SELF-REGULATION AND MATHEMATICS ACHIEVEMENT DURING THE COVID-19 PANDEMIC

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ABSTRACT

Self-regulation refers to a complex set of processes that control attentional, emotional, and behavioral impulses. Understandably, studies have shown that these processes have a significant impact on an individual's success in school environments. Further, research has highlighted that self-regulation processes are developmental and dynamic, gradually shaped over time by experiences and environments. Thus, unexpected disruptions to environments and expected experiences can negatively impact the development of self-regulation and produce negative secondary consequences, such as learning loss.

The COVID-19 pandemic brought about unexpected disruptions to the lives of most people. Emerging research demonstrates the toll the pandemic took on individuals' physical and mental health, work, connections to others, and finances. For a generation of students, there was an additional impact of school closures, shifts to online learning, and social distancing from peer groups.

In the present study, I examined how COVID-19 related stress and impacts interacted with the self-regulation of students in grades four through ten. Utilizing data from an ongoing longitudinal study, I fitted a series of multilevel models to evaluate whether COVID-19 stressors and impacts were predictive of worse student self-regulation and whether this had a negative effect on students' mathematics competence as measured by their performance on grade level assessments.

Results indicated that student self-regulation was a reliable and robust predictor of performance on grade-level mathematics competence measures. COVID-19 related impacts were associated with worse self-regulation, though COVID-19 stress did not have an effect on self-regulation. We found no evidence of significant interaction effects between COVID-19 related stress and impacts on the relationship between self-regulation and mathematics outcomes. This dissertation study contributes to a growing body of research aimed at understanding the far-reaching consequences of the COVID-19 pandemic, particularly for a generation of students whose learning, social, and home environments were disrupted. Future research should continue to examine self-regulation processes and learning consequences of COVID-19 as we are likely to observe ongoing effects for years to come.

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CHAPTER 1

INTRODUCTION

Early attempts to comprehend individual differences in school achievement were initially centered on intelligence. Researchers in intelligence documented a seemingly indisputable correlation between individual intelligence and academic attainment (Duckworth & Carlson, 2013). Nevertheless, these researchers were also among the first to acknowledge that factors beyond intelligence played a role in school success. Pioneers in intelligence testing, Alfred Binet and Theodore Simon (1916), asserted that, aside from intelligence, individuals must possess qualities such as attention, will, character, and ability to sustain efforts to succeed in academic environment. Another influential figure in intelligence testing, David Wechsler (1943), emphasized the significance of measuring "non-intellective" factors alongside intelligence to more accurately capture how genuine intelligent behavior translates into success in schools.

Despite the clear importance of skills outside of intelligence for school success, research into these factors was largely absent until the second half of the 20th century (Duckworth & Carlson, 2013). The exploration of these non-intellective factors took various forms, resulting in diverse multi-disciplinary research. Over time, a particular construct gained prominence: self-regulation. Self-regulation involves the "control of attentional, emotional, and behavioral impulses in the service of personally valued goals and standards" (Duckworth & Carlson, 2013, p. 209). It is conceptualized both as a process, encompassing self-monitoring, feedback, and behavior modulation to facilitate goal achievement, and as a trait, examining individual differences in impulse or constraint of cognitions, emotions, and/or behaviors (McCrae & Löckenhoff, 2010).

Given the multifaceted nature of regulation, researchers often focus on specific elements, commonly dividing self-regulation into the categories of cognitive regulation and emotional regulation. Cognitive regulation processes include sustaining attention, inhibitory control, self-reflection, metacognition, and planning, while emotional regulation processes involve appropriately moderating emotional responses to situational demands (Bandy & Moore, 2010). Researchers studying cognitive or emotional self-regulation often incorporate behavior into their conceptualizations of these processes, although some researchers discuss behavioral self-regulation separately. Behavioral self-regulation is a construct capturing the ability to integrate regulation processes (i.e., cognitive functions and emotional modulation) to form behavioral actions (McClelland et al., 2007).

Self- regulation, which permeates cognition, emotions, and behaviors, is multifaceted and has been linked to other aspects of individual experience, including academic achievement and school success. Research on self-regulation has shown that this construct is more predictive of academic performance than more objective measures like intelligence and achievement-test scores (Duckworth & Seligman, 2006). Regulation behaviors in early childhood predict later achievement across academic subjects from high school through college (McClelland et al., 2013). Additionally, students' ability to engage in regulation processes is associated with higher levels of academic attainment, engagement in more rigorous coursework, and the establishment of more positive relationships with teachers and peers within schools (Zimmerman & Pons, 1986; Eisenberg et al., 2010).

The importance of regulation processes and behaviors can also be explored within the context of specific coursework, such as mathematics. Regulatory processes like goal setting, self-monitoring, and metacognition are particularly beneficial for mathematics learning (Wang et al., 2019). Some researchers posit that the mindset required for success in mathematics depends on regulation (De Corte et al., 2000). Consequently, interventions that incorporate regulation processes into mathematics instruction, such as promoting self-monitoring during math problem solving, have been linked to improved overall math achievement outcomes (Schunk, 1996).

The ability to shape self-regulation through intervention highlights the bidirectional dynamic relationship between individuals and their environment, shaping these processes and traits (Zeman et al., 2006). Just as the regulation skills and abilities an individual brings to school shape their academic experience, the learning environment also shapes the developmental trajectory of regulation (Perry, 1998). Thus, specific school procedures, such as the demands of classrooms or homework assignments, have been linked to promoting the development of regulatory behaviors (Perry, 1998; Ramdass & Zimmerman, 2011).

Given the importance of the environment in shaping regulatory behaviors, the school shutdowns resulting from the COVID-19 pandemic raise intriguing considerations. In the spring of 2020, schools across America shut down to stop the spread of COVID-19, affecting approximately 55 million students and their families. In the best-case academic scenario, this event meant a somewhat smooth ad hoc transition to remote learning; in the worst-case scenario, it meant no access to instruction or other school services. Regardless of academic experience, no child or adolescent was exempt from the psychosocial stressors brought about by the pandemic. The impacts of this stressful, and for some traumatic, ongoing event are already evident in lowered academic performance, higher rates of mental health needs, and a sharp increase in behavioral dysregulation of students (Kuhfeld et al., 2022; U.S. Department of Education, 2022). The reverberating impacts of COVID-19 on students' academic, social, emotional, and behavioral trajectories will continue to unfold for years to come. It is critical that research continues to unpack the impact of this disruption to address, support, and remediate students' ongoing needs.

The aim of this study is to investigate students' self-regulation within the context of the COVID-19 pandemic. Data on students' regulation behaviors collected in the summer of 2021and summer 2022 was utilized to predict their mathematics competencies, as assessed through survey measures completed in the summer of 2022. The relationship between self-regulation and grade level mathematic competence was further examined with consideration given to the COVID-19-related stressors and impacts their families experienced. The following research questions will be addressed:

1. How does student self-regulation develop from one year to the next? Was this development negatively impacted by COVID-19 stress and impacts?
2. How well does self-regulation predict student performance on mathematics competence measures? Is this relationship moderated by COVID-19 stress and impacts?

Overall, this study endeavored to explore the dynamic relationship between regulation and achievement in an environment affected by COVID-19 disruptions.

The results have the potential to improve our understanding of how COVID-19 stressors and impacts influenced students' regulation development and academic progress. The findings could also help refine future interventions aimed at addressing the repercussions of COVID-19, enhancing students' educational experiences and outcomes as we continue to recover from the stress and disruption caused by the pandemic.

CHAPTER 2

LITERATURE REVIEW

Self-Regulation

Self-regulation is a multifaceted term encompassing a dynamic and intricate system of cognitions, emotional expressions, and behaviors (Vohs & Baumeister, 2004). Consequently, self-regulation emerges as a robust correlate for diverse individual outcomes such as academic achievement, physical and mental well-being, and personal and professional success (Vohs & Baumeister, 2004). To document and comprehend the significance of self-regulation and its underlying mechanisms, numerous definitions, theories, and frameworks have been proposed (Boekaerts et al., 2005). In an attempt to consolidate these diverse definitions, Vohs and Baumeister (2004) distilled the shared aspects to define self-regulation as any efforts by the human self to modify its own inner states or responses (p. 2). In essence, self-regulation can be succinctly framed as the control of attention, emotion, and behavior to achieve a goal (Duckworth & Carlson, 2013).

Conceptualizations of self-regulation may center on the construct as either a process or a trait (McCrae & Löckenhoff, 2010). As a process, self-regulation is linked to goal attainment, involving procedures such as self-monitoring, feedback, and behavior modulation to facilitate goal achievement (McCrae & Löckenhoff, 2010). Whereas, as a trait, self-regulation is conceptualized in terms of stable individual differences in the impulse or constraint of cognitions, emotions, and/or behaviors (McCrae & Löckenhoff, 2010).

Given the multidimensional nature of self-regulation, researchers often focus on discrete processes contributing to its creation rather than attempting to capture the entire construct at once. These processes are frequently delineated as cognitive self-regulation, emotional self-regulation, and behavioral self-regulation. While these areas of self-regulation will be discussed separately, it is crucial to acknowledge that self-regulation represents a dynamic system, with cognitive, emotional, and behavioral facets intricately linked and mutually informing one another (Vohs & Baumeister, 2004).

Cognitive self-regulation processes are associated with sustaining attention, inhibitory control, self-reflection, metacognition, and planning (Bandy & Moore, 2010). These processes contribute to regulation by inhibiting strong automatic responses, such as frustration, that may be maladaptive in specific environments (Cole et al., 2019). Thus, cognitive self-regulation represents the underlying abilities enabling an individual to identify the need for self-corrective adjustment and the capacity to execute that correction (Carver, 2004).

Emotional self-regulation processes involve an individual's ability to appropriately modulate emotional responses to the situational demands of both positive and negative scenarios (Bandy & Moore, 2010). In more detail, emotional regulation is the process of "initiating, avoiding, inhibiting, maintaining, or modulating the occurrence, form, intensity, or duration of internal feeling states" to adapt to environmental needs or achieve personal goals (Eisenberg & Spinrad, 2004, p. 338).

Although cognitive and emotional regulation are at times defined separately, it is vital to recognize their overlapping and interdependent nature. As discussed by Eisenberg and colleagues (2010), cognitive and emotional regulation are reciprocal processes; for example, cognitive regulation processes, such as attention, weaken when emotional states are unregulated.

Researchers investigating cognitive self-regulation often refer to these processes as executive functions, while those examining emotional regulation may address them as effortful control or temperament (Zhou et al., 2012). Literature review indicates considerable overlap in the conceptualizations of the targeted processes, measurement tools, and conclusions between researchers investigating executive functions or effortful control (Zhou et al., 2012). The primary difference lies in the contexts under investigation, with emotional regulation researchers focusing on emotionally charged environments and cognitive self-regulation researchers often working in emotionally neutral settings (e.g., laboratory settings) (Zhou et al., 2012).

This diversity in research contexts has led to further terminology distinctions in self-regulation, such as "hot" and "cold" self-regulatory processes (Metcalf and Mischel, 1999). Hot regulatory systems involve tempering emotions, such as problem-solving in contexts with opportunities for rewards or losses, whereas cold regulatory processes are associated with problem-solving in decontextualized abstract scenarios (Zelazo & Cunningham, 2007). Researchers acknowledge that hot and cold systems are often simultaneously involved in most problem-solving situations and should be regarded as mechanisms on a continuum rather than separate systems (Zhou et al., 2012).

While researchers studying cognitive or emotional self-regulation often incorporate behavior into their conceptualizations of those processes, some researchers discuss behavioral self-regulation separately. Behavioral self-regulation is a construct seeking to capture an individual's ability to integrate regulation processes (i.e., executive functions and emotional modulation) to form behavioral actions (McClelland et al., 2007). Those researching behavioral self-regulation emphasize that executive functions are the foundational elements for self-regulated behavior (McClelland et al., 2007). For instance, a student would require attentional and inhibitory control to fulfill the behavioral expectations of an independent work assignment in a classroom. In concrete terms, behavioral regulation is defined as the outward expression of executive function skills through observable actions, specifically gross motor movements. (Ponitz et al., 2009).

At times, when self-regulation processes are studied within academic environments and their correlation with school achievement, it's referred to as self-regulated learning. Self-regulated learning refers to a student's ability to motivate, engage in metacognition and active learning, and meet the behavioral expectations required for classroom learning (Zimmerman, 2008). It might include a particular disposition, such as a growth mindset, or its underlying process-oriented behaviors, such as goal-setting, self-monitoring, and strategy use (Zimmerman, 2008).

Throughout this project, the complex and multifaceted nature of self-regulation will be continuously emphasized. Researchers across diverse fields are intrigued by its strong correlation with personal and professional success and its adaptability through both environmental and intervention influences. While the variety of research perspectives enriches the field, the lack of uniformity in terminology can create confusion, as lamented by the National Institutes of Health, stating that "the lack of consistency and conceptual integration in how self-regulation is studied across a range of disciplines hinders our understanding of the basic mechanisms underlying many important health and developmental outcomes" (Department of Health and Human Services, n.d).

For the purposes of this project, self-regulation will be the term used as we investigate the process. However, research that discusses this same phenomenon but under different names (e.g., self-control, self-discipline, etc.), research that examines discrete elements of the process (e.g., inhibitory control), and research that examines the absence of self-regulation from a lens of deficits and psychopathology will also be reviewed.

In this project, self-regulation is measured using the Fast-Track Project Child Behavior Questionnaire. This questionnaire is adapted from The Child Behavior Checklist (CBCL; Achenbach & Edelbrock, 1991) and the Revised Behavior Problem Checklist (RBPC; Quay & Paterson, 1987). These forms capture self-regulatory behaviors broadly. Thus, for the purposes of this study, a definition that captures how both cognitive and emotional processes work together to elicit desired regulated behavior is most appropriate. Therefore, this project adopts the definition offered by Duckworth and Carlson (2013) that self-regulation is the process of controlling attention, emotion, and behavior for the purposes of reaching a valued goal.

Self-Regulation Development

Most self-regulation researchers propose a bi-directional, dynamic interaction between an individual and their environment as the driving force behind the development of self-regulation. This perspective captures the diverse and dynamic systems responsible for the unfolding and development of regulatory processes (Zeman et al., 2006). One of the most-cited frameworks illustrating this bi-directional relationship is that developed by

Kopp (1982). Kopp's framework elucidates how internal factors (e.g., attention, language proficiency, reasoning ability) and external factors (e.g., caregiver behaviors, social experience) concurrently interact to produce and shape regulation development (Cole et al., 2019). This developmental lens aligns with the consensus among researchers that regulation abilities cannot be neatly understood within specific stages of development. Instead, the environmental impact at different life stages should be considered, given the substantial ecological influence on regulatory skill development (Zimmerman, 2008).

Behaviors associated with emotional regulation are observed early and continue to develop into adulthood. As early as the first few weeks of life, infants begin adapting to unpleasant states by engaging in behaviors that may alter their experience (Kopp, 1989). For instance, making a sucking motion with their mouth (when not eating) is adopted to self-soothe and reduce distress (Kopp, 1989). During these formative years, emotional regulation is significantly influenced by the child's caregivers. Responsive caregiving can promote the use of adaptive emotional regulation strategies (e.g., speaking about feelings and/or self-advocacy), while punitive parenting styles can facilitate the development of maladaptive behavioral reactions (e.g., hitting, tantrums) instead of modulating emotion (Harrington et al., 2020).

In early childhood (ages 3-5 years), the emergence of executive functioning processes enables children to inhibit behaviors, focus their attention, and hold information in working memory (Blankson et al., 2017). These executive functions lay the foundation for children to grasp social norms of emotional expressions and develop theory of mind (Harrington et al., 2020). Participation in social norms and theory of mind facilitates the ongoing development of emotional regulation skills, allowing individuals to process and integrate social stimuli to produce behavior aligned with interpersonal and personal goals (Zeman et al., 2006). During the preschool years, children employ these newly developed skills to actively problem-solve rather than reflexively respond to stimuli (Harrington et al., 2020). Concurrent with prefrontal cortex development, skills associated with cognitive self-regulation (i.e., attention, working memory, inhibition) are strengthened during these preschool years. This developmental trajectory is protracted and remains susceptible to environmental influences throughout development (Fuhs et al., 2013).

Research indicates that the acquisition of regulation abilities begins to diverge along gender lines as early as kindergarten. Based on teacher-rating scales and performance on an observational task, female students demonstrate a greater ability to regulate their behaviors according to the demands of the school environment than their male peers during these early developmental years (Matthews et al., 2009). In fact, female students were shown to enter and exit kindergarten with stronger behavioral regulation than their male peers (Matthews et al., 2009). Although research findings are mixed, there are indications that this gender divide in regulation may explain the trend of females outperforming their male peers through elementary, middle, and high school, even when matched by achievement and IQ (Duckworth & Seligman, 2006).

Once children enter school, their continued regulation development is significantly influenced by their educational environments and their success (or lack thereof) in navigating associated new peer interactions and relationships, classroom rules, and academic expectations that come with schooling (Harrington et al., 2020). The utilization of these developing regulation processes is linked to children's likelihood of developing positive peer relationships, social competence, appropriate classroom behavior, and academic achievement (Harrington et al., 2020; Slot et al., 2017). For these reasons, measures of self-regulation are typically crucial in determining school readiness (Eisenberg et al., 2010).

As students progress through school, self-regulation becomes more closely intertwined with their achievement, social competence, classroom engagement, and school motivation (McClelland & Cameron, 2011). During middle childhood, social context (i.e., in the presence of family vs. in the presence of peers) becomes an important motivator and predictor of how children regulate and adapt their emotional expressions (i.e., more likely to regulate in the presence of peers) (Zeman et al., 2006). During these developmental years, differences along gender lines in displays of emotional regulation may become more pronounced. These differences may result from socialization efforts that emphasize male suppression of sadness displays and female suppression of anger displays (Zeman et al., 2006). Due to these socialization processes, females tend to substitute “undesirable” emotions for another (i.e., joy over anger), whereas males become more prone to neutralizing emotional expressions altogether (Zeman et al., 2006).

By adolescence, typically developing children can display emotional regulation abilities nuanced to factors of motivation, the type of emotion they are experiencing, and social and environmental contextual dynamics (Zeman et al., 2006). During this developmental period, emotions associated with social- or self-consciousness, such as shame and pride, become particularly salient in driving self-regulation, as adolescents experience heightened sensitivity to the evaluations of others (Zeman et al., 2006). By the close of adolescence, self-regulation is associated with the ability to act autonomously, make complex decisions, set and attain goals, and identify resources that can support and remediate personal limitations (Miller & Byrnes, 2001).

Measuring Self-Regulation

Given the multifaceted overt and covert processes involved in self-regulation, it is no wonder that there are myriad ways to measure the construct (and debate surrounding the best approach). Across disciplines of self-regulation study, researchers agree that an individual's self-regulation abilities are highly influenced by their environment, thus, efforts to move toward ecologically sensitive measures have been developed (Cleary et al., 2012). These efforts have included structured personal diaries (i.e., asking students to engage in "think-aloud" while working), using hypermedia for learning (i.e., software that traces student behavior on work products), and direct observation in particular contexts (Cleary et al., 2012). Researchers who advocate for these methods argue that self-report measures require retrospective accounts of behaviors or perceptions of behaviors that are decontextualized and not linked to specific tasks, thus lacking strong ecological meaning (Clearly et al., 2012). Further, questionnaires tend to reduce self-regulation to static moments, rather than a dynamic process (Diaz & Eisenberg, 2015). Despite these concerns, most self-regulation research utilizes self-report measures in the form of questionnaires (i.e., items completed using Likert-type scales) or structured interviews (Clearly et al., 2012). Some advocates of self-report measures highlight that self-report in this area is more ecologically valid than external raters (e.g., teachers), being that individuals themselves are more attuned to these internal processes and abilities (McClelland & Cameron, 2012).

Self-Regulation and Academic Achievement

Self-regulation traits and processes form the bedrock of academic achievement, playing a critical role in successfully navigating educational environments, maintaining focus, ignoring distractions, and demonstrating persistence (McClelland et al., 2015). Students' self-regulation abilities and the application of associated strategies have been consistently linked to higher academic achievement on both classroom measures and standardized assessments (Zimmerman & Pons, 1986). Highly regulated students exhibit more goal-directed behaviors, display heightened motivation and engagement with academics, and are more likely to engage in prosocial behaviors, fostering stronger relationships with peers and teachers, thereby positively impacting academic achievement (Eisenberg et al., 2010).

The manifestation of self-regulation behaviors in early childhood and kindergarten serves as a significant predictor of later reading and mathematics achievement in elementary, middle, high school, and college years (McClelland et al., 2006; Ponitz et al., 2009; McClelland et al., 2013). Even after controlling for variables such as IQ, age, ethnicity, and parent education level, self-regulation remains a crucial contributing factor to academic achievement (Duncan et al., 2007). Similarly, when accounting for variables like self-efficacy and prior achievement, students' regulatory behaviors show strong correlations with their grade point averages and teacher ratings of academic competence (Eisenberg et al., 2010). Some research has indicated that a student's ability to apply flexible strategies, supported by self-regulation processes, distinguishes high-achieving students from those with average performance (Zimmerman

& Pons, 1990). Further, studies conducted with high school students have demonstrated that self-regulatory behaviors predict final grades, as well as their interest and intention to pursue higher education (Nota et al., 2004).

The relationship between students' self-regulation and educational environments is reciprocal. Just as the self-regulatory mindsets and behaviors students bring to the classroom shape their academic experience, the expectations of the classroom and school environment play a role in shaping those regulation processes (Perry, 1998; Eisenberg et al, 2010; Ramdass Zimmerman, 2011). Students in classrooms that demand or encourage high engagement of self-regulation, such as promoting metacognition or checking work, tend to internalize these characteristics more than their peers in less structured classrooms (Perry, 1998). Moreover, procedures like homework can exert a strong positive influence on developing students' regulation behaviors, especially in middle and high school, as it necessitates self-motivation, inhibition, time management, planning, goal setting, and delaying gratification (Ramdass & Zimmerman, 2011).

Mathematics Learning

The connections between competence in mathematics and overall academic success, as well as later professional advancement, are substantial, as emphasized by the US Department of Education (1997) in their white paper titled "Mathematics Equals Opportunity." Proficiency in mathematics during K-12 settings correlates with increased rates of college enrollment, enhanced employment opportunities, and higher incomes (U.S. Department of Education, 1997). This positive impact on future opportunities is particularly pronounced for low-income students, highlighting the potential for upward social mobility through engagement with mathematics (U.S. Department of Education, 1997). The significance of mathematics is underscored by advocates for instructional reform in the United States, given the country's consistent below-average ranking in mathematics on the international stage (Organisation for Economic Co-operation and Development (OECD), 2019).

Mathematical competency, measurable as early as kindergarten, serves as a robust predictor of later math achievement throughout academic years (Claessens & Engel, 2013). While highlighting the cumulative nature of mathematical skill development, research indicates that specific K-12 coursework may be particularly influential in unlocking later opportunities. Mastery of high school algebra content, in particular, strongly correlates with college acceptance, obtaining a college degree, and achieving higher income brackets (National Mathematics Advisory Panel (NMAP), 2008).

While the importance of mathematics competence for future opportunities is established, this relationship is not uniform across individuals. Factors influencing the connection between mathematics education and later achievement include socioeconomic status, gender, emotional dispositions, instructional methods, and teacher characteristics (Grootenboer & Hemmings, 2007; NMAP, 2008). Economic and environmental factors, particularly in low-income communities, can limit access to rigorous math instruction, negatively impacting post-secondary opportunities and disproportionately affecting minoritized students (Gamoran et al., 1997; Battey, 2013).

Math anxiety also presents a significant barrier, leading students to avoid and disengage from mathematics coursework, negatively affecting knowledge, grades, standardized test scores, and reducing the likelihood of enrolling in advanced mathematics coursework (Ramirez et al., 2013). This anxiety can emerge as early as elementary school, establishing a detrimental foundation for students' educational journeys (Ramirez et al., 2013).

Educational environment factors, such as teacher characteristics and instructional pedagogies, also impact students' acquisition of mathematical mastery. Teachers' mathematical knowledge, measured by certifications or degrees, is consistently linked to student achievement, especially in high school (NMAP, 2008; Wayne & Youngs, 2003). While research does not exclusively support student-centered or teacher-directed pedagogies, specific practices, such as cooperative learning for computation skills, can facilitate the acquisition of specific concepts (Natasi & Clements, 2019; NMAP, 2008). The use of instructional software allowing repetitive skill practice has also shown positive impacts on mastering math concepts and improving problem-solving abilities (Roschelle et al., 2000; NMAP, 2008).

Self-Regulation and Mathematics Learning

Given the demands of learning mathematics in academic environments, which prioritize focused problem-solving over abstract conceptualization, many researchers underscore the significance of self-regulation characteristics for success in math achievement (De Corte et al., 2000). Some even propose that a specific mathematical disposition can only be attained through self-regulatory processes like metacognition and self-monitoring (De Corte et al., 2000). Thus, De Corte and colleagues (2000) posit that, as mathematics learning necessitates self-regulation processes for success, mathematics classes provide well-suited venues for explicit interventions to scaffold students' self-regulation skills, proving mutually beneficial to their mathematics acquisition.

Self-regulation processes, such as goal setting, self-monitoring/self-evaluation, and metacognition, positively impact mathematics learning (Wang et al., 2019). Growth mindset and resilience fostered by regulatory traits and processes correlate positively with mathematics performance (Park et al., 2016). Assisting students in setting goals and promoting self-evaluation during math problem-solving has been associated with improved motivation, task orientation, and overall math achievement outcomes (Schunk, 1996). Schunk (1996) suggests that structured opportunities for students to self-evaluate enable them to identify progress, building self-efficacy and motivation in the context of math learning. In another study, incorporating self-regulated learning processes, specifically metacognition, goal setting, and self-evaluation, into third-grade students' mathematics instruction enhanced their mathematical problem-solving abilities (Fuchs et al., 2003).

Some studies have explored the impacts of scaffolding self-regulation skills into mathematics lessons. Blair and Raver (2014) found that embedding self-regulation supports into kindergarten classroom instruction resulted in improvements in students' mathematics by the end of the year, with academic gains sustained into the following school year. These gains were notably significant in high-poverty schools, suggesting implications for education reform and addressing the achievement gap between low and high-income students (Blair & Raver, 2014). Similarly, a self-regulation intervention designed for students in Head Start classrooms was associated with higher mathematical achievement for students who were English language learners (Schmitt et al., 2015). Research examining the efficacy of an intervention promoting self-regulated learning strategies and mindsets successfully increased student regulation and motivation to engage in mathematics learning, especially for low-achieving students and those with learning disabilities (Fuchs et al., 1997). For low-achieving students, increased efforts were associated with enhanced mathematics learning, although these improvements were not observed for students with learning disabilities (Fuchs et al., 1997).

Other studies have delved into the role of regulation within specific mathematics subject areas. Research indicates that attentive regulated behavior in the classroom was a differentiator between students who successfully developed fraction skills and those who struggled with these skills (Hecht & Vagi, 2010). Similarly, Hansen and colleagues (2015) found that attentional control strongly correlated with predicting students' benefit from direct instruction and the acquisition of fraction knowledge. Attentional control has also been linked to fraction magnitude estimation and success in completing fraction arithmetic (Ye et al., 2016). Though Ye and colleagues (2016) emphasize the bidirectional nature between attention and fraction learning, if students attain fluency with mathematics concepts in prior coursework, they become less reliant on cognitive and attentional resources when solving fraction problems, resulting in greater efficiency and success in these tasks.

Research specifically investigating self-regulation processes in algebra learning highlights the necessity of regulatory behaviors for successful algebraic problem-solving. Algebra learning depends on applying previously learned mathematics skills and concepts, engaging in novel processes, and holding newly learned symbolic representations in mind—requiring concerted self-monitoring and attentional effort (Maccini et al.,1999). This attentional control is crucial to algebra mastery, as problem-solving often involves multiple steps, necessitating students to monitor their process while holding onto the symbolic meanings of symbols to determine the correctness of their solutions (Maccini et al.,1999).

Overall, the connections between regulatory processes, traits, and behaviors are intricately tied to overall academic outcomes, including success in specific subjects such as mathematics. As regulatory behaviors unfold through a protracted developmental period influenced by reciprocal interactions between the individual and the environment (e.g., school, home), it is crucial to consider how unexpected or disruptive experiences impact this person-environment interaction. The widespread personal and societal impacts of the COVID-19 pandemic, which disrupted traditional schooling, offer a unique opportunity to examine how unexpected disruptions can impact the relationship between self-regulation and learning.

COVID-19 Pandemic

The COVID-19 virus was declared a pandemic in March 2020, leading to the implementation of lockdowns by countries, states, and cities, resulting in the closure of social spaces, businesses, and schools. No individual or segment of society remained unaffected by the personal, medical, social, psychological, and economic impacts of the pandemic and the associated lockdowns (Feinberg et al., 2022; Fernández et al., 2020). It is undeniable that the repercussions of the COVID-19 pandemic will extend across generations, and comprehensively understanding these consequences will necessitate ongoing research studies for years to come. The focus of this study is to specifically examine the potential consequences for a subset of the 55 million U.S. students whose schools were shuttered, leading to a complete reconfiguration of their educational experiences.

COVID-19 School Disruptions

The COVID-19 pandemic is aptly described as "unprecedented," yet exploring studies on previous disruptive events affecting student access to school can offer insights into conceptualizing the expected impacts of this pandemic. Specifically, research on out-of-school time due to reasons such as weather emergencies or chronic absenteeism can draw interesting parallels and potentially provide insights into appropriate next steps for remedying the negative impacts of the pandemic on schooling.

Studies on school closures arising from natural disasters and inclement weather are especially relevant, given that these closures mirror the unexpected nature of COVID-19 school closures. Research indicates that each day a school is closed due to snow-related emergencies can have varying impacts, ranging from null effects to, as found in one study, a small reduction in mathematics achievement (Kuhfeld et al., 2020). While some of these studies note an overall null effect, a significant drop in mathematics achievement was found in schools with a high percentage of free or reduced lunch eligible students (Kuhfeld et al., 2020). Further, students affected by larger events like weather emergencies, such as Hurricane Katrina, have demonstrated small overall achievement drops extending into the subsequent school year (Kuhfeld et al., 2020).

Apart from students impacted by larger events, many students experience personal circumstances (e.g., illness, lack of transportation) leading to chronic absenteeism. On average, students missing ten days of school have lower end-of-year math scores than their peers (Kuhfeld et al., 2020). Students from low-income communities and racially minoritized identities are more likely to be chronically absent, facing stronger negative academic consequences, and are at a higher risk of permanent disengagement and eventual dropout (Garcia & Weiss, 2020).

