DIFFERENTIAL EFFECTS OF GOAL SETTING AND PLANNING CHARACTERISTICS ON ACADEMIC PERFORMANCE AMONG SCHOOL-AGED CHILDREN AND ADOLESCENTS IN SCHOOL-BASED MOTIVATIONAL INTERVIEWING

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## Dedication

To my nephew, Dara Lincoln, whose love has been an unwavering source of inspiration.

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# ABSTRACT

DIFFERENTIAL EFFECTS OF GOAL SETTING AND PLANNING CHARACTERISTICS ON ACADEMIC PERFORMANCE AMONG SCHOOL-AGED CHILDREN AND ADOLESCENTS IN SCHOOL-BASED MOTIVATIONAL INTERVIEWING



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School-Based Motivational Interviewing (SBMI) is a type of Motivational Interviewing (MI) utilized in the academic setting to increase students' motivation and academic performance (Strait et al., 2014; Strait et al., 2017). Prior research has shown inconsistent effects of SBMI on adolescents' academic performance. To better understand factors that may make SBMI more effective, this study examines extant data from two randomized control trials (n = 191) that found different effects of SBMI on middle school students' grades (Strait et al., 2017). Specifically, trained raters rated goals participants set while participating in SBMI based on established SMART goal characteristics: Specific, Measurable, Attainable, Relevant, and Timely (Doran, 1981, as cited in Lawlor & Hornyak, 2012). A two-level hierarchical linear model investigated the relationship between service providers' educational background and SMART goal attributes on students' post-treatment grades in English Language Arts (ELA), math, and science. The findings revealed that middle school students with graduate providers (i.e., graduated from college and enrolled in or starting clinical or school psychology doctoral programs in the forthcoming semester) exhibited significantly improved grades in ELA and math compared to those with undergraduate student providers (i.e., service providers with minimal prior experience in implementing either behavioral or academic interventions), corroborating Strait et al.'s (2017) hypothesis. The results also showed that the total SMART goal score had an unexpected statistically significant negative relationship with post-treatment ELA grades, which may relate to variance in scores and the method of scoring of the non-goal sheet completers. The findings also indicated that the Specificity of SMART goals had a negative relationship with ELA grades and that flexibility in goal setting (e.g., replacing a rigid daily reading goal with a flexible monthly book completion goal) may be beneficial. For math, the Attainable SMART goal characteristic had a marginally significant negative effect, while Relevance had a marginally significant positive impact on post-treatment grades. A mediation analysis did not support a significant indirect effect of provider education on grades through SMART scores. This study emphasizes the importance of service providers' educational background and flexible, relevant goal-setting in SBMI. Recommendations include employing graduate-level service providers and examining how the SMART goal criteria can be tailored and modified to align with the unique characteristics and objectives of SBMI interventions in schools (e.g., making necessary adjustments to accommodate the developmental levels of students, cultural diversity, or specific challenges within the educational context). Future research should investigate how SMART goal setting is implemented in SBMI (e.g., refined SMART goal rubrics, how each sub-item characteristic is phrased, and what it is inquiring about).

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INTRODUCTION

## Research Problem

Low academic performance among children and adolescents is a major concern in the United States, as it is related to emotional and behavioral issues, school dropouts, and lower career success (Al-Zoubi & Younes, 2015; Breslau et al., 2009; Lane et al., 2008). Indicators of low academic achievement include poor grade point average (GPA), low school attendance, high disciplinary referrals/suspension rates, and dropout (Geierstanger et al., 2004). The latest Nation's Report Card (2022) published by the National Assessment of Educational Progress (NAEP) indicates nationwide academic performance deficiency among middle-school students. Specifically, 26% and 29% of 8th-grade middle school students scored proficient in mathematics and reading at or above the NAEP. Reportedly, student scores in math and reading were 7% and 3% points lower, respectively, than in 2019 (Nation’s Report Cad, 2022). Importantly, research has shown that students' social-emotional competence and mental health are essential contributors to academic performance (Murphy et al., 2015; Panayiotou et al., 2019). For example, in a longitudinal study, Panayiotou et al. (2019) found that students with better social-emotional competence demonstrated better academic performance. Similarly, Murphy and colleagues (2015) found that students' mental health outcomes were significant predictors of academic success. Unfortunately, according to the U.S. Department of Health and Human Services (HHS, 2021), only 20% of children (ages 3 to 17) who suffer from mental, emotional, or behavioral disorders receive appropriate mental health interventions from a professional provider.

The pervasive nationwide deficits in academic performance combined with associated social, emotional, and behavioral problems have forced many schools to search for efficient educational methods/interventions that foster academic achievement and improve social-emotional-behavioral outcomes (Fazel et al., 2014). One popular, brief, and efficient intervention is School-Based Motivational Interviewing (SBMI), which researchers have shown can have positive effects on students' academic performance and mental well-being (Csillik, 2015; Frey et al., 2011; Shah et al., 2019; Strait et al., 2012b). However, while many studies have found SBMI promising, Strait and colleagues (2017) found that SBMI may produce inconsistent effects on middle school students' academic performance.

