overall lower performance in this area for this sample. When compared to norms developed by DuPaul and colleagues (1991), which indicated that average scores are typically about 72 (*SD* = 15.14), my study's sample is more than one standard deviation below average. Each dependent variable overall reflects that the sample was experiencing academic difficulties.

Table 8

Descriptive Statistics of Dependent Variables

	N	*M* or %	*SD*	Min	Max	Skewness (*SE Skew.)*	Kurtosis (*SE Kurt.)*
Dependent Variables							
Teacher-Rated Academic Performance	129	42.90	10.04	23.00	65.00	0.07 (0.21)	0.66 (0.42)
Reading Proficiency	129	22%	--	0	1	--	--
Mathematics Proficiency	129	34%	--	0	1	--	--

Note. Higher scores on teacher-rated academic performance indicates better academic performance.

Table 9 shows descriptive statistics for unstandardized and standardized independent variables and covariates at the student level used in multilevel models. Prior to standardization, the descriptive statistics for REDSOCS Off-Task Behavior suggested that the average percent of time during which the sample was off-task was 31.82. With regard to the SWAN Inattentive Scale, the unstandardized descriptive statistics suggested the sample in general was inattentive, as scores above one on this scale suggest difficulties. Due to the procedures used to develop a composite score, the mean score for inhibitory control was close to 0 with a standard deviation of .40. Regarding the Emotion Regulation Checklist, which prior to standardization could have scores ranging from 1 to 4 with higher scores suggesting better emotion regulation skills, descriptive statistics suggest higher levels of dysregulation in this sample, as scores above two suggest students are engaging in dysregulated behavior "often" or "almost always". Since the covariates gender and free/reduced lunch status were coded dichotomously, the values presented represent the percent of students who are male and qualified for free/reduced lunch, which comprises the majority of the sample.

Table 9

Descriptive Statistics of Unstandardized and Standardized Independent Variables and Covariates

	N	*M* or %	*SD*	Min	Max	Skewness (*SE Skew.*)	Kurtosis (*SE Kurt.*)
Independent Variables							
REDSOCS % Off-Task	129	31.82 (0.00)	19.16 (1.00)	1.67 (-1.57)	87.50 (2.91)	0.60 (0.21)	-0.16 (0.42)
SWAN Inattentive Scale	129	1.48 (0.00)	0.96 (1.00)	-2.00 (-3.64)	3.00 (1.58)	-0.51 (0.21)	.27 (0.42)
Inhibitory Control Composite	129	-0.02 (0.00)	0.86 (1.00)	-2.54 (-2.91)	1.37 (1.60)	-1.07 (0.21)	0.57 (0.42)
Emotion Regulation Checklist	129	2.66 (0.00)	0.40 (1.00)	1.46 (-2.98)	3.38 (1.79)	-0.52 (0.21)	-0.26 (0.42)
Covariates							
Gender (male)	129	68%	-	0	1	-	-
Receives Free/Reduced Lunch	129	76%	-	0	1	-	-

Note. Higher scores on the REDSOCS and the SWAN Inattentive Scale indicate higher levels of inattentive behavior. A higher score on the inhibitory control composite indicates poorer inhibitory control. A higher score on the Emotion Regulation Checklist indicates better emotion regulation skills. The scores in parentheses reflect descriptive statistics for standardized continuous predictors.

Table 10 displays the correlation matrix for the variables used in the multilevel model analyses. These correlations reflect associations among variables when clustering is not taken into account. Correlations between gender and most variables were not statistically significant, except for both measures of attention for which there were positive, statistically significant correlations. With respect to free/reduced lunch status, there were statistically significant negative correlations with inhibitory control, emotion regulation, and proficiency in reading and in mathematics. In addition, REDSOCS Off-Task Behavior and reading proficiency were also significantly correlated; however, not in the expected direction, as this correlation suggests that as inattention increases so does the chance of being proficient in reading. Furthermore, inhibitory control and teacher-rated academic performance yielded a positive, statistically significant correlation; however, there were no statistically significant correlations between inhibitory control and proficiency in reading or mathematics. Statistically significant correlations were found between emotion regulation and teacher-rated academic performance; however, no statistically significant correlations were found between emotion regulation and proficiency in reading or mathematics. Lastly, each dependent variable (i.e., teacher-rated academic performance, reading proficiency, and mathematics proficiency) yielded positive statistically significant correlations with the other dependent variables.

Table 10

Correlation Matrix for All Variables

	Teacher-Rated Academic Performance	Reading Proficiency	Math Proficiency	SWAN Inattentive	REDSOCS	Inhibitory Control	Emotion Regulation	Gender	Free/Reduced Lunch Status
Teacher-Rated Academic Performance	1	--	--	--	--	--	--	--	--
Reading Proficiency	0.27**	1	--	--	--	--	--	--	--
Math Proficiency	0.27**	0.44***	1	--	--	--	--	--	--
SWAN Inattentive	-0.69***	-0.12	-0.13	1	--	--	--	--	--
REDSOCS	-0.14	0.24**	0.02	0.20*	1	--	--	--	--
Inhibitory Control	0.36***	0.11	0.24**	-0.25**	-0.06	1	--	--	--
Emotion Regulation	0.38***	0.01	0.05	-0.35***	-0.16	0.23*	1	--	--
Gender	-0.08	0.13	0.11	0.21*	0.25**	-0.01	-0.14	1	--
Free/Reduced Lunch Status	-0.13	-0.18	-0.32***	0.00	-0.04	-0.22*	-0.23*	-0.11	1

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

Research Question One

In order to examine research questions one (i.e., What are the associations between key cognitive and emotional self-regulation mechanisms and teacher-rated academic performance, when controlling for gender and free/reduced lunch status?), multilevel regression was conducted using a top-down approach to multilevel modeling (Kim, Anderson, & Keller, 2014; Ryoo, 2011). Table 11 shows the results for the unconditional model, which indicated no statistically significant variation across groups, as indicated by the Wald *Z* test. The Wald *Z* test summarizes the ratio of the estimate to its standard error; however, this test is two-tailed and variances cannot be smaller than zero (Heck et al., 2014). As such, Hox (2010) recommended conducting the Wald *Z* test as one-tailed by dividing the significance level by two. Therefore, all significance levels reported were divided by two in order to obtain more accurate results. The Wald *Z* test of the unconditional model suggested that multilevel analysis was not warranted; however, the ICC value, which was 0.1057, indicated that 10.57% of the variance in teacher-rated performance was due to the grouping structure of the data (e.g., students within teachers). Given that the ICC value exceeded 7%, multilevel analysis was warranted (Snijders & Bosker, 1999). Additionally, multilevel analysis was necessary for maintaining analytic consistency across research questions and because teacher differences explained variance despite the lack of statistical significance evidence by the Wald *Z* test. Furthermore, although the number of child participants per teacher was small (M = 1.90, range: 1-7), the grouping structure of this study still violated the assumption of independence of observation for those who shared the same teacher. Thus, proceeding with multilevel modeling resulted in more accurate standard error estimates (Raudenbush & Bryk, 2002).

Table 11

Unconditional Model for Teacher-Rated Academic Performance

Variable	Estimate	*SE*	*t*-ratio
Fixed Effect			
Intercept	42.97***	0.94	45.49
Variable	**Variance**	***SE***	**Wald *Z***
Random Effect			
Intercept Between Participants	10.57	10.61	1.00
Level 1 Error	89.39	14.31	6.25***
Deviance (-2 Log Likelihood)		959.04	

Note. The Wald *Z* test was conducted as one-tailed for specified reasons.
*p < .05. **p < .01. ***p < .001.

Next, the full model for research question one was fit, which included all Level-1 variables. The only predictor variable that was trimmed from the model was attention as measured by REDSOCS Off-Task Behavior. Statistically significant predictor variables maintained in the model included attention as measured by the SWAN, inhibitory control, and emotion regulation. Results are presented in Table 12.

Once statistically significant predictors were obtained, additional exploratory analysis included systematically examining significant predictor variables as random effects. All predictor variables were first entered into the model simultaneously as random effects. As expected, this analysis was not possible due to failure of model convergence. Next, each predictor was entered into the model as random while other predictors remained fixed. No statistically significant variance components were yielded for any predictor variable modeled as a random effect. As such, all predictors were maintained as fixed effects in the final model.

Model deviance statistics were examined for all models with predictor variables modeled as fixed in order to determine the most parsimonious model. Tables 11 and 12 include the -2 Log

Likelihood values for each model, which were utilized to conduct a likelihood ratio test. This test follows a chi-square distribution with degrees of freedom equaling the difference in the number of parameters between two models (Heck et al., 2014). Adding predictors to the null model significantly improved the model's fit to the data. When comparing other models, the differences in model deviance values were small and not statistically significant; therefore, the restricted model (e.g., $Model_2$) was accepted as the best fit, as it provides a similar fit to the data with fewer parameter estimates.

Table 12

Multilevel Models of Teacher-Rated Academic Performance

	$Model_1$ (Full Model)			$Model_2$ (Final Model)		
Variable	Est.	*SE*	*t*-ratio	Est.	*SE*	*t*-ratio
Level 1 – Fixed Effects						
Intercept	43.12***	1.65	26.12	43.17***	1.65	26.23
REDSOCS Off-Task	-0.22	0.66	-0.33	-	-	-
SWAN Inattentive Scale	-6.03***	0.64	-9.48	-6.06***	0.63	-9.64
Inhibitory Control	1.67*	0.63	2.63	1.67*	0.64	2.62
Emotion Regulation	1.38*	0.68	2.04	1.39*	0.67	2.06
Gender (Male)	1.44	1.30	1.10	1.36	1.28	1.06
Free/Reduced Lunch	-1.59	1.48	-1.08	-1.58	1.48	-1.07
Variables	Variance	*SE*	Wald *Z*	Variance	*SE*	Wald *Z*
Level 2 - Random Effect						
Intercept Between Participants	15.00	6.84	2.19*	14.79	6.78	2.18*
Level 1 Error	32.35	5.82	5.56***	32.52	5.83	5.58***
Deviance Statistic (-2 Log Likelihood)		855.15			855.26	

Note. The Wald *Z* test was conducted as one-tailed for specified reasons. Gender was coded as male = 1 and female = 0. Free/reduced lunch was coded as receives free/reduced lunch = 1 and does not receive free/reduced lunch = 0. Deviance statistics were calculated using the null model as a comparison of fit. Continuous predictor variables were standardized.
*$p < .05$. **$p < .01$. ***$p < .001$.

Results of the final model indicated that the addition of the within-group predictors reduced the residual within-group variability (e.g., from 89.39 to 32.52) in comparison to the null model. This reduction in variance was then used to calculate a reduction in variance estimate for the within-teacher and between-teacher components of the model. It was calculated as follows:

$$\frac{(\sigma_{M1}^2 - \sigma_{M2}^2)}{\sigma_{M1}^2}$$

where M1 refers to the variance component for the unconditional model and M2 refers to the final model's variance component. This is calculated as 0.6253 [(89.39 – 33.52 = 55.87)/89.39 = 0.6250], which suggested that all predictors entered at Level-1 in the final model accounted for 62.5% of within-teacher variability in teacher-rated academic performance. The predictors also impacted the residual variability in intercepts at the teacher level. Specifically, the initial variance component for teachers from the null model was 10.57. After variables were added, the between-teacher variance in teacher-rated academic performance scores increased to 14.79. In addition, the initial variability in academic performance as measured by the APRS observed between teachers (e.g., the ICC) increased from 10.57% to 31.26% in the final model. Results also suggested that after the introduction of all predictor variables, there was still significant variability to be explained both within and between teachers. This indicated that other predictors within and between teachers might explain the residual variability in intercepts.

Overall, three of four predictor variables were significantly associated with teacher-rated academic performance on the APRS while controlling for gender and free/reduced lunch status. As a frame of reference, the APRS yields scores ranging from 16 to 80. As hypothesized, the SWAN Inattentive Scale was the strongest predictor of teacher- rated academic performance. Results indicated that a one standard deviation increase in inattention was associated with a 6.06 point decrease in teacher-rated academic performance, which is a decrease of 7.61%. Inhibitory control was also a significant predictor of academic performance, as expected. Results indicated that a one standard deviation increase in inhibitory control corresponded with a 1.67 increase (i.e., 2.09%) in teacher-rated academic performance. Lastly, as also expected, emotion regulation was associated with academic performance in a positive direction, as a one standard deviation increase in emotion regulation yielded an increase of 1.39 (i.e., 1.74%) in teacher-rated academic performance. One measure of inattention (i.e., the REDSOCS Off-Task Behavior), gender, and free/reduced lunch status were not significantly associated with academic performance.

Research Question Two

In order to examine research question two (i.e., What are the associations between key cognitive and emotional self-regulation mechanisms and academic performance, as measured by reading proficiency, when controlling for gender and free/reduced lunch status?), multilevel logistic regression was conducted using the same top-down approach as research question one. Table 13 shows the results for the unconditional model. There are several ways to interpret a multilevel logistic regression. First, it can be interpreted using log odds. The estimated log odds coefficient for the intercept is -1.28, which can be interpreted as the predicted log of odds that a student is proficient (Heck et al., 2012). Second, log odds can be transformed into an odds ratio using exponentiation. When using this interpretation, the influence of each predictor is multiplicative. Exponentiating the log odds coefficient in this case resulted in an odds ratio of 0.28.

Both the Wald *Z* test and the ICC value (i.e., 27.53% of the variability in reading proficiency lies between teachers) suggested significant variation across teacher groups, which justifies multilevel modeling. Furthermore, multilevel analysis was necessary for maintaining analytic consistency across research questions and because teacher differences explained variance despite the lack of statistical significance. Moreover, although the number of child participants per teacher was small as previously noted, the grouping structure still violated the assumption of independence of observation for those who shared the same teacher. Thus, proceeding with multilevel modeling as planned resulted in more accurate standard error estimates (Raudenbush & Bryk, 2002).