Seasonal learning studies, which focus on the effects of summer learning loss, commonly referred to as summer slide, can help predict expected learning outcomes resulting from pandemic-related school closures. Research on seasonal learning indicates that students often experience academic declines during the summer months, with more significant declines in mathematics than reading (Kuhfeld et al., 2020). However, findings are not always consistent, as some studies report students losing about three months' worth of mathematics over the summer, while others show zero change in competencies (Kuhfeld et al., 2020; Garcia & Weiss, 2020). Despite varying results, researchers agree that the summer months can contribute to widening the achievement gap between low and high socioeconomic status students, this trend is influenced by factors like access to educational resources within their home and community (Garcia & Weiss, 2020).

Overall, prior research on out-of-school time is illuminating. Patterns suggest that when students' learning is disrupted, they experience more significant learning losses in mathematics than other subjects, and that these losses disproportionately affect students from low-income communities and racially minoritized populations (Garcia & Weiss, 2020; Goldberg, 2021; Fahle et al., 2023). In fact, National Assessment of Educational Progress (NAEP) data collected in 2022 by the National Center for Education Statistics (NCES) suggest a similar pattern. Indeed, the 2022 NAEP scores imply even more pronounced setbacks for student learning and performance (NCES, 2022). Thus, suggesting that the education impacts of the COVID-19 pandemic may be more detrimental than previously experienced educational disruptions.

Virtual Instruction During COVID-19 School Closures

One of the most notable changes ushered in by COVID-19 was the almost universal transition to remote learning in K-12 education during the spring of 2020. Around 83% of America's students engaged in some form of virtual instruction during this period (Kuhfeld et al., 2020).

Empirical research comparing learning gains in in-person and remote settings during the pandemic has yielded varied outcomes. Tomasik and colleagues (2021) discovered substantial variability in learning gains during remote learning, with elementary school students experiencing a significant reduction in newly acquired information, while secondary school students generally maintained their learning pace in the remote environment. These patterns align with developmental expectations, as younger students may require more explicit instruction and have not fully developed executive skills like self-regulation for independent learning in virtual contexts (Tomasik et al., 2021).

Teachers reported reduced contact with students during COVID-19 remote learning, primarily relying on email for communication (Kuhfeld et al., 2020). Teachers estimated that students spent half the usual time learning compared to traditional in-person instruction, and virtual instruction often focused on reviewing previous lessons rather than introducing new skills (Kuhfeld et al., 2020; Goldberg, 2021).

Another barrier was the lack of access to online learning environments for many students, particularly those from low-income families and families of color (Goldberg, 2021). The "digital divide" became evident, as students of color and those from low-income households faced challenges accessing virtual instruction compared to their White and higher-income peers (Goldberg, 2021; Garcia & Weiss, 2020). During initial shutdowns, a Southern Education Foundation report revealed that one in five African American students lacked internet access at home, a number higher for students from low-income homes (Garcia & Weiss, 2020). Principals serving predominantly students of color and lower-income households reported losing touch with 30% of students and families, compared to 14% in wealthier, mostly white schools (Goldberg, 2021).

Further, schools across the United States faced challenges in providing appropriate instructional accommodations and pedagogies in the virtual environment (Kuhfeld et al., 2020). Parents of students with Individualized Education Programs (IEPs) were more likely to report that their children were not learning well in the virtual school setting (Goldberg, 2021). Despite efforts to offer suitable remote instruction for IEP students, research suggests that various personal, interpersonal, and environmental factors played a role in whether IEP students received adequate instruction (Kuhfeld et al., 2020). Further, the sudden shift to online teaching likely left many educators without the time or skills to adapt their instructional practices for the virtual environment. The sudden transition to online teaching may have left many educators ill-equipped to adapt their instructional methods, as demonstrated by the challenges observed in translating inquiry-oriented pedagogy to the virtual setting, which requires more explicit linkages between instruction and concepts (Sawchuk & Sparks, 2020).

Self-Regulated Learning in Online Environments

Existing research on the role of regulation in online learning environments offers potential insights into the repercussions of the shift to online education in response to COVID-19. Students may face challenges in online settings if they lack or fail to apply foundational self-regulated learning procedures and strategies (Azevedo, 2018). Consequently, self-regulated learning processes, encompassing time management, metacognition, effort, and critical thinking, are closely tied to successful learning in online environments (Broadbent & Poon, 2015).

While research in this area is complicated by the multitude of factors at play among students, their virtual learning space, and their physical environment, specific considerations can aid in the development of students' self-regulation capabilities in the online realm (Azevedo & Hadwin, 2005). In face-to-face instruction, passive strategies and the overall school environment may suffice to foster the development of student regulation, but explicit instruction and scaffolding become imperative in the online environment (Azevedo & Hadwin, 2005). Ideally, online instructional design should offer additional pacing support, actively monitor and encourage participation, and prompt students to reflect on their problem-solving approaches to enhance engagement and learning (Carter et al., 2020). Practices such as prompting, visual feedback, and reflective questions prove beneficial in cultivating self-regulated learning and improving academic performance in online environments (Wong et al., 2019).

Despite suggested best practices, researchers underscore that the impact of self-regulated learning strategies tends to be weaker in online learning environments compared to traditional classrooms (Broadbent & Poon, 2015). This discrepancy may be especially pronounced if teachers merely transpose in-person pedagogies to the online setting without leveraging the additional tools afforded by virtual classes (Broadbent & Poon, 2015). This is particularly pertinent as the impromptu shift to virtual learning during COVID-19 school shutdowns placed many teachers in the position of migrating in-person classroom lessons to online environments without adequate time, tools, or training to adapt pedagogy with virtual learning best practices (Sawchuk & Sparks, 2020). Under these circumstances, a student's personal characteristics, such as their self-regulation, may have assumed heightened importance during the period of online learning.

COVID-19 Impacts to Mathematics Learning

Researchers anticipate that a generation of learners will experience a regression, sometimes referred to as the "COVID-19 slide," in their academic achievement due to the repercussions of pandemic-induced school closures, with mathematics abilities being more adversely affected than other skills like reading (Sawchuk & Sparks, 2020). Studies conducted during the initial school shutdowns in Spring 2020 projected that upon returning to school in fall 2020, students would commence the year with only 37% to 50% of the learning gains expected from the previous year, particularly in mathematics (Kuhfeld et al., 2020). Alarmingly, students without stable or any access to remote learning were predicted to be a full year behind in mathematics (Kuhfeld et al., 2020).

Data collected in the fall of 2020 yielded mixed results across academic subjects, though generally math skills exhibited the most pronounced setbacks (Goldberg, 2021). Assessments from the Northwest Evaluation Association (NWEA) MAP Growth revealed a 5% to 10% decline in expected math achievement among students in fall 2020

(Goldberg, 2021). While another study indicated that students began the fall 2020 academic year with approximately 67% of their anticipated math knowledge (Goldberg, 2021). Although some academic progress occurred during the 2020-2021 school year, a complete recovery of lost instruction was not achieved, and by winter 2021, students were still lagging behind pre-pandemic expectations, particularly in mathematics (Goldberg, 2021).

NWEA reported that by fall 2021, students in grades 3-8 were averaging math scores below pre-pandemic levels, indicating a significant decline in performance (Kuhfeld et al., 2022). Notably, the data revealed not only a drop in average student mathematics performance during the initial school shutdowns but a continued decline into the second year of the pandemic, a trend not observed in other subjects like reading (Kuhfeld et al., 2022). Suggesting that students are consistently starting each consecutive year less prepared in mathematics than prior to the pandemic. This trend aligns with other studies indicating that, on average, students concluded the 2020-2021 school year approximately five months behind expectations in mathematics competencies (Dorn et al., 2021).

NAEP data, collected in 2022, further demonstrate the learning loss that occurred for students following the disruptions of the pandemic. Most startingly, the 2022 data captured the first ever drop in mathematics performance since data were first collected in 1973, underscoring the existence of true learning loss for students following the COVID-19 pandemic (NCES, 2022). Performance declines, from the last year data were collected (2020), were seen for all percentile levels of students, but were most pronounced for lower performing students (bottom 25th percentile) who showed scaled score declines of

11 points, while students in the top 75th percentile showed declines of 5 points (NCES, 2022). These higher performing students were also more likely to report that they had access to the necessary resources (i.e., reliable internet connection, computing devices, quiet space to work, etc.) to learn remotely, essential tools for continued learning during school closures (NCES, 2022). Furthermore, results demonstrated more significant average declines in mathematics performance for Black students, who exhibited a 13-point decrease, compared to White students who had a 5-point decrease (NCES, 2022). Overall, 2022 NAEP data suggest significant learning loss in students’ mathematics performance and underscore the increased vulnerability of learning loss for already marginalized (i.e., racially minoritized, lower resource) students.

COVID-19 Impacts to Self-Regulation

The onset of COVID-19 compelled students to abruptly transition to virtual learning, placing an immediate reliance on their regulatory processes and available home support systems for guidance in their education. Those with high levels of self-regulation demonstrated success in virtual education, while students grappling with these skills faced challenges and were more prone to disengagement (Garcia & Weiss, 2020). According to a representative sample of American students (n=7,705) in grades 9-12, approximately two-thirds of adolescents encountered difficulties completing schoolwork during virtual instruction (Krause et al., 2022).

Schools play a pivotal role in shaping students' self-regulation skills through activities, routines, and norms. Therefore, the replacement of the school environment with students' homes raises concerns about varying impacts, contingent on the context of their home life. Historical instances, such as the unexpected removal of the school environment post-Hurricane Katrina, revealed negative influences on students' behavioral regulation, including lower self-control and increased engagement in disruptive behaviors (Garcia & Weiss, 2020).

Moreover, home environments and lack of connection to peer groups may have been detrimental to students' emotional well-being, negatively affecting their developing regulation abilities. Estimates suggest that during shutdowns, 55% of American adolescents experienced emotional abuse from parents or caregivers, with higher rates observed among LGBTQIA community members and those from minoritized racial or ethnic groups (Krause et al., 2022). Black adolescents, in particular, experienced physical abuse at a rate 15%, higher than any other racial group (Krause et al., 2022). Chronic stress and abuse have been linked to poor emotional regulation, increased avoidance, internalizing and externalizing behaviors, and difficulties coping with future stress (Gruhn & Compas, 2020). Further, data collected internationally after COVID-19 lockdowns reported increased youth reports of anxiety, depression, psychological distress, irritability, loneliness, and stress (Panchal et al., 2021).

Recent federal research from the Institute of Education Sciences offers a comprehensive perspective on the enduring impacts of these experiences within school contexts. Seventy percent of public schools report an increase in students' mental health needs since the pandemic, and over eight in ten schools note "stunted" behavioral and socioemotional development among students since returning from lockdown (U.S. Department of Education, 2022). While slightly more than half of public schools report having resources to address these needs, the long-term feasibility and efficacy of these interventions remain uncertain (U.S. Department of Education, 2022).

This Study and Hypotheses

This study aims to contribute to the existing literature by further investigating the relationship between environmental factors and the development of self-regulation, as well as the relationship between self-regulation and academic achievement. Specifically, we will examine whether the development of self-regulation and its influence on academic performance are significantly affected by the stress and impacts of the COVID-19 pandemic for our participant sample that included students in grades four through ten and their parent or guardian.

Preliminary analysis included exploratory factor analysis and convergent validity analyses to examine the factor structure of the Fast-Track Project Child Behavior Questionnaire and validate the measure with established metrics of child behavior and regulation. It is hypothesized that, through factor analysis, the Fast Track Behavior Questionnaire, a unidimensional construct, will be able to produce two discernable factors that represent cognitive regulation and emotional regulation. The results of factor analysis will guide subsequent analyses of self-regulation in the study. Anticipated results of convergent validity tests include predictable correlations between the self-regulation questionnaire and established measures of personality and psychosocial functioning, namely the Pediatric Symptoms Checklist (Jellinek et al., 1999) and the Big Five Inventory (John & Srivastava, 1999). It is expected that:

1. Higher scores (poorer regulation) on the Fast Track Behavior Questionnaire will be correlated with the subscales of attention problems, internalizing problems, and externalizing problems on the Pediatric Symptoms Checklist (Achenbach & Edelbrock, 1991).

2. Higher scores (poorer regulation) on the Fast Track Behavior Questionnaire will positively correlate with neuroticism and negatively correlate with conscientiousness and agreeableness as measured through the Big Five Inventory (Gramzow et al., 2004).

Multilevel models were fitted to explore the development of self-regulation and its relationship with mathematics competence, as well as how COVID-19 stress and its impacts moderated this development and relationship. This was examined through two data points Time Zero, which represents data collected in 2020-2021 school year and Time One, which represents data collected during the 2021-2022 school year. The primary aim of this research is to assess whether this sample of students exhibits predictable patterns of self-regulation development and academic performance, and to ascertain if factors related to the COVID-19 pandemic have influenced this development and relationship in unforeseen ways.

Research Questions

1. How does child self-regulation change from Time Zero to Time One? Is this change significantly moderated by COVID-19 impacts and stress?
2. How does self-regulation predict performance on grade level math measures? Is this change significantly moderated by COVID-19 impacts and stress?

Hypotheses

1. Student self-regulation will improve from Time Zero to Time One, COVID-19 stress and impact will produce a significant negative impact on this development.
2. Student self-regulation will be a strong predictor of their performance on grade-level mathematics measures. I expect that this relationship will be significantly

negatively impacted by the amount of COVID-19 stress and impacts that were experienced by student participants and their family.

CHAPTER 3

METHODOLOGY

This study conducted an in-depth analysis of data derived from an ongoing, comprehensive research project that longitudinally investigates the effects of COVID-19 disruptions (e.g., school closures, remote learning, family stressors) on students' trajectories in mathematics learning. The data utilized in this study is sourced from two timepoints in that larger longitudinal project. Data within this dissertation consists of Time Zero data collected during the spring and summer of 2021, wherein respondents provided information pertaining to the 2020-2021 school year, and Time One data that was collected in the spring and summer of 2022, with respondents providing data related to the 2021-2022 school year. The focus of this study includes the following three overarching analyses:

1. An examination of how student self-regulation changed from Time Zero to Time One. Further analysis explored how COVID-19 impacts and stress moderated self-regulation development.
2. An examination of how student self-regulation at Time Zero predicted their grade-level math outcomes at Time One. Further analysis explored how COVID-19 stress and COVID-19 impact at Time Zero moderates this relationship.
3. An examination of how student self-regulation at Time One predicted their grade-level math outcomes at Time One. Further analysis explored how COVID-19 stress and COVID-19 impact at Time Zero moderates this relationship.

Participants

Initial recruitment (Time Zero) for this study was completed in the spring and summer of 2021. The Time Zero sample included students (*N* = 705) and their parents (*N*= 502) from 42 different U.S. states. The student participants were enrolled in fourth through tenth grade. Of these students, 46% identified as female, 52% as male, and 2% as non-binary/other. The race/ethnicity breakdown of the sample is 13% Asian or Asian-American, 4% Black or African American, 69% Caucasian, 7% Hispanic/Latinx, and 7% other. Of note, during our analyses involving racial information, participants who identified as Hispanic/Latinx ethnicity were grouped into the White racial identity category unless otherwise specified in their survey response (e.g., "Latina/Black"), in which case they were grouped with the appropriate racial category. The highest education level of the student's mother was also collected as a proxy for socioeconomic status (SES) and indicated that 59% of the mothers had graduate degrees, 28% Bachelor's degrees, and 13% Associate's degree or high school diploma.

The Time One sample, collected in the spring and summer of 2022, includes students (*N*=728) and their parents (*N*= 515) from 47 different U.S. states. Of the 728 student participants at Time One, 499 were return participants from Time Zero. The student participants were enrolled in fourth through tenth grade. Of these students 46 % identified as female, 51% as male, and 3% as non-binary/other. The race/ethnicity breakdown at Time One is not provided due to an error in data collection that wrongly assigned racial information of certain groups (i.e., individuals who marked that they identify as "African American/Black" in Time Zero were marked as "Asian" in Time

One), resulting in zero African American/Black individuals at Time One). For this reason, analyses that included racial demographic information used Time Zero racial demographic information only. The highest education level of the student participant's mother showed that 63% of the mothers had graduate degrees, 27% bachelor's degrees, 4% Associate's degree, and 6% had some college and/or a high school diploma.

Despite the study requirement that each student participant must have a corresponding parent participant, the total sample of student participants (*N*=934) does not match the number of parent participants (*N*=778) across the two time points. This discrepancy is because several parent participants had multiple children participating in the study. At Time Zero, 93 parents had more than one child in the study and 100 parents at Time One completed the parent report measure for more than one child. Parent participants were given a single ID to use across their multiple submissions for each child, thus explaining the seeming discrepancy between student participant and parent participant numbers. These ID numbers allowed me to enter family as variable in the analyses.

Measures

Fast-Track Project Child Behavior Questionnaire

The Fast-Track Project Child Behavior Questionnaire is a 20-item survey, derived from the Child Behavior Checklist (CBCL) (Achenbach & Edelbrock, 1991). This instrument is used to measure the self-regulation abilities of children and adolescents, encompassing aspects of cognitive and emotional self-regulation. Respondents, including students and their respective parents or guardians, evaluated the strength of each item on a four-point Likert-type scale, ranging from "1= all of the time" to "4 = none of the time."

Originally intended for self-report, the Fast-Track Project Child Behavior Questionnaire was not specifically designed for parent/guardian reporting. Consequently, certain items were modified to accommodate their input, such as the adjusted response option: such as “I wait my turn during activities” adjusted to "My child waits their turn during activities."

COVID-19 Experience Survey

Participating parents completed a survey that delved into the repercussions of the COVID-19 pandemic on themselves and their family. This survey, adapted from Cohen et al. (2020), explored various domains of potential impact, encompassing financial, emotional, social, and academic experiences. Respondents provided insights on a range of stressors, including questions such as, "To what extent were you stressed about contracting COVID-19 in the 2020-2021 school year" and "To what extent were you stressed about your child contracting COVID-19 in the 2020-2021 school year?" These inquiries prompted responses on a 5-point Likert-type scale, spanning from "Not at all," equating to a score of 0, to "Extremely," equating to a score of 4.

Parents were also presented with queries such as, "Thinking about the pandemic's impact on your own life, which of the following applies to you? This pandemic has..." requiring them to choose from options such as "Had a very significant financial impact," "Had a moderate impact (e.g., cutting spending on food, entertainment, and other expenses)," or "Had little to no financial impact." Survey responses were converted to a 0-2 scale with “had no impact,” equating to a score of 0, and “had a very significant impact,” equating to a score of 2.

Thus, it was determined that the COVID-19 experience survey should be split into two factors “COVID-19 Stress” and “COVID-19 Impact” to account for the differing topics and scales of the survey items. The resulting variable of “COVID-19 Stress” consisted of ten survey items, while “COVID-19 Impact” consisted of seven survey items.

Big Five Inventory

Personality was measured using the Big Five Inventory (BFI)—Parent/Teacher form (John & Srivastava, 1999). This 44-item measure has established validity and reliability for capturing five domains of personality: extroversion, agreeableness, conscientiousness, neuroticism, and openness (John & Srivastava, 1999). Parents of student participants will indicate responses regarding their student’s personality on items such as “I see my child as someone who... - Is full of energy” with a 5-point Likert-type Scale ranging from 1 (strongly disagree) to 5 (strongly agree). The BFI was used in preliminary analyses that investigated the validity of the Fast-Track Project Child Behavior Questionnaire (Gramzow et al., 2004).

Pediatric Symptom Checklist

Psychosocial Functioning is measured using the Pediatric Symptom Checklist (PSC; Jellinek et al., 1999). This 35-item measure has established validity in identifying school aged children who have difficulties with psychosocial functioning (Jellinek et al., 1999). In addition to a total score that assesses overall risk for psychosocial difficulty, the PSC produces three subscales; attention, internalizing, and externalizing (Jellinek et al., 1999). Parents will indicate responses regarding their student’s psychosocial behaviors such as “Complains of aches or pains”, “Spends more time alone”, and “Tires easily, little energy”, on a 3-point Likert-type Scale ranging from Never to Often. The PSC was used in preliminary analyses that investigated the validity of the Fast-Track Project Child Behavior Questionnaire (Achenbach & Edelbrock, 1991).

Mathematics Competence

Participating student’s mathematic competence was measured by their performance on grade-level mathematics content. This assessment is comprised of items measuring grade-level Common Core State Standards for mathematics (CCSS-M) content standards from the Partnership for Assessment of Readiness for College and Careers (PARCC) exams. The assignment of grade level assessment was determined by the level of math participants’ parents indicate their child has completed.

Procedures

Recruitment for this study utilized diverse channels, including online advertisements in private social media groups, listservs, and direct engagement with partnered school districts. The target demographic comprised students enrolled in grades four through ten and their parents. The recruitment process commenced in spring through summer 2021 and was repeated in spring through fall of 2022. During each data collection phase, participants were asked for their consent to be contacted for subsequent rounds, while new participants were also invited to partake in the survey.

The study exclusively involved survey completion via Qualtrics, with an estimated completion time of approximately 45 minutes. Initially, parents were presented with a consent form addressing their willingness to participate and seeking consent for their child's involvement. All essential information for informed consent was included in these forms. Upon parental agreement, participants were automatically redirected to the parental section of the surveys.

To ensure the authenticity of completed parent surveys and filter out bot-generated responses, a screening process was implemented. Surveys failing to meet authenticity criteria were excluded from the study data. Parents whose surveys passed screening received an email containing a $10 Amazon gift card as appreciation for their participation, along with a link for their child to complete the student portion of the study surveys.

Before completing their surveys, participating children were required to provide assent. The necessary information for informed assent was provided in these forms. Students who provided assent were automatically redirected to the student portion of the surveys. Similar to the parent surveys, completed student surveys underwent screening to verify authenticity. Surveys meeting screening criteria prompted an email to parents, who, in turn, received a $10 Amazon gift card in recognition of their child's participation in the study.

Variables

This study measured the relationship between student's self-regulation and their performance on grade-level math measures. Operational definitions for each variable are included below:

Self-regulation

Child participant self-regulation scores were derived from the Fast-Track Project Child Behavior Questionnaire. Higher total scores equate to poorer regulation.

Questionnaires were completed by parents and child participants of the study at both Time Zero and Time One.

Mathematics Performance

Mathematics performance refers to students' scores on grade-level math items selected from the PARCC exams, completed at Time One only. These math performance scores are standardized Z-scores, calculated for each grade-level assessment.

COVID-19 Stress

COVID-19 Stress is a composite developed during the preliminary analysis of this study. It refers to the mean score of five items from the COVID-19 Experience Survey, with each item scored on a scale from 0 to 4.

COVID-19 Impact

COVID-19 Impact refers to the sum score of seven items from the COVID-19 Experience Survey, which inquired about disruptions families experienced due to COVID-19. Each survey item was scored on a scale from 0 to 2.

Analyses

Preliminary Analyses of Fast-Track Project Child Behavior Questionnaire

Comprehensive literature review revealed limited information available regarding the Fast- Track Project Child Behavior Questionnaire. Thus, preliminary analyses were conducted to examine the structure of the Fast-Track Project Child Behavior Questionnaire to determine reliability of the survey as a unidimensional construct, as it was designed, and to determine whether two factors, cognitive self-regulation and emotional self-regulation, could be derived from the questionnaire. Item analysis was also conducted to determine if all Fast-Track Project Child Behavior Questionnaire items were necessary to support optimum reliability. The ten items from the questionnaire that were grouped to produce a hypothesized factor of child cognitive regulation from the parent-report included:

1. My child waits their turn during activities.
2. My child thinks before they act.
3. My child does what they are told to do.
4. When my child wants something, they are patient when waiting.
5. My child follows the rules.
6. My child sticks with an activity until it is finished.
7. My child can concentrate and focus on one activity at a time.
8. My child ignores kids who are fooling around in class.
9. My child tells new kids their name without being asked to tell it.
10. My child asks friends for help with their problems.

The ten items from the questionnaire that were grouped to produce a hypothesized factor of child emotional regulation from the parent-report included:

1. My child copes well with disappoint or frustration.
2. My child accepts it when things do not go their way.
3. My child's feelings get hurt.
4. When my child gets upset, they whine or complain.
5. My child controls their temper when there is a disagreement.
6. My child stops and calms down when they are frustrated of upset.

7. My child fights or argues with adults.
8. When people are angry with my child, my child controls their anger.
9. When someone tells my child a rule they think is unfair, they ask about the rule in a nice way.
10. When my child disagrees with me, my child yells and screams.

The ten items from the questionnaire that were grouped to produce a hypothesized factor of cognitive regulation from the child self- report included:

1. I wait my turn during activities.
2. I think before I act.
3. I do what I am told to do.
4. When I want something, I am patient in waiting.
5. I follow the rules.
6. I stick with an activity until it is finished.
7. I can concentrate and focus on one activity at a time.
8. I ignore kids who are fooling around in class.
9. I tell new kids my name without being asked to tell it.
10. I ask friends for help with my problems.

The ten items from the questionnaire that were grouped to produce a hypothesized factor of emotional regulation from the child self-report included:

1. I cope well with disappointment or frustration.
2. I accept it when things do not go my way.
3. My feelings get hurt.
4. When I get upset, I whine or complain.

5. I control my temper when there is a disagreement.
6. I stop and calm down when I am frustrated or upset.
7. I fight or argue with adults.
8. When people are angry with me, I control my anger.
9. When someone tells me a rule that is unfair, I ask about the rule in a nice way.
10. When I disagree with my parents, I yell and scream.

Furthermore, in light of the limited information available on the efficacy of the Fast-Track Project Child Behavior Questionnaire, preliminary analyses also included an examination of the questionnaire's convergent validity by comparing it with established measures of behavior, namely the Pediatric Symptom Checklist (PSC) and Big Five Inventory (BFI).

Preliminary Analyses of COVID-19 Experience Survey

The COVID-19 Experience Survey was designed by researchers conducting the ongoing longitudinal study from which this dissertation obtained data. For this current study, the COVID-19 Experience Survey was split into two separate factors, seven questions regarding COVID-19 Impacts were grouped and ten questions regarding COVID-19 Stress were grouped.

Given the untested nature of the produced factors, exploratory factor analysis was conducted to determine reliability of COVID-19 Impact and COVID-19 Stress items and identify whether all survey items were necessary to support reliability.

Preliminary Analyses of Grade-Level Mathematics Competence

Mathematic competence was measured by student performance on grade-level mathematics content. These assessments are comprised of items measuring grade-level

Common Core State Standards for mathematics (CCSS-M) content standards from The Partnership for Assessment of Readiness for College and Careers (PARCC) exams. Exploratory factor analysis was conducted, at each grade level, to determine reliability of questions and identify whether all survey items were necessary to support reliability.

Regression Analyses

Multilevel modeling, or hierarchical linear modeling (HLM), was used to answer the three main research questions of this study. HLM is particularly well-suited for analyzing this large dataset that contains; some missing data (i.e., participants entering the study at different time points) and some nested data (participants within families). Random intercepts at both the individual and family level were included to account for within and between group (family) variability.

The first research question investigated how child self-regulation, as measured by parent-report and self-report, changed from Time Zero to Time One. To determine this change we built multi-level models. I hypothesized that child self-regulation would improve from Time Zero to Time One. I also hypothesized the COVID-19 stress and impacts would have a significant negative effect on child self-regulation. Additional analyses (i.e., analysis of school types, mother income, racial identity, etc.) were also conducted to provide additional context to explain and understand child self-regulation change.

The next research questions examined how and if child self-regulation at Time Zero and Time One predicts performance on grade-level mathematic measures at Time One. I hypothesized that student self-regulation will serve as a strong predictor of student mathematic performance. The relationship between self-regulation and mathematics performance was further examined in the context of COVID-19 stress and COVID-19 impacts. I hypothesized that higher levels of COVID-19 stress and COVID-19 impact would negatively impact the relationship between self-regulation and grade-level mathematic performance. Additional analyses (i.e., analysis of school types, mother income, racial identity, etc.) were also conducted to provide additional context to examine the relationship between child self-regulation and mathematics performance.

CHAPTER 4

RESULTS

Preliminary Analyses

Parent-Reported Self-Regulation as a Unidimensional Construct

For the factor analysis of the parent-reported self-regulation, 1000 iterations were conducted to confirm the factor structure for this sample. An item analysis was performed to assess the necessity of all items in the Fast-Track Project Child Behavior Questionnaire to ensure optimal reliability.

Exploratory factor analysis indicated that the Fast-Track Project Child Behavior Questionnaire forms a reliable unidimensional construct of self-regulation in parent reports at both Time Zero and Time One. The questionnaire, comprising all twenty items, exhibited strong internal consistency, with a Cronbach's alpha of $\alpha = .88$. However, further item analysis suggested that removing two items with low factor loadings (.11 each), namely, “My child tells new kids their name without being asked to tell it” and “My child asks friends for help with their problems,” would enhance reliability, resulting in a Cronbach's alpha of $\alpha = .90$. This improvement in reliability, achieved by excluding the aforementioned two items, was consistently replicated at both Time Zero and Time One. Consequently, based on improved p-values and clinical judgment, these two items were excluded from the unidimensional construct, and the remaining eighteen items were retained for the parent-reported child self-regulation measure.

Parent-Reported Child Self-Regulation as a Two-Factor Construct

The exploratory factor analysis also investigated the feasibility of delineating two distinct self-regulation factors from the parent-reported data to represent cognitive and emotional regulation. Parallel analysis provided support for establishing these two factors within the parent-report of child self-regulation. Table 1 displays the factor correlations, revealing a robust positive correlation between the identified cognitive and emotional regulation factors.

Table 1. Correlation Matrix of Parent-Reported Child Self-Regulation

Factor Loadings

	PA1	PA2
My child follows the rules.	.74	–.06
My child can concentrate and focus on one activity at a time.	.69	–.06
My child sticks with an activity until it is finished.	.67	.01
My child does what they are told to do.	.67	.03
My child ignores kids who are fooling around in class.	.60	–.01
My child thinks before they act.	.48	.32
My child waits their turn during activities.	.47	.13
When my child wants something, they are patient when waiting.	.46	.26
When someone tells my child a rule that they think is unfair, they ask about the rule in a nice way.	.33	.19
My child asks friends for help with their problems.	.23	–.11
My child tells new kids their name without being asked to tell it.	.21	–.09
My child accepts it when things do not go their way.	–.04	.80
My child copes well with disappointment or frustration.	–.04	.77
My child stops and calms down when they are frustrated or upset.	.12	.62
My child controls their temper when there is a disagreement.	.09	.62
When my child disagrees with me, my child yells and screams.	–.03	–.56
When my child gets upset, they whine or complain.	.02	–.48
When people are angry with my child, my child controls their anger.	.20	.40
My child's feelings get hurt.	.12	–.39
My child fights or argues with adults.	–.08	–.31

Factor Correlations

	PA1	PA2
PA1	1	.70
PA2	.70	1

Subsequent item analysis was conducted to assess the reliability of these factors and to address items displaying low-item correlation or cross-loadings. For the ten items hypothesized to contribute to emotional regulation, internal consistency was strong, yielding a Cronbach's alpha of $\alpha = .80$. However, dropping two items, namely, “My child’s feelings get hurt,” and “My child fights or argues with adults” was found to enhance reliability, resulting in a Cronbach's alpha of $\alpha = .83$. This improvement in reliability was consistently replicated at both Time Zero and Time One, leading to the exclusion of these two items from the emotional-regulation construct in the parent-reported self-regulation measure.

