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THE ROLE OF SELF-REGULATION AND MINDSET IN THE ACADEMIC OUTCOMES OF LOW-INCOME STUDENTS

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ABSTRACT

THE ROLE OF SELF-REGULATION AND MINDSET IN THE ACADEMIC OUTCOMES OF LOW-INCOME STUDENTS

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The present study builds upon the existing research regarding the role of self-regulation and mindset as they relate to academic achievement. Currently, little is known regarding how self-regulation and mindset relate to the academic outcomes of low SES students as identified by their qualification for free or reduced-priced lunch (FRPL). The present study examined the relationship between self-regulation, mindset, and achievement for a sample of 44 low SES students in grades four through six to understand if these factors can predict academic outcomes in ELA and mathematics. This information is particularly valuable as schools often make investments in intervention programming to address student deficits and improve academic outcomes. If these factors do not significantly contribute to outcomes for this population, we must continue considering how we address the systemic issues that relate to SES and achievement (e.g., lack of resources, nutrition, etc.) to make a meaningful impact (García & Weiss, 2017b). Results of the current study indicate that self-regulation skills as measured with the SRSI-SR were not predictive of ELA or math achievement outcomes. Conversely, the relationship between mindset and achievement was significant for math state assessment scores and ELA report card grades. Despite some nonsignificant results, mindset scores appear to predict achievement across subject areas better than self-regulation scores. A model combining both factors was not supported at this time. Strengths and limitations of the current findings as well as implications for the field of school psychology and future directions are discussed.

Keywords: SES, achievement, self-regulation, growth mindset, fixed mindset, theories of intelligence

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Chapter I

Introduction

As of 2019, approximately 1 in 5 children in the United States under the age of 18 are living below the federal poverty threshold (FPT) and are considered poor (Koball et al., 2021). Although the FPT is defined as the least amount of income a family needs to meet their basic needs, the income required by the FPT standards is still often insufficient to meet the minimum needs of many families (Koball et al., 2021). Families may require twice as much income than that determined by the FPT in order to sustain an adequate quality of life (Cauthen & Fass, 2008). Presumably, those living just above the threshold and considered near-poor are likely experiencing similar difficulties. Of most concern, children are disproportionately overrepresented in this overall low-income population (i.e., poor and near-poor) compared to adults (Koball et al., 2021).

Socioeconomic Status and the Achievement Gap

Socioeconomic status (SES) is defined as "one's access to financial, social, cultural, and human capital resources" with consideration for parents' level of education, occupation, and family income (National Center for Education Statistics, 2012, p. 4). What is commonly referred to as the SES-achievement gap portrays a prime example of the challenges to achieving success and upward mobility across generations when individuals are faced with economic disadvantages (Hanushek et al., 2020). The achievement gap between wealthy and poor students is alarming, with significant differences in academic performance observed as early as kindergarten (Carnevale et al., 2019; Reardon & Portilla, 2016).

Review of literacy skill development indicates that those from low SES often fall years behind their high SES peers before entering high school (Reardon et al., 2013). These low SES students continue to demonstrate lower performance or decline in test performance across school years compared to high SES peers (Carnevale et al., 2019). Fast-forward through development, these differences will affect college enrollment and completion, career paths, and eventually, economic mobility (Bastedo & Jaquette, 2011; Carnevale et al., 2019; Ma et al., 2019; OECD, 2018). Though several explanations are provided for the SES-achievement gap, such as increasing income inequality or varying levels of parental investments in supplementary educational supports, this gap remains a global issue that has shown little improvement (Chmielewski, 2019; Coley et al., 2019; García & Weiss, 2017a; H. Park et al., 2016).

When it comes to supporting struggling learners or those at-risk of underperforming, resources in the home (e.g., access to books) have been found to be beneficial to a child's progress in the development of early literacy skills over time (Judge, 2013). As such, availability of these resources matters early on in a child's development. Home learning environments are a critical factor in the acquisition of early literacy skills through the parental provision of experiences, expectations, and available reading opportunities (Buckingham et al., 2013). Johnson et al. (2016) note that material deprivation found among low SES households (e.g., limited access to toys, books, and appropriate nutrition) negatively impacts cognitive development. According to White et al. (2016), SES and race have a greater influence on standardized achievement scores than other school-related factors, such as class size. Furthermore, socioeconomic status appears to account for a moderate proportion of the achievement gap between different racial and ethnic groups (Reardon et al., 2019).

The Associated Risks of Low SES and Poverty

Children living in socioeconomic disadvantage are often exposed to specific poverty-related factors, such as instability, disorganization within the home environment, and other cumulative life stressors (Roy & Raver, 2014; Sturge-Apple, et al., 2017). Developmentally, childhood stress is known to have lasting effects on an individual's cognitive skills, physical and socio-emotional health, and behavioral functioning as they transition to adulthood (Shonkoff & Garner, 2012). Structurally, children exposed to socioeconomic disadvantage demonstrate differences in brain areas required to support cognitive skills, such as language, executive functioning, and memory (Noble et al., 2015). Reilly and Downer (2019) argue that young children living in low-income households may experience impairments in emotion and behavior regulation that depends upon underlying cognitive and affective skills, and their findings support the importance of language in the development of emotion regulation in preschool children.

Additionally, experiences of chronic stress frequently associated with poverty can influence brain regions needed for adequate emotion regulation (i.e., amygdala and prefrontal cortex); stress due to low-income poses risks for functional impairments later in adulthood (Kim et al., 2013). Overall, regulatory processes needed to function both in school and society are at risk in this population due to the structural impacts highlighted above.

Given the challenges facing low SES children, it is necessary to continue exploring protective factors (i.e., factors that mitigate risk and promote positive outcomes) that can further support their academic achievement. Evaluating student factors that could respond to targeted intervention and support may be more feasible to address than changing school features, such as class size, the ratio of teachers and aides to students, and classroom resources that often depend upon the availability of funding. Instead, examining factors that could build academic resilience should be of top priority (e.g., see Williams et al., 2017). In this regard, two areas of interest include self-regulatory behaviors and mindset as they pertain to this unique population.

Chapter II

Literature Review

The Role of Self-Regulation

Self-regulation is a multifaceted construct. Though conceptualizations may vary (see Nigg, 2017), self-regulation is broadly defined as the ability to monitor and control emotional, behavioral, and attentional processes within a given situation (Kopp, 1982; Rademacher & Koglin, 2019; Willoughby, et al., 2011). This broader domain includes skills related to executive function (e.g., attention, cognitive flexibility, inhibitory control, and working memory), emotion regulation, and behavioral self-control (Allee-Herndon & Roberts, 2019; Zelazo et al., 2016). Of all the critical skills that develop during childhood, self-regulation skills are noted to be at risk in low SES children. Children in poverty often experience higher levels of uncertainty, lacking consistency in the rearing environment that correlates negatively with self-regulation (McCoy and Raver, 2014). Self-regulatory skills rapidly develop throughout early childhood through preschool age (Montroy et al., 2016). Previous longitudinal findings found that self-regulation skills increased from early childhood to middle childhood (approximately 8-9 years of age) but did not significantly change from this time point to early adolescence (Raffaelli et al., 2005). As such, further examining the relationship between academic achievement and self-regulation skills near this particular period may prove crucial for effectively changing academic outcomes for low SES children.

Literature often identifies self-regulation skills as the underlying abilities needed to perform well in school (Allee-Herndon & Roberts, 2019; Blair & Raver, 2015). Moreover, self-regulation skills play a crucial role in the development of school readiness and are predictive of other psychosocial outcomes, including academic achievement, social competence, and adaptability (Allee-Herndon & Roberts, 2019; Blair & Raver, 2015; Buckner et al., 2009; Ivcevic & Brackett, 2014).

Self-Regulation and SES

Due to the importance of self-regulation skills, numerous studies have examined the relationship between SES and the development of self-regulation in children and adolescents. Miller and colleagues (2017) found that a chaotic home environment and lack of family routine correlate negatively with emotion regulation, and biological stress factors may interact to influence outcomes for the latter. Moreover, children from low SES demonstrated weaker executive functioning skills in the area of inhibitory control (St. John et al., 2019). A meta-analysis of the literature indicates a small to medium positive correlation between SES and executive function (Lawson et al., 2018).

For those who have experienced poverty, self-regulation skills are thought to be critical in the prevention of psychopathology as weaknesses in this area lead to increased risk (Palacios-Barrios & Hanson, 2019). According to Roy and Raver (2014), children experiencing higher poverty-related risk at the preschool level subsequently demonstrated poorer performance in school in third grade across academic, behavioral, and self-regulatory domains compared to those with low risk. Additionally, children living in poverty or general economic disadvantage are more likely to present with associated weaknesses in attentional and inhibitory control (Evans & Kim, 2013). This finding aligns with an increased risk of Attention Deficit Hyperactivity Disorder (ADHD) symptoms and related difficulties among low SES children (Larsson et al., 2014; Russell et al., 2016).

Despite the challenges for low SES children noted above, the research provides several directions for improvement. According to Buckner and colleagues (2009), low-income children with good self-regulation demonstrated better adaptive functioning across academic, social, emotional, and behavioral measures. Self-regulation can be fostered at a very young age through intervention, such as exposure to models in a text who delay gratification (see Haimovitz et al., 2020). As such, self-regulation can support adaptive functioning in this at-risk population. Although individual differences in self-regulation are thought to persist throughout development (Raffaelli et al., 2005), there is also literature to suggest that these skills are malleable (Zelazo et al., 2016).

A growing body of literature has examined the potential for self-regulation interventions in supporting positive outcomes for children and adolescents. According to Pandey and colleagues' (2018) systematic review, most of the studies examined (approximately 85%) that included academic achievement as an outcome measure indicated a positive relationship between a wide range of self-regulation-based interventions (e.g., curriculum-based interventions, mindfulness and yoga, and social skills instruction) and academic performance. Most interventions used were curriculum-based and delivered by teachers in classrooms for students under the age of 10 years (Pandey et al., 2018). As such, addressing students' self-regulatory skills in at-risk populations may prove crucial to changing their trajectory. Therefore, it is necessary to examine further its relationship with other possible protective factors and their combined impact on academic outcomes.