Table 13

Unconditional Model for Reading Proficiency

Variable	Coefficient	*SE*	*t*-ratio
Fixed Effect			
Intercept	-1.28***	0.26	-4.84
Variable	**Estimate**	***SE***	**Wald *Z***
Random Effect			
Intercept Between Participants	1.25	0.69	1.80*

Note. The Wald *Z* test was conducted as one-tailed for specified reasons.
$^*p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Next, the full model for research question two was fit, which included all Level-1 predictor variables and covariates. Non-significant, trimmed predictor variables included emotion regulation and inhibitory control. Statistically significant predictor variables maintained in the model included attention, as measured by the SWAN Inattentive Scale and REDSOCS Off-Task Behavior. Free/reduced lunch was also a significant predictor of reading proficiency.

Once statistically significant predictors were obtained, additional exploratory analysis included systematically modeling the main significant predictor variables (i.e., REDSOCS Off-Task, SWAN Inattentive Scale) as random effects. The predictors were first entered into the model simultaneously as random effects. As expected, this analysis was not possible due to failure of model convergence. Next, each predictor was entered in the model as random while other predictors remained fixed. When REDSOCS Off-Task Behavior was entered into the model, the variance component was not statistically significant. When the SWAN Inattentive Scale was entered into the model as a random effect, the analysis was not possible due to failure of model convergence. Model convergence issues were likely related to the small number of students per teacher (M = 1.90, range: 1-7). As such, all predictors were maintained as fixed effects in the final model.

Results of all models with fixed effects are presented in Table 14, including the results for the final model, which indicated that attention, as measured by the SWAN Inattentive Scale and REDSOCS Off-Task Behavior, were significant predictors of reading proficiency while controlling for gender and free/reduced lunch status. Free/reduced lunch status, though a covariate, also accounted for a significant amount of variance in reading proficiency. The estimates for the two dichotomous predictors are given in terms of groups coded as one, which is males and receiving free/reduced lunch. The reference parameters were not included in Table 14, as they were redundant. Results are interpreted in terms of odds ratios, which are the exponentiated values of the estimates. In terms of the SWAN Inattentive Scale, which yielded a negative, statistically significant association, the odds ratio for reading proficiency was 0.54, which means that for every one standard deviation increase, the odds of being proficient in reading are 0.54 times lower after accounting for other Level-1 predictors. This is a 46% decrease in odds. Essentially, this means that higher scores on this measure of inattention correspond with decreased odds of being proficient in reading. With regard to REDSOCS Off-Task Behavior, results suggested a positive, statistically significant association and an odds ratio of 1.04. This suggests that for every one standard deviation increase on this measure, the odds of being proficient in reading are 1.04 times higher after accounting for other Level-1 predictors. This is a 4% increase in odds, which indicates a very small effect overall. This means that higher scores on this measure of inattention are associated with increased odds of being proficient in reading. Possible explanations for this unexpected direction of effect are considered in the discussion. Lastly, results yielded a positive, statistically negative association and an odds ratio of 0.33 between free/reduced lunch status and proficiency in reading. This indicates that for students who receive free/reduced lunch the odds of being proficient are 0.33 what they are for students who do not receive free/reduced lunch after accounting for other Level-1 predictors. This is a 67% decrease in odds, suggesting a relatively large effect.

Overall, attention as measured by the SWAN Inattentive Scale and REDSOCS Off-Task Behavior, and free/reduced lunch status were significantly associated with reading proficiency whereas inhibitory control, emotion regulation, and gender were not. Results suggested that greater inattention as measured by the SWAN Inattentive Scale increased the odds of being non-proficient in reading, as expected. Results also suggested that inattention as measured by REDSOCS Off-Task Behavior decreased the odds of being non-proficient in reading, which was not expected and clearly not aligned with extant literature. Furthermore, results indicated that free/reduced lunch status was a significant predictor, such that receiving free/reduced lunch decreased the odds of reading proficiency. Lastly, attention, as measured by the SWAN Inattentive scale was the strongest predictor of reading proficiency in the expected direction.

Table 14

Multilevel Models of Reading Proficiency

Variable	Model$_1$ (Full Model) Coeff. (*SE*)	Model$_1$ (Full Model) *t*-ratio	Model$_1$ (Full Model) Odds Ratio	Model$_2$ Coeff. (*SE*)	Model$_2$ *t*-ratio	Model$_2$ Odds Ratio	Model$_3$ (Final Model) Coeff. (*SE*)	Model$_3$ (Final Model) *t*-ratio	Model$_3$ (Final Model) Odds Ratio
Level 1 – Fixed Effects									
Intercept	-1.14 (0.64)	-1.77	0.32	-1.20 (0.62)	-1.94	0.30	-1.12 (0.62)	-1.82	0.33
REDSOCS Off-Task	0.58* (0.28)	2.07	1.78	0.59* (0.28)	2.12	1.81	0.58* (0.28)	2.11	1.04
SWAN Inattentive Scale	-0.61* (0.25)	-2.45	0.55	-0.57* (0.25)	-2.29	0.35	-0.61* (0.24)	-2.52	0.54
Inhibitory Control	0.30 (0.28)	1.04	1.34	0.27 (0.28)	0.98	1.32	-	-	-
Emotion Regulation	-0.14 (0.25)	-0.56	0.87	-	-	-	-	-	-
Gender (Male)	0.59 (0.51)	1.15	1.80	0.61 (0.50)	1.23	1.84	0.64 (0.50)	1.27	1.89
Free/Reduced Lunch	-1.07* (0.53)	-2.03	0.34	-1.01 (0.53)	-1.92	0.36	-1.11* (0.52)	-2.14	0.33
Variable	**Est.**	***SE***	**Wald *Z***	**Est.**	***SE***	**Wald *Z***	**Est.**	***SE***	**Wald *Z***
Level 2 - Random Effect									
Intercept Between Participants	1.69	0.89	0.06*	1.62	0.87	1.86*	1.50	0.82	1.82*

Note. The Wald *Z* test was conducted as one-tailed for specified reasons. Gender was coded as male = 1 and female = 0. Free/reduced lunch was coded as receives free/reduced lunch = 1 and does not receive free/reduced lunch = 0. Continuous predictor variables were standardized.
**p* < .05. ***p* < .01. ****p* < .001.

Research Question Three

In order to examine research question three (i.e., What are the associations between key cognitive and emotional self-regulation mechanisms and academic performance, as measured by mathematics proficiency, when controlling for free/reduced lunch?), multilevel logistic regression was conducted using the same top-down approach as research questions one and two. Table 15 shows the results for the unconditional model. As previously noted, there are several ways in which multilevel logistic regression can be interpreted. First, it can be interpreted using log odds. Second, log odds can be transformed into an odds ratio using exponentiation. When using this interpretation, the influence of each predictor is multiplicative. Exponentiating the log odds coefficient, in this case, resulted in the odds ratio of 0.47.

The Wald *Z* test of the unconditional model suggested that multilevel analysis was not warranted; however, the ICC value, which was 0.1976, indicated that 19.76% of the variance in mathematics proficiency was due to the grouping structure of the data (e.g., students within teachers). Given that the ICC value exceeded 7%, multilevel analysis was warranted (Snijders & Bosker, 1999). Additionally, multilevel analysis was necessary for maintaining analytic consistency across research questions and because teacher differences explained variance despite the lack of statistical significance. Moreover, although the number of child participants per teacher was small as previously noted, the grouping structure of this study still violated the assumption of independence of observation for those who shared the same teacher. Thus, proceeding with multilevel modeling as planned resulted in more accurate standard error estimates (Raudenbush & Bryk, 2002).

Table 15

Unconditional Model for Mathematics Proficiency

Variable	Coefficient	*SE*	*t*-ratio
Fixed Effect			
Intercept	-0.76	0.23	-3.35**
Variable	Estimate	*SE*	Wald *Z*
Random Effect			
Intercept Between Participants	0.81	0.51	1.58

Note. The Wald *Z* test was conducted as one-tailed for specified reasons.
$^*p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Next, the full model for research question three was fit, which included all Level-1 variables and covariates. Attention, as measured by REDSOCS Off-Task Behavior and the SWAN Inattentive Scale, and emotion regulation were trimmed from the model, as they were not statistically significant. Inhibitory control and free/reduced lunch status were the only statistically significant predictors.

Once statistically significant predictors were obtained, additional exploratory analysis included modeling inhibitory control as a random effect. When inhibitory control was added into the model as a random effect, the analysis was not possible due to failure of model convergence. As such, inhibitory control was maintained as a fixed effect in the final model.

Results of all models with fixed effects are presented Table 16, including results for the final model, which indicated that inhibitory control was a significant predictor of mathematics proficiency, while controlling for gender and free/reduced lunch status. Free/reduced lunch status was also a significant predictor of mathematics proficiency. The estimates for the two dichotomous predictors are given in terms of groups coded as one, which is males and receiving free/reduced lunch. The reference parameters were not included in Table 16, as they were redundant. Results are interpreted in terms of odds ratios, which are the exponentiated values of the estimates. In terms of inhibitory control, which yielded a positive, statistically significant association, the odds ratio for mathematics proficiency was 1.78, which means that for every one standard deviation increase in inhibitory control, the odds of being proficient in mathematics are 1.78 times higher after accounting for other Level-1 predictors. This is a 78% increase in odds, indicating a relatively large effect. This suggests that higher scores on inhibitory control corresponds with increased odds of being proficient in reading. Additionally, results indicated a negative, statistically significant association and an odds ratio of 0.22 for free/reduced lunch status. This indicates that for students who receive free/reduced lunch the odds of being proficient in mathematics are 0.22 what they are for students who do not receive free/reduced lunch after accounting for other Level-1 predictors. This is a 78% decrease in odds, which suggests a relatively large effect.

Overall, inhibitory control and free/reduced lunch status were significantly associated with mathematics proficiency. Inattention, as measured by both measures, emotion regulation, and gender were not significantly associated with mathematics proficiency level. Results indicated that students with better inhibitory control had increased odds of being proficient in mathematics, as expected. Additionally, results indicated that students receiving free/reduced lunch had decreased odds of being proficient in mathematics as compared to students who do not.

Table 16

Multilevel Models of Mathematics Proficiency

Variable	Model$_1$ (Full Model)			Model$_2$			Model$_3$			Model$_4$ (Final Model)		
	Coeff. (*SE*)	*t*-ratio	Odds Ratio	Coeff. (*SE*)	*t*-ratio	Odds Ratio	Coeff. (*SE*)	*t*-ratio	Odds Ratio	Coeff. (*SE*)	*t*-ratio	Odds Ratio
Level 1 – Fixed Effects												
Intercept	-0.26 (0.62)	-0.42	0.77	-0.26 (0.61)	-0.43	0.77	-0.34 (0.58)	-0.58	0.72	-0.16 (0.56)	-0.29	0.85
REDSOCS Off-Task	0.07 (0.24)	0.30	1.07	-	-	-	-	-	-	-	-	-
SWAN Inattentive Scale	-0.53 (0.27)	-1.98	0.59	-0.51 (0.27)	-1.89	0.60	-0.47 (0.24)	-1.95	0.63	-	-	-
Inhibitory Control	0.51 (0.27)	1.98	1.66	0.50 (0.26)	1.96	1.65	0.49 (0.24)	1.98	1.63	0.57* (0.24)	2.39	1.78
Emotion Regulation	-0.14 (0.24)	-0.58	0.87	-0.15 (0.24)	-0.63	0.86	-	-	-	-	-	-
Gender (Male)	0.76 (0.51)	1.49	2.13	0.77 (0.50)	1.56	2.17	0.79 (0.49)	1.62	2.21	0.52 (0.40)	1.28	0.76
Free/Reduced Lunch	-1.69*** (0.59)	-2.89	0.18	-1.69** (0.58)	-2.89	0.19	-1.62** (0.54)	-2.98	0.20	-1.51** (0.53)	-2.84	0.22
Variable	**Est.**	***SE***	**Wald *Z***	**Est.**	***SE***	**Wald *Z***	**Est.**	***SE***	**Wald *Z***	**Est.**	***SE***	**Wald *Z***
Level 2 - Random Effect												
Intercept Between Participants	1.64	0.80	2.05*	1.58	0.78	2.02*	1.57	0.77	2.04*	1.20	0.65	1.86

Note. The Wald *Z* test was conducted as one-tailed due for specified reasons. Gender was coded as male = 1 and female = 0. Free/reduced lunch was coded as receives free/reduced lunch = 1 and does not receive free/reduced lunch = 0. Continuous predictor variables were standardized.
**p* < .05. ***p* < .01. ****p* < .001.

CHAPTER 5: DISCUSSION

As research has shown, students with social-emotional difficulties often experience learning, achievement, and social concerns (Blair, 2002; Calkins et al., 2007; Lambert, 1988), and are at increased risk of adverse outcomes including truancy (Henry & Huizinga, 2007), school dropout (Henry et al., 2012), serious mental health concerns (Darke et al., 2003; Lambert, 1988), and involvement with the justice system (Fergusson & Horwood, 2003; Moffitt et al., 2011). This study focused on academic performance which may serve as a protective factor to mitigate the risks associated with social-emotional difficulties. My study examined associations among various self-regulatory mechanism (i.e., attention, inhibitory control, and emotion regulation) and academic performance specifically for students with social-emotional difficulties, as this information may suggest ways to strengthen interventions for this population of students.

Research in the area of self-regulation and academic performance is abundant; however, research on how these constructs are related for students with social-emotional difficulties is sparse. My research makes a unique contribution to the literature as one of the few studies to employ an integrative framework that includes both cognitive and emotional mechanisms of self-regulation in the investigation of academic performance specifically for students with social-emotional difficulties in early elementary school. Using data from a federally-funded self-regulation study, my study utilized multilevel regression and multilevel logistic regression to examine associations between various cognitive and emotional self-regulation mechanisms and academic performance after controlling for gender and free/reduced lunch status. Three outcome variables were investigated, including teacher rating of students' academic performance, reading proficiency, and mathematics proficiency. In this chapter, results are summarized by outcome variable and the significance and implications of these results are discussed. Implications for research and practice are also provided. I then conclude with a discussion of limitations and propose directions for future research.