Similarly, the ten items hypothesized to contribute to cognitive regulation exhibited good internal consistency, reflected in a Cronbach's alpha of $\alpha = .80$. Yet, item analysis indicated that dropping two items, specifically, “My child tells new kids their name without being asked to tell it,” and “My child asks friends for help with their problems,” would elevate reliability to $\alpha = .85$. This enhanced reliability was consistently replicated at both Time Zero and Time One, leading to the exclusion of these two items from the cognitive-regulation construct in the parent-reported self-regulation measure. However, because we modified the survey from its original format, all analyses were run a second time using the survey in its original format to check for any notable differences in outputs. If significant differences were found, they were reported and explored.

Child Self-Reported Self-Regulation as a Unidimensional Construct

For the factor analysis of the student self-report of self-regulation, iterations were set at 1000 to confirm factor structure for this sample. Item analysis was conducted to determine if all Fast-Track Project Child Behavior Questionnaire items were necessary to support optimum reliability.

Exploratory factor analysis suggested that Fast-Track Project Child Behavior Questionnaire is a reliable unidimensional construct of child self-regulation in self- report at Time Zero and Time One. The questionnaire, consisting of all twenty items, demonstrated good internal consistency, with a Cronbach's alpha of $\alpha = .86$. Item analysis indicated that dropping two items with low factor loadings (.19 each), “I tell new kids my name without being asked to tell it" and "I ask friends for help with my problems" would improve reliability at Time Zero, raising Cronbach's alpha to $\alpha = .87$, and at Time One, raising Cronbach's alpha to $\alpha = .88$. Thus, the two items were dropped and the remaining eighteen items were used in the unidimensional construct of child self-report of regulation.

Child Self-Reported Self-Regulation as a Two-Factor Construct

The exploratory factor analysis of child self-report responses regarding regulation did not substantiate the formation of two distinct regulation factors. Table 2 displays the factor correlation matrix, revealing generally weak loadings for many items and cross-loadings across the hypothesized factors. Consequently, the analysis of child reported self-regulation was constrained to a unidimensional construct, encompassing the eighteen items outlined previously.

Convergent Validity of Fast-Track Project Child Behavior Questionnaire

In light of the limited information available on the efficacy of the Fast-Track Project Child Behavior Questionnaire, we investigated its convergent validity by comparing it with established measures of behavior, namely the Pediatric Symptom Checklist (PSC) and Big Five Inventory (BFI).

Parent-reported levels of child self-regulation displayed statistically significant moderate positive correlations with the PSC Attention subscale ($r = .537$, $p < .001$), the PSC Internalizing subscale ($r = .361$, $p < .001$), and the PSC Externalizing subscale ($r = .607$, $p < .001$). These results indicate moderately robust and statistically significant relationships across these measures.

Table 2. Two- Factor Construct of Child Self-Report of Self-Regulation

Factor Loadings

	PA1	PA2
I follow the rules.	.66	.10
I do what I am told to do.	.64	−.03
When I want something, I am patient when waiting.	.63	−.09
When someone tells me a rule that I think is unfair, I ask about the rule in a nice way.	.60	.14
I can concentrate and focus on one activity at a time.	.58	.03
I stick with an activity until it is finished.	.57	.07
I think before I act.	.57	−.15
I ignore kids who are fooling around in class.	.56	.08
When people are angry with me, I control my anger.	.52	−.23
I stop and calm down when I am frustrated or upset.	.49	−.32
I wait my turn during activities.	.41	−.15
I tell new kids my name without being asked to tell it.	.41	.31
I control my temper when there is a disagreement.	.39	−.31
I ask friends for help with my problems.	.36	.23
When I disagree with my parents, I yell and scream.	.00	.52
When I get upset, I whine or complain.	−.02	.49
I cope well with disappointment or frustration.	.34	−.41
I accept it when things do not go my way.	.35	−.39
My feelings get hurt.	.01	.31
I fight or argue with adults.	−.12	.31

Factor Correlations

	PA1	PA2
PA1	1	−.46
PA2	−.46	1

Parent-reported levels of child cognitive self-regulation displayed statistically significant moderate positive correlations with the PSC Attention subscale ($r = .592$, $p < .001$) and the PSC Externalizing subscale ($r = .590$, $p < .001$). A weak positive correlation was found between parent report of child cognitive regulation and the PSC Internalizing subscale ($r = .280$, $p < .001$). Parent-reported levels of child emotional self-regulation displayed statistically significant moderate positive correlations with the PSC Attention subscale ($r = .319$, $p < .001$), the PSC Externalizing subscale ($r = .466$, $p < .001$), and the PSC Internalizing subscale ($r = .466$, $p < .001$).

The self-reported levels of child self-regulation revealed statistically significant moderate positive correlations with the PSC Attention subscale ($r = .315$, $p < .001$). Additionally, weak positive correlations were identified between child-reported self-regulation and the PSC Internalizing subscale ($r = .247$, $p < .001$) and the PSC Externalizing subscale ($r = .291$, $p < .001$).

Parent-reported child self-regulation exhibited a statistically significant moderate positive correlation with the BFI neuroticism scale ($r = .416$, $p < .001$). Furthermore, statistically significant moderate negative correlations were found between parent-reported child self-regulation on both the BFI Conscientiousness scale ($r = -.591$, $p < .001$) and the BFI Agreeableness scale ($r = -.542$, $p < .001$).

Parent-reported child cognitive self-regulation exhibited a statistically significant weak positive correlation with the BFI neuroticism scale ($r = .287$, $p < .001$). Statistically significant moderate negative correlations were found between parent-reported child cognitive self-regulation on both the BFI Conscientiousness scale ($r = -.622$, $p < .001$) and the BFI Agreeableness scale ($r = -.489$, $p < .001$).

Parent-reported child emotional self-regulation exhibited a statistically significant moderate positive correlation with the BFI neuroticism scale ($r = .479$, $p < .001$). Statistically significant moderate negative correlations were found between parent-reported child cognitive self-regulation on both the BFI Conscientiousness scale ($r = -.388$, $p < .001$) and the BFI Agreeableness scale ($r = -.468$, $p < .001$).

Child-reported self-regulation displayed a statistically significant weak positive correlation with the BFI neuroticism scale ($r = .277$, $p < .001$). Additionally, a statistically significant weak negative correlation was identified between the BFI Agreeableness scale ($r = .281$, $p < .001$) and child-reported self-regulation. Lastly, a statistically significant moderate negative correlation was found between the BFI Conscientiousness scale ($r = -.339$, $p < .001$) and child-reported self-regulation.

COVID-19 Stress

COVID-19 stress was assessed through parent responses to ten survey items, exploring stress for oneself, family, and the community in relation to general health, COVID-19 contraction, and educational implications. Exploratory factor analysis treated the ten survey items as a unidimensional construct, resulting in a Cronbach's alpha of $\alpha = .87$.

Given the distinct nature of survey questions, focusing on stress for general health, virus contraction, and educational implications, an exploration was made into the creation of three distinct factors of stress. However, the hypothesized three-factor model of COVID-19 stress was not supported by factor analysis, as illustrated in Table 3.

Specifically, two items related to contracting COVID-19 were found to align more closely with items pertaining to stress for general health. Meanwhile, questions related to current COVID-19 contraction factored together. Notably, only two of the three items hypothesized for the educational stress factor exhibited a strong relationship.

Creating factors related to current COVID-19 contraction and educational implications was deemed unfeasible due to the limits of two-item factors. This limitation would compromise the reliability, interpretability, and generalizability of those constructs. Consequently, the COVID-19 stress construct was reconceptualized to comprise the five items demonstrating a strong positive relationship. These items included questions about stress related to contracting COVID-19 during the 2020–2021

Table 3. Three-Factor Model of COVID-19 Stress

Factor Loadings

	PA1	PA2	PA3
stressed about your general health because COVID-19? - For your family?	.94	−.08	.00
stressed about your general health because COVID-19? - For you?	.87	.03	−.02
stressed about your general health because COVID-19? - For your community?	.59	.02	.17
To what extent were you stressed about contracting COVID-19 in 2020-2021 school year	.57	.31	.02
To what extent were you stressed about your child contracting COVID-19 in the 2020-2021 school year?	.49	.38	.02
To what extent were you stressed about contracting COVID-19 now?	−.02	.88	.01
To what extent were you stressed about your child contracting COVID-19 now?	.03	.87	.00
stressed about the educational implications of COVID-19... - For your family?	.01	.04	.78
stressed about the educational implications of COVID-19... - For your community?	−.03	−.04	.78
stressed about the educational implications of COVID-19... - For you?	.20	−.01	.35

Factor Correlations

	PA1	PA2	PA3
PA1	1	.69	.36
PA2	.69	1	.18
PA3	.36	.18	1

school year, for both oneself and one's child, as well as stress related to general health for oneself, one's family, and one's community. Exploratory factor analysis of this refined five-item construct demonstrated robust reliability, with Cronbach's alpha of $\alpha = .90$.

The adoption of this five-item construct provided a clear perspective on respondents' experience of health-related stress from COVID-19 during the 2020–2021 year. Including additional items would not only diminish reliability but also hinder interpretability and generalizability due to the disparate nature of item categories. Hence, the five-item construct of COVID-19 stress was calculated as the mean score of the resulting five items and utilized in the analyses for research questions.

COVID-19 Impact

COVID-19 impact was assessed by analyzing parent responses to seven survey items. Parents were queried about financial impacts, emotional effects on themselves and their children, and changes to their daily responsibilities. Response options ranged from "little to no impact" to "moderate impact" and "severe impact." Additionally, parents were asked to detail alterations to their child's exercise routines, connections to friends, and homework, with response options of "experienced more," "experienced less," and "experienced no change."

However, factor analysis of the seven COVID-19 impact questions revealed low item correlation and reliability, as reflected in a Cronbach's alpha of α = .43. Despite attempts to enhance reliability by dropping items, the varied nature of survey topics did not lead to a significant improvement in reliability alphas. Consequently, COVID-19 impact was quantified as a sum score of parent responses to each survey item, allowing for the examination of the cumulative effects of various impacts.

Grade-Level Mathematics Competence

Mathematic competence was measured by student- participant performance on assigned grade-level mathematics questions from PARCC exams. Descriptive information regarding the number of problems answer, median scores, and standard deviations are presented in Table 4. Exploratory factor analysis was conducted to determine reliability of grade-level math composites.

Grade four mathematics competence composite consisted of eleven items. Grade four items demonstrated strong internal consistency, with a Cronbach's alpha of α = .86.

Item analysis indicated that alpha could not be improved by dropping any of the eleven items.

Grade five mathematics competence composite consisted of twelve items. Grade five items demonstrated good internal consistency, with a Cronbach's alpha of $\alpha = .72$. Item analysis indicated that alpha could not be improved by dropping any of the twelve items.

Grade six mathematics competence composite consisted of twelve items. Grade six items demonstrated good internal consistency, with a Cronbach's alpha of $\alpha = .76$. Item analysis indicated that alpha could not be improved by dropping any of the twelve items.

Grade seven mathematics competence composite consisted of thirteen items. Grade seven items demonstrated good internal consistency, with a Cronbach's alpha of $\alpha = .81$. Item analysis indicated that alpha could be improved to $\alpha = .83$ by dropping two items, but ultimately these items were kept in the analysis to produce the best representation of grade seven competence as each question represents a different skill or competency.

Grade eight mathematics competence composite consisted of eleven items. Grade eight items demonstrated good internal consistency, with a Cronbach's alpha of $\alpha = .77$. Item analysis indicated that alpha could not be improved by dropping any of the eleven items.

High School mathematics competence composite consisted of ten items. High School items demonstrated good internal consistency, with a Cronbach's alpha of $\alpha = .71$.

Item analysis indicated that alpha could be improved to α = .72 by dropping one item, but this item was not removed as alpha improvements were not remarkable. Additionally, keeping all items was thought to be beneficial to produce the best representation of high school competence as each question represents a different skill or competency.

Table 4. Mathematic Competency Measures

Grade Level	*n*	# of items	Min	Max	Mean	SD
4th Grade	93	11	2.8	11.0	7.7	2.9
5th Grade	93	12	2.3	12.0	8.4	2.4
6th Grade	95	12	1.9	11.7	6.6	2.6
7th Grade	100	13	2.1	12.6	8.1	2.9
8th Grade	86	11	0.0	11.0	6.5	2.9
High School	172	10	0.0	10.0	4.6	2.4

Self-regulation Change From Time Zero to Time One

The first research question examined how child self-regulation changed from Time Zero to Time One. Factors such as gender, race, mother education, type of school (i.e., public, private etc.), format of school (i.e., in-person or virtual etc.), and COVID-19 stress and COVID-19 impact were considered. Self-regulation was conceptualized in four iterations; parent-reported child self-regulation, child cognitive self-regulation (based on parent report), child emotional self-regulation (based on parent report), and child self-reported regulation. Higher scores on regulation measures equated to poorer regulation.

Self-Regulation Time Zero to Time One

Parent-reported child self-regulation of their children revealed significant effects for time ($\beta = -3.63$, $p < .001$). Indicating a significant negative relationship between time and self-regulation, with self-regulation scores decreasing (indicating improvement in regulation) from Time Zero to Time One, as presented in Figure 1. Parent- reported child cognitive self-regulation ($\beta = -0.60$, $p < .001$) and emotional regulation ($\beta = -2.94$, $p < .001$) demonstrated similar patterns of the significant effects of time in improving their observed regulation abilities. Of note, the size of the improvement for emotional regulation is much larger. The model included two random intercepts: one for the individual child ($\tau_{00} = 27.37$) and another for their family ($\tau_{00} = 10.45$), indicating substantial variability in self-regulation within both children and families. The Intraclass Correlation Coefficient (ICC) was calculated to be .74, suggesting that a substantial proportion of the total variability in self-regulation is attributable to differences between children and families, rather than within-child or within-family variability. Interestingly, child self- report of self-regulation did not demonstrate a significant effect of time ($\beta = -0.23$, $p = .45$) on their ability to regulate.

Self-Regulation and Child Gender Time Zero and Time One

For analyses that included gender, female- identifying child participants were set as the reference group. The coefficients for both Male ($\beta = 0.14$, $p = .75$) and Nonbinary/Other ($\beta = 0.16$, $p = .88$) were not statistically significant, suggesting that child gender did not significantly influence parental report of child self-regulation. However, interaction effects between time and child gender were observed. Specifically,

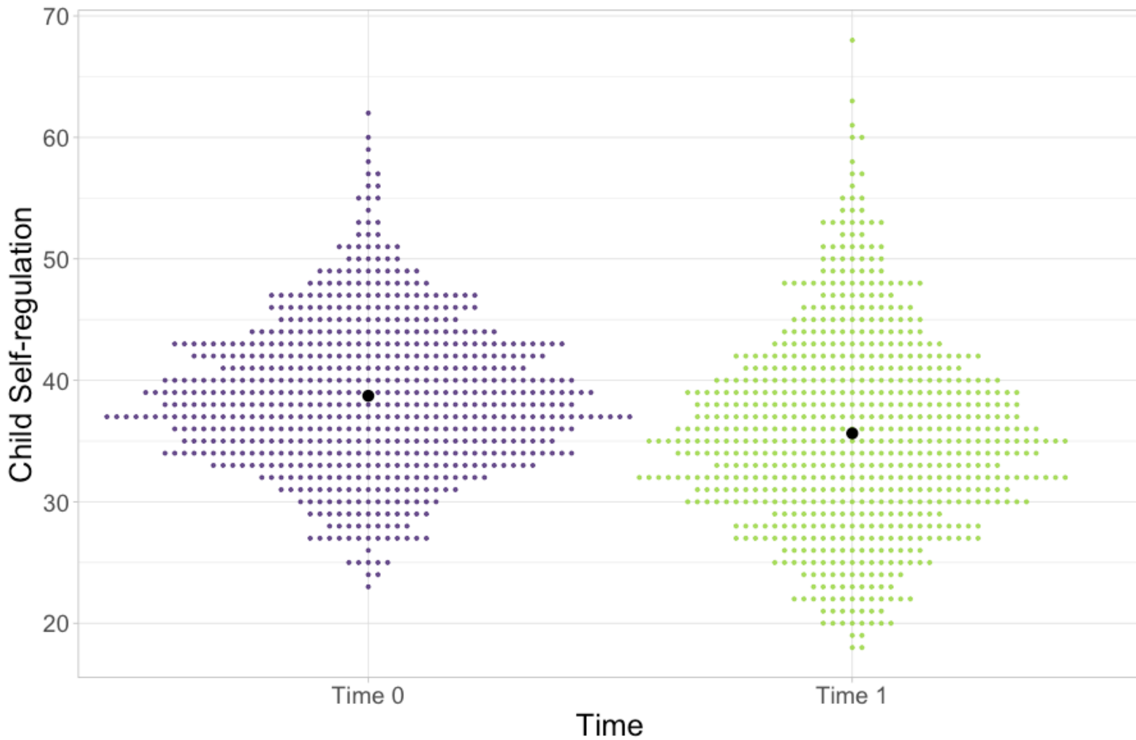

Figure 1. Parent-Report of Child Self-Regulation Change Time Zero to Time One.

the interaction of time and male gender was significant (β = −1.02, p = .02), suggesting that the effect of time on parent- report of child self-regulation differs across time, depending on the gender of the child (i.e., Male), this change is visualized in Figure 2. Whereas the interaction of time and the gender category of Nonbinary/Other was not significant (β = 0.29, p = .85), indicating no significant interaction effect between time and child gender category of Nonbinary/Other.

Parent-reported levels of child cognitive self-regulation did demonstrate a gender-effect. Namely, male gender was associated with statistically significant poorer ratings of cognitive regulation when compared with female identifying children (β = 0.54, p = .02).

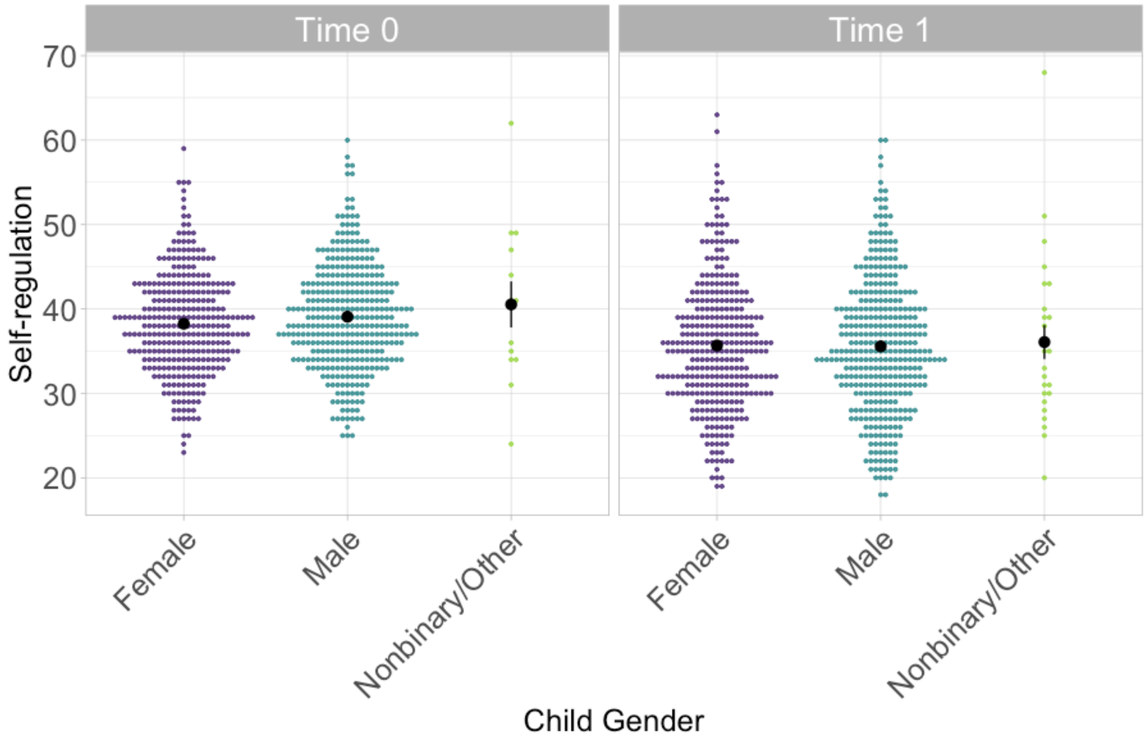

Figure 2. Parent-Report of Child Self-Regulation and Gender.

The coefficient for Nonbinary/Other gender identity (β = 0.53, *p* = .43) was not statistically significant, indicating no significant difference in cognitive self-regulation when compared to female identifying students, see Figure 3. Interaction effects between time and child gender were also observed regarding cognitive self-regulation. Specifically, the interaction of time and male gender was significant (β = −0.58, *p* = .034), suggesting that the effect of time on reported cognitive self-regulation differed depending on the gender of the child (i.e., Male). However, the interaction of time and Nonbinary/Other gender identity was not significant (β = −0.12, *p* = .89).

Parent- reported levels of child emotional regulation did not demonstrate a gender- effect. The coefficients for Male gender (β = −0.39, *p* = .07) and

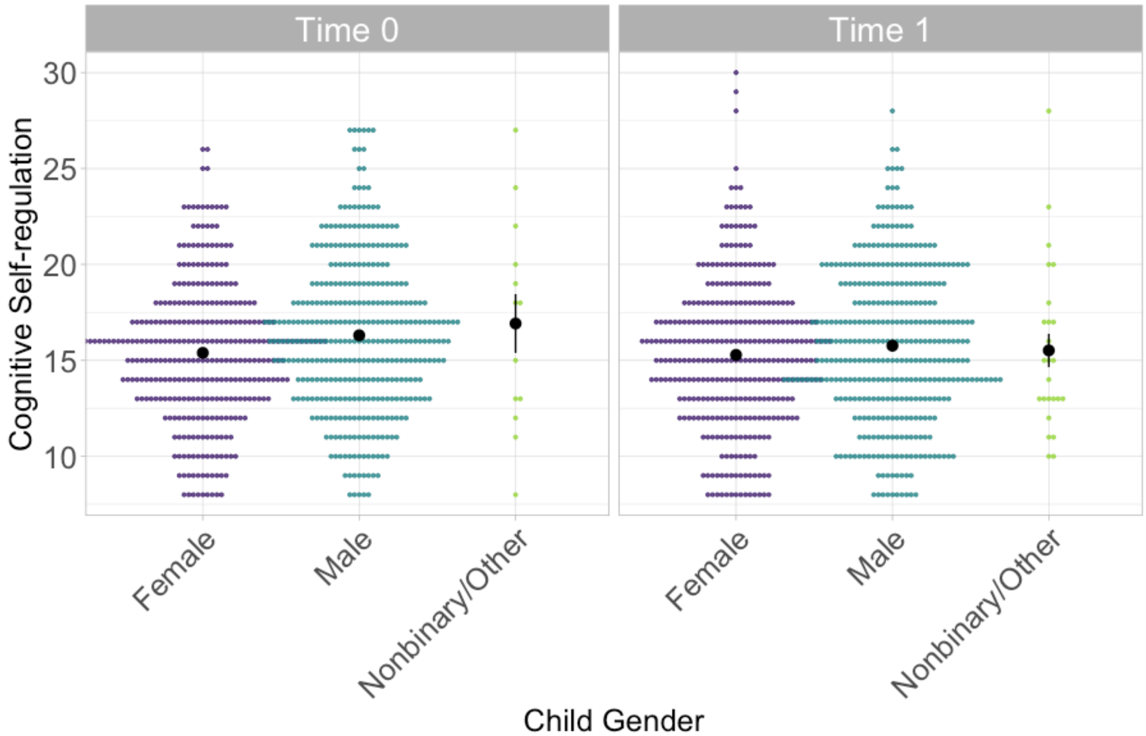

Figure. 3 Parent-Report of Child Cognitive Self-Regulation and Gender.

Nonbinary/Other gender identity (β = −0.19, p = .75) were not statistically significant, suggesting that child gender did not significantly influence parent reports of child emotional regulation. Interaction effects were also examined. The interaction of time and child gender was not significant for male children (β = −0.43, p = .12) or for children who identified as Nonbinary/Other (β = 0.12, p = .89), suggesting no significant interaction effect between time and child gender on parent report of child emotional regulation.

Finally, regarding gender effects of child self-reported regulation, neither Male (β = −0.16, p = .75) nor Nonbinary/Other gender identity (β = 1.18, p = .41) showed statistically significant coefficients when compared to the reference group of female children, indicating that child gender did not significantly predict how student participants reported their self-regulation. Interaction effects between time and child gender were also examined and did not demonstrate a gender effect for male children ($\beta = 0.86$, $p = .18$) or Nonbinary/Other child gender identity ($\beta = 0.94$, $p = .68$).

Self-Regulation and Child Race Time Zero and Time One

Students who identified as White represented the largest racial identity in the study sample, thus White racial identity was used as the reference group for analyses of race. Parent-report or child self-regulation demonstrated some effects of racial identity, as displayed in Figure 4. By parent report, Asian students exhibited significantly better levels of self-regulation compared to other racial groups, with a coefficient estimate of −2.61 ($p = .004$). However, the coefficients for Multiracial/Other ($\beta = -0.69$, $p = .51$) and Black ($\beta = -1.26$, $p = .31$) races were not statistically significant, suggesting no significant differences in child self-regulation compared to the reference group of White students. Interaction effects between time and race were also examined in the context of parent report of child self-regulation and did not demonstrate significant interaction effects across any of the race identity groups.

Parent report of child cognitive regulation demonstrated similar patterns, as seen in Figure 5. Parents of Asian students rated their children as demonstrating significantly better levels of cognitive self-regulation compared to other racial groups, with a coefficient estimate of −1.53 ($p = .007$). However, the coefficients for Multiracial/Other ($\beta = -0.54$, $p = .42$) and Black ($\beta = -0.56$, $p = .48$) racial identity were not statistically significant, suggesting no significant differences in observed cognitive self-regulation compared to the reference group of White students. Interaction effects between time and

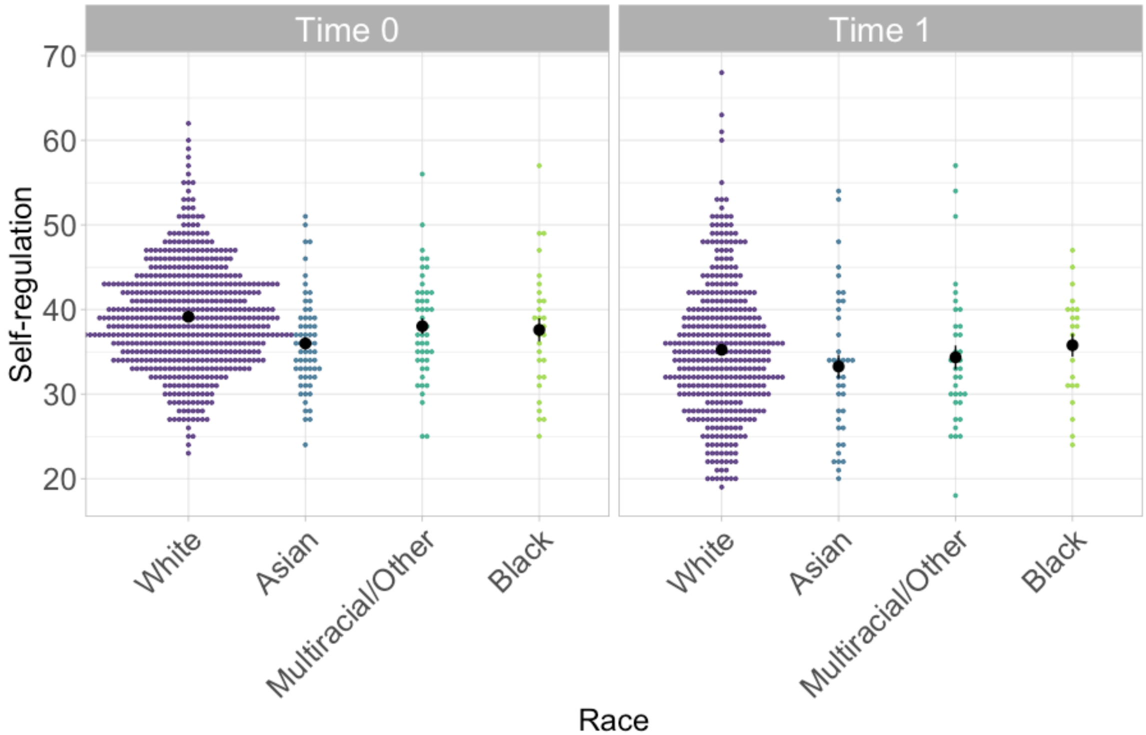

Figure 4. Parent-Report of Child Self-Regulation and Race.

race were also examined in the context of cognitive self-regulation. The positive interaction of time and Asian race was significant (β = 1.22, p = .02), indicating that the rate of change in cognitive self-regulation over time significantly differed for Asian students compared to other racial groups. The interaction of time and Multiracial/Other (β = 0.55, p = .34) and Black identity (β = 0.64, p = .37) were not statistically significant.