## Purpose of the Study

The main purpose of this proposed study is to use extant data from two randomized control trials (Strait et al., 2012b; Strait et al., 2017) to identify factors that contribute to the efficacy of SBMI on academic grades. The factors of interest include SBMI providers' educational background (e.g., less than a college degree or college graduate) and characteristics of goals set by students during SBMI. Specifically, this study examined a) the effects of setting Specific, Measurable, Attainable, Relevant, and Timely (SMART) goals on middle school students' academic grades, b) the effects of SBMI provider's educational background on middle school students' academic grades, c) the effects of SBMI provider's educational background on setting SMART goals, and d) whether total SMART goal quality mediates the relationship between service providers' educational background (graduate vs. undergraduate providers) and middle school students' academic post-treatment grades. The results of this study inform researchers and practitioners about potential variables that could bolster or weaken the effects of SBMI. The following chapter provides an in-depth overview of the literature addressing factors contributing to students' low academic performance, the need for brief interventions targeting motivation, SBMI, and the theory of change related to SBMI and goal setting.

## CHAPTER II:

## REVIEW OF LITERATURE

### Cost of Low Academic Performance

Low academic performance is often associated with emotional and behavioral issues, increased dropout rates, and lower overall health (Al-Zoubi & Younes, 2015; Breslau et al., 2009). Many social-emotional-behavioral problems lead to academic performance deficits among students (Lane et al., 2008), ultimately triggering and/or further exacerbating social-emotional-behavioral problems (Mundy et al., 2017a, 2017b). Therefore, it is incumbent on schools to provide academic and social-emotional support and interventions to students at risk of academic failure or mental health problems. Further, academic failure and dropout are economically costly to society—leading to high unemployment rates, increased incarcerations and institutionalizations, reduced tax revenues, and increased dependence on welfare and government-funded healthcare programs (McFarland et al., 2018). Thus, it is imperative for schools to provide efficient academic and social-emotional interventions that address mental health problems and improve academic performance.

### Factors Contributing to Low Academic Performance

Over the past few decades, many researchers have examined and identified factors contributing to low academic performance in children and adolescents (Al-Zoubi & Younes, 2015; Becker & Luther, 2002; Ehrenberg et al., 2001; Hanushek et al., 2003; Núñez et al., 2013; Tschannen-Moran & Barr, 2004; Wheeler et al., 2010). Factors pertinent to this proposal include motivation, planning (e.g., goal setting), and time management (Al-Zoubi & Younes, 2015; Ford & Roby, 2013; Lamas, 2015). Motivation involves the process of maintaining a desire and persistent effort toward goal-directed actions (Ormrod, 2008), particularly setting goals, and achieving desired outcomes. Prior research has consistently shown that setting personal goals is an effective motivational approach (Latham, 2004; Locke & Latham, 2002). Further, having a deliberate and strategic plan helps students effectively manage their time and implement strategies that aid in goal attainment (Macleod et al., 2008; Miller & Rollnick, 2013). Goals are achieved more effectively when broken down into smaller and more manageable steps, and when students achieve goals, their motivation increases along with their sense of self-efficacy (students' belief/confidence in their abilities to execute a task successfully; Locke & Latham, 2002; Miller & Rollnick, 2013). Accordingly, becoming/staying motivated, setting goals, and managing time to reach desired goals are interconnected skills necessary for students' academic success and progress.

As students shift from primary to secondary school (i.e., middle school), these factors become increasingly important for academic and mental health outcomes because this school transition coincides with a major biological transition—puberty. These changes have momentous implications on students' social and emotional experiences, including increased emotionality due to heightened activity in the affective node influencing the limbic portion of the brain responsible for processing the emotional significance of a social stimulus/reward (Burnett et al., 2011; Fischhoff et al., 1999; Grundman, 2010; Strait et al., 2012a; Usán et al., 2019). The associated heightened emotionality can hinder students' academic success during this transition, as perceived inadequacies can damage students' perception of their ability to thrive (Doll et al., 1996). Hence, ensuring middle school students remain academically motivated, mentally healthy, and successful during this transitionary period is essential for preventing future academic failure and dropout (Paus et al., 2008; South et al., 2007). The following section provides a brief overview of the literature on motivational interventions.

## The Need for Brief Interventions Targeting Motivation

Researchers have developed several strategies and intervention approaches that target an individual's motivation and promote behavior change in different settings (e.g., clinics, hospitals, and educational programs; Strait et al., 2014). Some of these approaches include Cognitive Behavioral Therapy (CBT; Kumar & Sebastian, 2011), Check and Connect (C&C; Maynard et al., 2014), and Behavioral Approaches (i.e., Functional Behavioral Assessments, FBA; Anderson et al., 2015). Unfortunately, these interventions, while often effective, are time-consuming and cost-intensive. For example, Kumar and Sebastian (2011) found that 12 sessions of CBT offered to students over 90 days improved students' self-efficacy and academic achievement. Maynard and colleagues (2014) found that students who received weekly C&C sessions for six months showed increased academic performance and fewer disciplinary referrals compared to students in the control group. Furthermore, previous research has shown that FBA interventions effectively increase student academic engagement and reduce problem behaviors (Anderson et al., 2015). However, FBA approaches are often only used for students with intellectual disabilities and require intensive observations and reinforcement schedules that can only be implemented by highly trained individuals (Anderson et al., 2015).