Theories of Intelligence: The Role of Mindsets

An additional potential marker of school success is an individual's mindset or internalized theory of intelligence. Within mindset theories, two types of mindsets are positioned at opposite ends of a spectrum from stable (entity theory, fixed mindset) to malleable (incremental theory, growth mindset; Dweck, 1999). Though various conceptual definitions of mindset exist, according to Dweck (1999), mindset regarding intelligence is inherently based upon these two theories in which an individual perceives intelligence as a stable construct unable to be changed (i.e., you either have it, or you don't) or as flexible and subject to change with effort. Those who inherently consider themselves smart may not be comfortable with things that put their abilities to the challenge if they are focused on the appearance of being intelligent (Dweck, 1999; Dweck, 2010). Theoretically, their implicit theory drives how they perform under difficult circumstances, perceive the need for effort or practice, and engage with learning experiences. Therefore, students' mindsets about their ability have the potential to play a significant role in influencing academic outcomes.

Furthermore, specific behaviors are associated with each theory. Those holding an entity theory or fixed mindset may engage in self-handicapping behaviors, such as procrastination, which permits the individual to rationalize other causes of poor performance, rather than their intellectual ability (Rickert et al., 2014). Moreover, they are less likely to put in effort, dislike criticism, and feel threatened by others' success (Dweck, 2006). Conversely, those with an incremental theory or growth mindset are more likely to demonstrate adaptive behaviors, such as persistence, increased effort, or other expressions of a positive strategy when presented with challenges or failure

(Blackwell et al., 2007; Rickert et al., 2014). These individuals continue to put in the effort when faced with an obstacle, use criticism to improve and find others' success as inspiring (Dweck, 2006). Holding an entity theory of intelligence can lead to a decline in intrinsic motivation over time (Haimovitz et al., 2011). As such, the importance of a growth mindset for promoting motivation and ultimately enhancing achievement and learning goals, or what Dweck (1999) considers mastery-oriented qualities, cannot be overlooked for low SES students facing some of life's greatest challenges.

Mindset messages can be transferred to children at home and in school through instructional practices, for better or worse (Gunderson et al., 2013; Gunderson et al., 2018; Park, Gunderson, et al., 2016; Rattan et al., 2012). Adults can affect a child's implicit theory at a relatively young age (i.e., between 1-2 years of age) and that influence can persist and predict academic performance years later (Gunderson et al., 2013; Gunderson et al., 2018). Growth mindset has gained momentum in promoting student success in the classroom, with changes to the way teachers provide praise for progress (i.e., saying, "I can see you worked really hard!" rather than, "You are really smart!"), model success in the face of challenges, and have students set targeted goals for things that are presently difficult for them (see Dweck, 2010; Rattan et al., 2015). Mindsets have shown to be predictive of performance over time. When controlling for prior achievement, adolescents with an incremental theory of intelligence (growth mindset) demonstrated an increase in academic success in mathematics over two years, while those with an entity theory (fixed mindset) showed little change or decline (Blackwell et al., 2007). Furthermore, motivation (e.g., increased effort and desire to learn) appeared to mediate this relationship; those with an incremental theory predicted a more significant motivation pattern of behavior, which then predicted a positive trend in mathematics achievement (Blackwell et al., 2007). These students were less likely to hold helpless beliefs regarding ability and were more likely to endorse doing something to address a setback or challenge. Additionally, initial mindset orientation was associated with performance on standardized tests in a group of third through sixth-grade students in which (though all students demonstrated decline in test performance over time) those with a growth mindset showed a slower decline in performance compared to those who indicated a fixed mindset (McCutchen et al., 2016). McCutchen and colleagues (2016) note that the perceived decline in performance may be attributed to overall slower growth rates in the sample as compared to national averages.

Interest in better understanding mindset towards intelligence and the implications for student achievement has steadily increased since 2016 given the number of published and unpublished studies in this area (Macnamara & Burgoyne, 2022). The effectiveness of mindset interventions for all students has not occurred without debate due to small effect sizes obtained in some randomized control trials (RCT) geared towards improving mindset and questionable reporting of results, such as exclusion of participants' data in published versions (see Miller, 2019; Macnamara & Burgoyne, 2022). Though their results are hopeful, Blackwell et al.'s (2007) previously mentioned study may also be subject to concerns regarding the significance of results due to design flaws in random assignment (see Macnamara & Burgoyne, 2022). According to Sisk and colleagues' (2018) first meta-analysis, the average correlation between a growth mindset and achievement was classified as weak and the second meta-analysis indicated a small average effect size for growth mindset interventions on academic achievement; however, they consider heterogeneity of the sample to be a contributing factor to this finding. While students' academic-risk status (i.e., defined by three levels - low or at no risk of failing, moderate or facing situational challenges that may affect performance, and high or considered at-risk of failing due to previous performance) did not significantly moderate the relationship between intervention and achievement in this study, SES did (Sisk et al., 2018). Low SES students who received a growth mindset intervention demonstrated significantly higher academic performance compared to controls (Sisk et al., 2018).

Additionally, Yeager and colleagues' (2019) RCT examined the benefits of a brief (under one hour) computer-based growth mindset intervention for ninth-grade students that taught them about the malleability of the brain and its ability to grow stronger when faced with challenging learning experiences. Their findings support the potential benefits of a brief growth mindset intervention on improving the academic performance of low-achieving ninth-grade students. These students demonstrated greater improvements in their core coursework GPAs (math, science, English, and social studies) compared to already high-achieving students (Yeager et al., 2019). In contrast with Sisk and colleagues' findings, there was a significant interaction between intervention and achievement group membership (Yeager et al., 2019). Based on the literature reviewed here, a growth mindset may be more critical for low SES students who often experience other obstacles and stressors that may affect achievement.

Mindsets and SES

Considering the implications of mindset and its potential, the conversation has shifted to its use in supporting those who experience the greatest difficulties in attaining equal academic achievement. Destin and colleagues (2019) found that ninth grade students from high SES households, as measured by maternal education level and free or reduced lunch status, were less likely to express a fixed mindset compared to students from low SES households. When examining mindset as a mediational variable in the SES-achievement relationship, Destin and colleagues (2019) found that mindset accounted for a small percentage of variance (between 2-7%). While this finding is statistically significant, mindset may not be the primary explanation for the achievement gap (Destin et al., 2019).

Claro and colleagues (2016) also evaluated the effects of both socioeconomic status and mindset on achievement. Findings from this study indicate that both factors were predictive of academic achievement (i.e., language and mathematics performance on state-administered standardized assessments) in a large sample of Chilean high school students. Furthermore, students from lower SES were more likely to demonstrate a fixed mindset compared to peers from higher SES (Claro et al., 2016). However, lower SES students with a growth mindset showed better performance on standardized assessment measures compared to their lower SES fixed mindset peers. Furthermore, this study also provided further evidence that SES status and mindset may be linked in which those at the lowest end are significantly more likely to report a fixed mindset compared to students at the opposite end of the economic spectrum. Finally, students from the lowest SES who reported having a growth mindset demonstrated test performance similar to wealthier fixed mindset peers, but not wealthier growth mindset peers (Claro et al., 2016). Theoretically, if every student had a growth mindset, those from wealthier families may still outperform those from more impoverished families. While these findings are informative, additional research is required to understand the generalizability to students educated in the United States and to those at the elementary level.

Mindset and Self-Regulation

There have been several studies examining the connection between self-regulation and implicit intelligence theories across various contexts. A meta-analysis indicated a predictive relationship between those holding an incremental theory and greater engagement in self-regulatory processes, including goal setting, operating, and monitoring (Burnette et al., 2013). Moreover, these factors further predicted actual goal achievement in the areas examined (e.g., academic or athletic goals; Burnette et al., 2013). Within this literature, there is an emphasis on goal identification and planning components of self-regulatory skills. From this integrative perspective, implicit theories affect the types of goals individuals pursue (performance vs. learning goals) and whether it stems from a position of approach or avoidance. Moreover, implicit theories appear associated with how individuals pursue their goals. As previously mentioned, those with a fixed mindset are more likely to engage in self-handicapping (helpless-oriented) behaviors compared to growth mindset individuals that are more likely to use strategies that promote mastery (Burnette et al., 2013). As such, incremental or growth mindsets may be a significant component of an individual's engagement in self-regulation of goal-directed behaviors.

Only a few studies to date have examined the relationship between mindset and self-regulatory behaviors often associated with school readiness and success in children, such as basic attention, emotional, and behavioral control as it relates to inhibition and other executive functions. In correlational analyses, executive function skills and behavioral self-regulation were found to mediate the relationship between motivational beliefs (stable vs. malleable, performance vs. mastery) and achievement in Kindergarten students (Compagnoni et al., 2019). Additionally, Wang et al. (2019) examined the utility of incorporating a self-regulation intervention with growth mindset components into a math intervention for struggling third graders. Students receiving this combination of interventions that addressed goal-setting, perseverance, maintaining attention to task, and a growth mindset perspective (e.g., the brain gets stronger as you learn) typically outperformed their peers receiving instruction as usual (control) or the math intervention without self-regulation and growth mindset components (Wang et al., 2019).

Given that interventions focused on mindset alone may not provide the strong positive effects to all students (see Sisk et al., 2018), understanding the relationship with other variables would be beneficial. Specifically, no known study has yet examined the relationship between mindset, self-regulation, and achievement as it pertains to the academic performance of low-SES students at the intermediate elementary level. As previously discussed, students from low SES households show a pattern of underperformance compared to high SES household peers across educational levels. Understanding the potential combined benefit of self-regulation and mindset for young students may assist in leveling their performance prior to their transition to the increased academic challenges presented at the secondary level.

Chapter III

The Present Study

The present study intends to build upon the existing research, examining how self-regulation and mindset relate to the academic outcomes of low SES students as identified by qualification for free or reduced-priced lunch (FRPL). The broad question of interest is whether the combination of these factors helps to ameliorate the adverse effects of low socioeconomic status on academic outcomes. As students who fall behind early on in their education are rarely able to catch up to their higher-achieving peers (García & Weiss, 2017a), it is necessary to continue evaluating factors that may improve performance earlier in a child's educational experience. Examination of academic growth across students from grades 1-5 indicates that despite greater growth rates, those with poor initial proficiency scores continued to trail behind higher proficiency peers in reading and mathematics after two years in school (Scammacca et al., 2020). Additionally, focusing on this population as determined by FRPL is clinically meaningful for schools given that it is a common way of identifying students in need of support.

The present study examined the relationship between self-regulation, mindset, and achievement for low SES students from grades 4-6 through regression analyses. Specifically, this study first evaluated the individual influence of self-regulation and mindset on student achievement in ELA and math. Second, this study examined whether self-regulation and mindset towards intelligence better predict academic achievement above that for each individual factor alone. Understanding the relationship between these factors is particularly valuable as schools often make investments in intervention programming to address student deficits. Assessing the relationship between these variables will assist in building the evidence-base for providing specific interventions targeting self-regulation skills and growth mindset in the school setting and the potential efficacy of an intervention targeting both. Considering the potential cost of implementing programs and the increasingly tight school budgets, evaluating their effectiveness in disadvantaged populations is crucial. Additionally, they will provide evidence for whether adaptive self-regulation skills and a growth mindset significantly contribute to improved achievement outcomes for low SES students. If not, we must continue considering how we address the systemic issues that relate to SES and achievement (e.g., lack of resources, nutrition, etc.) to make a meaningful impact (García & Weiss, 2017b).