Regarding emotional regulation, parents of Asian children rated their child's emotional self-regulation as significantly better when compared to other racial groups, with a coefficient estimate of −1.08 (p = .008). By contrast, the coefficients for Multiracial/Other (β = −0.20, p = .67) and Black (β = −0.68, p = .24) racial identity were not statistically significant, suggesting no significant differences in emotional self-

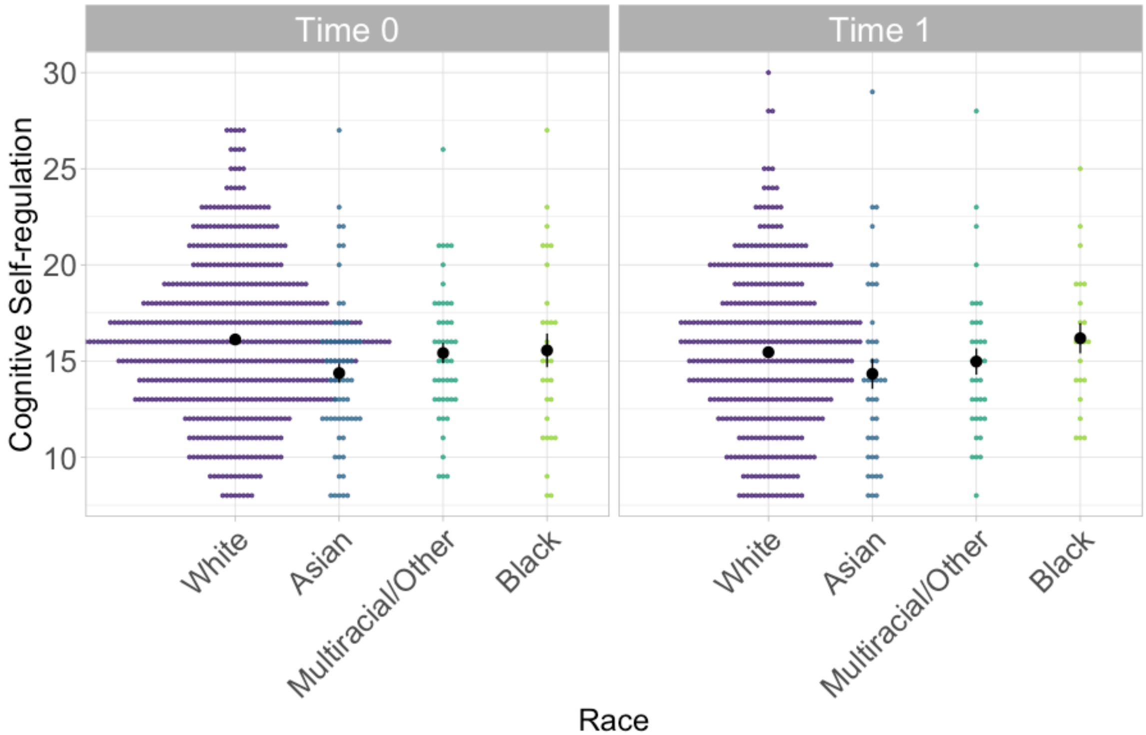

Figure 5. Parent- Report of Child Cognitive Self-Regulation and Race.

regulation compared to the White reference group. Interaction effects between time and race were also examined in the context of child emotional regulation. None of the interaction terms, including time and racial identity, Asian (β = 0.42, *p* = .412), Multiracial/Other, (β = 0.27, *p* = .626), and Black (β = 0.65, *p* = .333), were statistically significant.

Child self-report of their regulation demonstrated an effect of race, as displayed in Figure 6. Asian children rated themselves as having significantly better levels of self-regulation compared to other racial groups, with a coefficient estimate of −2.22 (*p* = .03). The coefficients for Multiracial/Other (β = −0.57, *p* = .63) and Black (β = 1.35, *p* = .33) races were not statistically significant, suggesting no significant differences in self-regulation compared to the reference group of White students. Interaction effects between time and race were also examined in the context of child self-reports of their regulation. None of the interaction terms were statistically significant; Asian, ($\beta = -1.00$, $p = .41$), Multiracial/Other, ($\beta = -0.34$, $p = .79$), and Black, ($\beta = -1.32$, $p = .42$).

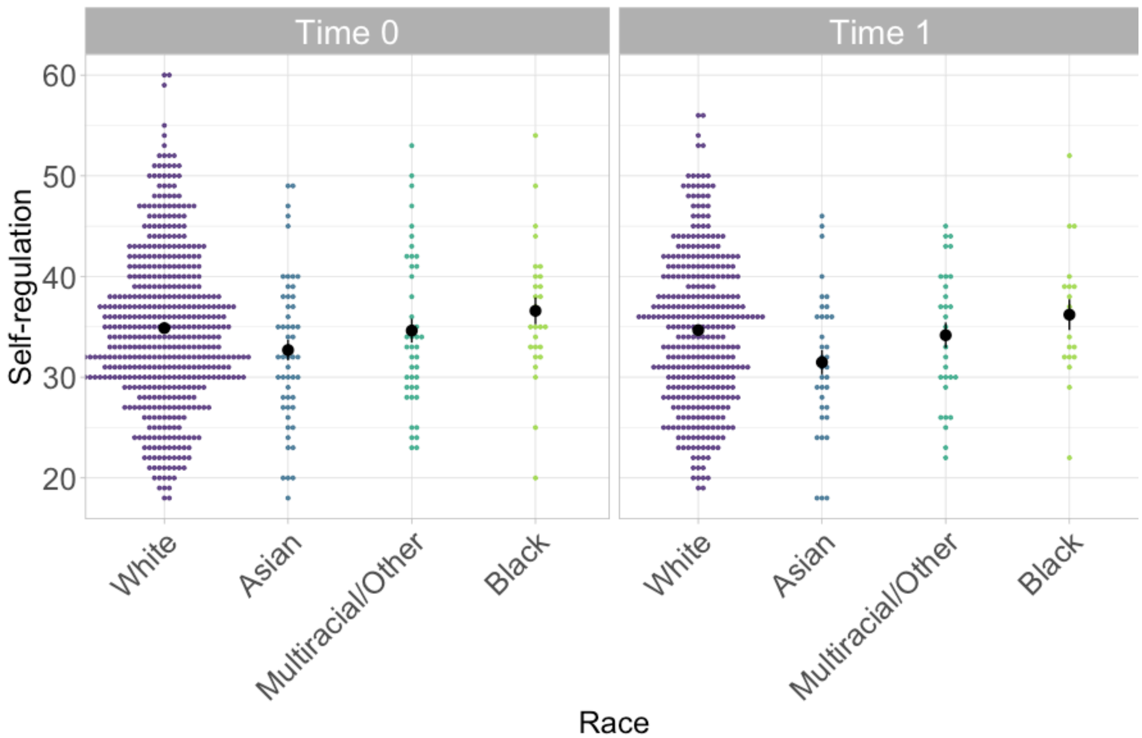

Figure 6. Child Self-Report of Self-Regulation and Race.

Self-Regulation and School Type Time Zero and Time One

Regarding school type, child participants were students at Charter, Cyber, Private, Public, and Home- School environments. Most students attended public schools and thus public school was set as the reference school type. School type reflects the type of school child participants were enrolled in during the 2020-2021 school year.

Charter schools showed a non-significant effect on parent report of child self-regulation ($\beta = 1.10$, $p = .31$), as did Cyber schools ($\beta = 0.50$, $p = .59$), Private schools

($\beta = -0.64$, $p = .431$) and Homeschooling ($\beta = 1.66$, $p = .16$). Interaction effects for time and school type did not reveal significant interactions that impacted parent-report of child self-regulation.

In regard to parent- report of child cognitive regulation, results revealed significant effects for Homeschool as a school type ($\beta = 1.38$, $p = .05$). Indicating that students in homeschool environments were rated as having worse cognitive self-regulation than students in other schooling environments, as seen in Figure 7. However, Charter ($\beta = 0.78$, $p = .23$), Cyber ($\beta = 0.49$, $p = .37$), and Private ($\beta = -0.41$, $p = .40$) school types did not show significant differences, when compared to the reference group of public school. Interaction effects between time and school type were also examined. The interaction between time and school type did not reach statistical significance in the context of cognitive self- regulation for Charter school ($\beta = 0.70$, $p = .19$), Cyber school ($\beta = -0.85$, $p = .09$), Homeschool ($\beta = 0.48$, $p = .46$), and Private school ($\beta = -0.63$, $p = .15$).

None of the effects for school type were statistically significant when examining emotional regulation: Charter school ($\beta = 0.34$, $p = .51$), Cyber school ($\beta = 0.05$, $p = .92$), Homeschool ($\beta = 0.34$, $p = .55$), and Private school ($\beta = -0.20$, $p = .61$). Similarly, the interaction between time and school type did not reach statistical significance in the context of child emotional self- regulation for Charter school ($\beta = 0.55$, $p = .29$), Cyber school ($\beta = -0.30$, $p = .54$), Homeschool ($\beta = -0.70$, $p = .27$), and Private school ($\beta = -0.02$, $p = .96$).

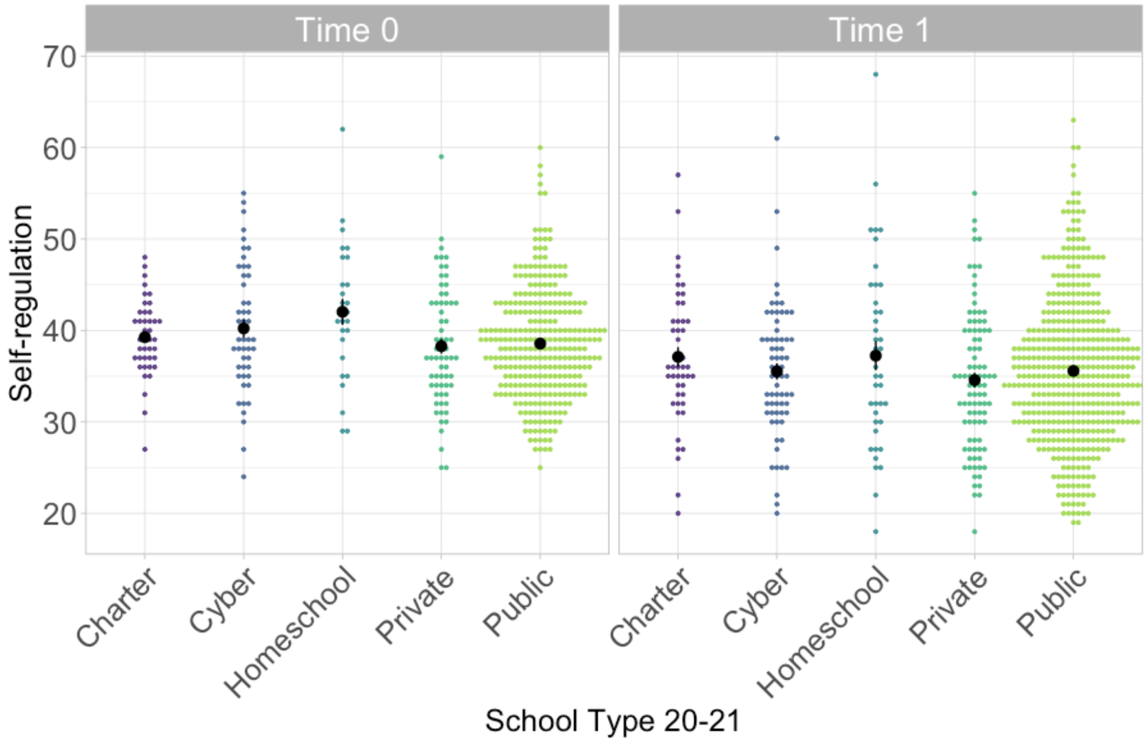

Figure 7. Parent-Report of Child Cognitive Self-Regulation and School Type.

Finally, school- type demonstrated significant effects on child self-report of their regulation, as displayed in Figure 8. Cyber school (β = 1.94, p = .05) and Homeschool (β = 3.86, p = .002) environments were found to significantly predict child report of their self-regulation, with students in Cyber school and Homeschool settings reporting poorer levels of self-regulation compared to the reference group of public-school students. However, the effect of Charter (β = 2.05, p = .072) and Private (β = −0.02, p = .99) school types were not significant predictors of child self-report of regulation. The interaction between time and school type did not reach statistical significance in the context of child-report of self-regulation for Charter school (β = −0.27, p = .82), Cyber school (β = −1.18, p = .28), Homeschool (β = −2.31, p = .13), and Private school (β = 0.69, p = .48).

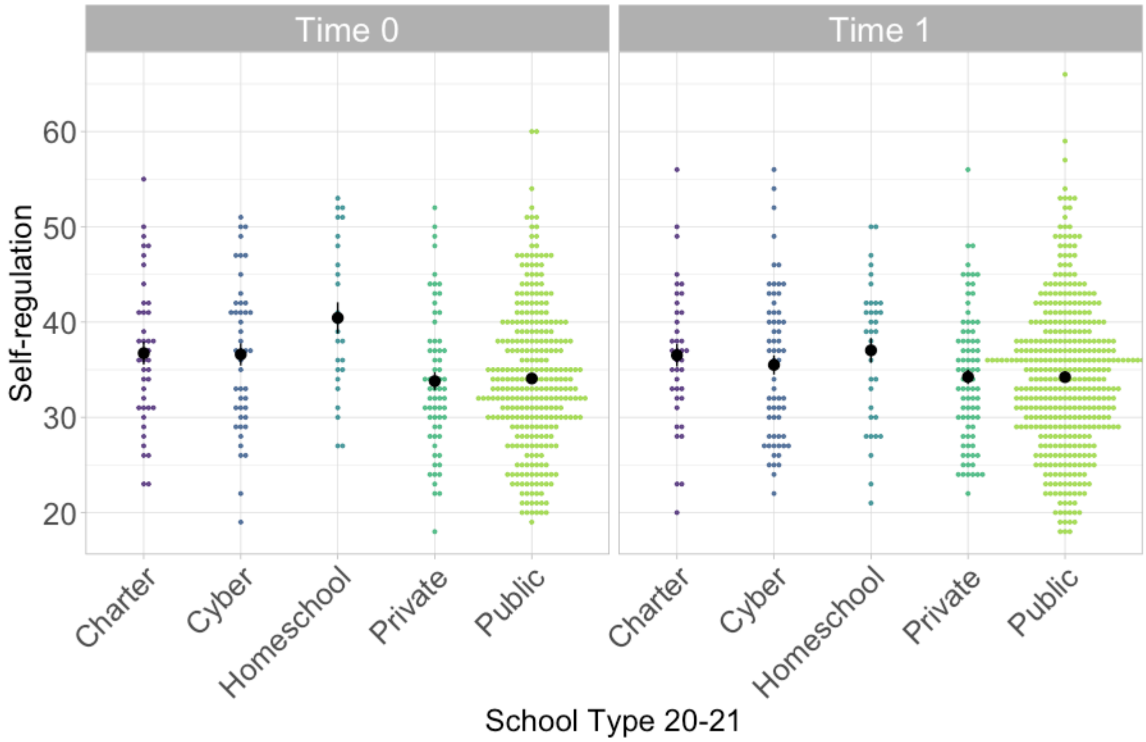

Figure 8. Child Self-Report of Self-Regulation and School Type.

Self-Regulation and School Format Time Zero and Time One

Child participants were asked to report if they spent any time in the 2020-2021 school year engaged in online learning. Their responses were collapsed into three categories of school format: *Mostly or Fully in Person*, *Hybrid* (denoting approximately 50% of time in virtual settings), and *Virtual* (denoting fully virtual students). The sample of students who were *Mostly or Fully in Person* was the largest group and was thus set as the reference group for the analysis.

School format was not a strong predictor of parent report of child self-regulation. Neither Virtual ($\beta = -0.81$, $p = .18$) nor Hybrid ($\beta = 0.35$, $p = .60$) school formats significantly predicted parent reported self-regulation of their children. Similarly, school format was not a significant predictor of child cognitive regulation for Virtual ($\beta = -0.43$,

p = .26) or Hybrid (β = 0.48, p = .29) formats, nor for child emotional regulation for Virtual (β = −0.35, p = .20) or Hybrid (β = −0.11, p = .71) formats. Consistent with these results, school format was not a significant predictor of child-reported self-regulation for Virtual (β = −0.58, p = .38) or Hybrid (β = 0.47, p = .51) formats.

Self-Regulation and Mother Education Time Zero and Time One

Data was collected on the highest education level of mothers of the child participants. Their responses included *No Diploma, High School, Some College*, *Associate's Degree*, *Bachelor's Degree*, and *Graduate Degree*. Mothers with graduate degrees represented the largest group and were thus set as the reference point for the analysis.

Regarding mother's education level, student participants of mothers with no diploma were rated as having significantly worse self-regulation (β = 5.30, p = .05). Interestingly, at Time Zero, some college was also found to be associated with poorer child-regulation, but this was not replicated at Time One. Other categories of mother's education level, including Associate's degree (β = −2.05, p = .09), Bachelor's degree (β = −0.68, p = .23), and high school diploma (β = −1.72, p = .51) did not significantly predict parent report of child self-regulation. In child report of their own self-regulation, only some college (β = 3.40, p = .02) was found to be a significant predictor of child report of their self-regulation. Whereas other categories of mother's education level, including Associate's degree (β = −0.55, p = .70), Bachelor's degree (β = 0.36, p = .58), High School Diploma (β = −3.00, p = .39), and no diploma (β = 1.38, p = .68), did not significantly predict child report of their self-regulation.

Self-Regulation and COVID-19 Impact Time Zero and Time One

The impact of COVID-19 at Time Zero was found to have a statistically significant effect on parent-report of child self-regulation ($\beta = 0.44$, $p < .001$), see Figure 9. Similarly, COVID-19 impact was a significant predictor of parent report of child cognitive regulation ($\beta = 0.27$, $p < .001$) and emotional regulation ($\beta = 0.17$, $p < .002$). These results were consistent with the significant effect of COVID-19 impact on child reports of their own regulation ($\beta = 0.75$, $p < .001$), displayed in Figure 10. Further, interaction effects between time and COVID-19 impact were statistically significant ($\beta = 0.29$, $p = .011$). This interaction effect indicates that the relationship between time and self-regulation is modified by the level of COVID impact at Time Zero. Specifically, the impact of time on self-regulation varies depending on the level of COVID impact experienced at the initial time point. When the COVID impact at Time Zero is higher, the effect of time on self-regulation is amplified, leading to poorer self-regulation over time compared to when COVID impact at Time Zero is lower. Overall, all analyses indicated that an increase in the amount of COVID-19 impact experienced by the family was associated with worse child regulation.

Self-Regulation and COVID-19 Stress Time Zero and Time One

COVID-19 stress did not have a statistically significant effect on parent-report of child self -regulation ($\beta = 0.03$, $p = .57$), child cognitive regulation ($\beta = 0.02$, $p = .53$), nor child emotional regulation ($\beta = 0.01$, $p = .70$). Similarly, COVID-19 stress was not a significant predictor of child report of their self- regulation ($\beta = 0.03$, $p = .59$). Results of all analyses suggest that COVID-19 stress experienced by a family did not impact child regulation.

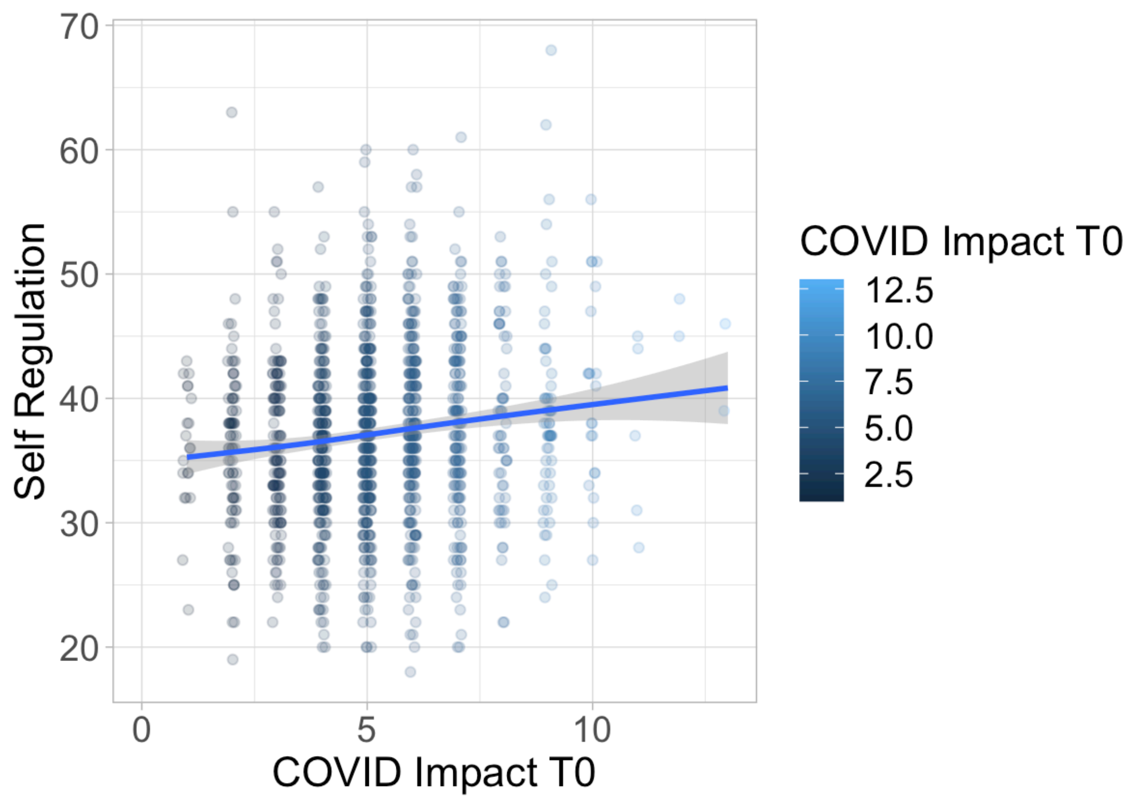

Figure 9. Parent Report of Child Self-Regulation and COVID-19 Impact.

Predictors of Child Participant Grade- Level Mathematics Performance

In order to answer research questions two and three, regression analyses were conducted to investigate the predictive role of various factors on child participant's performance on grade-level mathematics measures, collected at Time One. These factors include demographics, such as race, gender and mother education level, school-related variables, including school type and format (e.g., in-person, virtual), and child self-regulation scores assessed at both Time Zero and Time One, as reported by parents and through self-report. Additionally, consistent with research questions two and three, the interplay between self-regulation and mathematics performance will be explored within the context of COVID-19 stress and COVID-19 impacts reported by parents of participants.

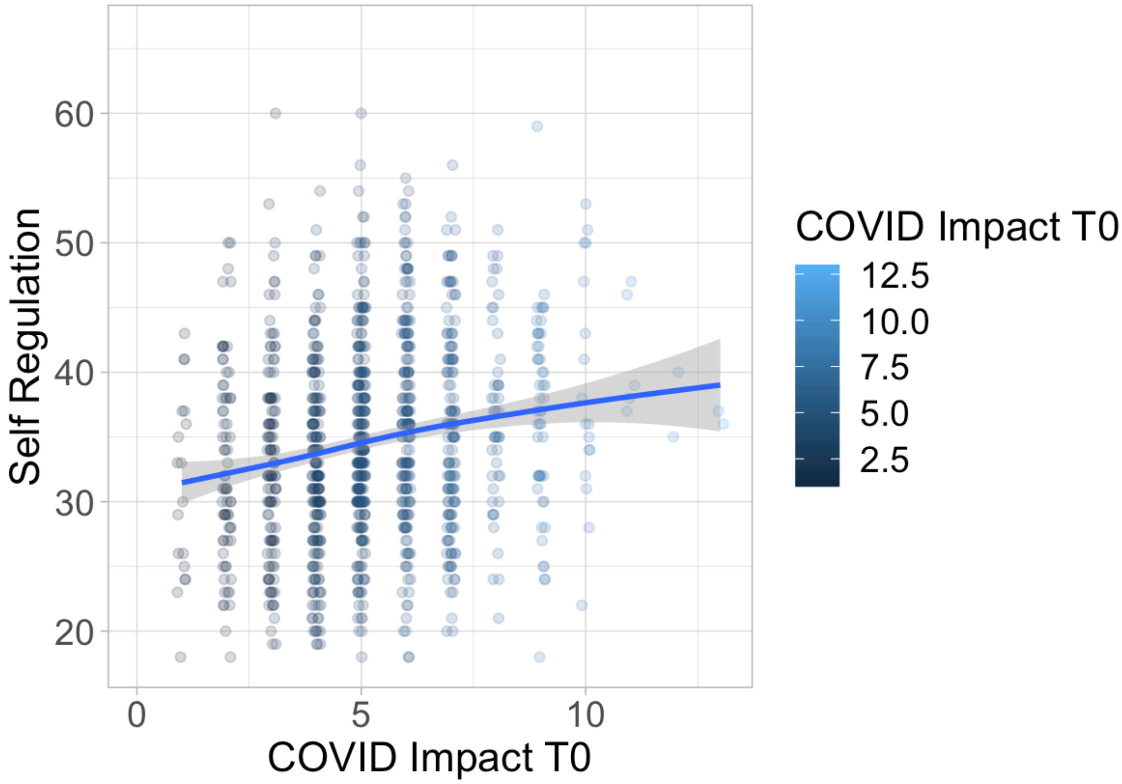

Figure 10. Child Self-Report of Self-Regulation and COVID-19 Impact.

Demographic and School Factors as Predictors of Mathematics Performance

In regard to analysis that included gender, female identifying students were set as the reference group. The coefficient for male identifying students was 0.08 (p = .42), suggesting a non-significant effect on math scores. Similarly, gender was not a significant predictor of math performance for nonbinary/other gender identifying students ($\beta = -0.48$, p = .22). Overall, the results suggest that child gender, including male and nonbinary/other genders, did not significantly predict students' mathematics performance.

When examining for effects of racial identity, White students were used as the reference group for analysis, as they represented the largest sample. Asian students performed significantly better than students of other racial identities ($\beta = 0.50$, p = .005) on grade-level mathematics measures. Whereas Black racial identity was associated with significantly lower performance on the math outcome measures (β = −0.44, p = .05). Multiracial/Other identity was not a significant predictor of math performance (β = 0.17, p = .39). Overall, racial identity was found to be a predictor of student performance on grade-level math performance, see Figure 11, though these results should be considered within the context of the uneven racial distribution of the sample.

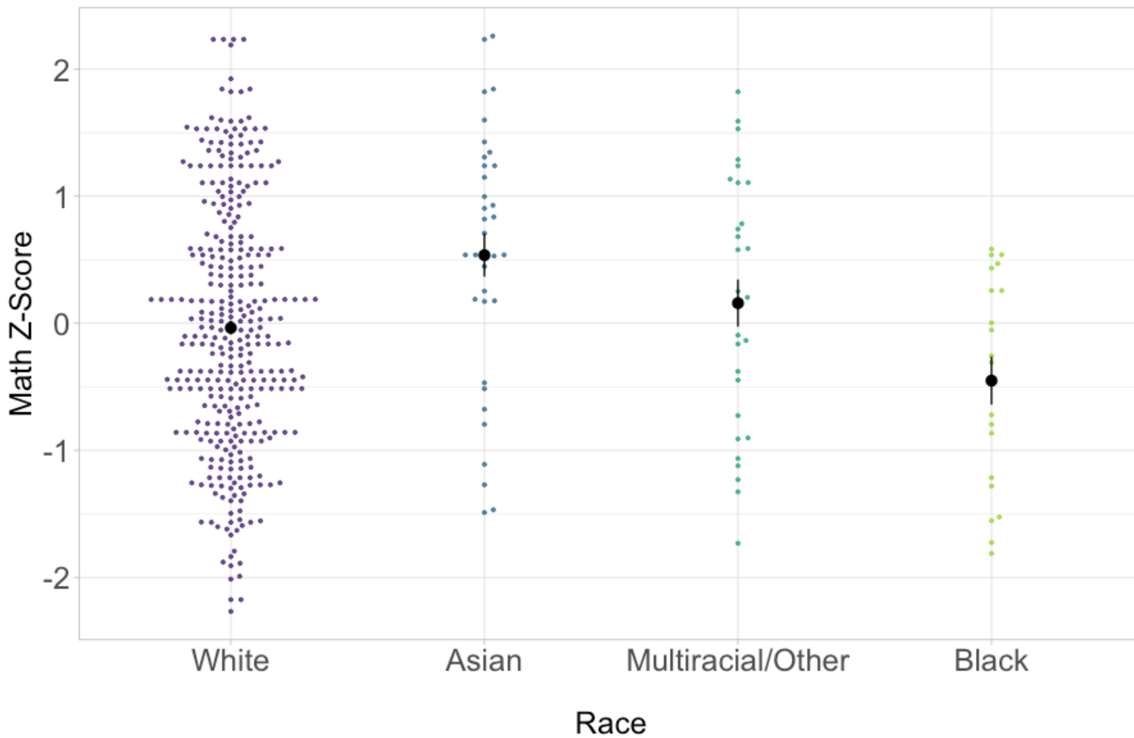

Figure 11. Child Performance on Mathematics Measures and Race.

The type of school attended demonstrated significant associations with performance on grade-level math outcomes. Public school was designated as the reference group due to its representation of the largest student cohort. The coefficients for students attending charter (β = −0.33, p = .06), cyber (β = −0.14, p = .36), and homeschools (β = −0.31, p = .19) were not statistically significant. However, notably, students attending private schools exhibited lower math scores compared to students attending other types of schools (β = −0.38, p = .01), see Figure 12. Regarding school format, virtual students were used as the reference group. No statistically significant effects were found for Mostly or Fully In-Person (β = − 0.21, p = .06) or Hybrid school (β = −0.09, p = .50) format.

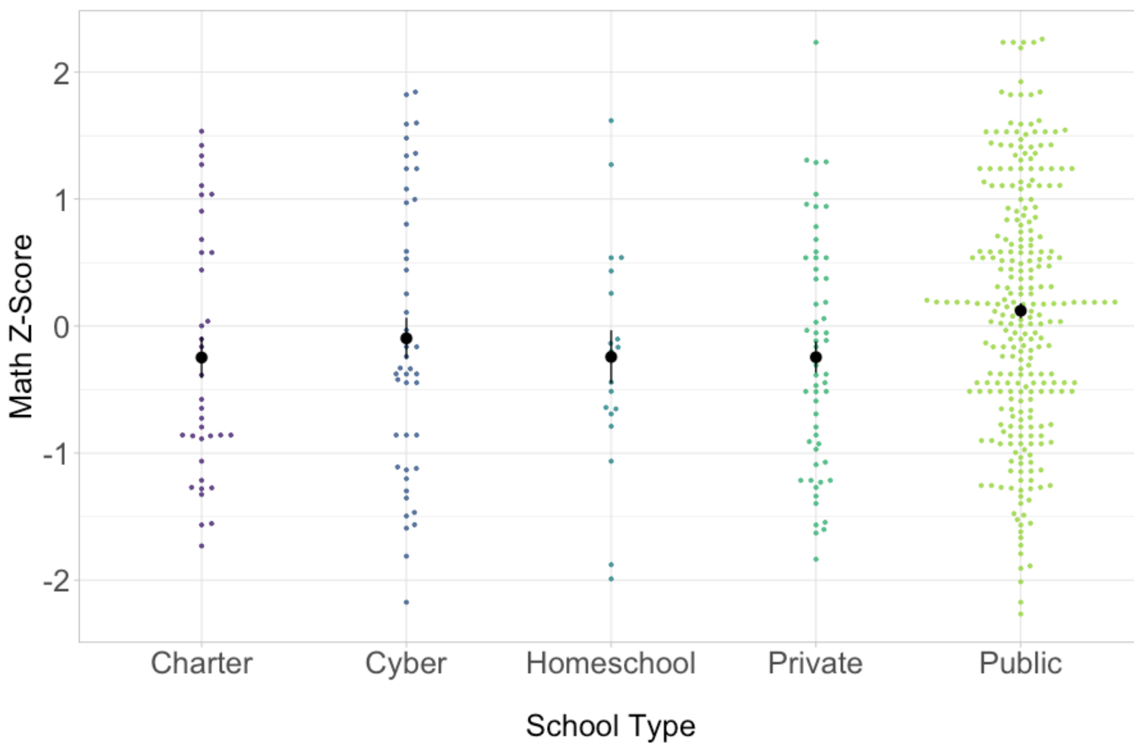

Figure 12. Child Performance on Mathematics Measures and School Type.