Taken together, while CBT, C&C, and FBA are effective interventions for enhancing individuals' motivation for behavioral change, they are not easy to implement in school settings due to their cost and duration (number/length of sessions, Heather, 2004; Project MATCH, 1997). High costs associated with these interventions and the current shortage of qualified mental health providers/professionals (HRSA, 2023) make these interventions inaccessible for many students and unaffordable for many under-resourced and often ethnically minoritized communities. On the contrary, brief interventions such as School-Based Motivational Interviewing (SBMI) have been shown to produce similar effects in less time, allowing providers to serve more students (Heather, 2004; Project MATCH, 1997). Accordingly, several recent SBMI interventions have focused on motivating students to set and achieve short-term academic goals, resulting in improved academic grades and behaviors (Terry et al., 2013, 2014a, 2014b; Strait et al., 2012b). The next section provides an overview of motivational interviewing (MI), specifically SBMI intervention designed to improve and leverage the crucial connection between motivation and academic performance of middle school students.

## The Promise of School-Based Motivational Interviewing (SBMI)

School-based motivational interviewing interventions have become popular over the past decade and aim to help students struggling with low academic performance (Strait et al., 2014; Strait et al., 2017). While SBMI has drawn considerable attention in recent years, motivational interviewing (MI) is not a new practice. Initially, MI began as a counseling approach for addiction recovery. MI is an intervention approach used to encourage behavioral changes, motivating individuals to develop plans and commit to changing behaviors misaligned with their values and goals (Miller & Rollnick, 2002, 2013; Rollnick & Miller, 1995). Numerous meta-analyses have shown strong and consistent empirical support for the efficiency of MI with adults and adolescents with substance abuse problems (e.g., Frey et al., 2011; Smedslund et al., 2011; Vasilaki et al., 2006). Vasilaki and colleagues (2006) systematically reviewed 22 studies that utilized brief MI interventions among at-risk non-dependent drinkers and concluded that MI effectively decreased alcohol consumption (combined effect size was 0.18). Jensen et al. (2011), in their meta-analytic review of 21 studies, also found MI interventions to be effective in treating adolescents with substance abuse problems, with a small but significant mean effect size (d = 0.173).

Similarly, Burke et al. (2003) reported MI interventions to have a positive and lasting effect on drinking (participants' drinking behavior diminished by 56%), diet, exercise, and drugs. The authors reported that MI showed better long-term outcomes compared to other treatments and no treatment conditions with small to medium effect sizes for drinking ($d = 0.25 – 0.53$), a moderate effect size for drug addiction ($d = 0.56$), and a moderate effect size for diet and exercise ($d = 0.53$). According to Burke and colleagues, MI also had a similar effect on social impact measures ($d = 0.47$), including, but not limited to, academic and social impairments. In the classic study, Project MATCH (1997), researchers compared three different treatment modalities for reducing problematic drinking, including 12 sessions of Cognitive Behavioral Therapy (CBT), a 12-step program, and four sessions of Motivational Enhancement Therapy (MET). They found that motivational interviewing was as effective as the CBT and 12-step interventions and more cost-effective since it took less time.

Because of the efficacy of MI in reducing substance use, researchers have modified and evaluated MI for other outcomes, including mental health problems (Lawrence et al., 2017) and medication adherence (Palacio et al., 2016). More recently, MI has been adapted for use in the academic setting. Today two different types of MI are used within the educational setting: a) consultative SBMI, mainly used with parents and educators (aiming to increase teacher/parent motivation to provide the necessary support for student/child behavior improvements to take place); and b) student-focused SBMI, which is used directly with students (Snape & Atkinson, 2016; Strait, 2019; Strait et al., 2014). This research predominantly focuses on student-focused SBMI, which has shown promise in supporting students' sense of autonomy and connectedness and reducing dropout rates among at-risk students (Iachini et al., 2016). Student-focused SBMI has also been shown to enhance student academic performance and participation (Strait et al., 2012b), social relationships (i.e., with parents, peers, and teachers; Frey et al., 2011; Shah et al., 2019), student emotional well-being, and self-confidence (Csillik, 2015; Shah et al., 2019). The following section reviews MI's core values and its four processes to provide a clearer understanding of how MI promotes positive behavioral change among students (i.e., evocation, collaboration, acceptance, and compassion; Miller & Rollnick, 2013).

## Spirit and Process of Motivational Interviewing (MI)

### Spirit of MI

The spirit of MI refers to the underlying principle and attitude it employs. The spirit of MI is fundamental to its efficacy and implicates the core values and foundation of MI (Miller & Rollnick, 2013). MI's underlying spirit includes evocation, collaboration, acceptance, and compassion. *Evocation* involves leveraging the client's internal strength to help move the individual towards *preparatory change-talk* to increase the individual's desire, belief in ability, reasons, and need for change, also known as the DARN acronym (Miller & Rollnick, 2013). Subsequently, moving toward mobilizing change-talk encourages the individual to commit to change through activation language and guides them to create an action plan to execute (Miller & Rollnick, 2013).
*Partnership/collaboration* between the student and the service provider is necessary for change to occur. When using MI, collaboration with the student is essential for mutual agreement on goals representing the student's values (Miller & Rollnick, 2013).
*Acceptance* involves four elements: absolute worth, accurate empathy, autonomy support, and affirmation. *Absolute worth* refers to the service provider's demonstration of unconditional acceptance and respect for the individual. The service provider is *autonomy-supportive* by respecting the individual's choice and actively expressing interest. Further, through *accurate empathy*, the service provider attempts to understand

the individual's perspective more effectively while using *affirmations* to recognize the individual's strengths and progress (Gagné, 2003; Miller & Rollnick, 2013). The final spirit of MI, *compassion*, stresses the necessity for active promotion of students' well-being and suggests that students' needs must be prioritized and supported, when necessary, which is an ethical standard (i.e., MI should not be utilized for personal benefits; Miller & Rollnick, 2013).