It is hypothesized that (1) self-regulatory skills will significantly predict academic achievement as measured by state assessment scores in ELA and mathematics, with higher mean scores predicting membership in a higher achievement group (2) mindset towards intelligence will significantly predict academic achievement as measured by state assessment scores in ELA and mathematics, with higher mean mindset scores (i.e., more malleable theory of intelligence or growth mindset) predicting membership in a higher achievement group (3) self-regulatory skills will significantly predict academic achievement as measured by report card grades in ELA and mathematics, with students with higher self-regulatory skills academically outperforming students with lower self-reported regulatory behaviors; (4) mindset towards intelligence will significantly predict academic achievement as measured by report card grades in ELA and mathematics with students with a more malleable theory of intelligence (i.e., growth mindset) academically outperforming students with a more stable theory of intelligence (i.e., fixed mindset); (5) combined higher self-regulatory skills and a more malleable belief regarding intelligence will be predictive of higher achievement in ELA and mathematics above and beyond each factor individually across measures of achievement.

Chapter IV

Methods

Participants

Study participants included 44 public school students in grades four, five, and six recruited from an elementary school and middle school in New Jersey. Only upper elementary students were included as previous findings suggest that younger students may not consistently demonstrate a defined understanding of theory of intelligence compared to older students (Cain & Dweck, 1995). Participants qualified for free or reduced-price lunch (FRPL), which was used as the proxy-based measure of household income to determine socioeconomic status for inclusion. Although a sample size of between 48-71 participants was targeted to address the research questions, difficulties in recruitment persisted. Any limitations in interpretation of data and hypothesis analysis due to sample size are noted and reviewed in both the results and discussion.

Procedures

Recruitment e-letters were sent by school administrators from approved sites to all parents/guardians of students in fourth, fifth, and sixth grade (see Appendix A). Data was collected electronically via Qualtrics surveys from June 9, 2022 through June 9, 2023. Academic achievement data for each participant was provided by school administrators according to a coded system and were deidentified during analysis.

Measures

Upon reviewing the recruitment letter, parents accessed a hyperlink that led them to the study's consent and permission forms (see Appendix B and C). Parents who provided consent for their own participation and permission for their child's participation were then prompted to complete the demographic questionnaire electronically using the Qualtrics system (see Appendix D). Upon completion, student names were exported to a listing to provide the school site for student questionnaire administration. Students were proctored the mindset and self-regulation skills questionnaire (discussed below) in their classrooms using the hyperlink provided to school administration. Child assent was obtained, and students only completed the study if they clearly indicated an interest in participation. If the student indicated “No,” survey administration would end.

Demographic Information. A demographic questionnaire of 9 items created for the purpose of this study by the investigator was used to collect participant information through parent report (see Appendix D). Parents/guardians completed the questionnaire for each child. After completing the questionnaire, parent participants had the option of providing their email address to be included in a raffle to receive a $25 Amazon e-gift card. Information obtained included student age, school, race/ethnicity, gender, qualification for free/reduced-price lunch, English language proficiency, special education status, and academic intervention services status. Specific special education classifications (i.e., Intellectual Disability, Learning Disability, and Autism Spectrum Disorder) were considered for exclusionary purposes. No students were excluded due to special education classification as any classified students did not fall into any of the above categories. Due to limitations in sample size, students identified as an English language learner were not excluded from analyses with the exception of one student with missing and unquantifiable achievement data. Additionally, students receiving academic intervention services were not excluded due to limitations in sample size. Participant demographic information is discussed further in the results.

Academic Achievement. Academic achievement data was obtained through administrative record review. Achievement data included student performance on state assessments in ELA and Mathematics as well as report card grades in ELA and math. The state assessments are meant to assess student achievement as it corresponds to state learning standards. On New Jersey Student Learning Assessments (NJSLAs), students receive scaled scores between 650-850 that are associated with a performance level. As scale scores vary between grade-levels and subject, and as such cannot be considered an equivalent continuous scale, performance levels treated as ordinal data were utilized for analyses. Performance levels are as follows: Level 1 (did not yet meet expectations), Level 2 (partially met expectations), Level 3 (approached expectations), Level 4 (met expectations), and Level 5 (exceeded expectations). Report card grades in ELA and mathematics were obtained for each student at the time the student completed the student questionnaires described below. Students in grades 4 and 5 receive ratings from teachers on a 4-point scale in various areas of functioning in each subject. Averages of those ratings were taken to create an overall report card score out of a 4.0. For 6th grade students, grade point averages (GPA) according to a 4.0 scale were provided in ELA and mathematics due to differences in reporting.

Identifiable student data was paired with a participant ID number assigned by the investigator in order to link information obtained from rating scales and subsequently protect students' confidentiality. Only the investigator and advising faculty member had access to the collected data.

Self-Regulation Skills. Students' self-regulation skills were measured using the Self-Regulation Strategy Inventory - Self-Report (SRSI-SR), a 28-item self-report measure to assess both adaptive and maladaptive regulatory behaviors as they relate to study habits, organization, homework completion, and asking for help (Cleary, 2006; Cleary et al., 2015) (see Appendix G). Previous factor analysis indicates three subscales on the measure: Managing Behavior and Environment (MBE), Seeking and Learning Information (SLI), and Maladaptive Regulatory Behaviors (MRB). The 12-items on the MBE subscale assess how one manages their learning environment (coefficient alpha = .88; Cleary, 2006). The 8-items on the SLI subscale focus on students' use of regulatory strategies to learn content and seek support (coefficient alpha = .84; Cleary, 2006). The 8-items on the MRB subscale assess poor self-regulatory skills, such as avoidance and procrastination (coefficient alpha = .72; Cleary, 2006). Psychometric information reported by Cleary (2006) was collected on a sample of high school students (ninth and tenth grade). When evaluated on a sample of middle school students (sixth and seventh grade), Cleary et al. (2015) report an overall scale coefficient alpha of .92. Slight differences in coefficient alphas were also obtained for each subscale: MRE was .87, SLI was .76, and MRB was .78 (Cleary et al., 2015).

Students responded to items on the measure according to a 5-point Likert scale ranging from 1 (almost never) to 5 (almost always). For example, students rate the frequency in which they engage in a behavior, such as: "I try to study in a quiet place." As with previous studies utilizing the measure (e.g., Cleary & Chen, 2009), subject-specific items were adapted. Unique to this study, rather than targeting a specific subject, these items targeted academic content in general (e.g., instead of, "I rely on my *science* class notes to study," the item read, "I rely on my class notes to study"). Scores on MRB-items will be reverse coded to align with the scores on the adaptive MBE and SLI subscales. The mean score of the 28 items was calculated in order to obtain an overall self-regulation score. Additionally, mean scores were obtained for each subscale for further analysis. There were no missing data points for the SRSI-SR.

Mindset / Theory of Intelligence. To assess students' own theory of intelligence, students completed the 6-item Implicit Theories of Intelligence Scale for Children - Self Form (Dweck, 1999) according to a 6-point Likert-type scale. The selected scale was provided in the "self" form rather than the "other" form since the primary goal is to understand how each student views their own intelligence rather than the intelligence of others in general (Dweck, 1999). For example, students rated the extent to which they agree with statements, such as: "You can learn new things, but you can't really change your basic intelligence." Students rated how much they agree with each item from 1 (Strongly Agree) to 6 (Strongly Disagree). Incremental or growth mindset items will be reverse coded. The mean score of the 6 items was calculated to obtain an overall mindset score. There were no missing data points for this scale. Though previous studies have employed a procedure for dichotomizing mindset scores in order to differentiate group membership (e.g., McCutchen et al., 2016), average mindset scores will be treated as a continuous variable with higher scores indicating a more malleable theory of intelligence (i.e., higher or stronger growth mindset on average). When the full 6-item scale was used with a sample of 373 7th grade students, Blackwell et al. (2007) found an internal reliability of .78, and test-retest reliability of .77 when 52 students were reassessed over a two-week period.

Analysis

Prior to addressing the specific research questions and hypotheses, the internal consistency reliability was obtained for this sample for the SRSI-SR. As the Implicit Theories of Intelligence Scale has been utilized and well-studied across a wide age-range from kindergarten through high school populations (see Costa and Faria, 2018), further examination into its reliability and structure was not deemed necessary at this time. Descriptive statistics and frequencies were calculated to analyze student demographic variables as indicated on the demographic questionnaire. Frequencies were obtained for each level of achievement on state assessment measures for the overall sample. Descriptive statistics are also reported for the sample's report card grades, mindset scores, and self-regulation scores.

Ordinal logistic regressions were performed to analyze the predictive relationship between self-regulation skills and state assessment performance in each subject. Ordinal logistic regressions were also performed to analyze the predictive relationship between mindset and scores on state assessment measures. A final ordinal logistic regression was performed including both predictor variables. Linear regressions were also performed to assess each predictor variable's relationship with academic achievement in each subject using report card grades. Sensitivity analyses were performed to further evaluate the significance of obtained results. Finally, due to acknowledged limitations in sample size and the increased chance of Type I error, Bayesian linear regression analyses were also conducted to determine the informative nature of the proposed predictive models using report card grades.

Chapter V

Results

Participant Demographics

A total of 45 participants were recruited for the study. Forty-four (44) participants were included in analyses. The summary of participant demographics can be found in Table 1. One student was excluded from all analyses due to missing and unquantifiable achievement data (i.e., no available state assessment scores and report grades of pass/fail). Students ranged in age from 9 to 12 years old, with a mean age of 10.3 years. The age of three participants (6.8%) was missing. The sample of participants was generally evenly distributed across gender, with 52.3% (n = 23) identifying as male and 47.7% (n = 21) identifying as female. In terms of ethnicity/race, nine identified as Caucasian/White (20.5%), eight identified as Latino or Hispanic (18.2%), 18 identified as Asian (40.9%), six identified as two or more (13.6%), and three participants did not respond (6.8%). While most participants were non-English Language Learners (non-ELLs; n = 34, 77.3%), five students were identified as English Language Learners (ELLs; 11.4%), one student's status was unsure (2.3%), and ELL status was not provided for four participants (9.1%).