When examining mother education level, graduate degree was designated as the reference group as it constituted the largest cohort in the sample. Results revealed that none of the categories of mother education, including Associate's degree (β = −0.14, p = .637), Bachelor's degree (β = −0.02, p = .864), high school diploma (β = −0.85, p = .227), some college (β = 0.05, p = .871), and no diploma (β = −1.05, p = .069), demonstrated statistically significant effects on student performance, see Figure 13.

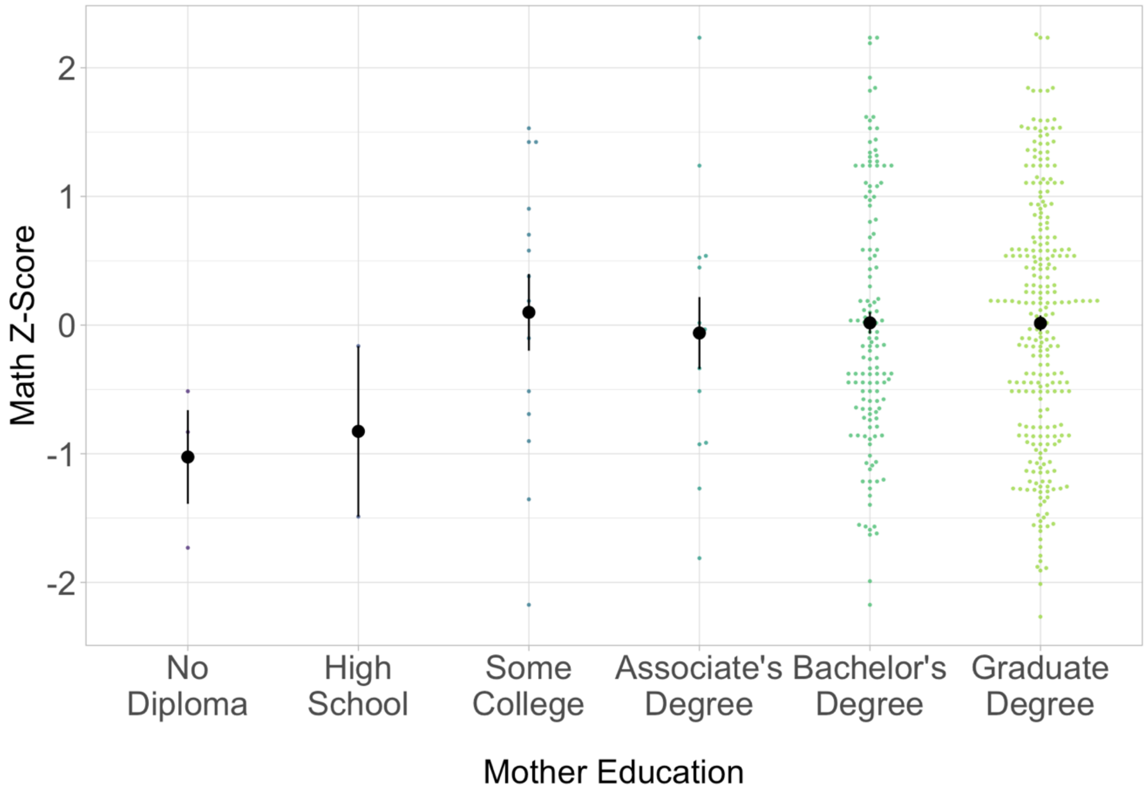

Figure 13. Child Performance on Mathematics Measured and Mother Education.

Results suggest that mother's attainment of some college education and beyond was associated with higher performance on mathematics measures, however this difference did not reach statistical significance. Overall, these findings suggest that mother education levels did not significantly predict students' mathematics performance.

COVID- 19 related stress and impact were examined as predictors of child participant's grade level mathematics performance. Results indicated that neither COVID-19 impact ($\beta = -0.04$, $p = .11$) nor COVID-19 Stress ($\beta = -0.01$, $p = .28$), were significant predictors of child participant's mathematics performance. Overall, these findings suggest a lack of relationship between COVID-19 factors and students' mathematics performance.

Self-Regulation as Predictor of Math Outcomes

The study investigated the influence of child self-regulation at both Time Zero and Time One on grade-level mathematics competence (measured at Time One). The hypothesis posited that higher scores on self-regulation measures (indicative of poor regulation) would be negatively associated with performance on grade-level math measures. Analysis of Time Zero and Time One self-regulation revealed significant effects of parent-reported child self-regulation (Time Zero: $\beta = -0.03$, $p < .001$; Time One: $\beta = -0.02$, $p < .001$), see Figure 14, child cognitive regulation (Time Zero: $\beta = -0.05$, $p < .001$; Time One $\beta = -0.05$, $p < .001$), and child emotional regulation (Time Zero: $\beta = -0.04$, $p < .008$; Time One: $\beta = -0.03$, $p < .009$) on grade-level mathematics competencies. Similarly, child self-report of regulation significantly predicted math performance (Time Zero: $\beta = -0.02$, $p < .001$ Time One: $\beta = -0.02$, $p < .001$), see Figure 15. Random effects analysis revealed significant variability in math scores across families ($\sigma^2 = .55$, $\tau_{00} = .40$, $ICC = .42$). Results suggest that students in the same families performed similarly on math measures. Overall, the results confirm the study hypothesis and indicate that child regulation serves as a significant predictor of mathematics performance across various measures of self-regulation.

Further analyses delved into interaction effects to ascertain whether the influence of self-regulation on performance on math measures varied across demographic identifiers and school factors. Notably, the interaction of racial identity did not achieve statistical significance for any racial group at Time Zero (Asian: $\beta = -0.01$, $p = .683$; Multiracial/Other: $\beta = -0.02$, $p = .483$; Black: $\beta = 0.05$, $p = .165$) or Time One, (Asian: $\beta = -0.02$, $p = .234$; Multiracial/Other: $\beta = -0.02$, $p = .309$; Black: $\beta = 0.06$, $p = .09$)

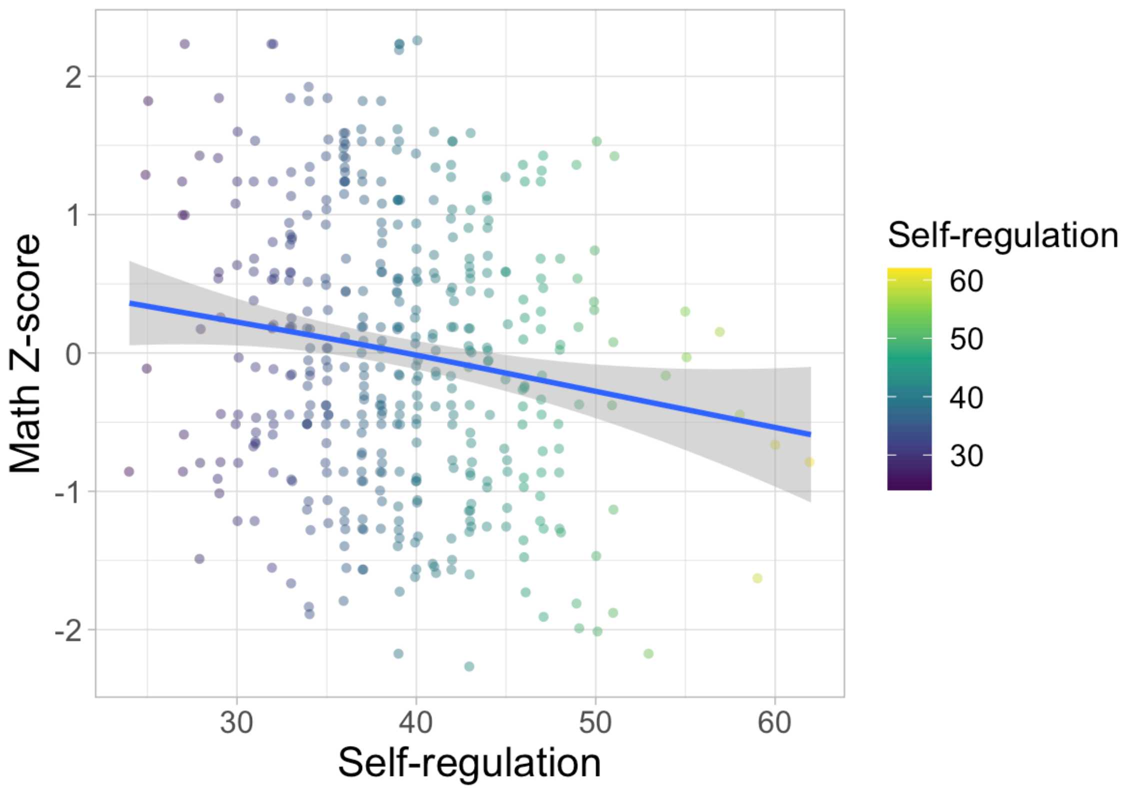

Figure 14. Parent-Report of Self-Regulation and Performance on Math Measures.

suggesting that the relationship between parent-reported child self-regulation and math performance remained consistent across racial groups. However, significant interaction effects emerged concerning child self-report of regulation. Although the interaction terms for Asian (Time Zero: $\beta = 0.01$, $p = .586$; Time One: $\beta = -0.02$, $p = .501$) or Multiracial/Other (Time Zero: $\beta = -0.03$, $p = .258$; Time One: $\beta = -0.00$, $p = .889$) racial identities did not reach statistical significance, the interaction term for Black participants was significant (Time Zero: $\beta = 0.10$, $p = .05$; Time One: $\beta = 0.08$, $p = .015$), indicating a distinct effect of self-reported regulation on math performance within this racial group.

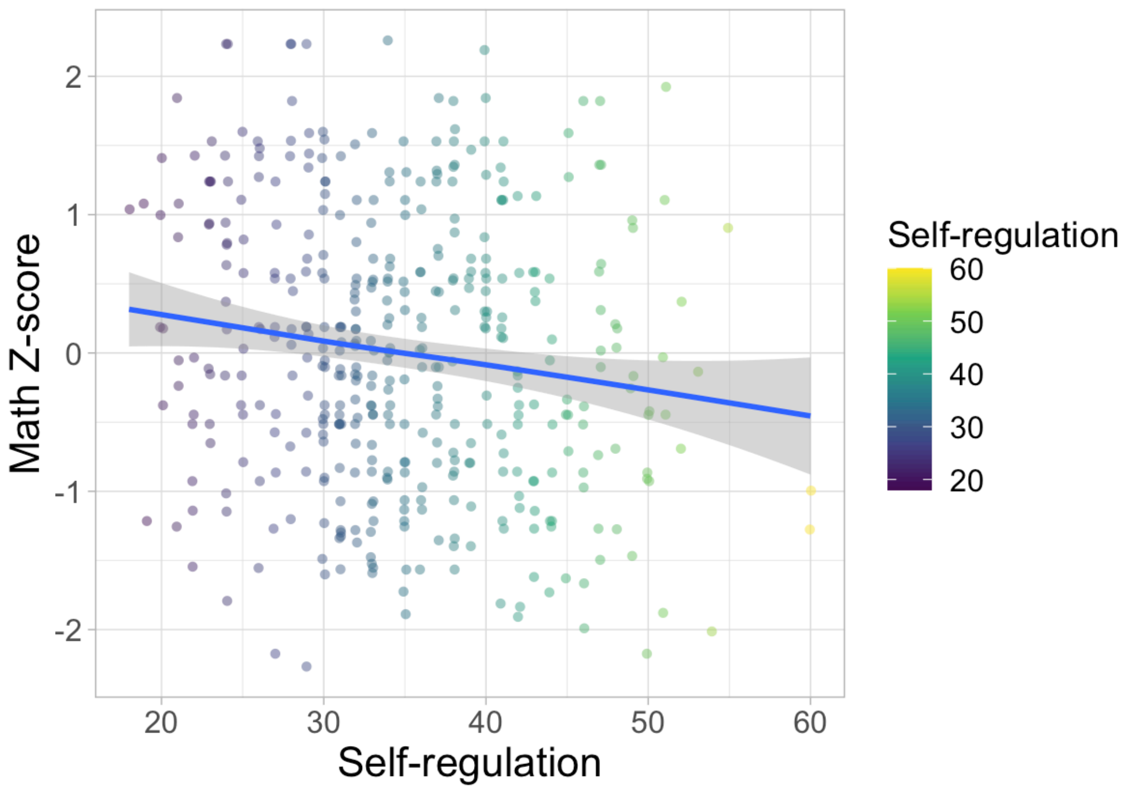

Figure 15. Child Self-report of Self-Regulation and Performance on Math Measures.

effects emerged concerning child self-report of regulation. Although the interaction terms for Asian (Time Zero: β = 0.01, p = .586; Time One: β = −0.02, p = .501) or Multiracial/Other (Time Zero: β = −0.03, p = .258; Time One: β = −0.00, p = .889) racial identities did not reach statistical significance, the interaction term for Black participants was significant (Time Zero: β = 0.10, p = .05; Time One: β = 0.08, p = .015), indicating a distinct effect of self-reported regulation on math performance within this racial group.

Furthermore, interaction effects between self-regulation and gender were explored. In the context of parent reported child self-regulation, none of the interaction terms reached statistical significance for either male (Time Zero: β = 0.01, p = .554; Time One: β = −0.00, p = .852) or nonbinary/other (Time Zero: β = 0.02, p = .527; Time One: β = 0.00, p = .94) gender groups. Similarly, none of the gender interaction terms with child self-reported regulation reached statistical significance for either male (Time Zero: $\beta = 0.00$, $p = .834$; Time One: $\beta = 0.01$, $p = .45$) or nonbinary/other (Time Zero: $\beta = -0.02$, $p = .734$; Time One: $\beta = -0.00$, $p = .99$) gender groups, suggesting that the relationship between self-regulation and math performance did not significantly differ based on child gender identity.

Moreover, interaction effects between parent-reported and child-reported self-regulation and mother's education level were examined. None of the interaction terms reached statistical significance for parent-reported child self-regulation and any education category at Time Zero (all $p > .05$). However, at Time One, a significant effect between parent-reported child self-regulation and math outcomes was noted when mothers held an Associate's degree ($\beta = -0.08$, $p = .02$); no other interaction effects for mother education were found at Time One. Similarly, when examining Time Zero and Time One child self-report of regulation, the analysis revealed a significant interaction when mothers held an Associate's degree (Time Zero: $\beta = -0.08$, $p = .03$; Time One: $\beta = -0.10$, $p = .01$); no other interaction effects for mother education were found. Overall, the results suggest that the relationship between self-regulation and math performance can significantly differ based on mother education.

Finally, interaction effects between self-regulation and school factors were explored. The interaction term for the Hybrid format reached statistical significance at Time Zero ($\beta = 0.06$, $p = .01$) and indicated a moderating effect, but this was not replicated at Time One ($\beta = 0.02$, $p = .22$). Mostly or Fully in Person format did not reach significance (Time Zero: $\beta = 0.02$, $p = .18$; Time One: $\beta = 0.02$, $p = .24$) in the context of parent-reported child self-regulation. Similarly, interaction effects between child-reported self-regulation and school format were examined, and the interaction term for both the Mostly or Fully In Person format (Time Zero: $\beta = -0.01$, $p = .71$; Time One: $\beta = 0.02$, $p = .24$) and the Hybrid format (Time Zero: $\beta = 0.02$, $p = .25$; Time One: $\beta = 0.02$, $p = .22$) did not reach statistical significance.

Interaction effects between parent- reported child self-regulation and school types did not reach statistical significance at Time Zero (Charter: $\beta = 0.04$, $p = .31$; Cyber: $\beta = -0.01$, $p = .57$; Homeschool: $\beta = -0.00$, $p = .895$; Private: $\beta = 0.00$, $p = .93$) or Time One(Charter: $\beta = 0.01$, $p = .52$; Cyber: $\beta = 0.00$, $p = .92$; Homeschool: $\beta = -0.01$, $p = .67$; Private: $\beta = 0.01$, $p = .39$). Furthermore, the interaction effects between child self-report of regulation and school types did not reach statistical significance for any category at Time Zero (Charter: $\beta = -0.01$, $p = .69$; Cyber: $\beta = -0.00$, $p = .88$; Homeschool: $\beta = 0.01$, $p = .78$; Private: $\beta = -0.00$, $p = .96$) or Time One (Charter: $\beta = -0.02$, $p = .49$; Cyber: $\beta = 0.00$, $p = .92$; Homeschool: $\beta = -0.01$, $p = .83$; Private: $\beta = -0.02$, $p = .44$). Results suggest that the type of school participants attended, and the formatting of that school did not moderate the relationship between self-regulation and math outcomes.

Interaction of COVID-19 Factors, Self-regulation, and Math Outcomes

Finally, we investigated for a potential interaction effect for COVID-19 factors on the relationship between self-regulation and math outcomes. I hypothesized that COVID-19 stress and impacts would be a significant moderator in this relationship. Analyses examining COVID-19 stress as a moderating variable yielded no evidence of significant interactions of COVID-19 stress on self-regulation at Time Zero and math outcomes, regardless of the self-regulation measure used in the analysis. Specifically, no evidence of an interaction was found for parent-reported child self-regulation ($\beta = -0.00$, $p = .32$; see

Figure 16), parent-reported cognitive self-regulation (β = −0.00, p = .32), parent-reported emotional self-regulation (β = −0.00, p = .53), or child self−reported regulation (β = −0.00, p = .83). Similarly, no interaction effect was found between COVID-19 stress and Time One measures of parent reported total self-regulation (β = 0.00, p = .99), cognitive self-regulation regulation (β = 0.00, p = .57), emotional self-regulation (β = −0.00, p = .80), and child self-reported regulation (β = −0.00, p = .32).

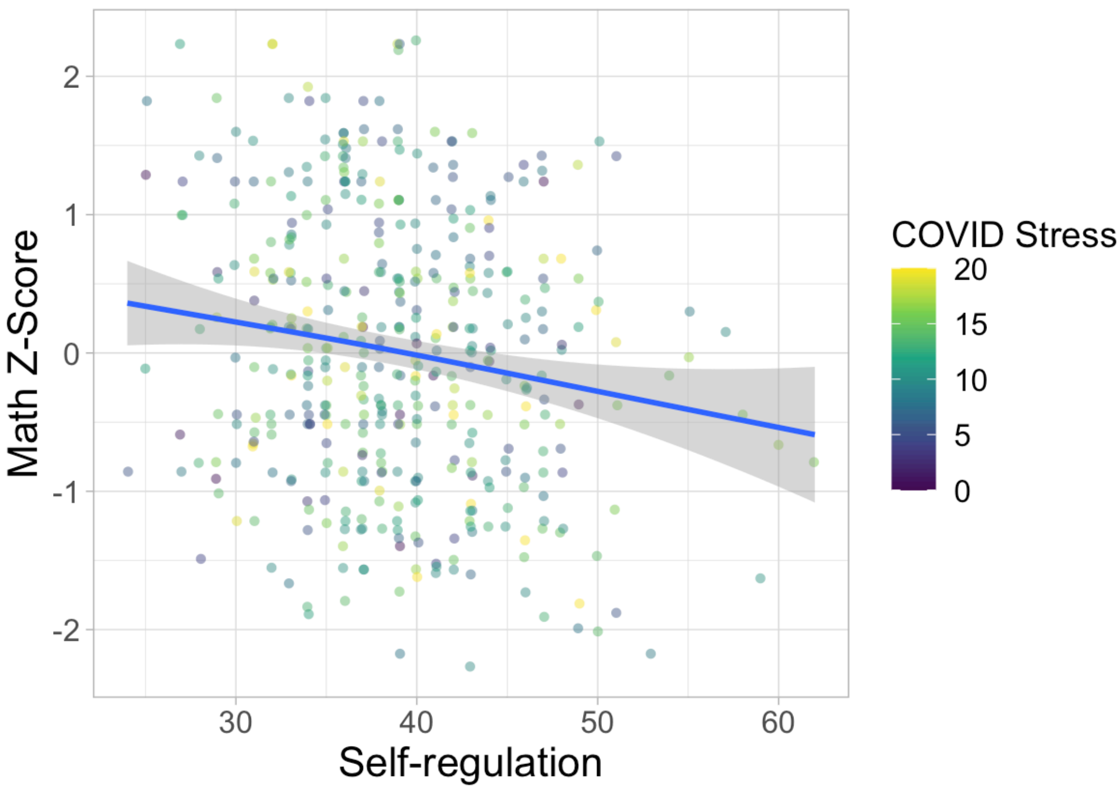

Figure 16. Parent Report of Self-Regulation, Math Performance, & COVID-19 Stress.

Similarly, analysis of COVID-19 impact as a moderating variable indicated no significant interaction of COVID-19 impact on self-regulation at Time Zero and math outcomes. Specifically, I found no evidence of interactions for parent reported child self-regulation (β = −0.01, p = .14; see Figure 17), parent reported cognitive self-regulation regulation (β = −0.01, p = .11), parent reported emotional self-regulation (β = −0.01, p = .19), or child self-reported regulation (β = −0.00, p = .57). Similarly, no interaction effect was found between COVID-19 impact and Time One measures of parent reported total self-regulation (β = −0.01, p = .07), parent reported cognitive self-regulation regulation (β = −0.01, p = .14), parent reported emotional self-regulation (β = −0.00, p = .53), and child self-reported regulation (β = −0.00, p = .46).

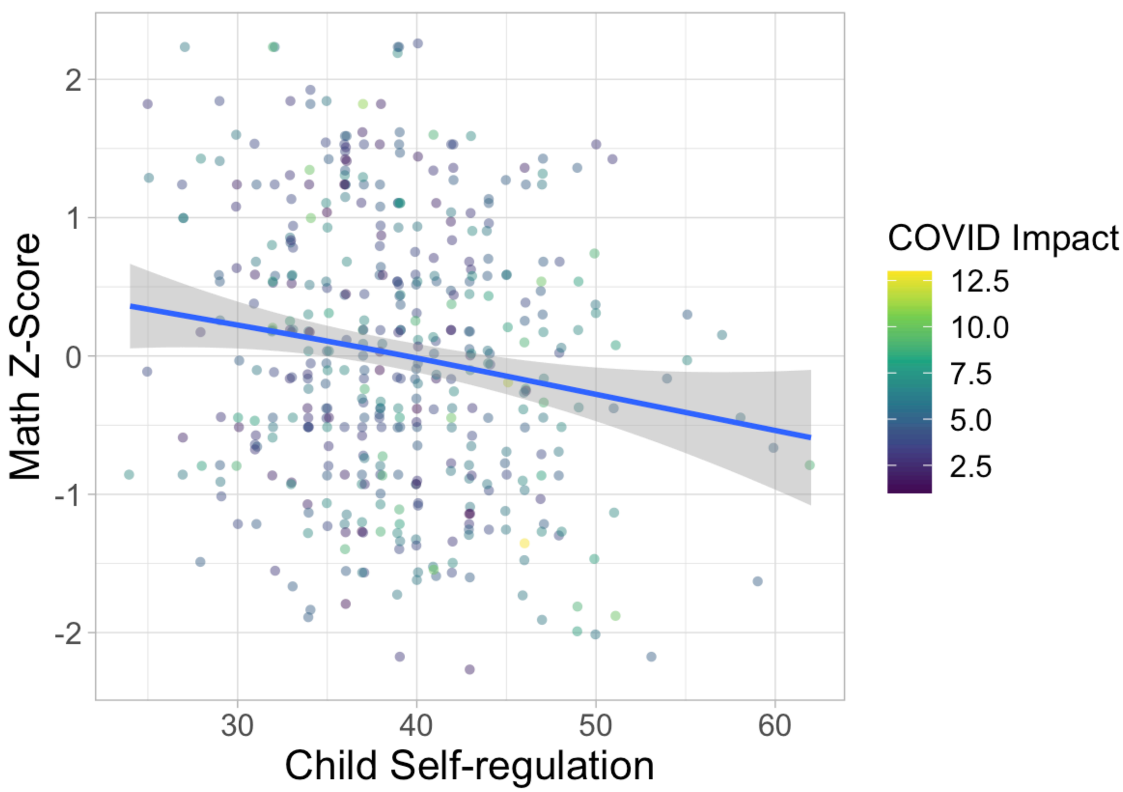

Figure 17. Parent Report of Self-Regulation, Math Performance, & COVID-19 Impact.

CHAPTER 5

DISCUSSION

The aim of this study was to explore the potential influence of COVID-19 stress and impacts on the self-regulation development among participating students, and how these variables are related to their mathematics performance. To accomplish this objective, we conducted several preliminary analyses to validate our measures and performed numerous multi-level regression analyses to test the hypotheses that students facing higher levels of COVID-19 stress and impacts would exhibit poorer self-regulation skills and thus, achieve lower scores in mathematics.

Overall, I found that student self-regulation strongly predicted performance in grade-level mathematics. While COVID-19 impacts were associated with poorer self-regulation, I found no evidence that stress from COVID-19 directly affected self-regulation. Notably, I also found no evidence that COVID-19 stress and impacts influenced student performance on grade-level mathematics. Similarly, there was no significant interaction between COVID-19 stress and impacts on the relationship between self-regulation and math outcomes. My results align with prior research that highlights the important relationship between self-regulation and academic achievement. However, the results of this study, limited by the demographics of our sample and methods, may not accurately reflect the impacts of COVID-19, especially on students' mathematics performance. Despite its limitations, this study provides valuable insights into how to continue the crucial research on understanding the extensive effects of the pandemic on students' emotional, behavioral, and academic outcomes.

Preliminary Analyses

Exploratory Factor Analyses of Fast-Track Project Child Behavior Questionnaire

For parent-reported child self-regulation, exploratory factor analysis confirmed a reliable unidimensional construct at both Time Zero and Time One, with strong internal consistency. Removing two items ("My child tells new kids their name without being asked to tell it" and "My child asks friends for help with their problems") with low factor loadings increased reliability. Consequently, the remaining eighteen survey items were used to measure the total parent report of child self-regulation. Of note, all analyses were conducted a second time with the survey in its original format containing all 20 items (i.e., without dropping the two identified items). These analyses yielded a similar pattern of results; they did not significantly change any of the outputs in terms of coefficients or *p*-values.

As predicted, the creation of two factors from the parent-report of child self-regulation, representing emotional regulation and cognitive regulation, was supported by exploratory factor analysis, with good internal consistency. Dropping items with low factor loadings (i.e., “My child’s feelings get hurt,” “My child fights or argues with adults”) from the hypothesized emotional regulation factor and two items (i.e., “My child tells new kids their name without being asked to tell it,” “My child asks friends for help with their problems”) from the hypothesized cognitive regulation factor enhanced reliability for each factor.

Regarding child self-report, the questionnaire demonstrated a reliable unidimensional construct with good internal consistency at both Time Zero and Time One. Dropping two items with low factor loadings (i.e., “I tell new kids my name without being asked to tell it" and "I ask friends for help with my problems") increased reliability at both timepoints. However, unlike parent report of child self-regulation, exploratory factor analysis did not support the formation of distinct emotional regulation and cognitive regulation factors due to many cross-factor loadings. Therefore, the analysis of child-reported regulation was limited to a unidimensional construct.

These findings contribute to the understanding of how the Fast-Track Project Child Behavior Questionnaire functions as a tool for assessing self-regulation in both parent-reported and child self-reported measures. Preliminary analyses supported the hypothesis that distinct factors of cognitive and emotional self-regulation could be derived from the parent- report construct, however the hypothesis was not confirmed in the context of child self-reported regulation. Although this finding did not support the hypothesized factors for child reported self-regulation, the cross-factor loadings are substantiated by prior research that has emphasized the considerable overlap between cognitive and emotional regulation processes (Zhou et al., 2012). Overall, the analyses highlight the importance of item analysis in enhancing the reliability of this measure and suggest that the questionnaire's unidimensional structure may be more appropriate for child self-reports compared to parent-reported measures. Further research on this measure could explore the robustness of these proposed factor structures.

Convergent Validity of Fast-Track Project Child Behavior Questionnaire

We then examined the convergent validity of the Fast-Track Project Child Behavior Questionnaire by comparing it with established measures of behavior and personality: the Pediatric Symptom Checklist (PSC) and the Big Five Inventory (BFI). Parent-reported levels of child self-regulation showed statistically significant moderate positive correlations with the PSC Attention, Internalizing, and Externalizing subscales, indicating a robust relationship across this measure. Similarly, self-reported levels of child self-regulation demonstrated statistically significant moderate positive correlations with the PSC Attention subscale and weak positive correlations with the Internalizing and Externalizing subscales, indicating a significant but weaker relationship. Furthermore, parent-reported child self-regulation exhibited statistically significant moderate positive correlations with the BFI neuroticism scale and moderate negative correlations with the BFI Conscientiousness and Agreeableness scales. Child-reported self-regulation also displayed statistically significant weak positive correlations with the BFI neuroticism scale and weak negative correlations with the Agreeableness scale, along with a moderate negative correlation with the Conscientiousness scale.

These findings suggest a consistent pattern of correlations between the Fast-Track Project Child Behavior Questionnaire and established measures of behavior and personality, supporting the hypothesized relationships between measures. These analyses support the validity, effectiveness, and utility of the Fast-Track Project Child Behavior Questionnaire for assessing child self-regulation behaviors and characteristics. Future analyses could further investigate the strength and robustness of these correlations with larger and more diverse data sets.

Preliminary Analysis of COVID-19 Measures

COVID-19 stress was measured through parent responses to ten survey items, exploring stress related to general health, virus contraction, and educational implications. While I explored the possibility of creating three distinct factors of stress, the hypothesized three-factor model was not supported by initial factor analysis due to the limited number of items per factor. Consequently, the COVID-19 stress construct was reconceptualized to comprise five items demonstrating a strong positive relationship. This refined five-item construct demonstrated robust reliability, providing a clear perspective on respondents' experience of health-related stress from COVID-19 during the 2020-2021 year.