Research Question One

Results of multilevel regression examining the associations between key cognitive and emotional self-regulation mechanisms and teacher-rated academic performance indicated that attention as measured by the SWAN Inattentive Scale, inhibitory control, and emotion regulation were each significant predictors. Results of this examination were aligned with my hypothesis that attention skills, inhibitory control, and emotion regulation would each predict teacher-rated academic performance, after controlling for gender and free/reduced lunch status. Results also supported my hypothesis that attention would be the strongest predictor of academic performance and that inhibitory control and emotion regulation would also be significant predictors. Such results support the extant literature on the associations between academic performance and attention (Barriga, et al., 2002; Breslau et al., 2009; Fuchs et al., 2005; Lan et al., 2011; Massetti et al., 2008; Preston et al., 2009; Polderman et al., 2010; Rabiner et al., 2004; 2012; Welsh et al., 2010), inhibitory control (Vuontela et al., 2013), and emotion regulation (Garner & Waajid, 2012; Graziano et al., 2007; Howse et al., 2003; Trentacosta & Izard, 2007). The results of this investigation also support research that indicates various cognitive and emotional self-regulatory mechanisms work in an integrative manner to influence learning and behavior (Bell & Wolfe, 2004; Blair, 2016; Calkins & Marcovitch, 2010; Carlson & Wang, 2007; Ursache et al., 2012). These findingsaddress a gap in research on the interconnectedness of these important constructs for early elementary students with social-emotional difficulties.

In terms of attention, it was expected that both the SWAN Inattentive Scale and REDSOCS Off-Task would be significant predictors of teacher-rated academic performance given that they are both measures of attentional functioning; however, only the SWAN Inattentive scale was a significant predictor. These results, in addition to the preliminary correlational analyses that yielded only a small correlation between the REDSOCS Off-Task Behavior and the SWAN Inattentive Scale (r = 0.20), may indicate that the SWAN Inattentive Scale and REDSOCS Off-Task Behavior are capturing differing aspects of attentional functioning and, therefore, relating differently to teacher-rated academic performance. This is a reasonable hypothesis, as teacher ratings presumably reflect a large sample of a child's observed behavior in the classroom over several weeks, whereas REDSOCS Off-Task Behavior reflects only two 10-minute snapshots which may vary depending on what the specific observed task encompassed (e.g., independent seatwork, listening to teacher lecture or reading, hands-on learning activities).

Another explanation for these differential associations is method bias, which is defined as the "effects that measuring two or more constructs with the same method may have on estimates of the associations between them" (Podsakoff, MacKenzie, & Podsakoff, 2012, p. 540). Given that the SWAN Inattentive Scale and the measure of academic performance (i.e., the APRS) were both completed by teachers, perhaps some of the observed covariation is due to the shared measurement method. This is a reasonable explanation for the different associations between the SWAN Inattentive Scale and REDSOCS Off-Task Behavior and teacher-rated academic performance; however, some administration factors may also have counterbalanced the potential method bias. For instance, these two measures have different scale properties and were separate on the teacher questionnaire from which this data extended (Podsakoff et al., 2012).

Research Question Two

Results of multilevel logistic regression examining the associations between cognitive and emotional indicators of self-regulation and academic performance, as indicated by proficiency in reading, indicated that attention, as measured by the SWAN Inattentive Scale and by REDSOCS Off-Task Behavior, were significant predictors, after controlling for gender and free/reduced lunch status. Free/reduced lunch status was also a significant predictor. Results indicated overall that students with poorer attention skills, as measured by the SWAN Inattentive Scale, were more likely to be non-proficient in reading, as expected. Contrary to expectations, however, results also indicated that students with more observed inattention on the REDSOCS were more likely to be proficient in reading, although the size of this effect was small as indicated by odds ratios. Lastly, results indicated that receiving free/reduced lunch increased the likelihood of being non-proficient in reading.

Some of the results of the final model for reading proficiency were aligned with my hypotheses and others were not. More specifically, I expected attention skills and emotion regulation to be significant predictors of proficiency in reading; however, only attention, as measured by the SWAN Inattentive Scale, was a statistically significant predictor of reading proficiency. This measure of attention was the strongest predictor of reading proficiency, which was aligned with expectations. REDSOCS Off-Task Behavior was also a statistically significant predictor of reading proficiency; however, the association was in a positive direction, such that better attention decreased the likelihood of being proficient in reading, which was not expected or aligned with extant literature. Neither inhibitory control or emotion regulation were statistically significant predictors of reading proficiency as expected.

Similar to research question one, results related to attention being a significant predictor of academic performance, specifically, reading proficiency, are aligned with existing literature. For instance, many researchers have found that attention, as measured by teacher report, is related to students' proficiency and performance in reading (Barriga et al., 2002; Breslau et al., 2009; Fuchs et al., 2005; Polderman et al., 2010; Rabiner et al., 2016; 2004). These results are understandable, as attentional skills enable students to not only focus on lessons, but they also help students concentrate on reading materials so they can engage in the various processes needed for effective reading (i.e., attending to/maintaining information across various paragraphs or pages of reading materials).

Regarding the other measure of attention, REDSOCS Off-Task Behavior, results were not aligned with expectations or extant literature, as the direction of the association between scores on this measure and the odds of reading proficiency suggested that more inattentive behaviors increased the odds of being proficient in reading. As noted, however, this was a very small effect. The unexpected nature of this association may extend from the measure itself. The REDSOCS is an interval coding system in which students were observed in their classrooms at two separate times. While this measure may provide a strong understanding of attentional function at those specific times, there is no guarantee that these data were gathered during reading, which may have influenced the outcome. In addition, this specific measure has not been previously examined in relation to academic outcomes, and may not have adequate reliability for doing so.

In terms of emotion regulation, the results of my study were not aligned with previous research, as several researchers have found statistically significant associations between children's emotion regulation and reading performance (Graziano, et al., 2007; Howse et al., 2003). This may be due to differences in the ages and the specific characteristics of the populations studied in previous studies and those of my research. For instance, researchers studying the associations between reading performance and emotion regulation typically examined younger children, whereas I investigated the connections for early elementary students with social-emotional difficulties. As such, emotion regulation may function differently in terms of reading proficiency for younger, preschool-aged children than for early elementary students with social-emotional difficulties. The sample used in my study also generally displayed limited variability in emotion regulation, which may have also contributed to the lack of significance.

The fact that free/reduced lunch status was a statistically significant predictor of reading proficiency aligns with extant literature. For instance, many researchers have found strong associations between SES and reading performance, such that students from families with a higher SES often perform more favorably in reading than students from families with a lower SES (Chatterji, 2006; Lee & Otaiba). This may be due to differences in various areas including academic skills at school entry (Byrnes & Wasik, 2009), academic language exposure (Galindo & Sonnenschein, 2015; Hindman, Skibbe, Miller, & Zimmerman, 2010), parent expectations (Sonnenschein & Galindo, 2015), or stress exposure (Hamoudi et al., 2015).

Research Question Three

The associations between key cognitive and emotional self-regulaton mechanisms and acaemic performance, as indicated by proficiency in mathematics, after controlling for gender and free/reduced lunch status, was examined using multilevel logisic regression. Inhibitory control and free/reduced lunch status were statistically significant predictors of proficiency in mathematics. Results indicated that students with poorer inhibitory control skills were more likely to be non-proficient in mathematics. In addition, receiving free/reduced lunch increased the likelihood of being non-proficient in mathematics.

Some of the results were aligned with my hypotheses and others were not. For example, I hypothesized that attention, inhibtory control, and emotion regulation would be statistically significant predictors of mathematics proficiency; however, inhibitory control was the only significant predictor when controlling for gender and free/reduced lunch status. The finding that inhibitory control predicted mathematics proficiency is aligned with previous research. For instance, one group of researchers found that inhibitory control was the only executive function related to mathematical performance (Espy et al., 2004). Several others found similar results (e.g., Hernández et al., 2017; Ng et al., 2015). The significance of inhibitory control makes sense in terms of proficiency in mathematics, as mathematics performance often requires individuals to inhibit dominant responses in favor of more desirable ones (Lubin et al., 2016). This finding is also substantiated by cognitive neuroscience literature, which has found that the prefrontal cortex is involved in both math problem-solving and inhibitory control tasks (Blair & Razza, 2007; Bull et al., 2008).

The results related to attention for this research question were not consistent with previous research. For example, extant literature indicates that attention is the most robust predictor of mathematics performance above and beyond other factors, such as executive functions (Lan et al., 2011). Other reasearchers have also found that attention accounts for a statistically significant amount of variance in mathematic performance (Preston et al., 2009). Additionally, similar trends have been found for students with social-emotional difficulties, as Barriga and colleagues (2002) found that teacher ratings of inattention were related to academic performance in mathematic. As such, it is likely other factors contributed to the lack of significance related to attention. One factor could be related to the measures of attention utilized in my study. Similar to research question two, perhaps the measures of attention are not capturing the type of attention related to strong performance in mathematics.

Results related to emotion regulation were also not expected or aligned with previous research, given that the experience of intense emotions has the potential to interfere in the learning process (Goleman, 2004). Additionally, various researchers have found that emotion regulation skills are related to achievement in mathematics (Graziano et al., 2007; Howse et al., 2003). The discrepancy in results may be a product of both the age of participants in my study as well as their particular characteristics, as previous studies on the associations between mathematics performance and emotion regulation skills were conducted with younger, preschool-aged children without social-emotional difficulties. As such, emotion regulation may function differently for older students with social-emotional difficulties, which would align with research on the development of emotion regulation that suggests that emotion regulation skills strengthen in early elementary school (Holodynski & Friedlemeier, 2005). The sample used in my study also generally displayed limited variability in emotion regulation, which may have also contributed to the lack of significance.

The fact that free/reduced lunch status was a statistically significant predictor aligns with extant literature. Researchers have found strong associations between SES and mathematics performance. Similar to the literature on reading performance and SES, students from families with a higher SES often perform better in mathematics in comparison to students from families with a lower SES (Mulligan et al., 2012). As aforementioned, this may be due to differences in various areas including academic skills at school entry (Byrnes & Wasik, 2009), academic language exposure (Galindo & Sonnenschein, 2015; Hindman, Skibbe, Miller, & Zimmerman, 2010), parent expectations (Sonnenschein & Galindo, 2015), or stress exposure (Hamoudi et al., 2015).

Teacher-Rated Academic Performance, Reading Proficiency, and Mathematics Proficiency

As indicated by the results of my study, associations between self-regulatory mechanisms and socio-demographic factors and academic performance varied depending on outcome. Inattention, inhibitory control, and emotion regulation were significant predictors of teacher-rated academic performance, whereas attention and free/reduced lunch status were predictive of reading proficiency, and mathematics proficiency was predicted by inhibitory control and free/reduced lunch status. These differences may be related to several factors, including specificity of outcome measures, content area or skills of focus, and perhaps different types of attention skills.

The differences in statistically significant predictors across research questions, while generally as anticipated, were also unexpected in some areas. This could be related to the specificity of both the predictors and outcomes measures. For instance, teacher-rated academic performance, which was measured by the APRS, was a more global assessment of students' success and productivity in the classroom, whereas proficiency in reading in mathematics are clearly content-area specific. In addition, various self-regulatory mechanisms were also assessed more globally, in that they were not specifically measured in any particular context (e.g., during reading or mathematics activities). As such, it makes sense that attention, inhibitory control, and emotion regulation were statistically significant predictors of the more global academic performance measured by the APRS. When examining more specific outcomes, however, such as reading and mathematics proficiency, some self-regulatory variables were not associated as expected. For example, it was expected that each measure of attention would be a statistically significant predictor of both reading and mathematics performance; however, this was not the case. This could be attributable to the fact that the SWAN Inattentive Scale was a more global assessment of attentional functioning and was not specific to a content area. The same rationale applies to REDSOCS Off-Task Behavior, as the interval data used to measure attentional skills may not have been gathered during a particular content area it was hypothesized to predict. Results may have been different if attention and perhaps other self-regulatory mechanisms had been measured within a specific content area.

When further honing in on outcome measures, it is obvious that teacher-rated academic performance, reading proficiency, and mathematics proficiency are all different ways in which a student can display success in school. Teacher-rated academic performance provides an understanding of students' success and productivity in the classroom, which includes consistency of work habits, frequency with which a student can recall previously taught information, accuracy of work, and percentage of work completed. Proficiency in reading and mathematics, however, provides information regarding students' performance in a specific content area. Perhaps a student's attention skills, inhibitory control, and emotion regulation skills have a more direct relationship to the skills assessed through teacher-rated academic performance than through reading and mathematics proficiency, as these are more general measures of functioning. It could also be that mathematics and reading proficiency levels, as measured in this study, were too broad to capture the differential ways in which various self-regulatory mechanisms might influence specific academic performance in those areas. For example, overall reading and mathematics proficiency does not provide fine-grained information regarding how attention, emotion regulation, and inhibitory control might relate to the various reading (e.g., decoding, comprehension) and mathematical processes (e.g., calculations, problem-solving) associated with proficiency in these areas.

One of the least expected deviations from hypotheses across research questions two and three was the finding related to attention skills. In research question two, attention was a statistically significant predictor of reading proficiency; however, it was not a statistically significant predictor of mathematics proficiency. While unexpected, the results of research question three highlight the possibility that different types of attention may be more associated with one type of academic performance than the others. For instance, results of these two research questions may suggest that attention skills are more important for reading than for mathematics, which was indicated in a meta-analysis (Jacob & Parkinson, 2015). This would make sense in the context of the classroom, as reading performance often encompasses attending to print materials for longer periods of time and across various lengths of print in order to comprehend what is written. Mathematics performance, on the other hand, may require less sustained attention, as a student may need to attend for shorter periods of time to solve one problem before moving on to the next. Indeed, mathematics proficiency may be more contingent on selective attention than on the sustained attention required for success in reading (Aylward et al., 1997; Preston et al., 2009).

Multi-Method Assessment

Previous researchers recommended using a multi-method approach to measure cognitive and emotional mechanisms of self-regulation, including attention, inhibitory control, and emotion regulation (e.g., Allan et al. 2014; Espy et al., 2004). Researchers have also recommended using assessment techniques that extend from both cognitive and developmental investigations of self-regulation (Allan et al., 2014). Thus, my study adopted this multidisciplinary approach and utilized several different measures (i.e., direct assessment, observation, and teacher-report) to assess each self-regulatory construct of interest. I intended to generate composite scores for each construct; however, this was only possible for inhibitory control, as measures of other constructs were not correlated strongly enough to combine into a composite. As such, predictor variables included an observational measure of attention, teacher-rated attention, the inhibitory control composite, and one measure of teacher-rated emotion regulation.