**Process of MI**

While the underlying spirit of MI describes the values and ideals the provider should bring into MI sessions and therapeutic relationships, the four processes of MI describe how to harness these values to motivate people for change. These processes include engaging, focusing, evoking, and planning. Miller and Rollnick (2013) note that these processes can recur and overlap within MI sessions, and each process lays a foundation for future processes. However, Miller and Rollnick (2013) emphasize that the processes are bidirectional. For example, a practitioner in the evocation stage may need to return to the engagement process instead of moving into the planning phase. The four MI processes provide a road map for learning about students' values, evoking change talk, and developing plans for change in school settings (Miller & Rollnick, 2013; Miller & Rose, 2009). For service providers to smoothly guide students through the four processes, they can use Open-ended questions, Affirmations, Reflections, and Summaries (OARS). The MI processes allow practitioners to effectively communicate with students by promoting "active listening," which involves OARS (Miller & Rollnick, 2002, 2013). The MI processes intend to lead the flow of effort and focus of discussion based on students' readiness to move toward change (e.g., the amount of time spent establishing rapport and trust may differ from student to student; Miller & Rollnick, 2013). Through OARS, the service provider/counselor develops rapport and examines students' problems through reflective listening and utilizing open-ended questions (e.g., tell me about your classes/grades; Miller & Rollnick, 2013). Expression of empathy is also vital in building a positive alliance, particularly since it is strongly associated with the success of the intervention (Miller & Rollnick, 2013).

Within MI, *engaging* the individual is a necessary initial first step, which allows the service provider to build rapport and learn about the students' values. Since a well-established counselor-client alliance is essential for effective counseling strategies, effective communication can promote MI engagement. According to Miller and Rollnick (2002, 2013), when individuals feel accepted and valued, they are more likely to share their thoughts, feelings, and values and explore change. The service provider can then use OARS to help students clarify their values and goals (Miller & Rollnick, 2013). Once service providers build rapport and help students refine their values and goals, they can use the process of *focusing* to collaboratively identify a problem behavior or individual need to discuss in more depth. An absence of a clear focus can result in ineffective discussions concerning change (Miller & Rollnick, 2013). In general, the focusing process is a transitional process that moves the conversation to the evocation stage.

Miller and Rollnick (2013) describe the process of *evoking* as the "heart of MI," it refers to evoking change talk related to adopting adaptive behaviors or stopping problematic behaviors. Preparatory change-talk and Mobilizing change-talk are the two major types of change-speech. *Preparatory change-talk* includes the desire (i.e., want), ability (e.g., self-efficacy and support), reasons (i.e., an advantage of change), and need (i.e., a disadvantage of the status quo) to change (DARN). *Mobilizing change-talk* consists of commitment, activation, and taking steps (CAT), which helps students make positive changes and set long-term goals/plans that could motivate and support them to adopt academic enabling techniques and refrain from maladaptive and risky behaviors.

Service Providers are trained to use OARS to evoke and reinforce both preparatory and mobilizing change talk. Service providers can specifically achieve preparatory change-talk by encouraging students to identify benefits to change (reason) and limitations of their present behavior (need; e.g., how does playing video games at night interfere with making good grades?; Miller & Rollnick, 2013; Miller & Rose, 2009). Notably, during this process, it is essential to reduce *sustain talk* (i.e., keeping the status quo) because while sustain talk is a normal part of ambivalence, the longer the student engages in sustain talk, the more they distance themselves from changing (Miller & Rollnick, 2013). OARS is used to increase and reinforce change talk and empathetically reduce sustain talk through simple reflections, redirections, and avoiding argumentation. Once the provider senses that the student is ready for change, the provider transitions the conversation to the planning stage.

*Planning* is the fourth and final MI process and involves MI's core spirit and skills (Miller & Rollnick, 2013). Once desired behavior change is identified and students' readiness to move forward is determined, the change planning process can begin. Service providers use OARS to help students develop a change plan. Change planning involves goal-setting (e.g., discussing long-term and short-term goals), creating a list of options (e.g., identifying specific steps necessary to achieve goals), and considering options and appropriate paths to take (e.g., considering plan B if plan A fails). Change planning also involves summarizing the plan (e.g., providing a summary using reflective listening) and exploring obstacles (e.g., reevaluating the plan for what worked and what did not; Miller & Rollnick, 2013). Once a clear plan is developed, providers use OARS to evoke a commitment for change. Importantly, Apodaca et al. (2016) found that clients' speech related to planning and committing to change was the most predictive of actual behavior change. Specifically, they discovered that the more clients discussed planning and committing to change, the more likely they were to change their behavior (Apodaca et al., 2016). Given that goals are at the heart of change plans, the current research project further explores Apodaca et al.'s (2016) findings to test whether the quality of goals within a change plan predicts future student outcomes, namely academic grades. The following section briefly reviews the most influential student-focused SBMI research that aims to improve academic performance.