Regarding COVID-19 impact, parent responses to seven survey items were analyzed. These items queried about financial impacts, emotional effects on themselves and their children, and changes to daily responsibilities. Factor analysis revealed low item correlation and reliability. Despite attempts to enhance reliability, the varied nature of survey topics did not lead to significant improvement. Consequently, COVID-19 impact was quantified as a sum score of parent responses to each survey item, allowing for the examination of the cumulative effects of various impacts.

These measures aimed to increase our understanding of the experience of COVID-19 related stress and impact among parents during the 2020-2021 school year. In the present study, these constructs were used to answer research questions regarding the influence of COVID-19 stress and impact on student learning during the pandemic.

Preliminary Analysis of Grade- Level Mathematics Measures

Mathematic competence was measured by child-participant performance on assigned grade-level mathematics questions. Exploratory factor analysis was conducted to determine the reliability of grade-level math composites. All grade-level mathematics competence composites demonstrated good internal consistency and reliability. Item analysis indicated that alpha could not be improved by dropping any items for grades four, five, six, and eight. However, for the grade seven and high school assessment, dropping two items could slightly improve alphas, but these items were retained to provide the best representation of grade level competence, as each question represented a different skill or competency. These findings provide insights into the reliability and representation of grade-level mathematics competence composites, contributing to the understanding of student performance in mathematics across different grade levels. The detailed analysis ensured the validity and robustness of the measurement tool used in assessing mathematics competence in this study.

Research Questions

Self-Regulation Change from Time Zero to Time One

We examined the change of child self-regulation from Time Zero to Time One, while considering various factors such as gender, race, maternal education, school type, format, and the impact of COVID-19 related stress and impacts. Self-regulation was assessed across four dimensions: parent-reported child self-regulation, parent-reported child cognitive regulation, parent-reported child emotional regulation, and child self-reported regulation.

Time emerged as a robust predictor of parent-reported child self-regulation, cognitive regulation, and emotional regulation, as child participants were rated as demonstrating significant improvements from Time Zero to Time One. Interestingly, child self-reports of regulation did not reveal a significant effect of time on their reported regulatory abilities. This pattern of results is consistent with research that highlights maturation effects in self-regulation development, as individuals gain these skills and behaviors over time (Fuhs et al., 2013; Harrington et al., 2020; Zimmerman, 2008). The significant improvements observed in parent-reported self-regulation metrics suggest that parental perceptions of their child's regulatory abilities may be influenced by developmental changes over the observed time period. Furthermore, the lack of significant change in child self-reports of regulation may reflect differences in perception or awareness of regulatory behaviors between parents and children, as suggested in previous research (Clearly et. al., 2012; Diaz & Eisenberg, 2015).

Examining the influence of child gender provided mixed results. Gender alone did not significantly affect parental or child reports of self-regulation. However, interactions between time and gender were notable, suggesting differences in the impact of time on parental reports of child self-regulation for male children. Specifically, male identifying children were reported to have made more significant improvements in their regulation across time. When examining the subscales of cognitive and emotional regulation, male gender was associated with significantly poorer ratings of cognitive regulation compared to females, but no significant gender differences were observed in emotional regulation. Overall, while gender effects varied the analyses suggested that male and nonbinary identifying students were perceived to have worse regulation than female identifying students. This perceived gender divide finds support in previous research indicating that females tend to be rated as exhibiting better regulation in environments such as school, though this perception is not consistently reflected in empirical studies (Matthews et al., 2009; Duckworth & Seligman, 2006).

Further, the interaction effect exhibited for male identifying children across time may be attributed to various factors, including socialization processes and developmental trajectories. Research suggests that societal expectations and gender norms may shape how individuals perceive and express self-regulatory behaviors (Matthews et al., 2009).

Furthermore, the differential impact of time on male self-regulation could also be influenced by individual differences in cognitive and emotional development, as well as environmental factors such as parenting styles and peer interactions (Duckworth & Seligman, 2006).

In terms of racial identity, Asian students were rated by their parents and themselves as exhibiting better self-regulation across all measures of regulation when compared to other racial groups. Further, interaction effects between time and race indicated differences in the rate of change in cognitive self-regulation over time for Asian students compared to other racial groups. The results suggested that although Asian students were rated as having better self-regulation, their rate of improvement from Time Zero to Time One was not as pronounced as students in other racial groups. There was no evidence of other effects for race and self-regulation.

These findings align with previous research indicating cultural differences in self-regulation processes and outcomes. For instance, research has suggested that Asian cultures tend to emphasize self-discipline, perseverance, collectivism, and deference to authority, which may contribute to higher levels of observed self-regulation among Asian individuals, as reflected by the participants in this study (Jaramillo et al., 2017). However, the observed differences in the rate of improvement in self-regulation over time among Asian students in this study warrant further investigation. It is possible that cultural factors, academic pressures, or social expectations may influence the trajectory of self-regulatory development among Asian students, which may underscore the general need for culturally sensitive and ecologically sensitive tools to measure self-regulation behaviors (Cleary et al. 2012; Diaz & Eisenberg, 2015).

I found no evidence that the amount of time students spent in-person, hybrid, or virtually learning was a predictive factor of child self-regulation. This result was consistent with initial analysis of school types (i.e., homeschool, traditional school, etc.) which indicated no significant differences in parent-reported child self-regulation across different settings. However, when examining the subscales of regulation, students who attended homeschooling environments were rated as having significantly worse cognitive regulation than students in other school environments. It is possible that parents perceived students in homeschool environments as having poorer cognitive regulation because parent-educators are tasked with addressing cognitive regulation deficits, such as inattention. Unlike teachers, who have exposure to hundreds of children in school environments, parent-educators may not have the same frame of reference for typical regulatory behavior (Gresham et al., 2010). Moreover, homeschooling may create an environment characterized by more intensive interaction between parents and children, blurring the boundaries between parental and instructional roles. This dual role could lead to increased redirection and scaffolding from parents, thus potentially influencing parental perceptions of child self-regulation (Gresham et al., 2010). While previous research has emphasized the significant role of the environment in shaping self-regulation, evidence regarding how this varies across different educational settings is mixed (Zimmerman, 2002). This may explain some of the patterns across settings in this dataset.

Regarding maternal education, higher levels of maternal education were linked with better child self-regulation in both parent-report and self-report. Specifically, when mothers had no diploma, child self-regulation was significantly worse when compared to cases in which mothers held degrees ranging from a high school diploma up to a graduate degree. Although the sample had few mothers without diplomas, and thus this finding should be considered with caution, the results hint at potential implications that have been found in prior research. Specifically, prior research has demonstrated the influence of maternal education on child development outcomes, including self-regulation (Davis-Kean, 2005; Cole et al., 2019). Maternal education has been identified as a key determinant of parenting practices and behaviors, with higher education levels associated with more favorable parenting behaviors, including increased involvement in children's academic activities and greater emotional support (Davis-Kean, 2005). Furthermore, parental stress, which may be influenced by educational attainment, has been shown to negatively impact parenting practices and, subsequently, child behavioral outcomes (Davis-Kean, 2005; Zimmerman, 2008). Therefore, the observed relationship between maternal education and child self-regulation underscores the multifaceted nature of parental influences on children's regulatory development. Specifically, these findings may reflect the complex interplay of modeling, access to resources, and environmental factors in shaping a child's regulatory development.

When analyzing the effects of COVID-19, I found that direct COVID-19 impacts had a significant effect on both parent-reported and child self-reported self-regulation, indicating poorer regulation with increased COVID-19 impact. Further, interaction effects demonstrated the increased vulnerability of those who experienced more COVID-19 impacts at Time Zero as their regulation was significantly worse over time. By contrast, I found no evidence that our measure of COVID-19-related stress was a significant influence on child self-regulation outcomes. These findings carry interesting implications as we navigate the continued repercussions of the COVID-19 pandemic. These results suggest that assessing impacts such as financial changes, increased parenting responsibilities, and altered routines within families may offer a more meaningful understanding of the persistent adverse effects of the pandemic, rather than solely focusing on perceived stress levels related to health.

These findings are consistent with research that highlights the multifaceted effect of the COVID-19 pandemic on families and children's well-being. Emerging research has demonstrated that direct exposure to COVID-19, including illness or death of family members, can have significant psychological and emotional consequences for children, affecting various domains of functioning, including self-regulation (Feinberg et al.,2022). Moreover, the disruption caused by the pandemic, including changes in family dynamics, financial strain, and disruptions in daily routines, can impact parenting practices and children's regulatory capacities (Feinberg et al.,2022). Therefore, the observed differential effects of COVID-19 incidents and stress on self-regulation underscore the importance of considering various dimensions of pandemic-related experiences when assessing their impact on children's development.

Predictors of Participant Grade-Level Mathematics Performance

Regression analyses were conducted to investigate the predictive role of various factors on child participants' grade-level mathematics performances. These factors included demographics, such as race, gender, and maternal education level, school-related variables, including school type and format (e.g., in-person, virtual), and child self-regulation scores assessed at both Time Zero and Time One, as reported by parents and through self-report. Additionally, the interplay between self-regulation and mathematics performance was explored within the context of COVID-19 stress and COVID-19 impact.

Demographic factors demonstrated variability in their effect on mathematics competence. Gender was not a significant predictor of mathematics performance, with female, male, and nonbinary/other gender-identifying students performing similarly. This is aligned with previous research has shown mixed findings regarding the relationship between gender and mathematics performance, with some studies suggesting gender differences in mathematical abilities, whereas others indicate no significant disparities between genders in math achievement (Grootenboer & Hemmings, 2007; NMAP, 2008; Penner & Paret, 2008).

Racial identity emerged as a significant predictor of performance on grade-level mathematics, with Asian students exhibiting significantly better performance and Black students showing worse performance compared to the reference group of White students. This pattern of results aligns with previous research indicating racial disparities in academic achievement, with Asian students often outperforming their peers and Black students facing persistent achievement gaps due to institutional failures in education systems that disproportionally impact Black/African American and Latino/Hispanic minoritized groups (Gamoran et al., 1997; Grootenboer & Hemmings, 2007; NMAP, 2008; Battey, 2013)

I found no evidence that maternal education level was a significant predictor of mathematic performance. However, though it did not reach levels of significance, the results did indicate a trend that attainment of some college or more was associated with higher student performance on the mathematics measures. This trend is consistent with previous studies that have highlighted the importance of parental education in shaping children's academic outcomes, with higher levels of parental education generally associated with better academic performance among children (Davis-Kean, 2005). I note that this study included an uneven distribution of parents in the education groups, which may have influenced the power to detect effects. This influence and other individual and family factors warrant further study.

The type of school attended and format of learning produced interesting results when predicting mathematics competence. Specifically, child participants attending private schools exhibited lower mathematics scores compared to students attending other types of schools, although none of the school formats (i.e., in-person, hybrid, virtual) were strong predictors of mathematics competence. Previous research has indicated that private school attendance may not guarantee superior academic outcomes, with factors such as school resources, teaching quality and pedagogy, school culture, curriculum content, and student demographics playing more substantial roles in shaping academic outcomes (NMAP, 2008; Wayne & Youngs, 2003; Natasi & Clements, 2019; Roschelle et al., 2000). However, the results of this study are not consistent with recent research, with larger more diverse samples, that has highlighted how school formats were critical in shaping students' academic experiences during COVID-19 lockdowns (Goldhaber et al., 2023). Thus, the results highlight how the experiences and unique characteristics of this study sample (i.e., mostly white, middle- to upper-income households) may not generalize to other more diverse groups. For this sample, examining other factors of schooling (i.e. culture, pedagogy) and home environments (i.e., parenting styles, resources/ social support) not examined in this study may produce more nuanced and accurate predictions of academic competence.

Finally, we investigated the role of COVID-19-related stress and impact as predictors of grade-level mathematics performance. Surprisingly, we found no evidence that either COVID-19 impact or COVID-19 stress were significant predictors of students' mathematics performance. These results suggest that COVID-19 factors may not have a direct relationship with students' performance in mathematics. These findings are somewhat unexpected given the widespread disruptions caused by the pandemic, including school closures, remote learning transitions, and disruptions to daily routines, all of which were anticipated, and have been shown, to have adverse effects on academic performance (Kuhfeld et al., 2020; Fahle et al., 2023). However, it is possible that other factors, such as individual resilience, home support systems, or instructional adaptations made by schools, mitigated the impact of COVID-19-related stress and disruptions on the sample students' mathematics performance (Garcia & Weiss, 2020). Furthermore, the results of this study may underscore how COVID-19 disproportionately affected education and learning among vulnerable populations (i.e., lower SES, minoritized racial groups), who were underrepresented in this study (Kuhfeld et al., 2020; Fahle et al., 2023). Therefore, further investigation is warranted to better understand the nuanced relationship between COVID-19 and academic outcomes in mathematics and other subject areas.

Self-Regulation as a Predictor of Mathematics Performance

The study examined the influence of student self-regulation at both Time Zero and Time One on grade-level mathematics competence measured at Time One. The hypothesis posited that higher scores on self-regulation measures, indicative of poor regulation, would be negatively associated with student performance on grade-level math measures. Analysis of Time Zero self-regulation revealed significant effects of parent-reported total child self-regulation, child cognitive regulation, and child emotional regulation on grade-level mathematics competencies. Similarly, Time Zero child self-report of regulation significantly predicted mathematics performance. These findings were replicated when analyzing the impact of Time One self-regulation on mathematics outcomes, with significant effects observed for all the regulation measures. These results confirm the study hypothesis, suggesting that child regulation significantly predicts mathematics performance.

Prior research has consistently highlighted the importance of self-regulation in academic achievement, with studies demonstrating its role in facilitating effective learning strategies, goal setting, and persistence (Duckworth & Seligman, 2006; Zimmerman, 2000). Additionally, longitudinal studies have shown that early self-regulation skills are strong predictors of later academic success (McClelland et al., 2015), which may explain why Time Zero self-regulation was just as robust a predictor of Time One mathematics competence as Time One self-regulation. Therefore, the findings of this study align with the extant literature on the critical role and predictive nature of self-regulation in academic performance (Duckworth & Seligman, 2006; Zimmerman & Pons, 1986; Eisenberg et al., 2010).

Interaction effects between demographic identifiers, school factors, and self-regulation were investigated to understand potential variations in the influence of self-regulation on grade-level mathematics competence. Notably, I found no evidence that racial identity moderated the relationship between parent-reported self-regulation and mathematics performance at either Time Zero or Time One, suggesting consistency across racial groups. However, significant interaction effects were observed for child self-report of regulation, particularly among Black participants, indicating distinct negative effects for this racial group. These findings align with prior research highlighting the differential impact of self-regulation on academic outcomes across racial identities (Battey, 2013; Gamoran et al., 1997; Grootenboer & Hemmings, 2007). Moreover, I found no evidence that gender moderated the relationship between self-regulation and mathematics performance, consistent with previous studies suggesting limited and/or overstated gender differences in self-regulation and mathematics achievement (Grootenboer & Hemmings, 2007; NMAP, 2008; Penner & Paret, 2008).

Some of the interactions explored, such as mother's education and school format, showed a notable moderating effect on the relationship between self-regulation and mathematics competence, but only at specific time points and within certain categories of self-regulation. When investigating mother's education as a moderator, a negative effect was observed solely within the category of Associate's degree and exclusively at Time One. Regarding the interaction effects of school format, only the hybrid format demonstrated a significant moderating effect at Time Zero. While these findings imply that maternal education level and school format may influence the relationship between self-regulation and mathematics performance, the observed effects do not seem robust. Further research is warranted to elucidate the nature of these effects, given their emergence within a limited subset of the sample and specific time frames.

Overall, while some interaction effects were observed, particularly concerning racial identity, maternal education, and school format, the robust positive relationship between self-regulation and mathematics performance remained relatively consistent across various demographic and school-related factors. These findings underscore the power of self-regulation and its implications for academic achievement, while also highlighting the importance of considering multifaceted individual and contextual factors that may influence this relationship.

COVID-19, Self-Regulation, and Mathematics Competence

Contrary to the hypothesized moderating role of COVID-19 stress and impacts, I found no evidence of significant interaction effects between COVID-19 related stress and impacts on the relationship between self-regulation and mathematics outcomes. These results are surprising given other studies that have highlighted the robust undisputable evidence of mathematics learning loss and overall negative impacts COVID-19 had on children's academic attainment (Fahle et al., 2023; Goldhaber et al., 2023; NCES, 2022). Failure to detect an effect within this study may serve to underscore how COVID-19 had a disproportionally negative influence on the learning outcomes of populations that were underrepresented in this study (NCES, 2022).

Differences Between Individuals and Families

Regression analyses explored random effects for both individual participants and their families. Results revealed significant variability in self-regulation within both children and families. This variability implies that both individual characteristics and family-level factors play significant roles in shaping self-regulation among children, as supported by prior research (Zemen et al., 2006; Cole et al., 2019). Moreover, the analysis of mathematics performance similarly showed substantial variability between families, underscoring the importance of family-level factors in influencing children's mathematics outcomes. This relationship between mathematics performance and family factors is found in prior studies (Zimmerman, 2008). Overall, these findings collectively emphasize the complex interplay between individual characteristics and family contexts in shaping children's development and academic performance.

Based on these findings, interventions aimed at improving self-regulation and mathematics performance, particularly when addressing academic disparities and ongoing emotional and behavioral challenges following the COVID-19 pandemic, should consider factors at both individual, family, and school-system levels (Dorn et al., 2021; Fahle et al., 2023; Feinberg et al., 2022). These interventions could concentrate on enhancing individual skills and strategies among children by involving family members and the broader school community (Zeman et al., 2006). Approaches may also include providing parents and teachers with resources and guidance on supporting student self-regulation skills through positive reinforcement, structured routines, and effective communication (Fuhs et al., 2013; Harrington et al., 2020; McClelland & Cameron, 2011).

Limitations and Considerations for Future Research

Limitations of the analyses include an imbalanced representation and distribution of racial identities and socioeconomic status (SES) amongst participants. The study consisted of an overrepresentation of Caucasian individuals from households with mothers who held Bachelor’s and graduate degrees, suggesting they came from higher income households. This uneven distribution should be acknowledged, as prior research has demonstrated how racial identity and socioeconomic status correlates with differences in mathematics achievement and self-regulation behaviors (Cole et al., 2019; Zimmerman, 2008; NCES, 2019). Consequently, our analyses, which were overrepresented in these demographic groups, may not have fully captured the significance of these factors in understanding self-regulation and academic achievement.

Moreover, the underrepresentation of minoritized and lower SES populations likely underestimates the true repercussions of COVID-19, as indicated by the results of other recent studies. The pandemic exacerbated systemic inequities, disproportionately affecting low SES and racially minoritized populations in terms of health outcomes, food insecurity, housing instability, financial strain, school resources, and other persistent disruptions (Lopez et al., 2021; NCES, 2022). These negative impacts have had reverberating consequences in students emotional (higher internalizing), behavioral (higher externalizing), and academic outcomes (learning loss) (Fahle et al., 2023; Goldhaber et al., 2023; NCES, 2022). The failure to detect an effect of COVID-19 stress and the limited effect of COVID-19 impact (only found to effect self-regulation not academics) in this study sample may suggest a lack of generalizability of our findings given the skewed demographics of the sample. Additionally, other contextual or individual factors not considered in this study, such as coping mechanisms, social support, or access to resources, may have influenced the impact of COVID-related stress and impacts on self-regulation and academic performance, as prior research has revealed these contextual factors to play moderating roles (Fahle et al., 2023; Goldhaber et al., 2023). Further research is needed to better understand the complex interplay between

COVID-19 related stress and impacts, self-regulation, and academic performance in diverse populations and educational settings.

Relatedly, the study focused solely on COVID-19 impacts and stress, and academic performance, at single time points, thus limiting the exploration of the pandemic's evolving effects over time. Extending this study to encompass multiple time points would facilitate a more accurate examination of the longitudinal effects of COVID-19 on academic outcomes. The significance of such an extension is underscored by data, such as the 2022 NAEP results, which unequivocally demonstrated significant mathematics learning loss among all students following the COVID-19 pandemic (NCES, 2022). While this learning loss is particularly pronounced for lower- resourced and racially minoritized student populations, it was also documented for higher-resourced and Caucasian students, who are well represented in this study (NCES, 2022). Therefore, the failure to detect an impact on mathematics performance in this study highlights the limitations of its methods rather than a true absence of effect. Thus, expanding the study to incorporate additional time points would offer a more nuanced, and accurate, understanding of the longitudinal impact of COVID-19 on academic outcomes. This approach would not only address the limitations observed in this study but also better contribute to ongoing efforts aimed at mitigating the reverberating impacts of the pandemic on children's social, emotional, behavioral, and academic outcomes.

Finally, while the COVID-19 stress composite developed for this study is valuable, its scope is limited. Despite benefiting from factor analysis, which enhanced the COVID-stress construct comprehensiveness, the measure focused on stress associated with health concerns and the risk of contracting the virus. Incorporating additional variables such as perceptions of the virus, geographical context (i.e., if families lived in cities or rural environments), susceptibility to infection, and other stressors could have provided a more nuanced and ecologically valid understanding of COVID-19 stress and its implications for families (Feinberg et al., 2022).

Further, considering the important role environment plays in the acquisition and development of self-regulation and overall academic attainment, this study is limited given that few contextual factors regarding home and school environments were explored (Zimmerman, 2008; Harrington et al., 2020). Future studies could investigate features of the home environment and family unit, such as the number of caregivers, parenting style, and the parent child-relationship, to better understand the relationship between household factors and child self-regulation (Zeman et al. 2006; Cole et al., 2019; Zimmerman, 2008). Similarly, exploring school factors, including classroom climate, instructional modes, and teacher-student relationships, may provide further insights into participant's acquisition and use of self-regulating behaviors (Harrington et al., 2020; Slot et al., 2017; Eisenberg at al., 2010).

Practical Implications of Measuring Self-Regulation and Conclusions

An underlying focus of this study was the process of measuring self-regulation. Our inclusion of both parent-report and child self-report of self-regulation prompts discussions related to prior research noting the challenges of capturing the dynamic processes of self-regulation. Some analyses in this study suggested a discrepancy between parent-reported and self-reported child self-regulation. This discrepancy between self-report and parent-report is consistent with prior research that has emphasized the difficulty of capturing the dynamic nature of self-regulation by relying on rating forms, as they are decontextualized and static, and raters, who are prone to bias and personal perception (Clearly et al., 2012; Diaz & Eisenberg, 2015). The dissimilarity in ratings and perception of regulation behaviors revealed in the data may support the use of self-regulation measures that are more ecologically sensitive and process-oriented in future studies (Cleary et al., 2012).

Furthermore, our study differentiated between subtypes of regulation, namely cognitive and emotional regulation. Notably, both cognitive and emotional regulation were highly correlated when used as either outcome or predictor measures. These findings align with previous research that has emphasized the interconnectedness and reciprocal nature of different forms of regulation (Vohs & Baumeister, 2004; Eisenberg et al., 2010). Future research could continue to investigate similarities and differences in types of regulation and test whether differentiating regulation types is worthwhile when used in different contexts (e.g., classroom settings) or with different raters (e.g., parent observation or self-report) (Cleary et al., 2012).

Overall, the findings from this study, combined with existing literature, underscore the role of self-regulation as a significant factor and a robust predictor of students' academic performance. Although the results of this study suggest little to no consequence of COVID-19 on the relationship between self-regulation and academic performance, our study is limited as it is just a snapshot in time. Extant literature supports the need for continuous monitoring of the impacts of these disruptions. This dissertation study contributes to a growing body of research aimed at understanding the far-reaching consequences of the COVID-19 pandemic, particularly for a generation of students whose learning, social, and home environments were disrupted. This area of research and intervention is particularly fruitful, as we are likely to observe ongoing consequences of the COVID-19 pandemic on students' emotions, behaviors, and learning for years to come.

REFERENCES

Achenbach, T. M., & Edelbrock, C. (1991). Child behavior checklist. *Burlington (Vt)*, *7*, 371-392.

Azevedo, R. (2018). Using hypermedia as a metacognitive tool for enhancing student learning? The role of self-regulated learning. In *Educational psychologist* (p. 199-209). Routledge.

Azevedo, R., & Hadwin, A. F. (2005). Scaffolding self-regulated learning and metacognition–Implications for the design of computer-based scaffolds. *Instructional science*, *33*(5/6), 367-379.

Bandy, T., & Moore, K. A. (2010). Assessing self-regulation: A guide for out-of-school time program practitioners. *Child Trends*, *23*(10), 1-7.

Battey, D. (2013). Access to mathematics: "A possessive investment in whiteness". Curriculum Inquiry, 43(3), 332-359.

Binet, A., & Simon, T. (1916). *The development of intelligence in children (The Binet-Simon Scale).* (E. S. Kite, Trans.). Williams & Wilkins Co.

Blankson, A. N., Weaver, J. M., Leerkes, E. M., O'Brien, M., Calkins, S. D., & Marcovitch, S. (2017). Cognitive and emotional processes as predictors of a successful transition into school. *Early education and development*, *28*(1), 1-20.

Blair, C., & Raver, C. C. (2014). Closing the achievement gap through modification of neurocognitive and neuroendocrine function: Results from a cluster randomized controlled trial of an innovative approach to the education of children in kindergarten. *PloS one*, *9*(11), e112393.

Boekaerts, M., Zeidner, M., & Pintrich, P. R. (Eds.). (2005). *Handbook of self-regulation*. Elsevier.

Broadbent, J., & Poon, W. L. (2015). Self-regulated learning strategies & academic achievement in online higher education learning environments: A systematic review. *The Internet and Higher Education*, *27*, 1-13.

Carter Jr, R. A., Rice, M., Yang, S., & Jackson, H. A. (2020). Self-regulated learning in online learning environments: strategies for remote learning. *Information and Learning Sciences*.

Carver, C. S. (2004). Self-regulation of action and affect. In R. F. Baumeister & K. D. Vohs (Eds.), *Handbook of self-regulation: Research, theory, and applications* (pp. 13–39). The Guilford Press.

Claessens, A., & Engel, M. (2013). How important is where you start? Early mathematics knowledge and later school success. *Teachers College Record*, *115*(6), 1-29.

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

Cole, P. M., Ram, N., & English, M. S. (2019). Toward a unifying model of self-regulation: A developmental approach. *Child development perspectives*, *13*(2), 91-96.

Davis-Kean, P. E. (2005). The influence of parent education and family income on child achievement: the indirect role of parental expectations and the home environment. Journal of family psychology, 19(2), 294.

De Corte, E., Verschaffel, L., & Op't Eynde, P. (2000). Self-regulation: A characteristic and a goal of mathematics education. In *Handbook of self-regulation* (pp. 687-726). Academic Press.

Department of Education (1997). *Mathematics equals opportunity*. White Paper prepared for US Secretary of Education Richard W. Riley.

Department of Health and Human Services. (n.d.) Part I: Overview information. National Institutes of Health. Retrieved from https://grants. nih.gov/grants/guide/rfa-files/rfa-ag-11-010.html

Diaz, A., & Eisenberg, N. (2015). The process of emotion regulation is different from individual differences in emotion regulation: Conceptual arguments and a focus on individual differences. *Psychological Inquiry*, 26(1), 37-47.

Dorn, E., Hancock, B., Sarakatsannis, J., & Viruleg, E. (2021). COVID-19 and education: The lingering effects of unfinished learning. McKinsey & Company, 27.

Duckworth, A. L., & Carlson, S. M. (2013). Self-regulation and school success. *Self-regulation and autonomy: Social and developmental dimensions of human conduct*, *40*, 208.

Duckworth, A. L., & Seligman, M. E. (2006). Self-discipline gives girls the edge: Gender in self-discipline, grades, and achievement test scores. *Journal of educational psychology*, *98*(1), 198.

Duncan, G. J., Dowsett, C. J., Claessens, A., Magnuson, K., Huston, A. C., Klebanov, P., ... & Japel, C. (2007). School readiness and later achievement. *Developmental psychology*, *43*(6), 1428.

Eisenberg, N., & Spinrad, T. L. (2004). Emotion-related regulation: Sharpening the definition. *Child development*, *75*(2), 334-339.

Eisenberg, N., Spinrad, T. L., & Eggum, N. D. (2010). Emotion-related self-regulation and its relation to children's maladjustment. *Annual review of clinical psychology*, *6*, 495-525.

Eisenberg, N., Valiente, C., & Eggum, N. D. (2010). Self-regulation and school readiness. *Early education and development*, *21*(5), 681-698.

Fahle, E. M., Kane, T. J., Patterson, T., Reardon, S. F., Staiger, D. O., & Stuart, E. A. (2023). School district and community factors associated with learning loss during the COVID-19 pandemic. Center for Education Policy Research at Harvard University: Cambridge, MA, USA.

Fernández Cruz, M., Álvarez Rodríguez, J., Ávalos Ruiz, I., Cuevas López, M., de Barros Camargo, C., Díaz Rosas, F., ... & Lizarte Simón, E. J. (2020). Evaluation of the emotional and cognitive regulation of young people in a lockdown situation due to the Covid-19 pandemic. *Frontiers in Psychology*, *11*, 565503.

Feinberg, M. E., A Mogle, J., Lee, J. K., Tornello, S. L., Hostetler, M. L., Cifelli, J. A., ... & Hotez, E. (2022). Impact of the COVID-19 pandemic on parent, child, and family functioning. Family Process, 61(1), 361-374.

Fuchs, L. S., Fuchs, D., Karns, K., Hamlett, C. L., Katzaroff, M., & Dutka, S. (1997). Effects of task-focused goals on low-achieving students with and without learning disabilities. *American Educational Research Journal*, 34(3), 513-543.

Fuchs, L. S., Fuchs, D., Prentice, K., Burch, M., Hamlett, C. L., Owen, R., & Schroeter, K. (2003). Enhancing third-grade student's mathematical problem solving with self-regulated learning strategies. *Journal of educational psychology*, *95*(2), 306.

Fuhs, M. W., Farran, D. C., & Nesbitt, K. T. (2013). Preschool classroom processes as predictors of children's cognitive self-regulation skills development. *School Psychology Quarterly*, *28*(4), 347.

Gamoran, A., Porter, A. C., Smithson, J., & White, P. A. (1997). Upgrading high school mathematics instruction: Improving learning opportunities for low-achieving, low-income youth. Educational Evaluation and Policy Analysis, 19(4), 325-338.

García, E., & Weiss, E. (2020). COVID-19 and Student Performance, Equity, and US Education Policy: Lessons from Pre-Pandemic Research to Inform Relief, Recovery, and Rebuilding. *Economic Policy Institute*.