In terms of attention measures, even though the SWAN Inattentive Scale and REDSOCS Off-Task Behavior were both designed to examine attention skills in the context of a classroom, these measures were not highly correlated ($r = .20$, $p < .05$). This may be related to the specificity of each of the measures. By design, the SWAN Inattentive Scale is a more global measure of attention skills that assesses various manifestations of attention commonly observed by a teacher (i.e., close attention to tasks, sustained attention, follow through with assignments, organization, etc.). REDSOCS Off-Task Behavior, on the other hand, provides a brief snapshot of an individual's sustained attentional functioning through off-task behavior observed by a trained research assistant. These methods differences likely contribute to why these two measures were not more strongly correlated, as they may be capturing different aspects of attentional functioning.

Regarding inhibitory control, three measures were used to measure this construct, one was a teacher rating of impulse control specific to academic tasks (i.e., APRS Impulse Control Scale) and the other two were direct child assessments (i.e., the Happy-Sad Stroop and the HTKS). Correlations, however, were only strong enough to generate a composite using the two child performance assessments ($r = .36$, $p < .001$). This was not unexpected, as the teacher measure was based on a different methodology and assessed impulsivity in a different context than the other measures. As noted, I excluded this from analyses given that it has not been as widely used as a measure of inhibitory control as direct child measures.

With regard to emotion regulation, two measures were used to assess this construct, one was a teacher rating of emotion regulation (i.e., Emotion Regulation Checklist) and the other was an observer assessment which was completed after the one-on-one direct child assessments (i.e., PSRA-AR Positive Emotion Scale). The correlation between these two measures, however, was not strong enough to generate a composite score with both measures ($r = .06$, $p > .05$). Thus, the Emotion Regulation Checklist, which is more commonly used, was the only measure of emotion regulation included in multilevel models. Given that emotion regulation has various components as highlight by Gross (2014) and Hoeksma and colleagues (2004), these measures may be examining different aspects of emotion regulation.

Overall, utilizing a multi-method approach is aligned with recommendations set forth by previous researchers and captures the theoretical conceptualization of self-regulation as multifaceted. However, from an analytical perspective, my study highlights difficulties related to how best to combine measures of a similar construct, particularly when various measures believed to capture the same construct are not highly correlated (Willoughby et al., 2014, 2016). In my study, many of the poor correlations may reflect methods differences. It is possible that different measures reflect different but equally valid components of a particular construct. Nonetheless, this suggests that further work on measuring different components of cognitive and emotional mechanisms of self-regulation is needed (Jones, Bailey, Barnes, & Partee, 2016) . This may also suggest that researchers need to better understand context-specific self-regulatory functioning, as the utility and importance of various cognitive and emotional self-regulatory mechanisms appears to vary depending context (Cleary, Callan, & Zimmerman, 2012; Cleary & Chen, 2009).

Implications for Practice

One of the purposes of my study was to better understand the connections between various cognitive and emotional mechanisms of self-regulation and academic performance, particularly for early elementary students with social-emotional difficulties, in an effort to highlight the importance of targeting needs across social-emotional, cognitive, and academic domains. Results indicate that cognitive and emotional self-regulation do indeed relate to academic performance, although the manner in which this occurs seems to be relatively complex and may be dependent on how academic performance is measured. Thus, interventions geared toward bolstering students' academic performance should also target attention, inhibitory control, and emotion regulation, as each of these mechanisms is important to students' academic success. Self-regulation should not take precedence over efforts geared toward academic skill acquisition; however, both self-regulation and academic performance should be viewed in a more connected manner, as both sets of skills are important for bolstering protective factors and mitigating risk associated with social-emotional difficulties and poor academic performance. Thus, research interventions and curricula in schools should be designed to improve both self-regulation skills as well as academic performance, as this may be a successful way to help foster students' short- and long-term success. In fact, the Institute of Education Sciences is calling for research related to integrating social-emotional and academic models in order to "advance our understanding of social and behavioral competencies and how they relate to success in school" (Institute for Education Sciences, 2018).

The results of my study also indicated, that for more general academic performance (i.e., consistency of work habits, accuracy of work, percentage of work completed), SES plays less of a role; however, when honing in on academic performance within specific content areas such as reading and mathematics, SES plays a much larger role. Even though my study and previous researchers have found that self-regulatory skills are essential for school success (e.g., Blair & Razza, 2015; Fuchs et al., 2005; Razza et al., 2012; Welsh et al., 2010), these skills alone may not be enough to change trajectories for students, particularly those from backgrounds of poverty. These associations found in my study and in others' work (e.g., Chatterji, 2006; Lee & Otaiba, 2015; Mulligan et al., 2012) suggest that schools' efforts to enhance student achievement also need to be geared toward factors related to poverty that adversely impact a child's school readiness and subsequent academic performance (i.e., nutrition, stress, early home environments). Thus, interventions that seek to help change poor trajectories for at-risk populations should include resources for not only building academic and self-regulation skills, but they should also target ways in which family, school, and community systems can operate to assuage some of the impact of high-poverty risk factors.

Limitations

My study offers an important extension of work that examines the associations of various self-regulatory mechanisms and academic performance for students with social-emotional difficulties; however, there are several limitations. First, my study's sample was too small for examining teacher and school-level predictors, or for modeling random effects. Next, my study examined predictors of academic performance in early elementary school students with social-emotional difficulties in a sample of students who predominantly received free/reduced lunch, which reflects an overall lower SES. Additionally, most students in my study were male. Thus, results may not generalize to students without social-emotional difficulties, females, or to students from families with different income levels. Also, aa measurement characteristic that may have influenced results is that there were several predictor and outcome variables that had limited variability. For instance, in terms of reading and mathematics proficiency, only 22% and 34% of students in my sample were proficient in these areas, respectively. In addition, proficiency in reading and mathematics was coded dichotomously, which reduced potential variability as well. One other variable with limited variability was emotion regulation, as the intervention study from which my research extended targeted students with difficulties in this area.

Another measure-related limitation, though one that is difficult to avoid when examining constructs that are distinct yet interrelated, is that the performance-based measures of inhibitory control used in my study likely also required some aspects of working memory, such that participants had to hold various rules in their mind while performing a subdominant task. Thus, while these measures are widely used and developmentally appropriate measures of inhibitory control, this does present limitations related to capturing pure measure of inhibitory control. This challenge is consistent with current debates in the field related to the dissociability of highly interrelated cognitive and emotional mechanisms of self-regulation and is commonly referred to as the task impurity problem (Miyake et al., 2000). As methodological and analytical approaches continue to advance in the field of self-regulation, researchers may identify ways to more purely assess cognitive and emotional mechanisms of self-regulation.

Future Research

Additional research is imperative for advancing understanding of associations between cognitive and emotional mechanisms of self-regulation and academic performance. In doing so, researchers will continue to identify more specific ways to help students achieve optimal social-emotional and academic outcomes. In this section, I have included recommendations for extending my research and suggestions for broader future research.

Extensions of current study. There are several important ways in which my research can be expanded to ask additional important questions related to the associations between cognitive and emotional self-regulation and academic performance. For instance, a similar investigation could include a larger, more diverse sample to improve power and generalizability. In addition, future researchers could utilize different measures of each construct to ascertain whether associations are similar to what was found in this study. Lastly, with a larger sample, additional Level-2 (i.e., teacher) and Level-3 (i.e., school) predictors could be added to a model to further investigate other factors that may influence associations between self-regulation and academic performance, particularly for students with social-emotional difficulties. Interesting Level-2 variables to explore would be class size and some teacher-related characteristics (e.g., teacher experience, job satisfaction, instructional quality or management skills, etc.). Level- 3 variables could include school climate and school-level factors (e.g., per pupil expenditures).

Recommendations for future research. Based on the results of my research and extant literature, future researchers can expand the literature on self-regulation and academic performance, particularly for students with social-emotional difficulties, in various ways. First, different analytical methods and research designs need to be utilized in order to make more causal inferences related to the associations between cognitive and emotional mechanisms of self-regulation and academic performance. For instance, Willoughby and colleagues (2012) recommend using randomized designs of curricula and/or programs designed to improve self-regulation to examine whether treatment effects mediate improvements in academic functioning, as this would be one of the strongest tests of whether there are causal associations between cognitive and emotional mechanisms of self-regulation and academic performance (Willoughby et al., 2012). Of note, the parent study from which this research extends is currently using a randomized design to examine whether the treatment effects of a self-regulation intervention will improve academic functioning for this sample of students, directly addressing this question.

Additionally, further research is needed to determine whether the associations between cognitive and emotional mechanisms of self-regulation and academic performance differ based on more specific characteristics of students' social-emotional difficulties. For instance, it would be interesting to examine whether associations between cognitive and emotional mechanisms of self-regulation and academic performance are different for students with more internalizing behaviors in comparison to students with externalizing behaviors (Barriga et al., 2002). This information could suggest ways in which interventions geared toward promoting self-regulation and academic success could be differentiated based on presenting difficulties.

Furthermore, future studies should be specifically designed to examine how various family, teacher, school, and community factors influence the associations between cognitive and emotional mechanisms of self-regulation and academic performance. Many of these factors have been examined in the context of academic and self-regulatory functioning (e.g., Blair & Razza, 2007; Burchinal et al., 2018); however, more integrated research is needed. This research could help identify ways in which family, teacher, school, and community systems can be targeted to foster positive self-regulatory and academic functioning.

Moreover, more research is needed to better understand associations between cognitive and emotional mechanisms of self-regulation and more specific performance in reading, mathematics, and other content areas. My study examined general academic performance as well as proficiency levels in reading and mathematics, thus focusing on a relatively limited set of academic performance variables. Future researchers could include more fine-grained areas of functioning within certain content areas including use of achievement tests. For instance, it would be interesting to better understand how self-regulatory mechanisms relate specifically to reading comprehension or to problem-solving in mathematics. This type of examination would provide a more specific understanding of associations between academic performance and various cognitive and emotional mechanisms of self-regulation. Some researchers have examined such associations. For instance, Purpura and colleagues (2017) found that inhibitory control was associated with most aspects of mathematics functioning, including subitizing and counting. In terms of reading, this team found that inhibitory control was associated with early reading concepts such as awareness of print (Purpura et al., 2017). Additional research in this area, however, is needed, particularly for students with social-emotional difficulties.

Lastly, further research is needed on how the various targets, phases, and processes of self-regulated learning outlined by Greene (2018) factor into associations between various mechanisms of cognitive and emotional mechanisms of self-regulation and academic performance. Using these concepts of self-regulated learning in examinations of self-regulation and academic performance can help hone in on specific learning-related self-regulatory behaviors that can be targeted to foster stronger academic outcomes. Incorporating concepts extending from the self-regulated learning literature will also help the field move toward a more integrated, multidisciplinary understanding of self-regulation and academic performance.

Summary

The purpose of my study was to investigate associations between cognitive and emotional mechanisms of self-regulations and academic performance in first and second grade students with social-emotional difficulties by addressing three main research questions: (1) What are the associations between key cognitive and emotional self-regulation mechanisms (e.g., attention, inhibitory control, and emotion regulation) and teacher-rated academic performance, when controlling for gender and free/reduced lunch status?, (2) What are the associations between key cognitive and emotional self-regulation mechanisms and academic performance as measured by proficiency in reading, when controlling for gender and free/reduced lunch status?, and (3) What are the associations between key cognitive and emotional self-regulation mechanisms and proficiency in mathematics, when controlling for gender and free/reduced lunch status? In order to examine these research questions, baseline data from a large intervention study with multi-method measures of self-regulation and academic performance were analyzed using multilevel regression and multilevel logistic regression.

Results of research question one indicated that attention, inhibitory control, and emotion regulation were significant predictors of teacher-rated academic performance, with attention being the strongest predictor. These results were aligned with my hypotheses. Results of research question two indicated that attention was a significant predictor of proficiency in reading. These results were mostly aligned with my hypotheses; however, emotion regulation was also expected to be a significant predictor. Lastly, results of research question three suggested that inhibitory control is a significant predictor of mathematics proficiency when controlling for free/reduced lunch status.

As secondary data analyses, my study understandably had several limitations; however, it makes two main contributions to the literature on self-regulation and academic performance. First, my study advances understanding of the links between attention, inhibitory control, and emotion regulation and teacher-rated academic performance as well as performance in reading and mathematics, particularly for early elementary students with social-emotional difficulties. Although previous researchers have examined each of these constructs, few have done so in an integrated manner. Second, my study extends the literature on self-regulation and academic performance to students in early elementary school. Many researchers have investigated connections between these constructs for preschoolers, but literature is sparse on the associations between these constructs for early elementary students. Future research should include similar investigations with larger, more diverse samples and other measures of cognitive and emotional mechanisms of self-regulation. Additionally, future research efforts should include using different analytical methods and research designs in order to support causal inferences, examining whether associations vary for students with different social-emotional difficulties (e.g., internalizing versus externalizing), investigating family, teacher, school, and community factors, developing a more fine-grained understanding of associations between various areas of functioning within content areas, and integrating examination of targets, phases, and processes of self-regulated learning in order to support a more comprehensive understanding of self-regulation and academic performance.

In conclusion, given the associations between various cognitive and emotional mechanisms of self-regulation and academic performance, particularly for students with social-emotional difficulties, my study helps inform interventions, as it highlights the need for interventions to focus on both self-regulation and academic skills in order to foster overall student success. In addition, given that SES was a significant predictor of academic performance, my study also suggests that bolstering self-regulation and academic skills may not be enough to change trajectories for students with social-emotional difficulties, thus suggesting that efforts also need to be geared toward factors related to poverty that adversely affect a child’s school readiness and subsequent academic success. As such, interventions must also target ways in which family, school, and community systems operate to lessen the influence of poverty-related risk factors.