## Student-Focused SBMI and Academic Performance

Atkinson and Woods (2003) conducted one of the earliest studies of MI in the educational setting with secondary school students. Using a small N design, they found that MI enhanced student attendance and punctuality, confidence, and academic behavior and outlook. A decade later, Strait et al. (2012b) conducted the first randomized control trial (RCT; N = 103) study, examining the impact of student-focused SBMI on academic grades, laying the foundation for the modern use of MI in school settings. Specifically, Strait et al. (2012b) found that a single MI session (i.e., Student-Checkup; SCU) enhanced student class participation, academic behavior, and grades, particularly in math, compared to a control group. The theoretical foundation of MI's appropriateness among adolescents combined with promising results from the randomized study increased the attention of researchers to this area. Later, Terry et al. (2013) replicated Strait et al.'s (2012b) study using a similar procedure (n = 49 students) and reported similar results, showing improved math grades in middle school students. Then, Terry et al. (2014a) conducted an experimental study to investigate the effectiveness of two MI sessions (i.e., SCU plus a booster session) on students' performance. The results showed that students who received an additional MI session (i.e., SCU booster session) had significantly higher math, science, and history grades than those who only received a single MI session (i.e., SCU). Subsequently, replication studies by Strait et al. (2019) and Terry et al. (2014b) further supported the positive outcomes associated with the SCU booster session.

While experimental studies show MI's positive impact on academic performance, it is still unclear how MI motivates students to make changes. Additionally, the literature has not adequately investigated the effect of service provider type (i.e., individuals of varying training backgrounds who implement MI sessions, e.g., paraprofessionals) on student outcomes. Notably, a study conducted by Strait et al. (2017) found that while school-based MI interventions (i.e., SCU) delivered by paraprofessionals (i.e., undergraduate psychology students) increased middle school students' effort self-efficacy (i.e., student outlook on class participation resulting in higher grades), it failed to have a significant impact on student academic performance (i.e., math grades). This raises critical questions regarding provider educational qualifications, specifically who can implement MI and why different providers may impact students differently. A hypothesis drawn from this study is that service providers with backgrounds in academic and behavioral interventions could likely better assist students in developing effective goals and plans for change, whereas providers without this background and only training in MI might be less effective in assisting students in developing quality goals and plans.

These insights necessitate a closer examination of the role goal setting plays in the MI process. Interestingly, most SBMI studies utilize goal setting thorough goal sheets to guide students' change plan development (see Strait et al., 2012b; Strait et al., 2019; Terry et al., 2013; Terry et al., 2014a; Terry et al., 2014b), which brings into focus the relevance of goal-setting in clarifying the mechanisms of change. The current research aims to bridge these gaps in the literature by examining variations in the quality of goals and planning characteristics across two published studies conducted by Strait and colleagues (2012b & 2017). These studies found contrasting results, as the providers' educational backgrounds varied between the two studies.

The following section discusses two prominent theories to further illuminate this matter: First, a brief overview of Self-Determination Theory (SDT; Deci & Ryan, 2002) offers insight into how SBMI processes can motivate students to set and attain academic goals. Second, Locke and Latham's (1990) Goal Setting Theory (GST) is discussed, which emphasizes the importance of setting Specific, Measurable, Attainable, Relevant, and Timely (SMART) goals during the MI planning process. GST is central to the proposed research questions, considering the impact of SBMI provider type on total SMART goal score and its characteristics, and the causal relationship between goal quality and academic performance.

## Theory of Change: Self-Determination Theory and Goal Setting Theory

### Self-Determination Theory

Self-Determination Theory (SDT) predicts that intrinsic motivation (i.e., motivation-related internal values and interests) leads to higher levels of task engagement and performance in comparison to external motivation (i.e., motivation related to gaining or avoiding external stimuli; Deci & Ryan, 2002; Ryan & Deci, 2017). A central sub-theory of SDT and relative to MI is the Basic Psychological Needs Theory (BPNT). BPNT posits that people's intrinsic motivation increases when they perceive the task context and related social environment as fulfilling three Basic Psychological Needs (BPN): autonomy, competence, and relatedness (Ryan & Deci, 2000). *Autonomy* involves an individual's perception of freedom to choose and make their own decisions. Specifically, students are more intrinsically motivated when given a choice and are not forced to participate in an activity (Deci & Ryan, 2002). *Competence* describes an individual's feeling of effectiveness and the belief in the ability to master and succeed

(Deci & Ryan, 2002). Individuals build a sense of competence with repeated mastery and successful experiences (Deci & Ryan, 2002; Ryan & Deci, 2017). Lastly, *relatedness* involves a sense of belonging and connectedness to others (Deci & Ryan, 2002). Several studies have shown that social environments that support BPN increase autonomous motivation (i.e., internal motivation; Deci & Ryan, 2002; Kaplan & Patrick, 2016; Sheldon & Gunz, 2009) and academic outcomes (Gottfried et al., 2009; Hardre & Reeve, 2003; Legault et al., 2006; Ryan & Deci, 2017; Vallerand et al., 1997).