The current sample generally appears comparable to the demographic composition of the schools as reported by the school district in terms of reported gender or sex (47% female and 53% male) and several ethnicity/race identities (i.e., 25.9% White, 41.6% Asian or Asian/Pacific Islander, and 23.1% Hispanic/Latino). The sample contained a greater percentage (13.6%) of individuals identifying as two or more races compared to the 5.1% reported by the district. No participants identified as Black/African

American only in this study. However, the district indicates that only 3.7% of their student body identifies as Black. Finally, more participants (11.4%) were identified by parents/guardians as ELLs compared to the 6.4% reported by the district.

Additionally, most participants were not receiving special education services (n = 34; 77.3%) while six participants were identified as a student receiving special education (13.6%). The special education status for four participants was not provided (9.1%). Of the six students receiving special education services, two were identified as Other Health Impaired (OHI; 33.3%), two indicated diagnoses of ADHD (33.3%), and two were not reported (33.3%). Finally, most participants were not receiving academic intervention services at the time of the study (n = 29; 65.9%). Three students were receiving reading intervention services only (6.8%), one student was receiving math intervention services only (2.3%), three students were receiving interventions for both reading and math (6.8%), three indicated uncertainties regarding intervention status (6.8%), and information was not provided for five participants (11.4%).

In terms of achievement range, Table 2 provides a summary of state assessment performance for the sample while Table 3 provides a summary of their report card grades. On the ELA state assessment, 2 students received a performance level of 1 (4.5%), 8 students received a performance level of 2 (18.2%), 10 students received a performance level of 3 (22.7%), 18 students received a performance level of 4 (40.9%), and 6 students received a performance level of 5 (13.6%). On the math state assessment, 1 student received a performance level of 1 (2.3%), 5 students received a performance level of 2 (11.4%), 14 students received a performance level of 3 (31.8%), 18 students received a performance level of 4 (40.9%), and 6 students received a performance level of 5 (13.6%). Referenced in Table 3, report card grade point averages in ELA ranged from 1-4 with a mean of 3.13 (*SD* = 0.725) while report card grade point averages in math ranged from 1-4 with a mean of 3.25 (*SD* = 0.682). Mean mindset towards intelligence scores ranged from 2.33 to 6 with an average mean score of 4.33 (*SD* = 0.993). Mean self-regulation scores ranged from 1.63 to 4.30 with an average mean score of 3.29 (*SD* = 0.564). According to the results of an independent samples t-test, there were no significant differences in ELA report card grades, math report card grades, mean mindset scores, or mean self-regulation scores based on reported gender group membership ($p > .05$; see Table 4). When considering ELL group membership, no significant differences were found in math report card grades, mean mindset scores, or mean self-regulation scores. However, differences were noted for report card grade performance in ELA ($t(37) = 2.6389$, $p = 0.012$). The 5 ELL students demonstrated lower performance with a mean score of 2.45 compared to the 34 non-ELL students (M = 3.30).

Given the varying nature of achievement data (i.e., ordinal and continuous scales), Spearman’s rank correlation coefficients (rho) were obtained to determine the associations between achievement scores as it is a non-parametric measure that does not assume a linear relationship. Considering a p value of .05 for determining statistical significance, all participants’ scores demonstrated a significant positive association with p-values <.001 (see Table 5), suggesting that higher ranks on state assessment scores correspond to higher report card grades. Although ELA state assessment scores were associated with all other achievement scores, ELA state assessment scores demonstrated the strongest association to ELA report card grades with a Spearman’s rho (ρ) of .694 (p = <.001). Math state assessment scores demonstrated a strong association to math report card grades ($\rho = .613$, $p = <.001$). Math state assessment scores also demonstrated a strong association to ELA report card grades ($\rho = .625$, $p = <.001$) and ELA state assessment scores ($\rho = .585$, $p = <.001$). Finally, ELA state assessment scores demonstrated a strong association to math report card grades as well ($\rho = .518$, $p = <.001$). Given the strength of associations, it was determined that participants' performance was generally consistent across measures.

Reliability of the SRSI-SR

Prior to completing analyses, reliability of the SRSI-SR was assessed as the age and grade-level of the current sample is younger than that of the original sample used for validation. The reliability of the SRSI-SR for this sample was adequate with a Cronbach's alpha of 0.853. However, analysis indicated that one item (item 18 – "I make pictures or drawings to help me learn") correlated negatively with the total scale. In terms of scale development by the original authors, this item was not meant to be reverse coded and was expected to correlate positively with the scale once all reverse coded items were corrected. As such, item 18 was removed from the scale to improve cohesiveness and reliability. With the item removed, a Cronbach's alpha of 0.861 was obtained. Subsequent analyses were conducted using a mean score derived from all remaining items.

An exploratory factor analysis (EFA) using principal axis factoring with an Oblimin rotation was attempted with item 18 removed to better understand the underlying structure of the scale for this sample of participants and the correlations among items. Although Bartlett's Test of Sphericity indicated that the measure met the needed assumptions for factor analysis ($\chi^2 = 642$, df = 351, $p <.001$), the Kaiser-Meyer-Olkin

(KMO) measure of sampling adequacy did not as the value was below 0.6 (see Table 6). Therefore, factor analysis to determine the underlying factor structure of the scale was not conducted and further analysis using the previously mentioned subscales (i.e., MBE, SLI, and MRB) was not completed.

Self-Regulation and State Assessment Performance

Ordinal logistic regressions were performed to analyze the predictive relationship between self-regulation skills and state assessment performance in each subject. When examining the relationship between mean self-regulation scores and ELA state achievement, the likelihood ratio test for the model was not statistically significant ($\chi^2 = 0.0340$, $p = 0.854$), suggesting that mean self-regulation scores were not significantly predictive of ELA state achievement when compared to a null model. Additionally, McFadden's pseudo-R^2 suggests an extremely small amount of variance in ELA state achievement can be explained by self-regulation scores alone ($R^2_{McF} = 2.71e\text{-}4$). Similarly, the likelihood ratio test for the model using mean self-regulation scores to predict math state achievement was non-significant ($\chi^2 = 7.62e\text{-}4$, $p = 0.978$). Once again, an extremely small amount of variance in math state achievement can be explained by self-regulation scores alone ($R^2_{McF} = 6.48e\text{-}6$).

Mindset and State Assessment Performance

Ordinal logistic regressions were also performed to analyze the predictive relationship between mindset towards intelligence and state performance in each subject. When examining the relationship between mean mindset scores and ELA state achievement, the likelihood ratio test for the model was not statistically significant ($\chi^2 = 2.24$, $p = 0.135$), suggesting that theory of intelligence was not significantly predictive of

ELA state achievement when compared to a null model. However, when examining the goodness of fit for this model compared to that of self-regulation scores, the deviance score decreased from 125 to 123 suggesting a slightly better fit. Comparison of the Akaike Information Criterion (AIC) also suggests a somewhat better fit (see Table 7). Although it did not reach significance, examination of the odds ratio indicates that on average, a unit increase in mean mindset score (i.e., higher growth mindset rating) is associated with 1.5 times higher odds of receiving a higher ranked state assessment score in ELA (p = 0.140). A small amount of variance in ELA state achievement can be explained by mindset scores alone (R^2_{McF} = 0.0178). Comparatively, mindset scores appear to account for more variance.

Conversely, the likelihood ratio test for the model using mean mindset scores to predict math state achievement was statistically significant (χ^2 = 5.22, p = 0.022). This suggests that the specified model is more likely than no model at all. Goodness of fit indices also indicate a better fit for the mindset scores model compared to that of self-regulation scores with a smaller Deviance of 112 compared to 117. A smaller AIC of 122 further supports a better fit (see Table 8). Further examination of the odds ratio indicates that on average, a unit increase in mean mindset score (i.e., higher growth mindset rating) is associated with 1.89 times higher odds of receiving a higher ranked state assessment score in math (p = 0.026). Approximately 4.45% of variance in math state achievement can be explained by mindset scores alone compared to that of self-regulation scores (R^2_{McF} = 0.0445). Despite nonsignificant results, mean mindset scores appear to predict state achievement scores across subject areas more than mean self-regulation scores.

Multiple Ordinal Logistic Regression with State Assessment Performance

A final ordinal logistic regression was performed including both predictor variables for each state assessment score. To assess for multicollinearity, the Variation Inflation Factor (VIF) was obtained to assess the correlation between the two independent variables (self-regulation and mindset). Multicollinearity was not deemed an issue (VIF = 1.03) so it can be assumed that the independent variables are not highly correlated with one another. When examining the relationship between mean mindset scores, mean self-regulation scores, and ELA state achievement, the likelihood ratio test for the model was not statistically significant ($\chi^2 = 2.26$, $p = 0.322$). Additionally, when comparing this model to the model containing mindset scores alone, the difference is also nonsignificant ($\chi^2 = .027$, $p = 0.869$). These findings suggest that the combination of predictors is not significantly associated with ELA state achievement (see Table 7). Though slight, the odds ratio for mean self-regulation scores as a predictor decreased from 1.09 ($p = 0.853$) to 0.923 ($p = .869$) for model 2 (mean mindset and mean self-regulation) while the odds ratio for mean scores as a predictor increased from 1.50 ($p = 0.140$) to 1.518 ($p = 0.142$). Refer to Table 9 for a summary. Taken altogether, though both are nonsignificant, mindset scores alone appear to have a larger impact on the odds of ELA state achievement.

When examining the relationship between mean mindset scores, mean self-regulation scores, and math state achievement, the likelihood ratio test for the model was not statistically significant ($\chi^2 = 5.63$, $p = 0.060$). Additionally, when comparing this model to the model containing mindset scores alone, the difference is also nonsignificant ($\chi^2 = .402$, $p = 0.526$). These findings suggest that the combination of predictors is not significantly associated with math state achievement (see Table 8). Furthermore, the odds ratio for mean self-regulation scores as a predictor decreased from 0.986 (p = 0.978) to 0.715 (p = .529) for model 2 (mean mindset and mean self-regulation) while the odds ratio for mean mindset scores as a predictor increased from 1.89 (p = 0.026) to 1.986 (p = 0.021) for model 2 (see Table 9). Once again, mindset scores alone appear to have a larger impact on the odds of math state achievement.

Self-Regulation, Mindset, and Report Card Grades

Additional analyses were conducted to determine if a similar relationship is obtained when assessing each predictor variable's relationship with academic achievement using report card grades. It was originally hypothesized that self-regulation skills would predict report card grades across ELA and math, with higher mean scores predicting higher achievement. A linear regression was used to determine whether mean self-regulation scores significantly predict ELA grades. Results of the model provided in Table 10 indicates that the relationship between mean self-regulation scores and ELA grades is not statistically significant ($F_{1,42} = 2.30$, $p = .137$). The correlation coefficient indicates a nonsignificant weak positive linear relationship ($r = .228$), and only approximately 2.94% of the variance in ELA report card grades can be explained by mean self-regulation scores (adjusted $R^2 = .0294$). Similarly, mean self-regulation scores did not significantly predict math grades ($F_{1,42} = 0.362$, $p = .551$). The original hypothesis was not supported; however, the relationship appears to be in the expected direction.