REFERENCES

Allan, N., Hume, L., Allan, D., Farrington, A., & Lonigan, C. (2014). Relations between inhibitory control and the development of academic skills in preschool and kindergarten: A meta-analysis. *Developmental Psychology*, *50*(10), 23–68. doi:10.1037/a0037493

Allan, N., & Lonigan, C. (2014). Exploring dimensionality of effortful control using hot and cool tasks in a sample of preschool children. *Journal of Experimental Child Psychology*, *122*, 33–47. doi:10.1016/j.jecp.2013.11.013

Arnett, A., Pennington, B., Friend, A., Willcutt, E., Byrne, B., Samuelsson, S., & Olson, R. (2011). The SWAN captures variance at the negative and positive ends of the ADHD symptom dimension. *Journal of Attention Disorders*, *17*(2), 152–162. doi:10.1177/1087054711427399

Aylward, G. P., Gordon, M., & Verhulst, S. J. (1997). Relationships between continuous performance task scores and other cognitive measures: Causality or commonality? *Psychological Assessment*, *4*(4), 325–336.

Bagner, D. M., Boggs, S. R., & Eyberg, S. M. (2010). Evidence-based school behavior assessment of externalizing behavior in young children. *Education and Treatment of Children*, *33*(1), 65–83.

Bailey, C., Denham, S., Curby, T., & Bassett, H. (2016). Emotional and organizational supports for preschoolers' emotion regulation: Relations with school adjustment. *Emotion*, *16*(2), 263–79. doi:10.1037/a0039772

Barriga, A.Q., Dorans, J.W., Newell, S.B., Morrison, E.M., Barbetti, V., & Robbins, B.D. (2002). Relationships between problem behaviors and academic achievement in adolescents: The unique role of attention problems. *Journal of Emotional and Behavioral Disorders*, *10*(4), 233-240.

Bassett, H., Denham, S., Wyatt, T., & Warren-Khot, H. (2012). Refining the preschool self-regulation assessment for use in preschool classrooms. *Infant and Child Development*, *21*(6), 596–616. doi:10.1002/icd.1763

Bell, M., & Wolfe, C. D. (2004). Emotion and cognition: An intricately bound developmental process. *Child Development*, *75*(2), 366–370. doi:10.1111/j.1467-8624.2004.00679.x

Below, J. L., Skinner, C. H., Fearrington, J. Y., & Sorrell, C. A. (2010). Gender differences in early literacy: Analysis of kindergarten through fifth-grade dynamic indicators of basic early literacy skills probes. *School Psychology Review*, *39*(2), 240–257.

Berger, A. (2011). *Self-Regulation: Brain, Cognition, and Development*. Washington, DC: American Psychological Association.

Berger, A., & Posner, M.I. (2000). Pathologies of brain attentional networks. *Neuroscience and Behavioral Review, 24*(1), 3-5.

Berger, A., Kofman, O., Livneh, U., & Henik, A. (2007). Multidisciplinary perspectives on attention and the development of self-regulation. *Progress in Neurobiology*, *82*(5), 256–86. doi:10.1016/j.pneurobio.2007.06.004

Blair, C. (2016). The development of executive functions and self-regulation: A bidrectional psychobiological model. In K.D. Vohs & R.F. Baumeister (Eds). *Handbook of Self-Regulation: Research, Theory, and Applications* (3rd Ed., 417-439). New York, NY: The Guilford.

Blair, C. (2002). School readiness: Integrating cognition and emotion in a neurobiological conceptualization of children's functioning at school entry. *The American Psychologist*, *57*(2), 111–27.

Blair, C., & Raver, C. (2015). School readiness and self-regulation: A developmental psychobiological approach. *Annual Review of Psychology*, *66*(1), 711–731. doi:10.1146/annurev-psych-010814-015221

Blair, C., & Razza, R. (2007). Relating effortful control, executive function, and false belief understanding to emerging math and literacy ability in kindergarten. *Child Development*, *78*(2), 647–63. doi:10.1111/j.1467-8624.2007.01019.x

Blair, C., & Ursache, A. (2011). A bidirectional model of executive functions and self-regulation. In K.D. Vohs & Baumeister (Eds.). *Handbook of Self-Regulation: Research, Theory, and Applications* (2nd Ed., 300-320). New York, NY: The Guilford Press.

Blair, C., Zelazo, P. D., & Greenberg, M. T. (2005). The measurement of executive function in early childhood. *Developmental Neuropsychology*, *28*(2), 561–571. doi:10.1207/s15326942dn2802_1

Borella, E., Carretti, B., & Pelegrina, S. (2010). The specific role of inhibition in reading comprehension in good and poor comprehenders. *Journal of Learning Disabilities*, *43*(6), 541–552. doi:10.1177/0022219410371676

Bradley, R.H., Doolittle, J., & Bartolotta, R. (2008). Building on the data and adding to the discussion: The experiences and outcomes of students with emotional disturbance. *Journal of Behavioral Education*, *17*(1), 4–23. doi:10.1007/s10864-007-9058-6

Bradley, R.H., Corwyn, R.F., Pipes McAdoo, H., Carcia Coll, C. (2001). The home environments of children in the Unites States part I: Variations by age, ethnicity, and povery status. *Child Development*, *72*(6), 1844-1867.

Breslau, J., Miller, E., Breslau, N., Bohnert, K., Lucia, V., & Schweitzer, J. (2008). The impact of early behavior disturbances on academic achievement in high school. *Pediatrics, 123*(6), 1472-1476. 10.1542/peds.2008-1406

Brites, Salgado-Azoni, C. A., Ferreira, T. L., Lima, R. F., & Ciasca, S. M. (2015). Development and applications of the SWAN rating scale for assessment of attention deficit hyperactivity disorder: a literature review. *Brazilian Journal of Medical and Biological Research*, *48*(11), 965–972. doi:10.1590/1414-431X20154528

Brock, L. L., Rimm-Kaufman, S. E., Nathanson, L., & Grimm, K. J. (2009). The contributions of "hot" and "cool" executive function to children's academic achievement, learning-related behaviors, and engagement in kindergarten. *Early Childhood Research Quarterly*, *24*(3), 337–349. doi:10.1016/j.ecresq.2009.06.001

Bull, R., & Lee, K. (2014). Executive functioning and mathematics achievement. *Child Development Perspectives*, *8*(1), 36–41. doi:10.1111/cdep.12059

Bull, R., Espy, K., & Wiebe, S. (2008). Short-term memory, working memory, and executive functioning in preschoolers: Longitudinal predictors of mathematical achievement at age 7 years. *Developmental Neuropsychology*, *33*(3), 205–228. doi:10.1080/87565640801982312

Burchinal, M., Carr, R., Vernon-Feagans, L., Blair, C., Cox, M., & Investigators. (2018). Depth, persistence, and timing of poverty and the development of school readiness skills in rural low-income regions: Results from the Family Life Project. *Early Childhood Research Quarterly*, *45*, 115–130. doi:10.1016/j.ecresq.2018.07.002

Byrnes, J. P., & Wasik, B. A. (2009). Factors predictive of mathematics achievement in kindergarten, first and third grades: An opportunity–propensity analysis. *Contemporary Educational Psychology*, *34*, 167–183.

Caine, RN, & Caine, G. (1991). *Making Connections: Teaching and the Human Brain.* Alexandria, VA: Association for Supervision and Curriculum Development.

Calkins, S., Blandon, A., Williford, A., & Keane, S. (2007). Biological, behavioral, and relational levels of resilience in the context of risk for early childhood behavior problems. *Development and Psychopathology*, *19*(3), 675–700. doi:10.1017/S095457940700034X

Calkins, S.D., & Marcovitch, S. (2010). Emotion regulation and executive functioning in early development: Mechanisms of control supporting adaptive functioning. In S.D. Calkins & M.A. Bell (Eds.). *Child Development at the Intersection of Emotion and Cognition* (37-57). Washington, DC: American Psychological Association.

Carlson, S., & Moses, L. (2001). Individual differences in inhibitory control and children's theory of mind. *Child Development*, *72*(4), 1032–1053. doi:10.1111/1467-8624.00333

Carlson, S., & Wang, T. (2007). Inhibitory control and emotion regulation in preschool children. *Cognitive Development*, *22*(4), 489–510. doi:10.1016/j.cogdev.2007.08.002

Caspi, A., Elder, G., & Bem, D. (1987). Moving against the world: Life-course patterns of explosive children. *Developmental Psychology*, *23*(2), 308. doi:10.1037/0012-1649.23.2.308

Chatterji, M. (2006). Reading achievement gaps, correlates, and moderators of early reading achievement: Evidence from the Early Childhood Longitudinal Study (ECLS) kindergarten to first grade sample. *Journal of Educational Psychology*, *98*(3), 489–507.

Chung, H.J., Weyandt, L.L., & Swentosky, A. (2014). The physiology of executive functioning. In S. Goldstein & J.A. Naglieri (Eds.) *Handbook of Executive Functioning* (13-27). New York, NY: Springer.

Clark, C., Pritchard, V., & Woodward, L. (2010). Preschool executive functioning abilities predict early mathematics achievement. *Developmental Psychology*, *46*(5), 1176–91. doi:10.1037/a0019672

Cleary, T. J., Callan, G. L., & Zimmerman, B. J. (2012). Assessing self-regulation as a cyclical, context-specific phenomenon: Overview and analysis of SRL microanalytic protocols. *Education Research International*, *2012*, 1–19. doi:10.1155/2012/428639

Cleary, T. J., & Chen, P. P. (2009). Self-regulation, motivation, and math achievement in middle school: Variations across grade level and math context. *Journal of School Psychology*, *47*(5), 291–314. doi:10.1016/j.jsp.2009.04.002

Cole, P., Martin, S., & Dennis, T. (2004). Emotion regulation as a scientific construct: Methodological challenges and directions for child development research. *Child Development*, *75*(2), 317–333. doi:10.1111/j.1467-8624.2004.00673.x

Cole, T., Daniels, H., & Visser, J. (2012). *The Routledge International Companion to Emotional and Behavioural Difficulties*. New York, NY: Routledge.

Cooper, & Cefai. (2013). Evidence-based approaches to social, emotional and behavior difficulties in schools. *KEDI Journal of Educational Policy, 10*(3), 81-101.

Crosnoe, R., & Cooper, C. (2010). Economically disadvantaged children's transitions into elementary school. *American Educational Research Journal*, *47*(2), 258–291. doi:10.3102/0002831209351564

Darke, S., Ross, J., & Lynskey, M. (2003). The relationship of conduct disorder to attempted suicide and drug use history among methadone maintenance patients. *Drug and Alcohol Review*, *22*(1), 21–25. doi:10.1080/0959523021000059794

Davidson, M., Amso, D., Anderson, L., & Diamond, A. (2006). Development of cognitive control and executive functions from 4 to 13 years: Evidence from manipulations of memory, inhibition, and task switching. *Neuropsychologia*, *44*(11), 2037–2078. doi:10.1016/j.neuropsychologia.2006.02.006

Dekker, M. C., Ziermans, T. B., & Swaab, H. (2016). The impact of behavioural executive functioning and intelligence on math abilities in children with intellectual disabilities. *Journal of Intellectual Disability Research*, *60*(11), 1086–1096. doi:10.1111/jir.12276

Denham, S., Bassett, H., & Zinsser, K. (2012). Early childhood teachers as socializers of young children's emotional competence. *Early Childhood Education Journal*, *40*(3), 137–143. doi:10.1007/s10643-012-0504-2

Diamond, A. (2013). Executive functions. *Annual Review of Psychology*, *64*(1), 135–168. doi:10.1146/annurev-psych-113011-143750

DiPerna, J. (2006). Academic enablers and student achievement: Implications for assessment and intervention services in the schools. *Psychology in the Schools*, *43*(1), 7–17. doi:10.1002/pits.20125

DiPerna, J., & Elliott, S. (1999). Development and validation of the academic competence evaluation scales. *Journal of Psychoeducational Assessment*, *17*, 207–225. doi:10.1177/073428299901700302

Djambazova-Popordanoska, S. (2016). Implications of emotion regulation on young children's emotional wellbeing and educational achievement. *Educational Review*, *68*(4), 1–19. doi:10.1080/00131911.2016.1144559

Duckworth, A., & Seligman, M. (2005). Self-discipline outdoes IQ in predicting academic performance of adolescents. *Psychological Science, 16*(12), 939–944. doi:10.1111/j.1467-9280.2005.01641.x

DuPaul, G., Rapport, M., & Perriello, L. M. (1991). Teacher ratings of academic skills: The development of the Academic Performance Rating Scale. *School Psychology Review, 20*(2), 284-300.

Eisenberg, N., Hofer, C., Sulik, M.J., & Spinrad, T.L. (2014). Self-regulation, effortful control, and their socioemotional correlates. In J.J. Gross (Ed.). *Handbook of Emotion Regulation* (157-172). New York, NY:The Guilford Press.

Eisenberg, N., Smith, C.L., Sadovsky, A., & Spinrad, T.L. (2004). Effortful control: Relations with emotion regulation, adjustment and socialization in childhood. In R.F. Baumester & K.D. Vohs (Eds.). *Handbook of Self-Regulation: Research, Theory, and Practice.* (1st Ed., 259-282). New York, NY: Guilford Press.

Eisenberg, N., & Spinrad, T. L. (2004). Emotion-related regulation: sharpening the definition. *Child Development*, *75*(2), 334–9. doi:10.1111/j.1467-8624.2004.00674.x

Eisenberg, N., Valiente, C., & Eggum, N. (2010). Self-regulation and school readiness. *Early Education and Development*, *21*(5), 681–698. doi:10.1080/10409289.2010.497451

Eisenberg, N., & Zhou, Q. (2016). Conceptions of execution function and regulation: When and to what degree do they overlap?. In J.A. Griffin, P. McCardle, & L.S. Freund (Eds.). *Executive Function in Preschool-Age Children: Integrating Measurement, Neurodevelopment, and Translational Research* (115-136). Washington, DC: American Psychological Association.

Else-Quest, N., Hyde, J., Goldsmith, & Hulle, C. (2006). Gender differences in temperament: A meta-analysis. *Psychological bulletin*, *132*(1), 33–72. doi:10.1037/0033-2909.132.1.33

Ensminger, M. E., & Slusarcick, A. L. (1992). Paths to high school graduation or dropout: A longitudinal study of a first-grade cohort. *Sociology of Education*, *65*(2), 95–113. doi:10.2307/2112677

Espy, K., McDiarmid, M., Cwik, M., Stalets, M., Hamby, A., & Senn, T. (2004). The contribution of executive functions to emergent mathematic skills in preschool children. *Developmental Neuropsychology*, *26*(1), 465–486. doi:10.1207/s15326942dn2601_6

Fay-Stammbach, T., Hawes, D., & Meredith, P. (2017). Child maltreatment and emotion socialization: Associations with executive function in the preschool years. *Child Abuse and Neglect*, *64*, 1–12. doi:10.1016/j.chiabu.2016.12.004

Fergusson, M. F., & Horwood, L. J. (2003). Resilience to childhood adversity: Results of a 21 year study (pp. 130–155). Cambridge: Cambrindge University Press.