Gresham, F. M., Elliott, S. N., Cook, C. R., Vance, M. J., & Kettler, R. (2010). Cross-informant agreement for ratings for social skill and problem behavior ratings: An investigation of the Social Skills Improvement System—Rating Scales. *Psychological assessment*, 22(1), 157.

Goldberg, S. B. (2021). Education in a pandemic: the disparate impacts of COVID-19 on America's students. *USA: Department of Education*.

Goldhaber, D., Kane, T. J., McEachin, A., Morton, E., Patterson, T., & Staiger, D. O. (2023). The educational consequences of remote and hybrid instruction during the pandemic. American Economic Review: Insights, 5(3), 377-392.

Gramzow, R. H., Sedikides, C., Panter, A. T., Sathy, V., Harris, J., & Insko, C. A. (2004). Patterns of self-regulation and the Big Five. *European Journal of Personality*, 18(5), 367-385.

Grootenboer, P., & Hemmings, B. (2007). Mathematics performance and the role played by affective and background factors peter grootenboer and brian hemmings. Mathematics education research journal, 19(3), 3-20.

Gruhn, M. A., & Compas, B. E. (2020). Effects of maltreatment on coping and emotion regulation in childhood and adolescence: A meta-analytic review. *Child abuse & neglect*, *103*, 104446.

Hansen, N., Jordan, N. C., Fernandez, E., Siegler, R. S., Fuchs, L., Gersten, R., & Micklos, D. (2015). General and math-specific predictors of sixth-graders' knowledge of fractions. *Cognitive Development*, *35*, 34-49.

Harrington, E. M., Trevino, S. D., Lopez, S., & Giuliani, N. R. (2020). Emotion regulation in early childhood: Implications for socioemotional and academic components of school readiness. *Emotion*, *20*(1), 48.

Hecht, S. A., & Vagi, K. J. (2010). Sources of group and individual differences in emerging fraction skills. *Journal of educational psychology*, *102*(4), 843.

Jaramillo, J. M., Rendón, M. I., Muñoz, L., Weis, M., & Trommsdorff, G. (2017). Children's self-regulation in cultural contexts: The role of parental socialization theories, goals, and practices. Frontiers in psychology, 8, 252480.

Jellinek, M. S., Murphy, J. M., Little, M., Pagano, M. E., Comer, D. M., & Kelleher, K. J. (1999). Use of the Pediatric Symptom Checklist to screen for psychosocial problems in pediatric primary care: a national feasibility study. *Archives of Pediatrics & Adolescent Medicine*, 153(3), 254-260.

John, O. P., & Srivastava, S. (1999). The Big-Five trait taxonomy: History, measurement, and theoretical perspectives.

Kopp, C. B. (1989). Regulation of distress and negative emotions: A developmental view. *Developmental Psychology, 25*(3), 343–354.

Krause, K. H., Verlenden, J. V., Szucs, L. E., Swedo, E. A., Merlo, C. L., Niolon, P. H., ... & Underwood, J. M. (2022). Disruptions to School and Home Life Among High School Students During the COVID-19 Pandemic—Adolescent Behaviors and Experiences Survey, United States, January–June 2021. *MMWR supplements*, *71*(3), 28.

Kuhfeld, M., Soland, J., & Lewis, K. (2022). Test score patterns across three COVID-19-impacted school years. *EdWorkingPaper: 22-521*, 37-62.

Kuhfeld, M., Soland, J., Tarasawa, B., Johnson, A., Ruzek, E., & Liu, J. (2020). Projecting the Potential Impact of COVID-19 School Closures on Academic Achievement. *Educational Researcher*, 49(8), 549–565. https://doi.org/10.3102/0013189X20965918

Lopez, L., Hart, L. H., & Katz, M. H. (2021). Racial and ethnic health disparities related to COVID-19. Jama, 325(8), 719-720.

Maccini, P., McNaughton, D., & Ruhl, K. L. (1999). Algebra Instruction for Students with Learning Disabilities: Implications from a Research Review. *Learning Disability Quarterly*, 22(2), 113–126. https://doi.org/10.2307/1511270

Matthews, J. S., Ponitz, C. C., & Morrison, F. J. (2009). Early gender differences in self-regulation and academic achievement. *Journal of educational psychology*, 101(3), 689.

McClelland, M. M., Acock, A. C., & Morrison, F. J. (2006). The impact of kindergarten learning-related skills on academic trajectories at the end of elementary school. Early childhood research quarterly, 21(4), 471-490.

McClelland, M. M., Acock, A. C., Piccinin, A., Rhea, S. A., & Stallings, M. C. (2013). Relations between preschool attention span-persistence and age 25 educational outcomes. *Early childhood research quarterly*, *28*(2), 314-324.

McClelland, M. M., & Cameron, C. E. (2011). Self-regulation and academic achievement in elementary school children. In R. M. Lerner, J. V. Lerner, E. P. Bowers, S. Lewin-Bizan, S. Gestsdottir, & J. B. Urban (Eds.), Thriving in childhood and adolescence: The role of self-regulation processes. New Directions for Child and Adolescent Development, 133, 29–44.

McClelland, M. M., & Cameron, C. E. (2012). Self-regulation in early childhood: Improving conceptual clarity and developing ecologically valid measures. *Child development perspectives*, 6(2), 136-142.

McClelland, M. M., Cameron, C. E., Wanless, S. B., Murray, A., Saracho, O., & Spodek, B. (2007). Executive function, behavioral self-regulation, and social-emotional competence. *Contemporary perspectives on social learning in early childhood education*, *1*, 113-137.

McClelland, M. M., John Geldhof, G., Cameron, C. E., & Wanless, S. B. (2015). Development and self-regulation. *Handbook of child psychology and developmental science*, 1-43.

McCrae, R. R., & Löckenhoff, C. E. (2010). Self-regulation and the five-factor model of personality traits.

Miller, D. C., & Byrnes, J. P. (2001). Adolescents' decision making in social situations: A self-regulation perspective. Journal of Applied Developmental Psychology, 22(3), 237-256.

National Center for Education Statistics (2019). Status and trends in the education of racial and ethnic groups. Indicator 11: Mathematics achievement. Retrieved from: https://nces.ed.gov/programs/raceindicators/indicator_rcb.asp

National Mathematics Advisory Panel (NMAP). (2008). Foundations for success: The final report of the National Mathematics Advisory Panel. Washington, DC: U.S. Department of Education.

Nota, L., Soresi, S., & Zimmerman, B. J. (2004). Self-regulation and academic achievement and resilience: A longitudinal study. International journal of educational research, 41(3), 198-215.

Organisation for Economic Co-operation and Development (OECD). (2019). PISA 2018 results (volume I): What students know and can do.

Panchal, U., Salazar de Pablo, G., Franco, M., Moreno, C., Parellada, M., Arango, C., & Fusar-Poli, P. (2021). The impact of COVID-19 lockdown on child and adolescent mental health: systematic review. *European child & adolescent psychiatry*, 1-27.

Park, D., Gunderson, E. A., Tsukayama, E., Levine, S. C., & Beilock, S. L. (2016). Young children’s motivational frameworks and math achievement: Relation to teacher-reported instructional practices, but not teacher theory of intelligence. *Journal of Educational Psychology*, *108*(3), 300.

Penner, A. M., & Paret, M. (2008). Gender differences in mathematics achievement: Exploring the early grades and the extremes. *Social Science Research*, *37*(1), 239-253.

Perry, N. E. (1998). Young children's self-regulated learning and contexts that support it. Journal of educational psychology, 90(4), 715.

Ponitz, C. C., McClelland, M. M., Matthews, J. S., & Morrison, F. J. (2009). A structured observation of behavioral self-regulation and its contribution to kindergarten outcomes. *Developmental psychology*, *45*(3), 605.

Quay, H. C., & Peterson, D. R. (1987). *Manual for the revised behavior problem checklist*. University of Miami.

Ramdass, D., & Zimmerman, B. J. (2011). Developing Self-Regulation Skills: The Important Role of Homework. *Journal of Advanced Academics*, *22*(2), 194–218. https://doi.org/10.1177/1932202X1102200202

Ramirez, G., Gunderson, E. A., Levine, S. C., & Beilock, S. L. (2013). Math anxiety, working memory, and math achievement in early elementary school. *Journal of Cognition and Development*, *14*(2), 187-202.

Roschelle, J. M., Pea, R. D., Hoadley, C. M., Gordin, D. N., & Means, B. M. (2000). Changing how and what children learn in school with computer-based technologies. The future of children, 76-101.

Sawchuk, S. S. S. D., & Sparks, S. D. (2020). Kids are behind in math because of COVID-19. Here's what research says could help. *Education Week*. https://www. edweek. org/teaching-learning/kids-are-behind-in-mathbecause-of-covid-19-here's-what-research-says-could-help/2020/12.

Schmitt, S. A., McClelland, M. M., Tominey, S. L., & Acock, A. C. (2015). Strengthening school readiness for Head Start children: Evaluation of a self-regulation intervention. *Early Childhood Research Quarterly*, *30*, 20-31.

Schunk, D. H. (1996). Goal and self-evaluative influences during children's cognitive skill learning. *American educational research journal*, *33*(2), 359-382.

Slot, P. L., Mulder, H., Verhagen, J., & Leseman, P. P. (2017). Preschoolers' cognitive and emotional self-regulation in pretend play: Relations with executive functions and quality of play. Infant and Child Development, 26(6), e2038.

Tomasik, M. J., Helbling, L. A., & Moser, U. (2021). Educational gains of in-person vs. distance learning in primary and secondary schools: A natural experiment during the COVID-19 pandemic school closures in Switzerland. *International Journal of Psychology*, 56(4), 566-576.

U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, School Pulse Panel (2021–22).

U.S. Department of Education. Institute of Education Sciences, National Center for Education Statistics, National Assessment of Educational Progress (NAEP), 2022 Mathematics Assessment.

Vohs, K. D., & Baumeister, R. F. (Eds.). (2004). *Handbook of self-regulation: Research, theory, and applications*. Guilford Publications.

Wang, A. Y., Fuchs, L. S., Fuchs, D., Gilbert, J. K., Krowka, S., & Abramson, R. (2019). Embedding self-regulation instruction within fractions intervention for third graders with mathematics difficulties. *Journal of Learning Disabilities*, *52*(4), 337-348.

Wayne, A. J., & Youngs, P. (2003). Teacher Characteristics and Student Achievement Gains: A Review. Review of Educational Research, 73(1), 89–122. https://doi.org/10.3102/00346543073001089

Wechsler, D. (1943). Non-intellective factors in general intelligence. *The Journal of Abnormal and Social Psychology*, *38*(1), 101.

Wong, J., Baars, M., Davis, D., Van Der Zee, T., Houben, G. J., & Paas, F. (2019). Supporting self-regulated learning in online learning environments and MOOCs: A systematic review. *International Journal of Human–Computer Interaction*, *35*(4-5), 356-373.

Ye, A., Resnick, I., Hansen, N., Rodrigues, J., Rinne, L., & Jordan, N. C. (2016). Pathways to fraction learning: Numerical abilities mediate the relation between early cognitive competencies and later fraction knowledge. *Journal of Experimental Child Psychology*, *152*, 242-263.

Zelazo, P. D., & Cunningham, W. A. (2007). Executive function: Mechanisms underlying emotion regulation.

Zeman, J., Cassano, M., Perry-Parrish, C., & Stegall, S. (2006). Emotion regulation in children and adolescents. *Journal of Developmental & Behavioral Pediatrics*, *27*(2), 155-168.

Zhou, Q., Chen, S. H., & Main, A. (2012). Commonalities and differences in the research on children's effortful control and executive function: A call for an integrated model of self-regulation. Child development perspectives, 6(2), 112-121.

Zimmerman, B. J. (2000). Attaining self-regulation: A social cognitive perspective. In *Handbook of self-regulation* (pp. 13-39). Academic press.

Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. Theory into practice, 41(2), 64-70.

Zimmerman, B.J. (2008). Theories of Self-Regulated Learning and Academic Achievement: An Overview and Analysis. In Zimmerman, B. J., & Schunk, D. H. (Eds.), *Self-regulated learning and academic achievement: Theoretical perspectives*. Routledge.

Zimmerman, B. J., & Pons, M. M. (1986). Development of a Structured Interview for Assessing Student Use of Self-Regulated Learning Strategies. American Educational Research Journal, 23(4), 614–628. https://doi.org/10.3102/00028312023004614

Zimmerman, B. J., & Martinez-Pons, M. (1990). Student differences in self-regulated learning: Relating grade, sex, and giftedness to self-efficacy and strategy use. Journal of Educational Psychology, 82(1), 51–59. https://doi.org/10.1037/0022-0663.82.1.51

APPENDIX A

ANNOTATED R CODE FOR PRELIMINARY ANALYSES

```
# Factor Analysis Code
```{r}
#Factor analysis was conducted for all variables used in the study.  Function for
conducting factor analysis and plotting the results was made.

#create vector of variable levels for t0 and t1
v_name_t0 <- d_t0_meta$new_label %>%
  `names<-`(str_remove(string = d_t0_meta$Variable_label,pattern =
fixed(d_t0_meta$Remove)) %>%
            str_trim())

v_name_t1 <- d_t1_meta$new_label %>%
  `names<-`(str_remove(string = d_t1_meta$Variable_label,pattern =
fixed(d_t1_meta$Remove)) %>%
            str_trim())

make_factor_analysis_plot <- function(d, nfactors,fm="pa", cor_heat=FALSE,
parallel=FALSE, loading=TRUE, ...) {
 fit <-  fa(d,nfactors = nfactors,fm=fm, ...) %>%
  fa.sort()
 if (cor_heat) {
 print( WJSmisc::cor_heat(d))
 }
 if (parallel) {
   print (WJSmisc::parallel_analysis(d))
 }
  if (loading) {
   print( WJSmisc::plot_loading(fit))
  }
 fit}

# parent sr t0
d_t0 %>%
  select(starts_with("parent_sr")) %>%
  rename(any_of(v_name_t0)) %>%
  make_factor_analysis_plot(nfactors = 2,cor_heat = F, parallel = T) +
  theme(text= element_text(sixe=20))
```
```

```
d_t0 %>%
  select(starts_with("parent_sr")) %>%
  rename(any_of(v_name_t0)) %>%
  make_factor_analysis_plot(nfactors = 2,cor_heat = F, parallel = T) +
theme(text = element_text(size = 20),   # Base text size
        axis.text.x = element_text(size = 20),  # X-axis labels
        axis.text.y = element_text(size = 40),  # Y-axis labels
        axis.title = element_text(size = 20),   # Axis titles
        legend.text = element_text(size = 20),  # Legend text
        strip.text = element_text(size = 20),
       strip.text = element_text(size = 20, margin = margin(b = 15))
  )

# parent sr t1
d_t1 %>%
  select(starts_with("parent_sr")) %>%
  rename(any_of(v_name_t1)) %>%
  make_factor_analysis_plot(nfactors = 2,cor_heat = F, parallel = F)

#child sr t0
d_t0 %>%
  select(starts_with("child_sr")) %>%
  rename(any_of(v_name_t0)) %>%
  make_factor_analysis_plot(nfactors = 2,cor_heat = F, parallel = T)  +
theme(text = element_text(size = 20),   # Base text size
        axis.text.x = element_text(size = 20),  # X-axis labels
        axis.text.y = element_text(size = 40),  # Y-axis labels
        axis.title = element_text(size = 20),   # Axis titles
        legend.text = element_text(size = 20),  # Legend text
        strip.text = element_text(size = 20),
       strip.text = element_text(size = 20, margin = margin(b = 15)) )

# child sr t1
d_t1 %>%
  select(starts_with("child_sr")) %>%
  rename(any_of(v_name_t1)) %>%
  make_factor_analysis_plot(nfactors = 1,cor_heat = F, parallel = F)

# BFI t0
d_t0 %>%
  select(starts_with("bfi")) %>%
  rename(any_of(v_name_t0)) %>%
  make_factor_analysis_plot(nfactors = 5,cor_heat = F, parallel = F)
```

```
# BFI t1
d_t1 %>%
  select(starts_with("bfi")) %>%
  rename(any_of(v_name_t1)) %>%
  make_factor_analysis_plot(nfactors = 5,cor_heat = F, parallel = F)

#PSC t0
d_t0 %>%
  select(starts_with("psc")) %>%
  rename(any_of(v_name_t0)) %>%
  make_factor_analysis_plot(nfactors = 4,cor_heat = F, parallel = F)

#PSC t1
d_t1 %>%
  select(starts_with("psc")) %>%
  rename(any_of(v_name_t1)) %>%
  make_factor_analysis_plot(nfactors = 4,cor_heat = F, parallel = F)

# COVID Impact t0
d_t0 %>%
  select(Scale=="COVID Impact T0") %>%
  rename(any_of(v_name_t0)) %>%
  # select(-Homework, -`daily responsibilities`) %>%
  make_factor_analysis_plot(nfactors = 1,cor_heat = F, parallel = F, max.iter=100000)

covid_impact_t0_items <- d_t0_meta %>%
  filter(Scale=="COVID Impact T0") %>%
  select(Variable_label, new_label) %>%
  deframe()

# COVID Impact t1
d_t1 %>%
  select(starts_with("covid_impact")) %>%
  rename(any_of(v_name_t1)) %>%
  make_factor_analysis_plot(nfactors = 1,cor_heat = F, parallel = F)
```

```
# COVID Stress t0 -
d_t0 %>%
  select(starts_with("covid_stress")) %>%
  rename(any_of(v_name_t0)) %>%
  make_factor_analysis_plot(nfactors = 3,cor_heat = F, parallel = F)
 +
theme(text = element_text(size = 20),   # Base text size
        axis.text.x = element_text(size = 20),  # X-axis labels
        axis.text.y = element_text(size = 40),  # Y-axis labels
        axis.title = element_text(size = 20),   # Axis titles
        legend.text = element_text(size = 20),  # Legend text
        strip.text = element_text(size = 20),
       strip.text = element_text(size = 20, margin = margin(b = 15)))

covid_stress_t0_items <- d_t0_meta %>%
  filter(Scale=="COVID Stress T0") %>%
  select(Variable_label, new_label) %>%
  deframe()

d_t0 %>%
  select(all_of(covid_stress_t0_items)) %>%
  psych::alpha(check.keys=TRUE)

d_t0 %>%
  select(all_of(covid_stress_t0_items)) %>%
  select(-`stressed about the educational implications of COVID-19... - For your
community?`,
         -`stressed about the educational implications of COVID-19... - For your family?`,
         -`stressed about the educational implications of COVID-19... - For you?`,
         -`To what extent were you stressed about your child contracting COVID-19 now?`,
         -`To what extent were you stressed about contracting COVID-19 now?`) %>%
  psych::alpha(check.keys=TRUE)

# COVID Stress t1
d_t1 %>%
  select(starts_with("covid_stress")) %>%
  rename(any_of(v_name_t1)) %>%
  make_factor_analysis_plot(nfactors = 1,cor_heat = F, parallel = F)

covid_stress_t1_items <- d_t1_meta %>%
  filter(Scale=="COVID Stress T1") %>%
  select(Variable_label, new_label) %>%
  deframe()
```

~~~
d_t1 %>%
  select(all_of(covid_stress_t1_items)) %>%
  psych::alpha(check.keys=TRUE)

```
#Item analysis of SR
```{r}
#Additional analyses were conducted to analyze the Fast-Track Questionnaire for reliability, determine quality of questionnaire items, and to test for viability of developing subscales of emotional and cognitive self-regulation from the unidimensional construct.

#Parent report t0- Unidimensional construct
parent_sr_t0_items <- d_t0_meta %>%
  filter(Scale=="Self-regulation (parent)") %>%
  select(Variable_label, new_label) %>%
  deframe()



#parent SR all items
d_t0 %>%
  select(all_of(parent_sr_t0_items))  %>%
  psych::alpha(check.keys=TRUE)

#parent SR dropped items
d_t0 %>%
  select(all_of(parent_sr_t0_items)) %>%
  select(-`My child tells new kids their name without being asked to tell it.`,
         -`My child asks friends for help with their problems.`) %>%
  psych::alpha(check.keys=TRUE)

d_t0 %>%
  select(all_of(parent_sr_t0_items)) %>%
  psych::alpha(check.keys=TRUE)

#Parent report t1- Unidimensional construct
parent_sr_t1_items <- d_t1_meta %>%
  filter(Scale=="Self-regulation (parent)") %>%
  select(Variable_label, new_label) %>%
  deframe()

d_t1 %>%
  select(all_of(parent_sr_t1_items)) %>%
  select(-`My child tells new kids their name without being asked to tell it.`,
         -`My child asks friends for help with their problems.`) %>%
  psych::alpha(check.keys=TRUE)
~~~

```
d_t1 %>%
  select(all_of(parent_sr_t1_items)) %>%
  psych::alpha(check.keys=TRUE)

#parent report emotional self-regulation t0
parent_sr_emotional_items <- d_t0_meta %>%
  filter(Scale=="Self-regulation (parent)"& Subscale== "Emotional") %>%
  select(Variable_label, new_label) %>%
  deframe()

d_t0 %>%
  select(all_of(parent_sr_emotional_items)) %>%
  select(-`My child's feelings get hurt.`,
         -`My child fights or argues with adults.`) %>%
  psych::alpha(check.keys=TRUE)

# child sr t1
d_t1 %>%
  select(all_of(parent_sr_emotional_items)) %>%
  make_factor_analysis_plot(nfactors = 1,cor_heat = F, parallel = F)

#parent report emotional self-regulation t1
parent_sr_emotional_items_t1 <- d_t1_meta %>%
  filter(Scale=="Self-regulation (parent)"& Subscale== "Emotional") %>%
  select(Variable_label, new_label) %>%
  deframe()

d_t0 %>%
  select(all_of(parent_sr_emotional_items)) %>%
  psych::alpha(check.keys=TRUE)

d_t0 %>%
  select(all_of(parent_sr_emotional_items)) %>%
  select(
    -`My child's feelings get hurt.`,-`My child fights or argues with adults.`) %>%
  psych::alpha(check.keys = TRUE)

#parent report cognitive self-regulation t0
parent_sr_cognitive_items <- d_t0_meta %>%
  filter(Scale=="Self-regulation (parent)"& Subscale== "Cognitive") %>%
  select(Variable_label, new_label) %>%
  deframe()

d_t0 %>%
  select(all_of(parent_sr_cognitive_items)) %>%
  psych::alpha(check.keys=TRUE)
```

```
d_t0 %>%
  select(all_of(parent_sr_cognitive_items)) %>%
  select(-`My child tells new kids their name without being asked to tell it.`,
        -`My child asks friends for help with their problems.`) %>%
  psych::alpha(check.keys=TRUE)

#self- report t0- Unidimensional construct
child_sr_t0_items <- d_t0_meta %>%
  filter(Scale=="Self-regulation (child)") %>%
  select(Variable_label, new_label) %>%
  deframe()

d_t0 %>%
  select(all_of(child_sr_t0_items)) %>%
  select(-`I tell new kids my name without being asked to tell it.`,
        -`I ask friends for help with my problems.`) %>%
  psych::alpha(check.keys=TRUE)

d_t0 %>%
  select(all_of(child_sr_t0_items)) %>%
  psych::alpha(check.keys=TRUE)

#self- report t1- Unidimensional construct
child_sr_t1_items <- d_t1_meta %>%
  filter(Scale=="Self-regulation (child)") %>%
  select(Variable_label, new_label) %>%
  deframe()

d_t1 %>%
  select(all_of(child_sr_t1_items)) %>%
  select(-`I tell new kids my name without being asked to tell it.`,
        -`I ask friends for help with my problems.`) %>%
  psych::alpha(check.keys=TRUE)

d_t1 %>%
  select(all_of(child_sr_t1_items)) %>%
  psych::alpha(check.keys=TRUE)

#self- report cognitive self-regulation t0
self_sr_cognitive_items <- d_t0_meta %>%
  filter(Scale=="Self-regulation (child)"& Subscale== "Cognitive") %>%
  select(Variable_label, new_label) %>%
  deframe()
```

```
d_t0 %>%
  select(all_of(self_sr_cognitive_items)) %>%
  psych::alpha(check.keys=TRUE)

#self- report emotional self-regulation t0
self_sr_emotional_items_t0 <- d_t0_meta %>%
  filter(Scale=="Self-regulation (child)"& Subscale== "Emotional") %>%
  select(Variable_label, new_label) %>%
  deframe()

d_t0 %>%
  select(all_of(self_sr_emotional_items_t0)) %>%
  psych::alpha(check.keys=TRUE)

d_t0 %>%
  select(all_of(self_sr_emotional_items_t0)) %>%
  select(-`My feelings get hurt.`,
         -`I fight or argue with adults.`) %>%
  psych::alpha(check.keys=TRUE)
```

#Student's math scores were converted to z-score by grade-level. A function was created to z-score their performance. Item analysis was conducted to evaluate for reliability and quality of the measures.

```
math_raw_to_main <-  function(d_raw, d_meta){
 #select main scale items
  v_math <- d_meta %>%
    filter(Main_Scale == 1) %>%
    pull(new_label)

  d_raw %>%
    select(child_id, grade, all_of(v_math))
}

# created function to z score grade level math data t1
math_main_to_z <- function(d) {
    d %>%
    pivot_longer(-c(child_id, grade)) %>%
    summarise(raw_total = sum(value, na.rm = TRUE),
              .by = c(child_id, grade)) %>%
    mutate(z_math = scale(raw_total) %>%
             as.numeric(),.by=grade) %>%
    select(child_id, grade, z_math)
}
```

```
# creating list columns and calculating reliability/ item analysis
d_math <-
  tibble(grade=c("4","5","6","7","8","hs"),
                d_raw=list(d_t1_4th_grade_raw, d_t1_5th_grade_raw, d_t1_6th_grade_raw,
d_t1_7th_grade_raw, d_t1_8th_grade_raw, d_t1_high_school_raw),
       d_meta=list(d_t1_4th_grade_meta, d_t1_5th_grade_meta, d_t1_6th_grade_meta,
d_t1_7th_grade_meta, d_t1_8th_grade_meta, d_t1_high_school_meta)) %>%
  mutate(d_main=map2(d_raw, d_meta, math_raw_to_main),
         d_z=map(d_main,math_main_to_z)) %>%
   mutate(fit=map(d_main, \(d) {
    d %>%
     select(-child_id, -grade) %>%
  psych::alpha()
  }),
  alpha_raw=map(fit, pluck("total")) %>%
    map_dbl("raw_alpha"),
  alpha_std=map(fit, pluck("total")) %>%
    map_dbl("std.alpha"),
  item_stats=map(fit,"item.stats"),
    alpha_drop=map(fit,"alpha.drop")) %>%
    mutate(alpha_item=map2(item_stats,alpha_drop, \(i,d) {
   bind_cols(
     i %>%
      select(r.drop, mean, sd),
    d %>%
      select(std.alpha)) %>%
      rownames_to_column("item")
  }))

#grade level math z-scores
d_math_z <- d_math %>%
  select(d_z) %>%
  unnest(d_z)
```

APPENDIX B

ANNOTATED R CODE FOR CREATION OF SCALES

```
# Make scales
```{r scale}
# Creation of scales and subscales that included T0 and T1 metadata were created.