When examining the linear relationship between mean mindset scores and ELA grades, the model was statistically significant ($F_{1,42} = 4.09$, $p = .050$). The correlation coefficient indicates a weak correlation ($r = 0.298$) suggestive of a positive linear relationship (see Table 10). Approximately 6.70% of the variance in ELA report card grades can be explained by mean mindset scores (adjusted $R^2 = .0670$). According to the results, a point increase in mean mindset score (higher growth mindset) would result in a 0.217 increase in ELA grade point average (see Table 11). Mean mindset scores did not significantly predict math grades ($F_{1,42} = 2.43$, $p = .126$). The correlation coefficient indicates a nonsignificant weak positive linear relationship ($r = .234$), and only approximately 3.22% of the variance in math report card grades can be explained by the mean mindset scores (adjusted $R^2 = .0322$). The original hypothesis was only partially supported.

Linear multiple regressions containing both predictor variables were conducted for each subject area. This model did not significantly predict ELA report card grades ($F_{2,41} = 2.75$, $p = 0.076$). A nonsignificant weak correlation was found between both predictors and ELA grades ($r = 0.344$). Approximately 7.52% of the variance in ELA report card grades can be explained by both mean mindset and mean self-regulation scores (adjusted $R^2 = .0752$). This model was not a significant improvement compared to the mindset only model ($\Delta R^2 = 0.0295$, $p = 0.248$). Additionally, similar findings were obtained when examining this model in relation to math report card grades. This model did not significantly predict math grades ($F_{2,41} = 1.24$, $p = 0.301$). A nonsignificant weak correlation was found between both predictors and math grades ($r = 0.239$). Once again, this model was not a significant improvement compared to the mindset only model ($\Delta R^2 = 0.00218$, $p = 0.760$). Model coefficients for report card grades in ELA and math are provided in Table 11.

According to sensitivity analyses using G*Power 3.1 (Faul et al., 2007), a linear regression with 44 participants and one predictor variable would be sensitive to a medium effect size of f^2 = 0.187 with 80% power and alpha of .05. If the model were to contain two predictor variables, it would be sensitive to a larger effect size of f^2 = 0.236. Cohen's f^2 effect sizes were obtained for each linear regression model by transforming the observed R^2 value. For the models containing self-regulation as a predictor, Cohen's f^2 effect sizes were 0.0547 for ELA and 0.0086 for math. For the models containing mindset as a predictor, Cohen's f^2 effect sizes were 0.0973 for ELA and 0.0579 for math. For the models containing both predictor variables, effect sizes were 0.1341 for ELA and 0.0603. This indicates that all effect sizes fall below the level required given the sensitivity analyses. As such, more participants would be required to detect the significance of a smaller effect if it exists.

Bayesian Multi-Model Linear Regressions

Due to limitations in sample size and the increased potential rate of a Type I error, Bayesian analysis methods were further employed to explore the relationship and likelihood of models given the present data. A Bayesian linear regression was conducted to assess whether ELA report card grades depend upon mean mindset scores, mean self-regulation scores, both, or neither (null model). The likelihood of each model was evaluated according to posterior probability, posterior odds, and Bayes factors to determine which model(s) and predictors were best supported by the observed data.

In terms of prior probability, each model was assumed to have the same likelihood of predicting the data prior to observation. The models for ELA report card grades are listed in Table 12 with the best fitting model (mean mindset scores only) listed first. After observing the data, the odds of the mean mindset score only model (BF_M) increased by a factor of 1.654 while the other models received decreased support. As such, the data appear most likely under the model containing only mean mindset scores as a predictor. In terms of relative predictive adequacy, the observed data are 1.486 times more likely under the mean mindset score model as the sole predictor compared to the null model that specifies no predictors, 1.56 times more likely compared to the two-predictor model, and 2.0 times more likely than the mean self-regulation score only model.

However, a Bayes factor between 1-3 is still considered anecdotal or weak evidence (Dienes, 2014). Comparatively, when examining posterior probabilities of each predictor anecdotally, mean mindset could be a better predictor of ELA report card grades for this sample as the posterior probability of including it in the model increased from 0.500 to 0.583 over mean self-regulation scores with a posterior probability of exclusion that increased from 0.500 to 0.594. Descriptively, the data increased prior odds for including mean mindset as a predictor by a factor of 1.399 (see Table 13).

A similar procedure was completed for math report card grades. These models are listed in Table 14. The data appear most likely under the null model which hypothesizes that neither mean mindset scores nor mean self-regulation scores predict math report card grades. After observing the data, the odds of the null model (BF_M) increased by a factor of 2.076. Though comparatively not the best model, it should be noted that the mean mindset score model did also receive increased odds ($BF_M = 1.413$) while all other models received decreased support.

Although the posterior probability of both predictors given the data decreased (see Table 15), mean self-regulation received much more reduced support compared to mean mindset. Considering the inverse of the Bayes inclusion factor, the data decreased prior odds for including mean mindset as a predictor by a factor of 1.22 while the data decreased prior odds for including mean self-regulation as a predictor by a factor of 2.695.

Chapter VI

Discussion

The study investigated the relationship between self-reported self-regulation skills, mindset towards intelligence, and academic achievement in ELA and mathematics in a population of low SES students from grades 4-6. To better understand the relationship between these variables, several hypotheses were examined using various methods of regression analyses to determine the individual and combined predictive power of self-regulation skills and mindset on students' academic performance.

The first hypothesis asserted that self-regulatory skills would significantly predict academic achievement as measured by state assessment scores in ELA and mathematics, with higher mean scores predicting membership in a higher achievement group. Given the available data, this hypothesis was not supported. Self-regulation skills as measured by the SRSI-SR accounted for an essentially negligible amount of the variance in ELA state scores (R^2_{McF} = 2.71e-4) and math state scores (R^2_{McF} = 6.48e-6). This finding was unexpected given the literature as interventions focused on the development of self-regulation skills have been found to have a positive association with academic outcomes (Pandey et al., 2018). In light of these results, there could be possible limitations not only due to sample size but also the sampling adequacy of the measure used to assess self-regulation skills. Although the reliability of the SRSI-SR was adequate, it may be tapping into only a portion of self-regulation skills needed for achievement on a state test. Moreover, though uncertain, these findings may also be an artifact of the targeted subgroup (i.e., low SES students) given the literature indicating positive correlations between SES and self-regulation and executive functioning skills (Lawson et al., 2018; Evans & Kim, 2013).

It is also pertinent to acknowledge the potential negative impact the COVID-19 pandemic experience may have had on students' development of self-regulation skills. Additional research is currently needed to further understand what type of influence, if any, expectations of remote learning, extended quarantine periods within the home, and changes to typically maintained routines may have had on students' self-regulation skills. Raghunathan and colleagues (2022) have provided preliminary evidence through a longitudinal study of 45 children between the ages of 4-13 years indicating decreases in self-regulation skills and increases in impulsivity when comparing their functioning before the pandemic to during the pandemic. This finding was specific to children that experienced four or more reported disruptions to family life during the pandemic. As such, children experiencing increased stress and likely more uncertainty within the household as a result of the COVID-19 pandemic may demonstrate challenges with adaptive regulatory behaviors.

Second, it was hypothesized that mindset towards intelligence would significantly predict academic achievement as measured by state assessment scores in ELA and mathematics, with higher mean mindset scores (i.e., a more malleable theory of intelligence or growth mindset) predicting higher achievement. Contrary to the hypothesis, mixed findings were obtained. While mindset did not significantly predict ELA state achievement scores, it did for math state achievement scores. Odds ratio results indicate that on average, a unit increase in mean mindset score (i.e., higher growth mindset rating) was associated with 1.89 times higher odds of receiving a higher ranked state assessment score in math. It should also be noted that although the relationship between mindset and ELA state scores was nonsignificant, mindset appeared to be a better possible predictor of performance than self-regulation scores. Though nonsignificant, the observed relationship seems to move in the direction hypothesized (i.e., positive relationship) for both subjects. This finding is interesting and may provide support for existent literature that suggests mindset-based interventions, and therefore mindset towards intelligence, are thought to have a stronger effect on achievement for low SES students compared to other subgroups (Burnette et al., 2022; Sisk et al. 2018).

The third hypothesis posited that self-regulation skills would significantly predict academic achievement as measured by report card grades in ELA and mathematics, with students with higher self-regulatory skills academically outperforming students with lower self-reported regulatory behaviors. Contrary to this position, the hypothesis was not supported as results of the model were not significant for either academic area. Descriptively, a weak positive linear relationship was indicated between ELA report card grades and mean self-regulation scores. Similarly, a weak positive linear relationship was indicated for math report card grades. Once again, this finding is surprising given existing literature. However, the previously mentioned limitations of sample size and sampling of the SRSI-SR may apply in this circumstance as well. Nevertheless, the weak positive correlations appear to move in the direction of the hypothesized relationship, particularly for ELA report card grades.

The fourth hypothesis claimed that mindset towards intelligence would significantly predict academic achievement as measured by report card grades in ELA and mathematics with students with a more malleable theory of intelligence (i.e., growth mindset) academically outperforming students with a more stable theory of intelligence (i.e., fixed mindset). This hypothesis was only partially supported. While a nonsignificant weak positive linear relationship was found for mindset and math report card grades, a statistically significant finding was obtained for the positive linear relationship between mindset and ELA report card grades. These findings indicate a similar direction of relation for each subject area when compared to analyses using state assessment scores although significance was found for math state scores and not ELA state scores. Interestingly, this speaks to the ways in which the assessment measure itself may affect the observed relationship. Overall, the findings from this hypothesis support current literature indicating a positive correlation between mindset and achievement.

The final hypothesis originally asserted that a model combining both self-regulation skills and mindset towards intelligence would predict achievement across all measures above and beyond what each factor contributes individually, with higher self-regulatory skills and a more malleable theory of intelligence predicting higher achievement. This hypothesis was examined using ordinal multiple regressions for state assessment scores and linear multiple regressions and Bayesian analyses for report card grades. This hypothesis was not supported for state achievement scores, suggesting that the combination of predictors is not significantly associated with performance on state tests. Additionally, there was little difference noted in the model containing both self-regulation and mindset when comparing it to the mindset only model. Anecdotally, mindset scores alone appeared to have a larger impact on the odds of both ELA and math state achievement.