Fisher, A., & Kloos, H. (2016). Development of selective sustained attention: The roles of executive functions. In J.A. Griffin, P. McCardle, & L.S. Freund (Eds.). *Executive Function in Preschool-Age Children: Integrating Measurement, Neurodevelopment, and Translational Research* (215-237). Washington, DC: American Psychological Association.

Fleming, C., Haggerty, K., Catalano, R., Harachi, T., Mazza, J., Gruman, D., … Gruman, D. (2005). Do social and behavioral characteristics targeted by preventive interventions predict standardized test scores and grades? *Journal of School Health*. doi:10.1111/j.1746-1561.2005.00048.x

Fogarty, RJ. (2009). *Brain-compatible classrooms*. Thousand Oaks, CA: Corwin.

Fuchs, L., Compton, D., Fuchs, D., Paulsen, K., Bryant, J., & Hamlett, C. (2005). The prevention, identification, and cognitive determinants of math difficulty. *Journal of Educational Psychology*, *97*(3), 493. doi:10.1037/0022-0663.97.3.493

Fuhs, M., Farran, D., & Nesbitt, K. (2015). Prekindergarten children's executive functioning skills and achievement gains: The utility of direct assessments and teacher ratings. *Journal of Educational Psychology*, *107*(1), 207. doi:10.1037/a0037366

Fuhs, M., Nesbitt, K., Farran, D., & Dong, N. (2014). Longitudinal associations between executive functioning and academic skills across content areas. *Developmental Psychology*, *50*(6), 1698. doi:10.1037/a0036633

Galindo, C., & Sonnenschein, S. (2015). Decreasing the SES math achievement gap: Initial math proficiency and home learning environments. *Contemporary Educational Psychology*, *43*, 25–38. doi:10.1016/j.cedpsych.2015.08.003

Garner, O'Connor, & Narad. (2013). The relationship between ADHD symptom dimensions, clinical correlates and functional impairments. doi:10.1097/DBP.0b013e3182a39890

Garner, P. (2010). Emotional competence and its influences on teaching and learning. *Educational Psychology Review*, *22*(3), 297–321.

Garner, & Waajid. (2012). Emotion knowledge and self-regulation as predictors of preschoolers' cognitive ability, classroom behavior, and social competence. *Journal of Psychoeducational Assessment*, *30*(4), 330–343. doi:10.1177/0734282912449441

Garon, N., Bryson, S. E., & Smith, I. M. (2008). Executive function in preschoolers: A review using an integrative framework. *Psychological Bulletin*, *134*(1), 31–60. doi:10.1037/0033-2909.134.1.31

Gestsdottir, S., von Suchodoletz, A., Wanless, S., Hubert, B., Guimard, P., Birgisdottir, F., … McClelland, M. (2014). Early behavioral self-regulation, academic achievement, and gender: Longitudinal findings from France, Germany, and Iceland. *Applied Developmental Science*, *18*(2), 90–109. doi:10.1080/10888691.2014.894870

Ginn, N., Seib, A., Boggs, S.R., & Eyberg, S.M. (2009). *Manual for the Revised Edition of the School Observation Coding System (REDSOCS).*

Gold, A., Ewing-Cobbs, L., Cirino, P., Fuchs, L., Stuebing, K., & Fletcher, J. (2013). Cognitive and behavioral attention in children with math difficulties. *Child Neuropsychology*, *19*(4), 420–437. doi:10.1080/09297049.2012.690371

Goleman, D. (2004). *Building Academic Success on Social and Emotional Learning.* New York, NY: Teachers College Press.

Gomez, R., Vance, A., & Gomez, R. (2013). Maternal ratings of the ADHD Symptoms. *Journal of Attention Disorders*, *20*(5), 414–423. doi:10.1177/1087054713514606

Goodman, R. (1997). The Strengths and Difficulties Questionnaire: A research note. *Journal of Child Psychology and Psychiatry*, *38*(5), 581–586. doi:10.1111/j.1469-7610.1997.tb01545.x

Goodman, R., Ford, T., Simmons, H., Gatward, R., & Meltzer, H. (2000). Using the Strengths and Difficulties Questionnaire (SDQ) to screen for child psychiatric disorders in a community sample. *The British Journal of Psychiatry*, *177*(6), 534–539. doi:10.1192/bjp.177.6.534

Gray, Rogers, Martinussen, & Tannock. (2015). Longitudinal relations among inattention, working memory, and academic achievement: testing mediation and the moderating role of gender. *PeerJ.* 3(5), 1-26, 10.7717/peerj.939

Graziano, P., & Hart, K. (2016). Beyond behavior modification: Benefits of social–emotional/self-regulation training for preschoolers with behavior problems. *Journal of School Psychology*, *58*, 91–111. doi:10.1016/j.jsp.2016.07.004

Graziano, P., Reavis, R., Keane, S., & Calkins, S. (2007). The role of emotion regulation in children's early academic success. *Journal of School Psychology*, *45*(1), 3–19. doi:10.1016/j.jsp.2006.09.002

Greene, J. A. (2018). *Self-regulation in Education*. New York, NY: Routledge.

Gregory, A., Skiba, R., & Noguera, P. (2009). The achievement gap and the discipline gap. *Educational Researcher*, *39*(1), 59–68. doi:10.3102/0013189x09357621

Gross, J. J. (2014). Emotion regulation: Conceptual and empirical foundations. In J.J. Gross (Ed.). *Handbook of Emotion Regulation* (3-20). New York, NY:The Guilford Press.

Guimard, Hubert, Crusson-Pondeville, & Nocus. (2012). Behavioral self-regulation and academic achievement in prekindergarten and kindergarten. *Psychologie Française*, *57*(3), 143–159. doi:10.1016/j.psfr.2012.07.001

Hamoudi, A., Murray, D. W., Sorenson, L., & Fontaine, A. (2015). *Self-regulation and toxic stress: A review of ecological, biological, and developmental studies of self-regulation and stress* (No. 2015-30). Washington, D.C.: Office of Planning, Research, and Evaluation, Administration for Children and Familiies, U.S. Department of Health and Human Services.

Heck, R. H., Thomas, S. L., & Tabata, L. N. (2014). *Multilevel and Longitudinal Modeling with IBM SPSS*. New York, NY: Routledge.

Hedges, L. (2008). What are effect sizes and why do we need them? *Child Development Perspectives*, *2*(3), 167–171. doi:10.1111/j.1750-8606.2008.00060.x

Henry, & Huizinga. (2007). School-related risk and protective factors associated with truancy among urban youth placed at risk. *The Journal of Primary Prevention, 28,* 505-518. doi: 10.1007/s10935-007-0115-7

Henry, Knight, & Thornberry. (2012). School disengagement as a predictor of dropout, delinquency, and problem substance use during adolescence and early adulthood. *Journal of Youth and Adolescence, 41,* 156-166. doi:10.1007/s10964-011-9665-3

Hernández, M., Valiente, C., Eisenberg, N., Berger, R., Spinrad, T., VanSchyndel, S., … Thompson, M. (2017). Elementary students' effortful control and academic achievement: The mediating role of teacher–student relationship quality. *Early Childhood Research Quarterly, 40*, 98–109. doi:10.1016/j.ecresq.2016.10.004

Hindman, A. H., Skibbe, L. E., Miller, A., & Zimmerman, M. (2010). Ecological contexts and early learning: Contributions of child, family, and classroom factors during Head Start, to literacy and mathematics growth through first grade. *Early Childhood Research Quarterly*, *25*(2), 235–250. doi:10.1016/j.ecresq.2009.11.003

Hinshaw. (1992). Externalizing behavior problems and academic underachievement in childhood and adolescence: causal relationships and underlying mechanisms. *Psychological Bulletin*, *111*(1), 127–55.

Hoeksma, J., Oosterlaan, J., & Schipper, E. (2004). Emotion regulation and the dynamics of feelings: A conceptual and methodological framework. *Child Development*, *75*(2), 354–360. doi:10.1111/j.1467-8624.2004.00677.x

Holodynski, M., & Friedlemeier, W. (2005). *Development of Emotions and Emotion Regulation.* New York, NY: Springer.

Howse, R., Calkins, S., Anastopoulos, A., Keane, S., & Shelton, T. (2003). Regulatory contributors to children's kindergarten achievement. *Early Education and Development*, *14*(1), 101–120. doi:10.1207/s15566935eed1401_7

Hox, J. J. (2010). *Multilevel Analysis Techniques and Applications* (2nd ed.). New York, NY: Routledge.

Hubert, B., Guimard, P., Florin, A., & Tracy, A. (2015). Indirect and direct relationships between self-regulation and academic achievement during the nursery/elementary school transition of French students. *Early Education and Development*, *26*(5-6), 685–707. doi:10.1080/10409289.2015.1037624

Huizinga, M., Dolan, C. V., & van der Molen, M. W. (2006). Age-related change in executive function: developmental trends and a latent variable analysis. *Neuropsychologia*, *44*(11), 2017–36. doi:10.1016/j.neuropsychologia.2006.01.010

Jacob, R., & Parkinson, J. (2015). The potential for school-based interventions that target executive function to improve academic achievement. *Review of Educational Research*, *85*(4), 512–552. doi:10.3102/0034654314561338

Jacobs, J., Boggs, S., Eyberg, S., Edwards, D., Durning, P., Querido, J., … Funderburk, B. (2000). Psychometric properties and reference point data for the revised edition of the school observation coding system. *Behavior Therapy, 31*(4), 695–712. doi:10.1016/S0005-7894(00)80039-8

Jones, S. M., Bailey, R., Barnes, S. P., & Partee, A. (2016). *Executive Function Mapping Project* (No. 2016-88). Washington, DC: U.S. Department of Health and Human Services.

Jordan, N., Kaplan, D., Olah, L. N., & Locuniak, M. N. (2006). Number sense growth in kindergarten: A longitudinal investigation of children at risk for mathematics difficulties. *Child Development*, *77*(1), 153–175. doi:10.1111/j.1467-8624.2006.00862.x

Kessler, R. C., Amminger, G. P., Aguilar-Gaxiola, S., Alonso, J., Lee, S., & Ustun, B. (2007). Age of onset of mental disorders: A review of recent literature. *Current Opinion in Psychiatry*, *20*(4), 359–364.

Kim, J.-S., Anderson, C. J., & Keller, B. (2014). *Multilevel Analysis of Assessment Data* (1st ed., pp. 489–424). Boca Raton, FL: CRC Press.

Kim, S., Nordling, J., Yoon, J., Boldt, L., & Kochanska, G. (2013). Effortful ccontrol in “hot” and “cool” tasks differentially predicts children’s behavior problems and academic performance. *Journal of Abnormal Child Psychology, 41*(1), 43–56. doi:10.1007/s10802-012-9661-4

Klingberg, T. (2006). Development of a superior frontal–intraparietal network for visuo-spatial working memory. *Neuropsychologia*, *44*(11), 2171–2177. doi:10.1016/j.neuropsychologia.2005.11.019

Kramer, H. J., Hanson Lagattuta, K., & Sayfan, L. (2015). Why is Happy-Sad more difficult? Focal emotional information impairs inhibitory control in children and adults. *Emotion*, *15*(1), 61–72. doi:10.1037/emo0000023

Ladd, Birch, & Buhs. (1999). Children’s social and scholastic lives in kindergarten: related spheres of influence? *Child Development, 70*(6), 1373–400.

Lagattuta, K., Sayfan, L., & Monsour, M. (2011). A new measure for assessing executive function across a wide age range: children and adults find happy-sad more difficult than day-night. *Developmental Science*, *14*(3), 481–489. doi:10.1111/j.1467-7687.2010.00994.x

Lambert. (1988). Adolescent outcomes for hyperactive children. Perspectives on general and specific patterns of childhood risk for adolescent educational, social, and mental health problems. *The American Psychologist*, *43*(10), 786–99. doi:10.1037/0003-066X.43.10.786

Lan, X., Legare, C., Ponitz, C., Li, S., & Morrison, F. (2011). Investigating the links between the subcomponents of executive function and academic achievement: A cross-cultural analysis of Chinese and American preschoolers. *Journal of Experimental Child Psychology*, *108*(3), 677–692. doi:10.1016/j.jecp.2010.11.001

Lane, K.L., Wehby, J., & Barton-Atwood, S.M. (2005). Students with and at risk for emotional and behavioral disorders: Meeting their social and academic needs. *Preventing School Failure*, *9*(2), 6-9. doi:10.3200/PSFL.4

Lavigne, J. V., Meyers, K. M., & Feldman, M. (2016). Systematic review: Classification accuracy of behavioral screening measures for use in integrated primary care settings. *Journal of Pediatric Psychology*, *41*(10), 1091–1109. doi:10.1093/jpepsy/jsw049

Lawson, G., Hook, C., & Farah, M. (2017). A meta-analysis of the relationship between socioeconomic status and executive function performance among children. *Developmental Science*, *21*(2), 1-22. doi:10.1111/desc.12529

Lee, J. (2016). *The Anatomy of Achievement Gaps*. New York, NY: Oxford University Press.