Importantly, MI fosters a supportive therapeutic environment that aligns with BPN, enhancing intrinsic motivation for the individual to actively participate in MI discussions and set and commit to achieving goals (Markland et al., 2005; Patrick & Williams, 2012; Vansteenkiste et al., 2012). MI providers use non-judgmental reflective listening and affirmations to create safe and accepting environments that promote perceptions of *relatedness* (Markland et al., 2005; Miller & Rollnick, 2013; Wilding, 2015). When students feel understood and accepted, they are more likely to discuss and explore their values, behaviors, and goals. SBMI providers also support *autonomy* by using open-ended questions that guide students to freely choose values, goals, and behaviors to discuss and change. To promote feelings of competency and self-efficacy (Markland et al., 2005; Miller & Rollnick, 2013), SBMI providers use OARS to guide students to discuss past successes and current strengths and resources to aid in goal attainment. Ultimately, through a combination of technical and relational MI skills, providers help students feel autonomous, competent, and accepted, which in turn helps motivate students to set, commit, and attempt to attain their goals.

Consequently, providers with advanced and specialized graduate training may be more effective in employing and achieving relational and technical MI skills, mainly since fidelity and skill in delivering MI interventions are crucial for it to be effective

(Madson & Campbell, 2006). However, it is essential to note that while motivation to set, commit, and attempt change is likely necessary, it is insufficient alone for actual goal attainment. Therefore, it is predicted that goal and plan content, not just the act of setting and committing to a goal, strongly influences actual goal attainment. This prediction is supported by Locke and Latham's (1990) Goal Setting Theory, as described in the following section.

**Goal-Setting Theory**

Locke's and Latham's (1990; 2002) Goal-Setting Theory (GST) is a motivational framework that suggests that setting specific and challenging goals can effectively improve performance and focus. Goal-setting has effectively increased individuals' motivation toward behavior change and accomplishing desired tasks in various environments (e.g., healthcare, sports, psychotherapy, and leadership), including schools (Latham & Locke, 2007). GST of motivation posits that a positive association exists between goals and task performance (Latham & Locke, 2007). However, goals alone do not naturally improve learning and motivation. Specifically, GST suggests setting appropriate goals (i.e., specific, proximal in time, and challenging goals) and receiving consistent feedback regarding progress can improve individuals' motivation and performance (Locke & Latham,1990). Prior research stresses the importance of considering several goal characteristics that influence goal quality, ultimately impacting learning and motivation. According to Locke and Latham (2002), attributes such as specificity, difficulty, commitment (i.e., importance and self-efficacy), feedback, and task complexity define goal quality. For example, specific and challenging goals increase efforts toward attaining a task compared to easy and/or unclear goals (Locke & Latham, 2006). Per Locke and Latham (2002), challenging assignments increase students' self-efficacy, which increases goal commitment and the likelihood of goal attainment.

Similar to Locke and Latham (2002), Schunk (2003) also describes prominent characteristics of a high-quality goal as its proximity (i.e., short-term versus long-term goals), specificity, and difficulty. In contrast, Doran (1981, as cited in Lawlor & Hornyak, 2012) describes high-quality goals as those identified as Specific, Measurable, Attainable, Relevant and Timely (SMART) goals. SMART goals are supported by Locke and Latham's (1990) goal-setting theory, which provides a helpful framework for developing a change plan.

***SMART Goals***

SMART goal setting is a helpful approach used within the MI framework to ensure student motivation, determination, and support competence (Ballesteros & Tutistar, 2014). Locke and Latham's (1990) GST supports the usefulness of SMART goal setting. *Specific* goals include explicit details about what the student wants to accomplish (e.g., "I intend to improve my overall math grade by at least one letter grade" as opposed to "I plan to do my best to improve my grades"). *Measurable* goals include how students assess their progress using clear measurement(s) strategies (e.g., "I intend to improve my math grade by at least one letter grade by studying three times a week" instead of "I intend to improve my math grade by studying more"). *Attainable* goals are defined as goals that are within reason of the student's abilities and can be achieved (e.g., "I plan to increase my current grade of a D to a B" instead of "increasing my F to an A"). *Relevant* goals appropriately relate to the individual's needs and values. This study determined students' goal relevance based on whether their goals are related to their academic success). Thus, a goal based on improving one's piano skills is an example of an irrelevant educational goal. Finally, *Timely* goals determine a specific date for accomplishing goals (e.g., "I intend to improve my math grade by at least one letter grade by the end of the semester through studying three times a week, two hours a day").

Prior research supports SMART goal effectiveness in increasing student motivation and academic performance. According to Lunenburg (2011), goals that are specific, challenging yet achievable, accepted by all parties, time-bounded, and easily employed to assess performance and provide feedback are most effective in increasing motivation. Dotson (2016) found that setting SMART goals can effectively enhance high student motivation levels and improve academic performance, reporting that 69% of students who participated in goal setting increased their reading growth performance. Similarly, in a study among seventh and ninth-grade students, Ballesteros and Tutistar (2014) found a strong positive association between SMART goals and perceived competence in listening comprehension among middle and high school students. The authors also indicated that setting SMART goals helped students improve their learning and planning skills (Ballesteros & Tutistar, 2014). Additionally, Jung (2007) stressed the usefulness of setting SMART goals in enhancing students' academic performance.