Bayesian multi-model linear regressions were used to further examine which model was most probable in predicting report card grades given the data. The mindset only model appeared to be the best fitting model compared to all other models for ELA report card grades, receiving increased support after observation of the present data. However, given the size of the Bayes factor, this is still considered only anecdotal or weak evidence. Nevertheless, it was 1.56 times more likely compared to the two-predictor model containing both mindset and self-regulation scores. On the other hand, the null model received the most support given the data for math report card grades. After observing the data, the odds of the null model increased by a factor of 2.076. While still not the best predicted model for math report card grades, the mindset only model did also receive increased odds while all other models containing self-regulation scores received decreased support. Across both Bayesian regression analyses, self-regulation received the most decreased support as a predictor given posterior probabilities.

Taken altogether, the findings provide some anecdotal support for the relationship between mindset and achievement for this sample. The limited support for the combined model suggests that these factors may not work as well in tandem as originally hypothesized, which is in opposition of prior literature (see Burnette et al., 2013; Compagnoni et al., 2019). While unexpected, the discrepancy in current findings based on the present sample may also relate to limitations further discussed below.

Strengths and Limitations of the Current Study

The current study evaluated the relationship of mindset towards intelligence and self-regulation skills using two different forms of frequently used achievement data. While state assessments often provide a summative representation of a student's learning in each area, report grades are obtained throughout the year during the learning process to gauge students' progress at each time point. Therefore, understanding factors that can predict performance across different types of assessments can be informative for school-based intervention development, implementation, and progress monitoring. Although most findings from this study provide only anecdotal observations given limitations discussed below, it moves the meter in a helpful direction. Furthermore, this study was conducted specifically examining a focal group of interest when it comes to theories of intelligence (see Burnette et al., 2022). Additionally, this study provided an extension of research into understanding self-reported mindsets and self-regulation skills in a younger population (i.e., upper elementary students) as previous studies utilizing self-report methods were conducted at the secondary level and other studies focused on the effects of interventions rather than the underlying influential factors.

In terms of limitations, significant weaknesses are noted in the sample and participant selection. Despite active recruitment efforts, sample size fell below desired numbers that would have provided improved confidence in the obtained analyses. Sample size limitations can lead to increased chance of Type I error, affecting the reliability, generalizability, and statistical power of the study. With the limited sample, the analyses were subject to increased potential influences of more extreme scores and less desirable variability in achievement performance levels. Furthermore, report card grade point averages may be considered an imperfect measure due to variations in grading systems between 4^{th}-5^{th} grade and 6^{th} grade students.

Given limitations in sample size, students receiving academic intervention services were not excluded from the study sample. Additionally, excluding this population would have restricted the range of academic achievement performance given that students who are below grade-level expectations are likely receiving additional academic intervention services in school. As such, intervention status may be a possible confounding variable. Similarly, ELLs were not excluded as originally proposed due to the limited sample. Therefore, it is unclear whether the command of the English language could be a confound. Although no differences were found between groups for math grades, mindset score, or self-regulation score, there was a significant difference found for ELA grade performance. Moreover, the impact ELL membership may have had on standardized state assessments is uncertain. Furthermore, participants were included using FRPL as a proxy measure for SES which only considers income and disregards other components that may account for an individual's SES, such as parental level of education and occupation (National Forum on Education Statistics, 2015). Unfortunately, collection of this data was not feasible to obtain for the purpose of this study and future directions may explore this area. Nonetheless, identification of low SES status using FRPL qualification is not uncommon in the literature (see Sisk, 2018). As such, it may still be not only the most feasible but the most meaningful when identifying subgroup populations to examine the effects of mindset on student achievement outcomes when heterogeneity exists between SES groups (Burnette et al., 2022).

Additionally, limitations may exist due to chosen measures, specifically the self-report measure of self-regulation. From a surface-level examination of scale content, the self-regulation scale used for the purpose of this study primarily focused on what may be summarized very generally as study skills with arguably some underlying aspects of attentional, behavioral, and inhibitory control. Cleary et al. (2015) characterized these adaptive and maladaptive regulatory behaviors as those required for self-regulated learning. However, other facets of emotional control and executive functioning aspects were limited in the composition of the scale. Additionally, the complete SRSI-SR scale did not behave exactly as expected for this sample as item 18 demonstrated an unexpected negative correlation with the overall scale and therefore was removed when calculating mean scores.

Finally, student participation in a social-emotional learning (SEL) program targeting either self-regulation and/or mindset related concepts may present a possible confound. According to information available from participating schools, all students receive a curriculum in fourth and fifth grade for one month focused on “Growth Mindset,” another month focused on “Resilience/Goal Setting,” and another month on “Decision Making,” all of which relate to the various factors assessed in the current study in some way. As all students receive this information, students may in general demonstrate similar responses across measures despite variability in actual achievement if they have learned to respond in certain ways to these types of questions.

Directions for Future Research

Macnamara & Burgoyne (2022) highlight the concerns and inconsistencies in the reported effectiveness of mindset-based interventions as many intervention-based studies do not hold to elements of best practice in the intervention design (e.g., use active control conditions, a priori power analyses, random assignment, blinding, and manipulation checks). Additionally, Burnette et al. (2022) note the heterogeneity in effects across studies for growth mindset interventions on academic achievement. Of particular interest, and most relevant for the current study, Burnette et al. (2022) found a similar pattern to that obtained by Sisk et al. (2018) in which larger effects were observed for low SES students, indicating that average effect sizes were low (i.e., $d = 0.09$) due to heterogeneity. Burnette et al. (2022) calls for the importance of understanding focal groups and how group membership may moderate the relationship between mindset and achievement outcomes. While the current study did not focus on the effectiveness of a mindset intervention, it did provide some indication in support of a positive relationship between mindset towards intelligence and achievement for low SES students. Future research should be conducted further exploring the relationship between these factors with a much larger sample size for this age group.

Additionally, future research may examine other facets of self-regulation that may yield more promising results for improved achievement levels in this subgroup. Due to sample size limitations, a generalized statement regarding the role of self-regulation skills in achievement as measured by this self-report scale may not be appropriate. Examining the use of this scale with a larger sample of elementary students would be appropriate for future research. Future studies may also consider using a well-validated self-report measure, such as the Behavior Rating Inventory of Executive Function, Second Edition (BRIEF2), when examining a predictive model containing both self-regulation and mindset.

Given the mixed findings, future research should seek to further explore the different effects mindset and self-regulation skills have on various areas of achievement with a much larger sample size. Similar to the novelty in this study, future studies should also focus on the predictive ability of each factor on varying measures of achievement to determine whether the strength of the relationships change. Additional consideration should be made for the range of achievement in the sample. It could be possible that students have academic difficulties that are unrelated to mindset or self-regulation skills (e.g., lower skillset or exposure to inadequate instruction). Therefore, future studies may focus on generally average performing students to see if differences in mindset or self-regulation skills can differentiate students performing on level and above level. Finally, consideration for ELL status as a factor should be included with a larger, representative sample with an equivalent number of ELL students and non-ELL students.

Implications for the Practice of School Psychology

The present study builds upon the existing research regarding the role of self-regulation and mindset in academic achievement for low SES students. Results of the current study indicate that self-regulation skills as measured with the SRSI-SR were not predictive of ELA or math achievement outcomes. Conversely, the relationship between mindset and achievement was significant for math state assessment scores and ELA report card grades. Despite nonsignificant results, mindset scores appear to predict achievement across subject areas better than self-regulation scores. A model combining both factors was not supported at this time. However, given the limitations of the current study, the potential relationship between these factors cannot be completely dismissed.

Macnamara & Burgyone (2022) call into question whether mindset interventions are predictive of achievement as studies examining the effects of these interventions are typically unclear in whether they are tapping into the latent construct of a "growth mindset." Given findings from Burnette et al. (2022), Sisk et al. (2018), and anecdotal observations from the current study, there appears to be tentative support for the relationship between this latent construct and achievement for low SES students. Whether or not significant improvements in achievement can be expected, fostering a growth mindset in students from low SES backgrounds certainly does not appear to be harmful to their success and may be associated with some positive increases in performance. However, practitioners should remain wary of the anticipated size of potential effects.

Practicing school psychologists should consider the pros and cons of implementing interventions addressing mindset in consideration of associated costs, time, and perceived student outcomes. Mindset interventions may better serve select students based upon identified risk factors as a tier 2 or 3 intervention rather than a universal intervention for all students at tier 1. As such, future studies are still necessary to determine appropriateness of mindset interventions at each tier. Despite some small promise, it has still been found that other skills, such as metacognition, may also be necessary for mindset to have a meaningful impact on student learning (e.g., Wang et al., 2021). Ultimately, when working to support an at-risk population like low SES students, it is important to consider any trade-offs between investing in certain programming toted to address student deficits in totality or addressing systemic issues (e.g., lack of resources) that continue to impact performance at large (García & Weiss, 2017b).

Table 1

Participant Demographics

	Students (*N = 44*)	
Characteristics	*N*	*%*
Age		
9	10	22.7%
10	16	36.4%
11	9	20.5%
12	6	13.6%
Missing	3	6.8%
Gender		
Male	23	52.3%
Female	21	47.7%
Ethnicity/Race		
Caucasian/White	9	20.5%
Latino or Hispanic	8	18.2%
Asian	18	40.9%
Two or more	6	13.6%
Prefer not to answer/missing	3	6.8%
English Language Learner (ELL) status		
Yes	5	11.4%
No	34	77.3%
Unsure	1	2.3%
Prefer not to answer/missing	4	9.1%
Special education status		
Yes	6	13.6%
Other Health Impairment	2	
"ADHD"	2	
Not Reported	2	
No	34	77.3%
Prefer not to answer/missing	4	9.1%
Academic intervention service status		
Yes for reading	3	6.8%
Yes for math	1	2.3%
Yes for reading and math	3	6.8%
No	29	65.9%
Unsure	3	6.8%
Prefer not to answer/missing	5	11.4%

Table 2

Frequencies for State Assessment Scores

	Students (*N = 44*)	
Score Performance Levels	*N*	*%*
English Language Arts and Literacy (ELA)		
1	2	4.5%
2	8	18.2%
3	10	22.7%
4	18	40.9%
5	6	13.6%
Mathematics		
1	1	2.3%
2	5	11.4%
3	14	31.8%
4	18	40.9%
5	6	13.6%

Table 3

Descriptive Statistics for Report Card Grades, Mean Mindset Scores, and Mean Self-Regulation Scores