Lee, J., Moon, S., & Hegar, R. (2011). Mathematics Skills in Early Childhood: Exploring Gender and Ethnic Patterns. *Child Indicators Research*, *4*(3), 353–368. doi:10.1007/s12187-010-9088-9

Lee, J., & Otaiba, S. (2015). Socioeconomic and gender group differences in early literacy skills: a multiple-group confirmatory factor analysis approach. *Educational Research and Evaluation*, *21*(1), 40–59. doi:10.1080/13803611.2015.1010545

Lee, K., Bull, R., & Ho, R. (2013). Developmental changes in executive functioning. *Child Development*, *84*(6), 1933–1953. doi:10.1111/cdev.12096

Lee, K., Ng, S., Pe, M., Ang, S., Hasshim, M., & Bull, R. (2012). The cognitive underpinnings of emerging mathematical skills: Executive functioning, patterns, numeracy, and arithmetic. *British Journal of Educational Psychology*, *82*(1), 82–99. doi:10.1111/j.2044-8279.2010.02016.x

Lench, H., & Levine, L. (2005). Effects of fear on risk and control judgements and memory: Implications for health promotion messages. *Cognition and Emotion*, *19*(7), 1049–1069. doi:10.1080/02699930500203112

Liew, J. (2012). Effortful control, executive functions, and education: Bringing self-regulatory and social-emotional competencies to the table. *Child Development Perspectives*, *6*(2), 105–111. doi:10.1111/j.1750-8606.2011.00196.x

Lindberg, S., Hyde, J., Petersen, J., & Linn, M. (2010). New trends in gender and mathematics performance: A meta-analysis. *Psychological Bulletin*, *136*(6), 1123. doi:10.1037/a0021276

Logan, S., & Johnston, R. (2010). Investigating gender differences in reading. *Educational Review*, *62*(2), 175–187. doi:10.1080/00131911003637006

Lonnemann, J., Linkersdörfer, J., Hasselhorn, M., & Lindberg, S. (2013). Gender differences in both tails of the distribution of numerical competencies in preschool children. *Educational Studies in Mathematics*, *84*(2), 201–208. doi:10.1007/s10649-013-9488-0

Lubin, A., Rossi, S., Lanoë, C., Vidal, J., Houdé, O., & Borst, G. (2016). Expertise, inhibitory control and arithmetic word problems: A negative priming study in mathematics experts. *Learning and Instruction*, *45*, 40–48. doi:10.1016/j.learninstruc.2016.06.004

Maguin, E., & Loeber, R. (1996). Academic performance and delinquency. *Crime and Justice*, *20*, 145–264.

Malone, A., & Fuchs, L. (2014). Comparing the contribution of teacher versus tutor ratings of inattentive behavior in predicting mathematics achievement. *Remedial and Special Education*, *35*(6), 378–386. doi:10.1177/0741932514539855

Marks, G. (2008). Accounting for the gender gaps in student performance in reading and mathematics: evidence from 31 countries. *Oxford Review of Education*, *34*(1), 89–109. doi:10.1080/03054980701565279

Massetti, G., Lahey, B., Pelham, W., Loney, J., Ehrhardt, A., Lee, S., & Kipp, H. (2008). Academic achievement over 8 years among children who met modified criteria for attention-deficit/hyperactivity disorder at 4–6 years of age. *Journal of Abnormal Child Psychology*, *36*(3), 399–410. doi:10.1007/s10802-007-9186-4

Matthews, J. S., Marulis, L., & Williford, A. (2014). Gender processes in school functioning and the mediating role of cognitive self-regulation. *Journal of Applied Developmental Psychology*, *35*(3), 128–137. doi:10.1016/j.appdev.2014.02.003

Matthews, Ponitz, & Morrison. (2009). Early gender differences in self-regulation and academic achievement. *Journal of Educational Psychology*, *101*(3), 689-704. doi:10.1037/a0014240

McAuley, T., & White, D. (2011). A latent variables examination of processing speed, response inhibition, and working memory during typical development. *Journal of Experimental Child Psychology*, *108*(3), 453–468. doi:10.1016/j.jecp.2010.08.009

McClelland, M., & Cameron, C. (2011). Self-regulation and academic achievement in elementary school children. *New Directions for Child and Adolescent Development*, *2011*(133), 29–44. doi:10.1002/cd.302

McClelland, M., & Cameron, C. (2012). Self-regulation in early childhood: Improving conceptual clarity and developing ecologically valid measures. *Child Development Perspectives*, *6*(2), 136–142. doi:10.1111/j.1750-8606.2011.00191.x

McClelland, M., Cameron, C., Connor, C., Farris, C., Jewkes, A., & Morrison, F. (2007). Links between behavioral regulation and preschoolers' literacy, vocabulary, and math skills. *Developmental Psychology*, *43*(4), 947–59. doi:10.1037/0012-1649.43.4.947

McClelland, M., Cameron, C., Duncan, R., Bowles, R., Acock, A., Miao, A., & Pratt, M. (2014). Predictors of early growth in academic achievement: the Head-Toes-Knees-Shoulders task. *Frontiers in Psychology*, *5*, 599. doi:10.3389/fpsyg.2014.00599

McCoy, D., & Raver, C. (2011). Caregiver emotional expressiveness, child emotion regulation, and child behavior problems among head start families. *Social Development*, *20*(4), 741–761. doi:10.1111/j.1467-9507.2011.00608.x

McLaughlin, K., Green, J., Gruber, M., Sampson, N., Zaslavsky, A., & Kessler, R. (2012). Childhood adversities and first onset of psychiatric disorders in a national sample of US adolescents. *Archives of General Psychiatry*, *69*(11), 1151–60. doi:10.1001/archgenpsychiatry.2011.2277

Merikangas, K., He, J.P., Burstein, M., Swanson, S., Avenevoli, S., Cui, L., … Swendsen, J. (2010). Lifetime prevalence of mental disorders in U.S. adolescents: results from the National Comorbidity Survey Replication-Adolescent Supplement (NCS-A). *Journal of the American Academy of Child and Adolescent Psychiatry*, *49*(10), 980–9. doi:10.1016/j.jaac.2010.05.017

Merriman, D., Codding, R., Tryon, G., & Minami, T. (2016). The effects of group coaching on the homework problems experiences by secondary students with and without disabilities. *Psychology in the Schools*, *53*(5), 457–470. doi:10.1002/pits.21918

Metcalfe, & Mischel. (1999). A hot/cool-system analysis of delay of gratification: Dynamics of willpower. *Psychological Review*, *106*(1), 3–19.

Miller, M., Giesbrecht, G., Müller, U., McInerney, R., & Kerns, K. (2012). A latent variable approach to determining the structure of executive function in preschool children. *Journal of Cognition and Development*, *13*(3), 395–423. doi:10.1080/15248372.2011.585478

Miyake, A., & Friedman, N. (2012). The nature and organization of individual differences in executive functions. *Current Directions in Psychological Science*, *21*(1), 8–14. doi:10.1177/0963721411429458

Miyake, A., Friedman, N., Emerson, M., Witzki, A., Howerter, A., & Wager, T. (2000). The unity and diversity of executive functions and their contributions to complex "frontal lobe” tasks: A latent variable analysis. *Cognitive Psychology*, *41*(1), 49–100. doi:10.1006/cogp.1999.0734

Moffitt, T., Arseneault, L., Belsky, D., Dickson, N., Hancox, R., Harrington, H., … Caspi, A. (2011). A gradient of childhood self-control predicts health, wealth, and public safety. *Proceedings of the National Academy of Sciences of the United States of America*, *108*(7), 2693–8. doi:10.1073/pnas.1010076108

Monette, S., Bigras, M., & Guay, M.-C. (2011). The role of the executive functions in school achievement at the end of Grade 1. *Journal of Experimental Child Psychology*, *109*(2), 158–173. doi:10.1016/j.jecp.2011.01.008

Montalbano, C., Murray, D. W., Kuhn, L. J., LaForett, D. R., & Cavanaugh, A. M. (2017). *Student success and attention, emotion regulation, and oppositional behavior*. Poster presented at the meeting of the American Psychological Association, Washington DC.

Morris, A., John, A., Halliburton, A., Morris, M., Robinson, L., Myers, S., … Terranova, A. (2013). Effortful control, behavior problems, and peer relations: What predicts academic adjustment in kindergartners from low-income families? *Early Education and Development*, *24*(6), 813–828. doi:10.1080/10409289.2013.744682

Mulligan, G.M., Hastedt, S., and McCarroll, J.C. (2012). First-time kindergartners in 2010-11: First findings from the kindergarten rounds of the Early Childhood Longitudinal Study, kindergarten class of 2010-11 (ECLS-K:2011) (NCES 2012-049). U.S. Department of Education. Washington, DC: National Center for Education Statistics. Retrieved April 24, 2018 from http://nces.ed.gov/pubsearch.

Murray, D. W., Rosanbalm, K., Christopolous, C., & Hamoudi, A. (2015). *Self-regulation and toxic stress: Foundations for understanding self-regulation from an applied developmental perspective* (No. 2015-21). Office of Planning, Research and Evaluation: U.S. Department of Health and Human Services.

Murray, K.T., & Kochanska, G. (2002). Effortful control: Factor structure and relation to externalizing and internalizing behaviors. *Journal of Abnormal Psychology, 30*(5), 503-514.

Neuenschwander, R., Röthlisberger, M., Cimeli, P., & Roebers, C. (2012). How do different aspects of self-regulation predict successful adaptation to school? *Journal of Experimental Child Psychology*, *113*(3), 353–371. doi:10.1016/j.jecp.2012.07.004

Ng, F., Tamis-LeMonda, C., Yoshikawa, H., & Sze, I. (2015). Inhibitory control in preschool predicts early math skills in first grade. *International Journal of Behavioral Development*, *39*(2), 139–149. doi:10.1177/0165025414538558

Nigg, J. T. (2017). Annual research review: On the relations among self-regulation, self-control, executive functioning, effortful control, cognitive control, impulsivity, risk-taking, and inhibition for developmental psychopathology. *Journal of Child Psychology and Psychiatry, and Allied Disciplines, 58*(4), 361–383. doi:10.1111/jcpp.12675

Obradović, J., Portilla, X., & Ballard, P. (2016). Biological sensitivity to family income: differential effects on early executive functioning. *Child Development, 87*(2), 374–384. doi:10.1111/cdev.12475

Oldfield, Hebron, & Humphrey. (2016). The role of school-level protective factors in overcoming cumulative risk for behavior difficulties in children with special educational needs and disabilities. *Psychology in the Schools, 53*(8), 831-845. *doi*:10.1002/pits.21950

Perfect, M., Levine-Donnerstein, D., Archbold, K., Goodwin, J., & Quan, S. (2014). The contribution of sleep problems to academic and psychosocial functioning. *Psychology in the Schools*, *51*(3), 273–295. doi:10.1002/pits.21746

Perou, R., Bitsko, R. H., Blumberg, S. J., Pastor, P., Ghandour, R. M., Gfroerer, J. C., … Huang, L. N. (2013). *Mental Health Surveillance Among Children in the United States*. Centers for Disease Control and Prevention.

Peterson, S.E., & Posner, M.I. (2012). The attention system of the human brain: 20 years after. *Annual Review of Neuroscience, 35*, 73-89. doi: 10.1146/annurev-neuro-062111-150525

Pingault, J., Tremblay, R., & Vitaro, F. (2011). Childhood trajectories of inattention and hyperactivity and prediction of educational attainment in early adulthood: a 16-year longitudinal population-based study. *American Journal of Psychiatry, 168,* 1164–1170.

Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. *Annual Review of Psychology*, *63*(1), 539–569. doi:10.1146/annurev-psych-120710-100452

Polderman, Boomsma, Bartels, Verhulst, & Huizink. (2010). A systematic review of prospective studies on attention problems and academic achievement. *Acta Psychiatrica Scandinavica*, *122*(4), 271–284. doi:10.1111/j.1600-0447.2010.01568.x

Ponitz, C., McClelland, M., Matthews, & Morrison, F. (2009). A structured observation of behavioral self-regulation and its contribution to kindergarten outcomes. *Developmental Psychology*, *45*(3), 605–19. doi:10.1037/a0015365

Posner, M.I., & Petersen, S.E. (1990). The attention system of the human brain. *Annual Review of Neuroscience, 13*, 25-42.

Posner, M., & Rothbart, M. (2007). Research on attention networks as a model for the integration of psychological science. *Annual Review of Psychology, 58*, 1–23. doi:10.1146/annurev.psych.58.110405.085516

Power, T., Mautone, J., Soffer, S., Clarke, A., Marshall, S., Sharman, J., … Jawad, A. (2012). A family–school intervention for children with ADHD: Results of a randomized clinical trial. *Journal of Consulting and Clinical Psychology*, *80*(4), 611. doi:10.1037/a0028188

Preston, A.S., Heaton, S.C., McCann, S.J., Watson, W.D., & Selke, G. (2009). The role of multidimensional attentional abilities in academic skills of children with ADHD. *Journal of Learning Disabilities*, *42*(3), 240-249. doi: 10.1177/0022219408331042

Purpura, D., Schmitt, S., & Ganley, C. (2017). Foundations of mathematics and literacy: The role of executive functioning components. *Journal of Experimental Child Psychology, 153*, 15–34. doi:10.1016/j.jecp.2016.08.010

Rabiner, D.L., Carrig, M.M., & Dodge, K.A. (2016). Attention problems and academic achievement: Do persistent and earlier-emerging problems have more adverse long-term effects?. *Journal of Attention Disorders*, *20*(11), 946-957. doi: /1177/1087054713507974

Rabiner, D.L., Murray, D.W., Skinner, A., & Malone, P.S. (2010). A randomized trial of two promising computer-based interventions for students with attention difficulties. *Journal of Abnormal Child Psychology, 38*(1), 131–142. doi:10.1007/s10802-009-9353-x

Rabiner, D.L., Malone, P.S., & the Conduct Problems Prevention Research Group (2004). The impact of tutoring on early reading achievement for children with and without attention problems. *Journal of Abnormal Child Psychology, 32*(3), 273-284.

Ramsden, S., & Hubbard, J. (2002). Family expressiveness and parental emotion coaching: their role in children's emotion regulation and aggression. *Journal of Abnormal Child Psychology*, *30*(6), 657–67.

Rasmussen, M., & Laumann, K. (2012). The academic and psychological benefits of exercise in healthy children and adolescents. *European Journal of Psychology of Education*, *28*(3), 945–962. doi:10.1007/s10212-012-0148-z

Raver, C.C. (2004). Placing emotional self-regulation in sociocultural and socioeconomic contexts. *Child Development, 75*(2), 346-353.

Raver, C. C., Carter, J. S., McCoy, D. C., Roy, A., Ursache, A., & Friedman, A. (2012). Testing models of children's self-regulation within educational contexts: Implications for measurement. *Advances in Child Development and Behavior*, *42*, 245–270.