#creating metadata for the scales
d_t0_meta_variables <- d_t0_meta %>%
  filter(Main_Scale==1 &  is.na(item_drop)) %>%
  select(Scale, Subscale, Reverse, new_label, max, min) %>%
  mutate(Reverse=ifelse(is.na(Reverse),0,Reverse)) %>%
  rename(name=new_label)

#info about scales
d_t0 %>%
  select(child_id,all_of(d_t0_meta_variables$name)) %>%
  pivot_longer(-child_id) %>%
  left_join(d_t0_meta_variables, by = join_by(name)) %>%
  mutate(scale_max=max(value,na.rm = TRUE),
         scale_min=min(value,na.rm = TRUE),
         .by = c(Scale, Subscale)) %>%
  select(Scale, Subscale, scale_max, scale_min) %>%
  unique() %>%
print(n=23)

d_t1_meta_variables <- d_t1_meta %>%
  filter(Main_Scale==1 & is.na(item_drop)) %>%
  select(Scale, Subscale, Reverse, new_label, max, min) %>%
  mutate(Reverse=ifelse(is.na(Reverse),0,Reverse)) %>%
  rename(name=new_label)

d_t1 %>%
  select(child_id,all_of(d_t1_meta_variables$name)) %>%
  pivot_longer(-child_id) %>%
  left_join(d_t1_meta_variables, by = join_by(name)) %>%
  mutate(scale_max=max(value,na.rm = TRUE),
         scale_min=min(value,na.rm = TRUE),
         .by = c(Scale, Subscale)) %>%
  select(Scale, Subscale, scale_max, scale_min) %>%
  unique() %>%
  print(n=30)
```
```

```
#create subscales t0
d_t0_subscales_long <- d_t0 %>%
  select(child_id,all_of(d_t0_meta_variables$name)) %>%
    pivot_longer(-child_id) %>%
  left_join(d_t0_meta_variables, by = join_by(name)) %>%
  mutate(value=ifelse(Reverse==1, max+min-value, value)) %>%
  mutate(items_per_scale=n(),
         items_missing_per_scale=sum(is.na(value)),
         .by = c(Scale, Subscale, child_id)) %>%
  mutate(percent_missing=items_missing_per_scale/items_per_scale) %>%
    # summarise(percent_missing= mean(percent_missing, na.rm=TRUE), .by = c(Scale,
Subscale, child_id)) %>%
    # filter(percent_missing < .5 & percent_missing !=0)
  summarise(value=mean(value* items_per_scale, na.rm=TRUE), .by = c(Scale,
Subscale, child_id)) %>%
  mutate(name= paste0(Scale, ifelse(is.na(Subscale),"", paste0("_", Subscale)))) %>%
  select(-Scale, -Subscale) %>%
   filter(!(name %in% c("Pediatric Symptom Checklist", "BRIEF2_BRIEF consistency",
"COVID Impact T0")))

#full scales t0 (no subscales)
d_t0_scales_long <- d_t0 %>%
  select(child_id,all_of(d_t0_meta_variables$name)) %>%
    pivot_longer(-child_id) %>%
  left_join(d_t0_meta_variables, by = join_by(name)) %>%
  mutate(value=ifelse(Reverse==1, max+min-value, value)) %>%
  mutate(items_per_scale=n(),
         items_missing_per_scale=sum(is.na(value)),
         .by = c(Scale, child_id)) %>%
  mutate(percent_missing=items_missing_per_scale/items_per_scale) %>%
  summarise(value=mean(value* items_per_scale, na.rm=TRUE), .by = c(Scale,
child_id)) %>%
  rename(name= Scale) %>%
  filter(name %in% c("Self-regulation (parent)", "COVID Impact T0", "COVID Stress
T0", "Self-regulation (child)"))

d_t0_scales <- bind_rows(d_t0_scales_long, d_t0_subscales_long) %>%
  pivot_wider() %>%
  mutate(time=0)

bind_rows(d_t0_scales_long, d_t0_subscales_long) %>%
  mutate(n=n(), .by= c(name, child_id)) %>%
  filter(n>1) %>%
  pull (name) %>%
  unique()
```

```
#create subscales t1
d_t1_subscales_long <- d_t1 %>%
  select(child_id,all_of(d_t1_meta_variables$name)) %>%
    pivot_longer(-child_id) %>%
  left_join(d_t1_meta_variables, by = join_by(name)) %>%
  mutate(value=ifelse(Reverse==1, max+min-value, value)) %>%
  mutate(items_per_scale=n(),
         items_missing_per_scale=sum(is.na(value)),
         .by = c(Scale, Subscale, child_id)) %>%
  mutate(percent_missing=items_missing_per_scale/items_per_scale) %>%
  summarise(value=mean(value* items_per_scale, na.rm=TRUE), .by = c(Scale,
Subscale, child_id)) %>%
  mutate(name= paste0(Scale, ifelse(is.na(Subscale),"", paste0("_", Subscale)))) %>%
  select(-Scale, -Subscale) %>%
   filter(!(name %in% c("Pediatric Symptom Checklist", "BRIEF2_BRIEF
consistency")))

#full scales t1 (no subscales)
d_t1_scales_long <- d_t1 %>%
  select(child_id,all_of(d_t1_meta_variables$name)) %>%
    pivot_longer(-child_id) %>%
  left_join(d_t1_meta_variables, by = join_by(name)) %>%
  mutate(value=ifelse(Reverse==1, max+min-value, value)) %>%
  mutate(items_per_scale=n(),
         items_missing_per_scale=sum(is.na(value)),
         .by = c(Scale, child_id)) %>%
  mutate(percent_missing=items_missing_per_scale/items_per_scale) %>%
  summarise(value=mean(value* items_per_scale, na.rm=TRUE), .by = c(Scale,
child_id)) %>%
  rename(name= Scale) %>%
  filter(name %in% c("Self-regulation (parent)", "Self-regulation (child)"))

d_t1_subscales_long %>%
  ggplot(aes(x= value)) +
  geom_density()+
  facet_wrap(vars(str_wrap(name, 20)),scales = "free")

d_t1_scales <- bind_rows(d_t1_scales_long, d_t1_subscales_long) %>%
  pivot_wider() %>%
  mutate(time=1)
```

#Merge T0 and T1

```
```{r}
#T0 and T1 scales and demographics were merged together.

d_t01_scales <- bind_rows(
  d_t0_scales %>%
    rename(`COVID Impact` = `COVID Impact T0`, `COVID Stress` = `COVID Stress
T0`) %>%
    left_join(
      d_t0 %>%
        select(child_id, child_gender, grade_level, family_id),
      by = join_by(child_id)
    ) ,
  d_t1_scales %>%
    rename(`COVID Impact` = `COVID Impact T1`, `COVID Stress` = `COVID Stress
T1`) %>%
    left_join(
      d_t1 %>%
        select(child_id, child_gender, grade_level, family_id),
      by = join_by(child_id)
    )
) %>%
  mutate(family_id = factor(family_id)) %>%
  left_join(d_t0 %>%
            select(child_id, race, mother_education, school_format),
          by = join_by(child_id)) %>%
  select(grade_level, time, everything()) %>%
  left_join(
    d_t1 %>%
      select(
        child_id,
        state,
        household_income,
        number_children,
        `school type_20_21`,
        `school type_21_22`
      ),
    by = join_by(child_id)
  ) %>%
  left_join(d_t0_scales %>%
            select(child_id, `COVID Impact T0`, `COVID Stress T0`),
          by = join_by(child_id)) %>%
  mutate(race = fct_infreq(race)) %>%
  mutate(
    school_format = factor(school_format)
```
```

APPENDIX C

ANNOTATED R CODE FOR HYPOTHESIS TESTING

```
# RQ1: Self-regulation change T0 to T1
```{r}
#Research Question 1 investigated child self-regulation change from T0 to T1. It was
hypothesized that student development of self-regulation from T0 to T1 would be
negatively impacts by COVID-19 Stress and Impacts. Below is the code for how this was
investigated in the context of parent-report child self-regulation. The change was also
examined in the context of demographic factors. Analyses were repeated with parent
report of child cognitive self-regulation, emotional self-regulation, and child self-report
of self-regulation

#parent-report total SR t0 to t1
#null
fit0 <- lmer(`Self-regulation (parent)` ~ 1 + (1 | child_id) + (1 | family_id), data=
d_t01_scales)
sjPlot::tab_model(fit0)

fit0 <- lmer(`Self-regulation (parent)` ~ 1 + (1 | child_id/ family_id), data= d_t01_scales)
sjPlot::tab_model(fit0)

#add time
fit_time <- lmer(`Self-regulation (parent)` ~ 1 + factor(time) + (1 | child_id) + (1 |
family_id), data= d_t01_scales)
sjPlot::tab_model(fit_time)
sjPlot::plot_model(fit_time, type="pred")

# Each model is followed by code for a plot of the output.
d_t01_scales %>%
        mutate(time=factor(time, levels= c (0,1), labels= c("Time 0", "Time 1"))) %>%
    rename(`Time`= time) %>%
      rename(`Child Self-regulation`= `Self-regulation (parent)`) %>%
  ggplot(aes(`Time`,`Child Self-regulation`)) +
  geom_beeswarm( size= .7, alpha= .8, aes(color= `Time`)) +
  stat_summary() +
  # facet_grid(cols = vars(time)) +
  theme_light() +
  theme(legend.position = "none",
text = element_text(size = 16),
axis.title = element_text(size = 18),
axis.text = element_text(size = 16))+
  scale_color_viridis_d(begin= .1, end = .85, option = "D")
```
```

```
#add gender
fit_gender <- lmer(`Self-regulation (parent)` ~ 1 + factor(time) + child_gender + (1 |
child_id) + (1 | family_id), data= d_t01_scales)
sjPlot::tab_model(fit_gender)
summary(fit_gender)

d_t01_scales %>%
  mutate(time = factor(
    time,
    levels = c (0, 1),
    labels = c("Time 0", "Time 1")
  )) %>%
  rename(`Child Gender` = child_gender) %>%
  rename(`Self-regulation` = `Self-regulation (parent)`) %>%
  ggplot(aes(`Child Gender`, `Self-regulation`)) +
  geom_beeswarm(size = .7, alpha = .8, aes(color = `Child Gender`)) +
  stat_summary() +
  facet_grid(cols = vars(time)) +
  theme_light() +
  theme(
    legend.position = "none",
    text = element_text(size = 16),
    axis.title = element_text(size = 18),
    axis.text = element_text(size = 18),
    axis.text.x = element_text(angle = 45, hjust = 1),
    strip.text = element_text(size=20)
  ) +
  scale_color_viridis_d(begin = .1,
                        end = .85,
                        option = "D")

#gender and time interaction
fit_gender_time <- lmer(`Self-regulation (parent)` ~ 1 + factor(time) * child_gender + (1 |
child_id) + (1 | family_id), data= d_t01_scales)
sjPlot::tab_model(fit_gender_time)

#add child race
fit_race <- lmer(`Self-regulation (parent)` ~ 1 + factor(time) + race + (1 | child_id) + (1 |
family_id), data= d_t01_scales)
sjPlot::tab_model(fit_race)

d_t01_scales %>%
        mutate(time=factor(time, levels= c (0,1), labels= c("Time 0", "Time 1"))) %>%
  filter(!is.na(race)) %>%
  rename(Race= race) %>%
  rename(`Self-regulation`= `Self-regulation (parent)`) %>%
```

```
  ggplot(aes(Race,`Self-regulation`)) +
  geom_beeswarm( size= .7, alpha= .8, aes(color= Race)) +
  stat_summary() +
  facet_grid(cols = vars(time)) +
  theme_light() +
  theme(legend.position = "none",
    text = element_text(size = 16),
    axis.title = element_text(size = 18),
    axis.text = element_text(size = 18),
    axis.text.x = element_text(angle = 45, hjust = 1),
    strip.text = element_text(size=20)
  ) +
  scale_color_viridis_d(begin = .1,
                        end = .85,
                        option = "D")

#race and time interaction
fit_race_time <- lmer(`Self-regulation (parent)` ~ 1 + factor(time) * race + (1 | child_id)
+ (1 | family_id), data= d_t01_scales)
sjPlot::tab_model(fit_race_time)

#covid impact
fit_covid_impact <- lmer(`Self-regulation (parent)` ~ 1 + factor(time) + `COVID Impact
T0` + (1 | child_id) + (1 | family_id), data= d_t01_scales)
sjPlot::tab_model(fit_covid_impact)

d_t01_scales %>%
                  mutate(time=factor(time, levels= c (0,1), labels= c("Time 0", "Time 1")))
%>%
    rename(`Self Regulation`= `Self-regulation (parent)`) %>%
  ggplot(aes(`COVID Impact T0`,`Self Regulation`, color= `COVID Impact T0`)) +
  geom_jitter(alpha =.2, width = .1, height= 0)+
  geom_smooth(method="gam")+
    theme_light() +
  scale_x_continuous(limits= c(0,NA)) +
  theme(
    plot.title = element_text(size = 20),
    axis.title.x = element_text(size = 16),
    axis.title.y = element_text(size = 16),
    axis.text.x = element_text(size = 14),
    axis.text.y = element_text(size = 14),
    legend.title = element_text(size = 16),
    legend.text = element_text(size = 14)
  )
```

```
#covid impact and time interaction
fit_covid_impact_time <- lmer(`Self-regulation (parent)` ~ 1 + factor(time) * `COVID
Impact T0`+ (1 | child_id) + (1 | family_id), data= d_t01_scales)
sjPlot::tab_model(fit_covid_impact_time)

#covid stress
fit_covid_stress <- lmer(`Self-regulation (parent)` ~ 1 + factor(time) + `COVID Stress
T0` + (1 | child_id) + (1 | family_id), data= d_t01_scales)
sjPlot::tab_model(fit_covid_stress)

d_t01_scales %>%
            mutate(time=factor(time, levels= c (0,1), labels= c("Time 0", "Time 1")))
%>%
  ggplot(aes(`COVID Stress T0`,`Self-regulation (parent)`, color= time)) +
  geom_jitter(alpha =.2, width = .1, height= 0)+
  geom_smooth(method="gam")+
  scale_x_continuous(limits= c(0,NA))

#covid stress and time interaction
fit_covid_stress_time <- lmer(`Self-regulation (parent)` ~ 1 + factor(time) * `COVID
Stress T0`+ (1 | child_id) + (1 | family_id), data= d_t01_scales)
sjPlot::tab_model(fit_covid_stress_time)

#fit mother education
d_t01_scales$mother_education <-factor(d_t01_scales$mother_education)
d_t01_scales$mother_education <- relevel(d_t01_scales$mother_education, ref =
"Graduate degree (e.g., Masters, Doctorate, MD, etc.)")

fit_mother_education <- lmer(`Self-regulation (parent)` ~ 1 + factor(time) +
mother_education + (1 | child_id) + (1 | family_id) , data= d_t01_scales)
sjPlot::tab_model(fit_mother_education)

d_t01_scales %>%
       mutate(time=factor(time, levels= c (0,1), labels= c("Time 0", "Time 1"))) %>%
  filter(!is.na(mother_education)) %>%
  mutate(mother_education= factor(mother_education, levels= c("Some regular high
school, no diploma", "Regular high school diploma", "Some college, no degree",
"Associate's degree", "Bachelor's degree", "Graduate degree (e.g., Masters, Doctorate,
MD, etc.)"), labels= c("No Diploma", "High School", "Some College", "Associate's
Degree", "Bachelor's Degree", "Graduate Degree"))) %>%
  rename(`Mother Education`= mother_education) %>%
    rename(`Self-regulation`= `Self-regulation (parent)`) %>%
  ggplot(aes(`Mother Education`,`Self-regulation`)) +
  geom_beeswarm( size= .7, alpha= .8, pch= 16, cex=.7,aes(color= `Mother Education`))
+
  stat_summary() +
```

```
  facet_grid(cols = vars(time)) +
  theme_light() +
  theme(legend.position = "none",
    text = element_text(size = 16),
    axis.title = element_text(size = 18),
    axis.text = element_text(size = 18),
    axis.text.x = element_text(angle = 45, hjust = 1),
    strip.text = element_text(size=20)
  ) +
  scale_color_viridis_d(begin = .1,
                        end = .85,
                        option = "D")

# fit school format
d_t01_scales %>%
  select(school_format) %>%
  mutate(school_format= factor(school_format) %>%
         fct_collapse(`Mostly or Fully In Person`= c("No, I go to in-person school and have
always been in-person this school year", "In-person, but did virtual learning at some point
during the school year", "No, I go to in-person school now but did learn online at some
point this year"),
                        Hybrid= c("Virtually some days (hybrid)", "Yes, I learn virtually some
days"),
                        Virtual= c("Fully virtual", "Yes, I am fully virtual"))) %>%
  count(school_format)

d_t01_scales$school_format <-factor(d_t01_scales$school_format)
d_t01_scales$school_format <- relevel(d_t01_scales$school_format, ref = "Mostly or
Fully In Person")

fit_school_format <- lmer(`Self-regulation (parent)` ~ 1 + factor(time) + school_format +
(1 | child_id) + (1 | family_id), data= d_t01_scales)
sjPlot::tab_model(fit_school_format)

d_t01_scales %>%
       mutate(time=factor(time, levels= c (0,1), labels= c("Time 0", "Time 1"))) %>%
    filter(!is.na(school_format)) %>%
  rename(`School Format`= school_format) %>%
  ggplot(aes(`School Format`,`Self-regulation (parent)`)) +
  geom_beeswarm( size= .7, alpha= .8, aes(color= `School Format`)) +
  stat_summary() +
  facet_grid(cols = vars(time)) +
  theme_light() +
  theme(legend.position = "none") +
  scale_color_viridis_d(begin= .1, end = .85, option = "D")
```

```
# school type
d_t01_scales$`school type_20_21` <-factor(d_t01_scales$`school type_20_21`)
d_t01_scales$`school type_20_21` <- relevel(d_t01_scales$`school type_20_21`, ref =
"Public")

fit_school_type <- lmer(`Self-regulation (parent)` ~ 1 + factor(time) + `school
type_20_21` + (1 | child_id) + (1 | family_id), data= d_t01_scales)
sjPlot::tab_model(fit_school_type)

d_t01_scales %>%
  mutate(time = factor(
    time,
    levels = c (0, 1),
    labels = c("Time 0", "Time 1")
  )) %>%
  filter(!is.na(`school type_20_21`)) %>%
  filter(!(`school type_20_21` == "NA")) %>%
  rename(`School Type 20-21` = `school type_20_21`) %>%
  rename(`Self-regulation` = `Self-regulation (parent)`) %>%
ggplot(aes(`School Type 20-21`, `Self-regulation`)) +
  geom_beeswarm(size = .7,
                alpha = .8,
                aes(color = `School Type 20-21`)) +
  stat_summary() +
  facet_grid(cols = vars(time)) +
  theme_light() +
  theme(legend.position = "none",
    text = element_text(size = 16),
    axis.title = element_text(size = 18),
    axis.text = element_text(size = 18),
    axis.text.x = element_text(angle = 45, hjust = 1),
    strip.text = element_text(size=20)
  ) +
  scale_color_viridis_d(begin = .1,
                        end = .85,
                        option = "D")

#schooltype and time interaction
fit_school_type_time <- lmer(`Self-regulation (parent)` ~ 1 + factor(time) * `school
type_20_21`+ (1 | child_id) + (1 | family_id), data= d_t01_scales)
sjPlot::tab_model(fit_school_type_time)
```

#RQ 2: How did child Self-Regulation Predict their Math Outcomes T1. Was this relationship impacted by COVID-19 stress and impacts?

```{r}
#Research question two examined how self-regulation predicted student performance on grade-level math measures and whether this relationship was impacted by COVID stress and impacts. Demographic factors were also explored for their predictive power of student mathematics performance. The analyses are repeated to account for the different measures of self0regulation included in this study. Code includes plots for significant findings.

#null
fit_math_scales_null <- lmer( z_math ~ 1 + (1 | family_id) , data= d_math_scales_t0)

#Parent SR T0
fit_math_SRT0 <- lmer( z_math ~ 1  + `Self-regulation (parent)` + (1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_SRT0)

d_math_scales_t0 %>%
  mutate(time=factor(time, levels= c (0,1), labels= c("Time 0", "Time 1"))) %>%
  rename(`Self-regulation` = `Self-regulation (parent)`) %>%
  rename(`Math Z-score` = z_math) %>%
  ggplot(aes(`Self-regulation`,`Math Z-score`, color = `Self-regulation`)) +
  geom_jitter(
    alpha = .5,
    width = .1,
    height = 0,
    pch = 16
  ) +
  geom_smooth(method = "gam") +
  scale_x_continuous(limits = c(NA, NA)) +
  theme_light() +
  scale_color_viridis_c()+
  # facet_grid(cols = vars(time)) +
  theme(
    text = element_text(size = 16),
    axis.title = element_text(size = 16),
    axis.text = element_text(size = 12),
    legend.title = element_text(size = 14),
    legend.text = element_text(size = 12),
    strip.text = element_text(size = 14)
  )

#cognitive SR
fit_math_SRcogT0 <- lmer( z_math ~ 1  + `Self-regulation (parent)_Cognitive` + (1 | family_id) , data= d_math_scales_t0)
```

```
#emotional SR
fit_math_SRemoT0 <- lmer( z_math ~ 1  + `Self-regulation (parent)_Emotional` + (1 |
family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_SRemoT0)

#child SR
fit_math_childSRT0 <- lmer( z_math ~ 1  + `Self-regulation (child)` + (1 | family_id) ,
data= d_math_scales_t0)
sjPlot::tab_model(fit_math_childSRT0)

#SR T0 and race
#parent SR
fit_math_race_SR0 <- lmer( z_math ~ 1  + `Self-regulation (parent)` + race + (1 |
family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_race_SR0)

#Parent SR T0 and race interaction
fit_math_race_SR0_2 <- lmer( z_math ~ 1  + `Self-regulation (parent)` * race + (1 |
family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_race_SR0_2)

#cognitive SR and race interaction
fit_math_race_SRcogT0 <- lmer( z_math ~ 1  + `Self-regulation (parent)_Cognitive` *
race + (1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_race_SRcogT0)

#parent emoSR and race interaction
fit_math_scales_race_emoSRT0 <- lmer( z_math ~ 1  + `Self-regulation
(parent)_Emotional` * race + (1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_scales_race_emoSRT0)

#child SR T0 and race interaction
fit_math_scales_race_childSRT0 <- lmer( z_math ~ 1  + `Self-regulation (child)` * race +
(1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_scales_race_childSRT0)

d_math_scales_t0 %>%
     # mutate(time=factor(time, levels= c (0,1), labels= c("Time 0", "Time 1"))) %>%
  rename(`Race`= race) %>%
  ggplot(aes(`Race`,z_math)) +
  geom_beeswarm( size= .7, alpha= .8, aes(color= `Race`)) +
  stat_summary() +
  facet_grid(cols = vars(time)) +
  theme_light() +
  theme(legend.position = "none") +
  scale_color_viridis_d(begin= .1, end = .85, option = "D")
```

```
d_math_scales_t0 %>%
  mutate(time = factor(
    time,
    levels = c (0, 1),
    labels = c("Time 0", "Time 1")
  )) %>%
    rename(`Child Self-regulation (SR)` = `Self-regulation (child)_T1`) %>%
  ggplot(aes(`Child Self-regulation (SR)`, race, color = `race`)) +
  geom_jitter(
    alpha = .5,
    width = .1,
    height = 0,
    pch = 16
  ) +
  # geom_smooth(method = "gam") +
  # scale_x_continuous(limits = c(NA, NA)) +
  theme_light() +
  scale_color_viridis_c()

d_math_scales_t0 %>%
    # mutate(time=factor(time, levels= c (0,1), labels= c("Time 0", "Time 1"))) %>%
  ggplot(aes(`Self-regulation (parent)`,z_math, color= z_math)) +
  geom_jitter(alpha =.2, width = .1, height= 0)+
  geom_smooth(method="gam")+
  scale_x_continuous(limits= c(0,NA))

#Parent SR T0 and gender
fit_math_gender_SR0 <- lmer( z_math ~ 1  + `Self-regulation (parent)` + child_gender +
(1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_gender_SR0)
#Parent SR T0 and gender interaction
fit_math_gender_SR0_2 <- lmer( z_math ~ 1  + `Self-regulation (parent)` * child_gender
+ (1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_gender_SR0_2)

d_math_scales_t0 %>%
        # mutate(time=factor(time, levels= c (0,1), labels= c("Time 0", "Time 1"))) %>%
  rename(`Gender`= child_gender) %>%
  ggplot(aes(`Gender`,z_math)) +
  geom_beeswarm( size= .7, alpha= .8, aes(color= `Gender`)) +
  stat_summary() +
  facet_grid(cols = vars(time)) +
  theme_light() +
  theme(legend.position = "none") +
  scale_color_viridis_d(begin= .1, end = .85, option = "D")
```

```
#cognitive SR and gender interaction
fit_math_scales_gender_SRcogT0 <- lmer( z_math ~ 1  + `Self-regulation
(parent)_Cognitive` * child_gender + (1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_scales_gender_SRcogT0)

#parent emoSR and gender interaction
fit_math_scales_gender_emoSRT0 <- lmer( z_math ~ 1  + `Self-regulation
(parent)_Emotional` * child_gender + (1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_scales_gender_emoSRT0)

#child SR T0 and gender interaction
fit_math_scales_gender_childSRT0 <- lmer( z_math ~ 1  + `Self-regulation (child)` *
child_gender + (1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_scales_gender_childSRT0)

#mother education
#Parent SR T0 and mother education interaction
fit_math_mother_SRT0 <- lmer( z_math ~ 1  + `Self-regulation (parent)` *
mother_education + (1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_mother_SRT0)

#cognitive SR and mother education interaction
fit_math_mother_SRcogT0 <- lmer( z_math ~ 1  + `Self-regulation (parent)_Cognitive` *
mother_education + (1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_mother_SRcogT0)

#parent emoSR and mother education interaction
fit_math_mother_emoSRT0 <- lmer( z_math ~ 1  + `Self-regulation (parent)_Emotional`
* mother_education + (1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_mother_emoSRT0)

#child SR T0 and mother education interaction
fit_math_mother_childSRT0 <- lmer( z_math ~ 1  + `Self-regulation (child)` *
mother_education + (1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_mother_childSRT0)

#Parent SR T0 and school format
fit_math_scales_format_SR0 <- lmer( z_math ~ 1 + `Self-regulation (parent)`+
school_format + (1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_scales_format_SR0)

#Parent SR T0 and school format interaction
fit_math_scales_format_SR0_2 <- lmer( z_math ~ 1  + `Self-regulation (parent)` *
school_format + (1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_scales_format_SR0_2)
```

```
#cognitive SR and school format interaction
fit_math_scales_format_SRcogT0 <- lmer( z_math ~ 1  + `Self-regulation
(parent)_Cognitive` * school_format + (1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_scales_format_SRcogT0)

#parent emoSR and school format interaction
fit_math_scales_format_emoSRT0 <- lmer( z_math ~ 1  + `Self-regulation
(parent)_Emotional` * school_format + (1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_scales_format_emoSRT0)

#child SR and school format interaction
fit_math_scales_format_childSRT0 <- lmer( z_math ~ 1  + `Self-regulation (child)` *
school_format + (1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_scales_format_childSRT0)

d_math_scales_t0 %>%
        # mutate(time=factor(time, levels= c (0,1), labels= c("Time 0", "Time 1"))) %>%
  rename(`School Format`= school_format) %>%
  ggplot(aes(`School Format`,z_math)) +
  geom_beeswarm( size= .7, alpha= .8, aes(color= `School Format`)) +
  stat_summary() +
  facet_grid(cols = vars(time)) +
  theme_light() +
  theme(legend.position = "none") +
  scale_color_viridis_d(begin= .1, end = .85, option = "D")

#Parent SR T0 and school type
d_math_scales_t0$`school type_20_21` <-factor(d_math_scales_t0$`school type_20_21`)
d_math_scales_t0$`school type_20_21` <- relevel(d_math_scales_t0$`school
type_20_21`, ref = "Public")

fit_math_scales_type_SR0 <- lmer( z_math ~ 1 + `Self-regulation (parent)`+ `school
type_20_21` + (1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_scales_type_SR0)

#Parent SR T0 and school type interaction
fit_math_scales_type_SR0_2 <- lmer( z_math ~ 1  + `Self-regulation (parent)` * `school
type_20_21` + (1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_scales_type_SR0_2)

d_math_scales_t0 %>%
  filter(!is.na(`school type_20_21`)) %>%
  rename(`School Type`= `school type_20_21`) %>%
  ggplot(aes(`School Type`,z_math)) +
  geom_beeswarm( size= .7, alpha= .8, aes(color= `School Type`)) +
  stat_summary() +
```

```
  facet_grid(cols = vars(time)) +
  theme_light() +
  theme(legend.position = "none") +
  scale_color_viridis_d(begin= .1, end = .85, option = "D")

#cognitive SR and school type interaction
fit_math_scales_type_SRcogT0 <- lmer( z_math ~ 1  + `Self-regulation
(parent)_Cognitive` * `school type_20_21` + (1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_scales_type_SRcogT0)

#parent emoSR and school type interaction
fit_math_scales_type_emoSRT0 <- lmer( z_math ~ 1  + `Self-regulation
(parent)_Emotional` * `school type_20_21` + (1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_scales_type_emoSRT0)

#child SR T0 and school type interaction
fit_math_type_childSRT0 <- lmer( z_math ~ 1  + `Self-regulation (child)` * `school
type_20_21` + (1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_type_childSRT0)

#Parent SR T0 and COVID stress
fit_math_covid_stress_SR0 <- lmer( z_math ~ 1 + `Self-regulation (parent)`+ `COVID
Stress` + (1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_covid_stress_SR0)

#Parent SR and covid stress interaction
fit_math_covid_stress_SR0_2 <- lmer( z_math ~ 1  + `Self-regulation (parent)` *
`COVID Stress` + (1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_covid_stress_SR0_2)

#cognitive SR and covid stress interaction
fit_math_covid_stress_SRcogT0 <- lmer( z_math ~ 1  + `Self-regulation
(parent)_Cognitive` * `COVID Stress` + (1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_covid_stress_SRcogT0)

#parent emoSR and covid stress interaction
fit_math_covid_stress_emoSRT0 <- lmer( z_math ~ 1  + `Self-regulation
(parent)_Emotional` * `COVID Stress` + (1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_covid_stress_emoSRT0)

#child SR and covid stress interaction
fit_math_covid_stress_childSRT0 <- lmer( z_math ~ 1  + `Self-regulation (child)` *
`COVID Stress` + (1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_covid_stress_childSRT0)
```

```
#Parent SR T0 and COVID impact
d_math_scales_t0$`COVID Impact`

fit_math_scales_covid_impact_SR0 <- lmer( z_math ~ 1 + `Self-regulation (parent)`+
`COVID Impact` + (1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_scales_covid_impact_SR0)

#Parent SR and COVID impact interaction
fit_math_covid_impact_SR0_2 <- lmer( z_math ~ 1  + `Self-regulation (parent)` *
`COVID Impact` + (1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_covid_impact_SR0_2)

d_math_scales_t0 %>%
  mutate(time = factor(
    time,
    levels = c (0, 1),
    labels = c("Time 0", "Time 1")
  )) %>%
    rename(`Self-regulation` = `Self-regulation (parent)`) %>%
      rename(`Math Z-Score` = z_math) %>%
  ggplot(aes(`Self-regulation`, `Math Z-Score`, color = `COVID Stress`)) +
  geom_jitter(
    alpha = .5,
    width = .1,
    height = 0,
    pch = 16
  ) +
  geom_smooth(method = "gam") +
  scale_x_continuous(limits = c(NA, NA)) +
  theme_light() +
  scale_color_viridis_c() +
  # facet_grid(cols = vars(time)) +
  theme(
    text = element_text(size = 16),
    axis.title = element_text(size = 16),
    axis.text = element_text(size = 12),
    legend.title = element_text(size = 14),
    legend.text = element_text(size = 12),
    strip.text = element_text(size = 14)
  )

d_math_scales_t0 %>%
                # mutate(time=factor(time, levels= c (0,1), labels= c("Time 0", "Time 1")))
%>%
  ggplot(aes(`Self-regulation (parent)`,z_math, color= `Self-regulation (parent)`)) +
  geom_jitter(alpha =.2, width = .1, height= 0)+
```

```
  geom_smooth(method="gam")+
  scale_x_continuous(limits= c(0,NA))

#cognitive SR and COVID impact interaction
fit_math_covid_impact_SRcogT0 <- lmer( z_math ~ 1  + `Self-regulation
(parent)_Cognitive` * `COVID Impact` + (1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_covid_impact_SRcogT0)

#parent emoSR and COVID impact interaction
fit_math_covid_impact_emoSRT0 <- lmer( z_math ~ 1  + `Self-regulation
(parent)_Emotional` * `COVID Impact` + (1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_covid_impact_emoSRT0)

#child SR and COVID impact interaction
fit_math_covid_impact_childSRT0 <- lmer( z_math ~ 1  + `Self-regulation (child)` *
`COVID Impact` + (1 | family_id) , data= d_math_scales_t0)
sjPlot::tab_model(fit_math_covid_impact_childSRT0)

d_math_scales_t0 %>%
  mutate(time = factor(
    time,
    levels = c (0, 1),
    labels = c("Time 0", "Time 1")
  )) %>%
    rename(`Child Self-regulation` = `Self-regulation (parent)`) %>%
    rename(`Math Z-Score` = z_math) %>%
  ggplot(aes(`Child Self-regulation`, `Math Z-Score`, color = `COVID Impact`)) +
  geom_jitter(
    alpha = .5,
    width = .1,
    height = 0,
    pch = 16
  ) +
  geom_smooth(method = "gam") +
  scale_x_continuous(limits = c(NA, NA)) +
  theme_light() +
  scale_color_viridis_c()+
  # facet_grid(cols = vars(time)) +
  theme(
    text = element_text(size = 16),
    axis.title = element_text(size = 16),
    axis.text = element_text(size = 12),
    legend.title = element_text(size = 14),
    legend.text = element_text(size = 12),
    strip.text = element_text(size = 14))
```