	N	Mean	Median	SD	Minimum	Maximum
ELA Report Card	44	3.13	3.19	0.725	1.00	4.00
Math Report Card	44	3.25	3.31	0.682	1.00	4.00
Mean Mindset Score	44	4.33	4.58	0.993	2.33	6.00
Mean Self-Regulation Score	44	3.29	3.35	0.564	1.63	4.30

Table 4

Independent Samples T-Test

	t(42)	p	Mean difference	SE difference
		Gender		
ELA Report Card	-0.513	0.611	-0.1131	0.221
Math Report Card	-0.430	0.670	-0.0893	0.208
Mean Mindset Score	-0.964	0.341	-0.2892	0.300
Mean Self-Regulation Score	0.360	0.720	0.0620	0.172

	t(37)	p	Mean difference	SE difference
		ELL		
ELA Report Card	2.6389	0.012	0.9529	0.323
Math Report Card	1.9887	0.054	0.6065	0.305
Mean Mindset Score	0.5304	0.599	0.2490	0.470
Mean Self-Regulation Score	0.0980	0.922	0.0246	0.251

Table 5

Achievement Data Correlation Matrix

		ELA Report Card	**Math Report Card**	**ELA State Assessment**	**Math State Assessment**
ELA Report Card	Spearman's rho	—			
	df	—			
	p-value	—			
Math Report Card	Spearman's rho	0.624	—		
	df	42	—		
	p-value	< .001	—		
ELA State Assessment	Spearman's rho	0.694	0.518	—	
	df	42	42	—	
	p-value	< .001	< .001	—	
Math State Assessment	Spearman's rho	0.625	0.613	0.585	—
	df	42	42	42	—
	p-value	< .001	< .001	< .001	—

Table 6

KMO and Bartlett's Test for Self-Regulation Strategy Inventory (SRSI-SR)

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.503
Bartlett's Test of Sphericity	χ^2	642
	df	351
	p-value	<.001

Table 7

Model Comparison of Fit Indices for ELA State Assessment Scores

Model	Deviance	AIC	R^2_{McF}	Overall Model Test Likelihood Ratio			Model Comparison		
				χ^2	df	p	Change in χ^2	df	p
Self-Regulation	125	135	2.71e-4	0.0340	1	0.854			
Mindset	123	133	0.0178	2.24	1	0.135			
Mindset and Self-Regulation	123	135	0.0181	2.26	2	0.322	0.0270	1	0.869

Note. χ^2 difference is relative to the Mindset model. The dependent variable 'ELAState' has the following order: 1 | 2 | 3 | 4 | 5.

Table 8

Model Comparison of Fit Indices for Math State Assessment Scores

Model	Deviance	AIC	R^2_{McF}	Overall Model Test Likelihood Ratio			Model Comparison		
				χ^2	df	p	Change in χ^2	df	p
Self-Regulation	117	127	6.48e-6	7.62e-4	1	0.978			
Mindset	112	122	0.0445	5.22	1	0.022			
Mindset and Self-Regulation	112	124	0.0479	5.63	2	0.060	0.402	1	0.526

Note. χ^2 difference is relative to the Mindset model. The dependent variable 'MathState' has the following order: 1 | 2 | 3 | 4 | 5.

Table 9

Model Coefficients for State Assessment Scores

Predictor	Estimate	95% Confidence Interval		SE	Z	p	Odds ratio
		Lower	Upper				
			ELA				
Self-Regulation	0.0874	-0.858	1.03	0.474	0.185	0.853	1.09
Mindset	0.406	-0.125	0.962	0.275	1.48	0.140	1.50
Mindset and Self-Regulation							
Mindset	0.4171	-0.129	0.993	0.284	1.469	0.142	1.518
Self-Regulation	-0.0807	-1.047	0.891	0.488	-0.165	0.869	0.923
			Math				
Self-Regulation	-0.0141	-1.06	0.973	0.513	-0.0275	0.978	0.986
Mindset	0.638	0.0896	1.22	0.287	2.22	0.026	1.89
Mindset and Self-Regulation							
Mindset	0.686	0.117	1.295	0.298	2.302	0.021	1.986
Self-Regulation	-0.336	-1.413	0.695	0.533	-0.630	0.529	0.715

Table 10

Model Fit Indices for Report Card Grades

Model	R	R^2	ΔR^2	Adjusted R^2	RMSE	Overall Model Test			
						F	df1	df2	p
				ELA					
Self-Regulation	0.228	0.0519		0.0294	0.697	2.30	1	42	0.137
Mindset	0.298	0.0887		0.0670	0.684	4.09	1	42	0.050
Mindset and Self-Regulation	0.344	0.1183	0.0295	0.0752	0.673	2.75	2	41	0.076
				Math					
Self-Regulation	0.0925	0.00855		-0.0151	0.671	0.362	1	42	0.551
Mindset	0.234	0.0547		0.0322	0.656	2.43	1	42	0.126
Mindset and Self-Regulation	0.239	0.0569	0.00218	0.0109	0.655	1.24	2	41	0.301

Note: ΔR^2 is relative to the Mindset model.

Table 11

Model Coefficients for Report Card Grades

Predictor	Estimate	95% Confidence Interval		SE	t	p	β
		Lower	Upper				
			ELA				
Self-Regulation							
Intercept	2.170	0.8704	3.470	0.644	3.37	0.002	
Self-Regulation	0.293	-0.0967	0.682	0.193	1.52	0.137	0.228
Mindset							
Intercept	2.193	1.23	3.155	0.477	4.60	<.001	
Mindset	0.217	4.17e-4	0.434	0.107	2.02	0.050	0.298
Mindset and Self-Regulation							
Intercept	1.562	0.1135	3.011	0.717	2.18	0.035	
Mindset	0.192	-0.0288	0.412	0.109	1.76	0.087	0.263
Self-Regulation	0.225	-0.1628	0.613	0.192	1.17	0.248	0.175
			Math				
Self-Regulation							
Intercept	2.887	1.636	4.138	0.620	4.657	<.001	
Self-Regulation	0.112	-0.263	0.486	0.186	0.602	0.551	0.0925
Mindset							
Intercept	2.560	1.6378	3.482	0.457	5.60	<.001	
Mindset	0.161	-0.0472	0.369	0.103	1.56	0.126	0.234
Mindset and Self-Regulation							
Intercept	2.3985	0.9879	3.809	0.698	3.434	0.001	
Mindset	0.1541	-0.0605	0.369	0.106	1.450	0.155	0.2245
Self-Regulation	0.0576	-0.3201	0.435	0.187	0.308	0.760	0.0477

Table 12

Bayesian Model Comparison for ELA Report Card Grades

Models	P(M)	P(M|data)	BF_M	BF_{10}	R^2
Mindset model	0.250	0.355	1.654	1.000	0.089
Null model	0.250	0.239	0.942	0.673	0.000
Mindset + Self-Regulation model	0.250	0.228	0.885	0.641	0.118
Self-Regulation model	0.250	0.178	0.648	0.500	0.052

Table 13

Posterior Summary for ELA Report Card Grades

								95% Credible Interval	
Coefficient	P(incl)	P(excl)	P(incl|data)	P(excl|data)	$BF_{inclusion}$	Mean	SD	Lower	Upper
Intercept	1.000	0.000	1.000	0.000	1.000	3.133	0.107	2.927	3.361
Mindset	0.500	0.500	0.583	0.417	1.399	0.099	0.112	-0.006	0.355
Self-Regulation	0.500	0.500	0.406	0.594	0.682	0.083	0.150	-0.067	0.454

Table 14

Bayesian Model Comparison for Math Report Card Grades

Models	P(M)	P(M|data)	BF_M	BF_{10}	R^2
Null model	0.250	0.409	2.076	1.000	0.000
Mindset model	0.250	0.320	1.413	0.783	0.055
Self-Regulation model	0.250	0.141	0.491	0.344	0.009
Mindset + Self-Regulation model	0.250	0.130	0.449	0.318	0.057

Table 15

Posterior Summary for Math Report Card Grades

								95% Credible Interval	
Coefficient	P(incl)	P(excl)	P(incl|data)	P(excl|data)	$BF_{inclusion}$	Mean	SD	Lower	Upper
Intercept	1.000	0.000	1.000	0.000	1.000	3.255	0.102	3.053	3.457
Mindset	0.500	0.500	0.450	0.550	0.819	0.057	0.089	0.000	0.267
Self-Regulation	0.500	0.500	0.271	0.729	0.371	0.018	0.091	-0.108	0.273

Appendix

Appendix A: Recruitment e-letter sent to parents/guardians.

Dear Parents/Guardians of [INSERT GRADE-LEVEL] students attending [SCHOOL NAME],
You and your child are invited to participate in an important study to learn more about how children view their intelligence, the skills or strategies they use to work towards their learning goals, and their academic performance. This study will be conducted by Jamilah Lindo, a Psy. D. student in the St. John's University School Psychology program. Her faculty advisor is Dr. Imad Zaheer at St. John's University.
Children from low socioeconomic backgrounds tend to demonstrate lower academic performance compared to wealthier peers. The goal is to explore protective factors in their academic achievement. This research will help us better understand how some ways of thinking and some strategies can help children succeed in school. This information can then help inform the types of school-based supports that are provided. The study will be done through a record review and brief surveys. Parents of participating students will be asked to complete a brief background survey. With your permission, your child will be asked to complete two brief surveys. This research was approved by the St. John's University Institutional Review Board, protocol number IRB-FY2022-187.

The consent form, parent permission form, and background survey can be found at the link below:
https://stjohns.az1.qualtrics.com/jfe/form/SV_ab0I96RqtlkXsfc
Thank you for your time, your assistance with this study, and your important contribution!

Jamilah Lindo, M.S.
Doctoral Student, School Psychology
Department of Psychology
St. John's University
Queens, NY, 11439
Jamilah.lindo14@stjohns.edu

Appendix B: Parental Consent Form.

Parental Consent Form

You have been invited to take part in a research study to learn more about the relationship between how children view their intelligence, the skills or strategies they use to work towards their learning goals, and their academic performance.

This study will be conducted by Jamilah Lindo, Department of Psychology, St. John's College of Liberal Arts and Sciences, St. John's University, as part of her doctoral dissertation. Her faculty sponsor is Dr. Imad Zaheer, Department of Psychology, St. John's College of Liberal Arts and Sciences, St. John's University.

If you agree to be in this study, you will be asked to do the following:
1. Complete a questionnaire about your child's background (age, gender, free or reduced-price lunch status, etc.).
2. Permit the investigator access to your child's 2022-2023 report card grades and state assessment scores.