Razza, R., Martin, A., & Brooks-Gunn, J. (2012). The implications of early attentional regulation for school success among low-income children. *Journal of Applied Developmental Psychology*, *33*(6), 311–319. doi:10.1016/j.appdev.2012.07.005

Rezazadeh, S., Wilding, J., & Cornish, K. (2011). The relationship between measures of cognitive attention and behavioral ratings of attention in typically developing children. *Child Neuropsychology*. doi:10.1080/09297049.2010.532203

Rhoades, B., Warren, H., Domitrovich, C., & Greenberg, M. (2016). Examining the link between preschool social–emotional competence and first grade academic achievement: The role of attention skills. *Early Childhood Research Quarterly*, *26*(2), 182–191. doi:10.1016/j.ecresq.2010.07.003

Robinson, J., & Lubienski, S. (2011). The Development of Gender Achievement Gaps in Mathematics and Reading During Elementary and Middle School. *American Educational Research Journal*, *48*(2), 268–302. doi:10.3102/0002831210372249

Rogers, M., Hwang, H., Toplak, M., Weiss, M., & Tannock, R. (2011). Inattention, working memory, and academic achievement in adolescents referred for attention deficit/hyperactivity disorder (ADHD). *Child Neuropsychology*, *17*(5), 444–458. doi:10.1080/09297049.2010.544648

Rothbart, M. K., & Bates, J. E. (2006). Temperament. In W. Damon, R. Lerner, & N. Eisenberg (Eds.) *Handbook of Child Psychology* (6th Ed.). New York, NY: Wiley.

Rouse, H., & Fantuzzo, J. (2016). Multiple risks and educational well being: A population-based investigation of threats to early school success. *Early Childhood Research Quarterly, 24*(1), 1–14. doi:10.1016/j.ecresq.2008.12.001

Ryoo, J. (2011). Model Selection with the Linear Mixed Model for Longitudinal Data. *Multivariate Behavioral Research*, *46*(4), 598–624. doi:10.1080/00273171.2011.589264

Schimmack, U. (2005). Attentional interference effects of emotional pictures: threat, negativity, or arousal? *Emotion, 5*(1), 55-66.

Schmeichel, B., Vohs, K., & Baumeister, R. (2003). Intellectual performance and ego depletion: Role of the self in logical reasoning and other information processing. *Journal of Personality and Social Psychology*, *85*(1), 33. doi:10.1037/0022-3514.85.1.33

Schmeichel, B.J., & Demaree, H.A.(2010). Working memory capacity and spontaneous emotion regulation: High capacity predicts self-enhancement in response to negative feedback. *Emotion, 10*(5), 739-744.

Schmitt, S., Geldhof, J., Purpura, D., Duncan, R., & McClelland, M. (2017). Examining the relations between executive function, math, and literacy during the transition to kindergarten: A multi-analytic approach. *Journal of Educational Psychology*, *109*(8), 1120. doi:10.1037/edu0000193

Schunk, D. H, & Greene, J.A. (2018). Historical, contemporary, and future perspectives on self-regulated learning and peformance. In D.H. Schunk & J.A. Greene (Eds.) *Handbook of Self-Regulation of Learning and Performance* (2nd Ed., 1-15). New York, NY: Routledge.

Schunk, D.H., & Zimmerman, B. (1997). Social origins of self-regulatory competence. *Educational Psychologist*, *32*(4), 195–208. doi:10.1207/s15326985ep3204_1

Schutz, P., & Davis, H. (2010). Emotions and self-regulation during test taking. *Educational Psychologist, 35*(4), 243–256. doi:10.1207/s15326985ep3504_03

Shaul, S., & Schwartz, M. (2014). The role of the executive functions in school readiness among preschool-age children. *Reading and Writing*, *27*(4), 749–768. doi:10.1007/s11145-013-9470-3

Shields, & Cicchetti. (1997). Emotion regulation among school-age children: the development and validation of a new criterion Q-sort scale. *Developmental Psychology*, *33*(6), 906–16.

Silverman, I. W. (2003). Gender differences in delay of gratification: A meta-analysis. *Sex roles*, *49*(9-10), 451–463.

Skiba, R., Chung, C.-G., Trachok, M., Baker, T., Sheya, A., & Hughes, R. (2014). Parsing disciplinary disproportionality. *American Educational Research Journal*, *51*(4), 640–670. doi:10.3102/0002831214541670

Smith-Donald, R., Raver, C., Hayes, T., & Richardson, B. (2007). Preliminary construct and concurrent validity of the Preschool Self-regulation Assessment (PSRA) for field-based research. *Early Childhood Research Quarterly*, *22*(2), 173–187. doi:10.1016/j.ecresq.2007.01.002

Snijders, T. A., & Bosker, R. J. (1999). *Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling*. London: Sage.

Sonnenschein, S., & Galindo, C. (2015). Race/ethnicity and early mathematics skills: Relations between home, classroom, and mathematics achievement. *The Journal of Educational Research*, *108*(4), 261–277. doi:10.1080/00220671.2014.880394

Spencer, S., Steele, C., & Quinn, D. (1999). Stereotype threat and women's math performance. *Journal of Experimental Social Psychology*, *35*(1), 4–28. doi:10.1006/jesp.1998.1373

St. Clair-Thompson, H. L., & Gathercole, S. E. (2006). Executive functions and achievements in school: Shifting, updating, inhibition, and working memory. *The Quarterly Journal of Experimental Psychology*, *59*(4), 745–759. doi:10.1080/17470210500162854

Stammbach, T., Hawes, D., & Meredith, P. (2014). Parenting influences on executive function in early childhood: A review. *Child Development Perspectives*, *8*(4), 258–264. doi:10.1111/cdep.12095

Stevens, J. (2001). *Applied Multivariate Statistics for the Social Sciences* (4th ed.). Hillsdale, NJ: Lawrence Erlbaum Associates.

Stone, L., Otten, R., Engels, R., Vermulst, A., & Janssens, J. (2010). Psychometric properties of the parent and teacher versions of the Strengths and Difficulties Questionnaire for 4- to 12-year-olds: A review. *Clinical Child and Family Psychology Review*, *13*(3), 254–274. doi:10.1007/s10567-010-0071-2

Swanson, J., Schuck, S., Porter, M., Carlson, C., Hartman, C., Sergeant, J., … Lakes, K. (2012). Categorical and dimensional definitions and evaluations of symptoms of ADHD: History of the SNAP and the SWAN rating scales. *The International Journal of Educational and Psychological Assessment*, *10*(1), 51.

Tabachnick, B.G., & Fidell, L.S. (2012). *Using Multivariate Statistics* (5th Ed.). Upper Saddle River, NJ: Pearson Education, Inc.

Tremblay, Masse, Perron, Leblanc, Schwartzman, & Ledingham. (1992). Early disruptive behavior, poor school achievement, delinquent behavior, and delinquent personality: Longitudinal analyses. *Journal of Consulting and Clinical Psychology*, *60*(1), 64. doi:10.1037/0022-006X.60.1.64

Tannock, R. (2003). Neuropsychology of attention disorders. In I. Rapin & S. Segalowitz (Eds.), *Handbook of Neuropsychology* (2nd Ed., 753–784). Amsterdam: Elsevier.

Tremblay, Masse, Perron, Leblanc, Schwartzman, & Ledingham. (1992). Early disruptive behavior, poor school achievement, delinquent behavior, and delinquent personality: Longitudinal analyses. *Journal of Consulting and Clinical Psychology*, *60*(1), 64. doi:10.1037/0022-006X.60.1.64

Trentacosta, C., & Izard, C. (2007). Kindergarten children’s emotion competence as a predictor of their academic competence in first grade. *Emotion*, *7*(1), 77. doi:10.1037/1528-3542.7.1.77

Tyson, D. F., Linnenbrink-Garcia, & Hill, N. E. (2009). Regulating Debilitating Emotions in the Context of Performance: Achievement Goal Orientations, Achievement-Elicited Emotions, and Socialization Contexts. *Human Development*, *52*(6), 329–356. doi:10.1159/000242348

Ursache, A., Blair, C., & Raver, C. (2012). The promotion of self-regulation as a means of enhancing school readiness and early achievement in children at-risk for school failure. *Child Development Perspectives*, *6*(2), 122–128. doi:10.1111/j.1750-8606.2011.00209.x

Valiente, C., Eisenberg, N., Haugen, R., Spinrad, T., Hofer, C., Liew, J., & Kupfer, A. (2011). Children’s effortful control and academic achievement: Mediation through social functioning. *Early Education and Development*, *22*(3), 411–433. doi:10.1080/10409289.2010.505259

Valiente, C., Eisenberg, N., Spinrad, T., Haugen, R., Thompson, M., & Kupfer, A. (2013). Effortful control and impulsivity as concurrent and longitudinal predictors of academic achievement. *The Journal of Early Adolescence*, *33*(7), 946–972. doi:10.1177/0272431613477239

Valiente, C., Lemery-Chalfant, K., & Swanson, J. (2010). Prediction of kindergartners' academic achievement from their effortful control and emotionality: Evidence for direct and moderated relations. *Journal of Educational Psychology*, *102*(3), 550. doi:10.1037/a0018992

Valiente, C., Lemery-Chalfant, K., Swanson, J., & Reiser, M. (2008). Prediction of children's academic competence from their effortful control, relationships, and classroom participation. *Journal of Educational Psychology*, *100*(1), 67–77. doi:10.1037/0022-0663.100.1.67

Van der Ven, S. H. G., Kroesbergen, E., Boom, J., & Leseman, P. (2012). The development of executive functions and early mathematics: A dynamic relationship. *British Journal of Educational Psychology*, *82*(1), 100–119. doi:10.1111/j.2044-8279.2011.02035.x

Vlachos, F., & Papadimitriou, A. (2015). Effect of age and gender on children's reading performance: The possible neural underpinnings. *Cogent Psychology*, *2*(1), 1045224. doi:10.1080/23311908.2015.1045224

Von Suchodoletz, A., Gestsdottir, S., Wanless, S., McClelland, M., Birgisdottir, F., Gunzenhauser, C., & Ragnarsdottir, H. (2013). Behavioral self-regulation and relations to emergent academic skills among children in Germany and Iceland. *Early Childhood Research Quarterly*, *28*(1), 62–73. doi:10.1016/j.ecresq.2012.05.003

Vuontela, V., Carlson, S., Troberg, A.-M., Fontell, T., Simola, P., Saarinen, S., & Aronen, E. (2013). Working memory, attention, inhibition, and their relation to adaptive functioning and behavioral/emotional symptoms in school-aged children. *Child Psychiatry and Human Development*, *44*(1), 105–122. doi:10.1007/s10578-012-0313-2

Wanless, S., McClelland, M., Acock, A., Ponitz, C., Son, S.-H., Lan, X., … Li, S. (2011). Measuring behavioral regulation in four societies. *Psychological Assessment*, *23*(2), 364–78. doi:10.1037/a0021768

Welsh, J., Nix, R., Blair, C., Bierman, K., & Nelson, K. (2010). The development of cognitive skills and gains in academic school readiness for children from low-income families. *Journal of Educational Psychology*, *102*(1), 43. doi:10.1037/a0016738

Wiebe, S., Espy, K., & Charak, D. (2008). Using confirmatory factor analysis to understand executive control in preschool children: I. Latent structure. *Developmental Psychology*, *44*(2), 575. doi:10.1037/0012-1649.44.2.575

Wiebe, S., Sheffield, T., Nelson, J., Clark, C., Chevalier, N., & Espy, K. (2011). The structure of executive function in 3-year-olds. *Journal of Experimental Child Psychology*, *108*(3), 436–452. doi:10.1016/j.jecp.2010.08.008

Willner, C., Gatzke-Kopp, L., Bierman, K., Greenberg, M., & Segalowitz, S. (2015). Relevance of a neurophysiological marker of attention allocation for children's learning-related behaviors and academic performance. *Developmental Psychology*, *51*(8), 1148–1162. doi:10.1037/a0039311

Willoughby, M., Blair, C., Wirth, Greenberg, M., & Investigators, T. (2010). The measurement of executive function at age 3 years: Psychometric properties and criterion validity of a new battery of tasks. *Psychological Assessment*, *22*(2), 306. doi:10.1037/a0018708

Willoughby, M., Holochwost, S., Blanton, Z., & Blair, C. (2014). Executive functions: Formative versus reflective measurement. *Measurement: Interdisciplinary Research and Perspectives*, *12*(3), 69–95. doi:10.1080/15366367.2014.929453

Willoughby, M., Kupersmidt, J., & Voegler-Lee, M. (2012). Is preschool executive function causally related to academic achievement? *Child Neuropsychology*, *18*(1), 79–91. doi:10.1080/09297049.2011.578572

Willoughby, M. T., Blair, C. B., & Investigators, F. (2016). Measuring executive function in early childhood: A case for formative measurement. *Psychological Assessment*, *28*(3), 319–30. doi:10.1037/pas0000152

Wolfe, C., & Bell, M. (2007). The integration of cognition and emotion during infancy and early childhood: regulatory processes associated with the development of working memory. *Brain and Cognition*, *65*(1), 3–13.

Young, D., Levy, F., Martin, N., & Hay, D. (2009). Attention deficit hyperactivity disorder: A Rasch Analysis of the SWAN rating scale. *Child Psychiatry and Human Development*, *40*(4), 543–559. doi:10.1007/s10578-009-0143-z

Zhou, Q., Chen, S., & Main, A. (2012). Commonalities and differences in the research on children's effortful control and executive function: A call for an integrated model of self-regulation. *Child Development Perspectives*, *6*(2), 112–121. doi:10.1111/j.1750-8606.2011.00176.x

Zimmerman, B. J., & Schunk, D. H. (2011). Self-regulated learning and performance: An introduction and an overview. In D.H. Schunk & B.J. Zimmerman (Eds). *Handbook of Self-Regulation of Learning and Performance* (1st Ed., 1–12). New York, NY: Routledge.

Zoromsk, A. K., Owens, J. S., Evans, S. W., & Brady, C. E. (2005). Identifying ADHD symptoms most associated with impairment in early childhood, middle childhood, and adolescence using teacher report. *Journal of Abnormal Child Psychology*, *43*, 1243–1255. doi:10.1007/s10802-015-0017-8