Moreover, it is important to note that while research has shown the positive effects of SMART goals on student motivation and academic performance (Lunenburg, 2011; Dotson, 2016; Ballesteros & Tutistar, 2014), it is equally crucial to consider how the quality of these goals can mediate the relationship between service providers' educational background (graduate versus undergraduate) and middle school students' academic performance. According to the goal-setting theory (Locke & Latham, 2006), the quality of goals plays a significant role in enhancing academic motivation and performance. Previous studies have also demonstrated that service providers' educational background positively impacts students' academic progress and success (Hickman et al., 2020). Therefore, it is essential to consider the educational training differences among the service providers who implemented goal-setting strategies in the SBMI interventions conducted by Strait and colleagues in 2012 and 2017. This research project aimed to investigate the impact of SMART goal setting within SBMI on academic grades while examining whether the providers' educational background influenced the quality of SMART goal setting.

## Topics to Investigate

This project aggregates data from two student-focused SBMI studies to examine differences in academic performance based on the providers’ educational background (i.e., undergraduate or graduate) compared to a control group (no providers). Further, this study investigates whether SMART goal characteristics influence middle school students' academic performance (i.e., grades) and whether total SMART goal quality mediates the relationship between SBMI providers' educational background (graduate vs. undergraduate) and middle school students’ academic performance. This project also investigated which goal characteristics were the most predictive of post-treatment grades. It was hypothesized that higher levels of goal specificity, measurability, attainability, relevance, and timeliness would lead to improved academic performance. Specificity was suggested to be the primary criterion for setting a high-quality goal and achieving enhanced results (Locke et al., 1981). Hence, goal specificity was predicted to be the most predictive of middle school students’ academic performance. It was also hypothesized that SBMI providers who had completed college and were enrolled in or starting clinical or school psychology doctoral programs in the upcoming semester would help middle school students set higher total SMART goal quality than the students in the control group (no providers) and those with undergraduate providers with minimal prior experience in implementing either behavioral or academic interventions. A final hypothesis was that the educational background of the service provider might indirectly influence students’ academic outcomes by impacting the quality of the goals the students set. Hence, it was hypothesized that total SMART goal quality differences among middle school students would mediate the relationship between providers' educational backgrounds and students’ academic grade outcomes.

To better understand the factors that may impact middle school students' academic performance and progress, it was crucial to consider the discrepancies in educational training among service providers' educational backgrounds. In the studies conducted by Strait and colleagues in 2012b and 2017, the service providers played a key role in introducing and instructing students on goal setting and planning. These studies emphasize the significance of exploring how different types of service providers can potentially impact the quality of the SMART goals students set and their post-treatment grades. To this end, this study answers the following research questions to guide the investigation of the current research project:

(1) How do service providers' educational backgrounds influence middle school students' post-treatment grade outcomes compared to a school-as-usual control group and when controlling for pre-treatment grades?

(2) Does the overall quality of SMART goals predict middle school students' academic performance?

(3) Which goal characteristics are the most predictive of post-treatment grade outcomes?

(4) Does service providers’ educational background (graduate vs. undergraduate students; note undergraduates are consider paraprofessionals as they have less than a 4-year degree and not working towards or have obtain licensure) influence the total SMART score and specific SMART goal characteristics?

(5) Does the overall SMART goal quality mediate the relationship between service providers’ educational background (graduate vs. undergraduate students) and grade outcomes?

# CHAPTER III:

# METHOD

## Participants

The sample size of this study consisted of 191 middle school students. The current research used data from participants in two published studies on the Student Checkup (Strait et al., 2012b; Strait et al., 2017). The first published study (Strait et al., 2012b) included 103 middle school student participants, and the second published study (Strait et al., 2017) included 87 middle school student participants. Throughout this proposal, these studies are referred to as the original SCU study (Strait et al., 2012b) and the paraprofessional study (Strait et al., 2017). The following provides demographic information for each study (see Table 1 for more details).

Participants (n = 103) in the original SCU study (Strait et al., 2012b) attended a public middle school in the Southeast United States and were either in the sixth (54%), seventh (21%), or eighth (25%) grades. Females accounted for 50% of the participants. Thirty-three percent identified as European American/White, 58% as African American/Black, and 7% as Middle Eastern, Asian, Hispanic, or multiracial, and 2% were missing. In the original SCU study (Strait et al., 2012b), participants were randomly assigned to a school as usual control group (n = 53) or a treatment group (n = 50). Participants in the treatment group participated in a single SCU/MI session. The SCU providers (n = 5) had college degrees and enrolled in or began the clinical or school psychology doctoral programs the following semester.

Participants (n = 88) in the paraprofessional study (Strait et al., 2017) were recruited from general education classes and attended a public middle school in the South-Central United States. Participants were in the sixth (48%), seventh (31%), and eighth (21%) grades, and 69% identified as female and 31% as male. Of the participants, 58% identified as European American/White, 40% as African American/Black, and 2% as Asian American or Other. Similar to the original SCU study (Strait et al., 2012b), participants in the paraprofessional study (Strait et al., 2017) were randomly assigned to a school as usual control group (n = 46) or a treatment group (n = 42). Participants in the treatment group participated in a single SCU session. The service providers (n = 11) in the paraprofessional study (Strait et al., 2017) were undergraduate students with limited mental health, behavioral health, or academic mentoring/coaching experience.

## Measures

This study used school grades to measure academic performance and the SMART Goals Rubric to measure goal characteristics. The following describes each measure in detail.