Participation in this study will involve no more than 5 minutes of your time to complete the questionnaire. There are no known risks associated with your participation in this research beyond those of everyday life.

Although you will receive no direct benefits, this research may help us better understand how some ways of thinking and some strategies can help children succeed in school.

Confidentiality of your research records will be strictly maintained by keeping parental permission and parental consent forms separate from data to make sure your child's name and identity will not become known or linked with any information you provided. Personally identifiable information will be replaced with research identification codes (ID codes). Access to these codes will be limited to the investigator and faculty sponsor. Master lists will be stored separately from the data and destroyed as soon as reasonably possible. All electronic data are stored in password-protected computers and files.

Your responses will be kept confidential with the following exception: the researcher is required by law to report to the appropriate authorities, suspicion of harm to yourself, to children, or to others.

Participation in this study is voluntary. You may refuse to participate or withdraw at any time without penalty. For the questionnaire, you have the right to skip or not answer any questions you prefer not to answer. Nonparticipation or withdrawal will not affect your child's grades or academic standing.

If there is anything about the study or your participation that is unclear or that you do not understand, if you have questions or wish to report a research-related problem, you may contact Jamilah Lindo at 516-972-0072, jamilah.lindo14@stjohns.edu, or the faculty sponsor, Dr. Imad Zaheer, at 718-990-5928, zaheeri@stjohns.edu.

For questions about your rights as a research participant, you may contact the University's Institutional Review Board, St. John's University, Dr. Raymond DiGiuseppe, Chair digiuser@stjohns.edu 718-990-1955 or Marie Nitopi, IRB Coordinator, nitopim@stjohns.edu 718-990-1440.
You have received a copy of this consent document to keep.

Agreement to Participate

Do you accept the terms and conditions of this study?

Yes, I accept the terms and conditions of this study and consent to participate.

No, I do not accept the terms and conditions of this study and do NOT consent to participate.

Appendix C: Parental Permission Form.

Parental Permission Form

Your child has been invited to take part in a research study to learn more about the relationship between how children view their intelligence, the skills or strategies they use to work towards their learning goals, and their academic performance.

This study will be conducted by Jamilah Lindo, Department of Psychology, St. John's College of Liberal Arts and Sciences, St. John's University, as part of her doctoral dissertation. Her faculty sponsor is Dr. Imad Zaheer, Department of Psychology, St. John's College of Liberal Arts and Sciences, St. John's University.

If you give permission for your child's participation in this study, your child will be asked to do the following:

1. Complete a questionnaire about his/her thoughts about what it means to be smart or intelligent; and
2. Complete a questionnaire about his/her study habits and learning strategies

Participation in this study will involve approximately 20 minutes of your child's time to complete the questionnaires. There are no known risks associated with your child's participation in this research beyond those of everyday life.

Although your child will receive no direct benefits, this research may help us better understand how some ways of thinking and some strategies can help children succeed in school.

Confidentiality of your child's research records will be strictly maintained by keeping parental permission and parental consent forms separate from data to make sure your child's name and identity will not become known or linked with any information you provided. Personally identifiable information will be replaced with research identification codes (ID codes). Access to these codes will be limited to the investigator and faculty sponsor. Master lists will be stored separately from the data and destroyed as soon as reasonably possible. All electronic data are stored in password-protected computers and files.

Your child's responses will be kept confidential with the following exception: the researcher is required by law to report to the appropriate authorities, suspicion of harm to yourself, to children, or to others.

Participation in this study is voluntary. Your child may refuse to participate or withdraw at any time without penalty. Your child also has the right to skip or not answer any questions he/she prefers not to answer. Nonparticipation or withdrawal will not affect your child's grades or academic standing.

If there is anything about the study or your child's participation that is unclear or that you do not understand, if you have questions or wish to report a research-related problem, you may contact Jamilah Lindo at 516-972-0072, jamilah.lindo14@stjohns.edu, or the faculty sponsor, Dr. Imad Zaheer at 718-990-5928, zaheeri@stjohns.edu.

For questions about your child's rights as a research participant, you may contact the Institutional Review Board, St. John's University, Dr. Raymond DiGiuseppe, Chairperson, digiuser@stjohns.edu, 718-990-1955 or 718-990-1440.

You have received a copy of this parental permission form to keep.

Permission to Participate

Name of minor subject:	______________________ Name of Child	
Parent's **Signature** & **date**	______________________ Parent's Signature	____________ Date

Appendix D: Demographics Questionnaire.

1. Student Name (First and Last)
   a. __________ (Short Answer Space)

2. Student Age
   a. ________ (Short Answer Space)

3. School:
   a. __________ (Short Answer Space)

4. What gender does your child identify as?
   a. Male
   b. Female
   c. Other________ (Short Answer Space)
   d. Prefer not to answer

5. Please specify your child's ethnicity.
   a. Caucasian
   b. Black/African-American
   c. Latino or Hispanic
   d. Asian
   e. Native American
   f. Native Hawaiian or Pacific Islander
   g. Two or More
   h. Other/Unknown
   i. Prefer not to say

6. Does your child qualify for free or reduced-priced lunch?
   a. Yes
   b. No
   c. Unsure

7. Is your child considered an English Language Learner / Limited English Proficiency?
   a. Yes
   b. No
   c. Unsure
   d. Prefer not to answer

8. Does your child currently receive services and/or program support through an Individualized Education Plan (IEP)?

a. Yes, my child is classified as: _________________ (Short Answer Space)
b. No
c. Prefer not to answer

9. Does your child receive academic intervention services (AIS) in school (e.g., small-group reading or math support in addition to typical classroom instruction)?
   a. Yes, he/she receives intervention services for reading.
   b. Yes, he/she receives intervention services for math.
   c. Yes, he/she receives intervention services for reading and math.
   d. No, he/she does not receive any academic intervention services.
   e. Unsure
   f. Prefer not to answer

Appendix E: Child Assent Script.

Child Assent for Children under Age 12

(To be read aloud to the child)

My name is Jamilah Lindo. I work with parents and children, but I am also a student. Right now, I am trying to learn more about how children think about what it means to be smart or intelligent. I also want to learn more about children's study habits, how they work towards their goals, and what strategies they use to learn.

If you agree, you will be asked to answer questions about your study habits, learning strategies, and how you view your intelligence. It should take less than 20 minutes. You may be helping us understand how some ways of thinking and some strategies can help children succeed in school.

If you agree to help us, you should know that your teacher and classmates won't know how you answered these questions. You should also know that if you decide to help us or if you decide to say "no," your choice will not affect your grades.

There are no right or wrong answers.

Please talk this over with your parents before you decide if you want to be in my study or not. I will also ask your parents to give their permission for you to be in this study, but even if your parents say "yes," you can still say "no" and decide not to be in the study.

If you don't want to be in my study, you don't have to be in it. Remember, being in the study is up to you and no one will be upset if you don't want to be in the study or if you decide to stop after we begin, that's okay, too. Also, remember that no one else, not even your parents, will know how you answered these questions.

You can ask any questions that you have about the study. If you have a question later that you didn't think of now, you can ask your parents, teacher, or other trusted adult to call me at: 516-972-0072.

Would you like to answer some questions?

[Child answers yes or no; only a definite yes may be taken as consent to participate.]

Appendix F: Implicit Theories of Intelligence Scale for Children - Self Form.

Read each sentence below and then choose the one number that shows how much you agree with it. There are no right or wrong answers.

1. You have a certain amount of intelligence, and you really can't do much to change it.	1 Strongly Agree	2 Agree	3 Mostly Agree	4 Mostly Disagree	5 Disagree	6 Strongly Disagree
2. Your intelligence is something about you that you can't change very much.	1 Strongly Agree	2 Agree	3 Mostly Agree	4 Mostly Disagree	5 Disagree	6 Strongly Disagree
3. You can learn new things, but you can't really change your basic intelligence.	1 Strongly Agree	2 Agree	3 Mostly Agree	4 Mostly Disagree	5 Disagree	6 Strongly Disagree
4. No matter who you are, you can change your intelligence a lot.	1 Strongly Agree	2 Agree	3 Mostly Agree	4 Mostly Disagree	5 Disagree	6 Strongly Disagree
5. You can always greatly change how intelligent you are.	1 Strongly Agree	2 Agree	3 Mostly Agree	4 Mostly Disagree	5 Disagree	6 Strongly Disagree
6. No matter how much intelligence you have, you can always change it quite a bit.	1 Strongly Agree	2 Agree	3 Mostly Agree	4 Mostly Disagree	5 Disagree	6 Strongly Disagree

Appendix G: Self-Regulation Strategy Inventory - Self-Report.

Read each sentence below and then choose the one number that shows how often it is true for you. There are no right or wrong answers.

1. I make sure no one disturbs me when I study.	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Almost Always
2. I try to study in a quiet place.	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Almost Always
3. I think about the types of questions that might be on a test.	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Almost Always
*4. I ask my teacher about the topics that will be on upcoming tests.	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Almost Always
*5. I rely on my class notes to study.	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Almost Always
6. I study hard even when there are more fun things to do at home.	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Almost Always
7. I quiz myself to see how much I am learning during studying.	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Almost Always
8. I make a schedule to help me organize my study time.	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Almost Always
9. I use binders or folders to organize my materials.	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Almost Always
*10. I lose important worksheets or materials.	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Almost Always

*11. I avoid getting extra-help in school.	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Almost Always
*12. I wait until the last minute to study for tests.	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Almost Always
13. I try to forget about the things I have trouble learning.	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Almost Always
*14. I try to see how my notes from class relate to things I already know.	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Almost Always
*15. I try to identify the format of upcoming tests.	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Almost Always
16. I try to study in a place that has no distractions (e.g., noise, people talking).	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Almost Always
17. I ask my teacher questions when I do not understand something.	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Almost Always
*18. I make pictures or drawings to help me learn concepts.	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Almost Always
19. I give up or quit when I do not understand something.	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Almost Always
*20. I forget to bring home my materials when I need to study.	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Almost Always
21. I tell myself exactly what I want to accomplish during studying.	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Almost Always

22. I look over my homework assignments if I don't understand something.	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Almost Always
23. I avoid asking questions in class about things I don't understand.	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Almost Always
24. I tell myself to keep trying when I can't learn a topic or idea.	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Almost Always
25. I carefully organize my study materials so I don't lose them.	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Almost Always
26. I let others interrupt me when I am studying.	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Almost Always
27. I think about how best to study before I begin studying.	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Almost Always
28. I finish all of my studying before I play video games or with my friends.	1 Almost Never	2 Rarely	3 Sometimes	4 Often	5 Almost Always

*Subject-specific items adapted to reflect academic content in general

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