### Grades

In each study (i.e., Strait et al. 2012b; 2017), grade transcripts were obtained for each participant's quarterly grades in math, English Language Arts (ELA), and science. Strait and colleagues (2012b & 2017) obtained parental consent prior to receiving school data. All grades were based on a 100-point scale. Each student's first three (first, second, and third) quarterly grades for each subject (i.e., math, ELA, and science) were averaged and used as pre-treatment grades, consistent with Strait et al.'s past studies (2012b; 2017). Similarly, student grades for the fourth quarter were used as post-treatment grades (Strait et al., 2019).

### SMART Goals Rubric

An adapted version of the SMART Goals Rubric, the SMART-Goal Evaluation Method (SMART-GEM) by Bowman and colleagues (2015) was employed to evaluate the quality of students' goals using five criteria: Specificity, Measurability, Attainability, Relevance, and Timeframe (i.e., Timely).

Given that the current study focused on middle school students within an educational setting, distinct changes were made to the SMART-GEM rubric to ensure proper use of the rubric when scoring SMART goals for middle school students. These changes were essential to ensure that the rubric was appropriately adapted and effective for evaluating and scoring the SMART goals of middle school students in an educational context.

First, the specificity criterion in the original SMART-GEM rubric from Bowman et al. (2015) specified that the goal must be "described in terms of observable behavior, what the client would be doing" and include conditions for "performing or maintaining the goal task." Conversely, for the Specific criteria, the current study modified the audience from "client" to "student." It included "conditions/plans that would help them obtain the goal," essentially shifting focus from healthcare settings to an educational context. Furthermore, the SMART characteristics varied from the usual SMART goal acronym. Bowman and colleague's SMART-GEM rubric contained an 'Activity-based' component rather than 'Attainable,' emphasizing how the "client would achieve the goal by providing an intervention (i.e., participate in weekly groups, using a technique, practice or part practice of an activity or task)." The modified rubric for the current study replaced this with the 'Attainable' criterion, which included two sub criterions: 1) The goal is "within reason of the student's abilities and can be achieved (note: if student's ability is unknown, compare to an average student's ability)" and 2) The goal describes "feasible actions, interventions, and/or plans (e.g., complete weekly homework, sit near teacher, study) the student would use to achieve their goal."

Another notable change was Bowman and colleagues' rubric's 'Review' section, which necessitated "planned progress review(s)." In contrast, the current study introduced a 'Relevant' section, specifying that the goal must meet two sub criterion: 1) "a clear connection with school success" and 2) "plans to achieve goals have a clear connection with school success." Finally, both rubrics encompassed a 'Timeframe' section. The original SMART-GEM rubric required that "the goal includes the timeframe within which the outcome should be achieved (i.e., Within one week, by date, end of term 2)," but the current study offered examples more pertinent to academic timelines, such as "end of the academic semester or year."

Moreover, the SMART-GEM rubric guided raters to use a dichotomous scale (i.e., 0 = no, 1 = yes) to answer questions related to each SMART criterion. Questions relating to a distinct goal characteristic were summed to create scores for each distinct criterion. Specificity was scored based on three questions; thus, total specificity scores range from 0 to 3, where 0 indicated the absence, and 3 (i.e., yes to all three questions) indicated the full presence of Specificity. Measurability, Attainability, and Relevance were scored on a scale from 0 to 2 (i.e., two questions per construct), with 0 representing the absence and 2 representing the full presence of measurability, attainability, and relevance. Timeframe was scored on a scale from 0 to 1, with 0 representing the absence and 1 representing the presence of the characteristic. For example, in the Timeframe criterion, a goal with a precise date for accomplishment within the school year was assigned a score of 1, whereas a goal without a precise date or with a date beyond the school year was assigned a score of 0. The score for each SMART goal characteristic for an individual student was calculated by summing the scores on the associated questions. A Total SMART Score (overall goal quality score) was also calculated for each student by summing the five subscale scores, with a possible range of 0 to 10.

Bowman et al. (2015) reported excellent content validity for individual and total SMART-GEM subscales using the Content Validity Index (CVI; *individual subscale* CVI *ranging from* 0.90 *to* 1.00; *total SMART CVI* = 0.99). Bowman and colleagues also reported extremely high internal consistency for total SMART goal scores ($\alpha = 0.995$). In the current study, two classes of reliability estimates were investigated: (1) inter-rater reliability to assess the reliability of the SMART goal subscales and the total scores across different raters, and (2) internal consistency to evaluate the reliability of total SMART goal score across all five subscales (i.e., Specificity, Measurability, Attainability, Relevance, and Timeframe).

To ensure the reliability of students' SMART goal scores, two raters were trained to code student goals and calculate interrater reliability (IRR) for 25% of the data. The raters were provided with materials and training regarding SMART goals and proper use of the SMART-GEM rubric (15 training sessions, approximately 2 hours each, and 30 hours total). Initially, the raters rated several practice goals (n = 10) using the SMART-GEM rubric as part of the training process. Once the raters completed scoring the goals, their scores for each goal were reviewed and discussed, comparing the raters' scores to the researcher's (author of the current study's) scores for each goal. This comparison facilitated the identification of potential scoring errors in scoring and ensured a shared understanding of the rubric and its application in scoring each goal before beginning to code actual student goals. Training and practicing ratings continued until practice inter-rater reliability reached 80% or higher from the three most recent rating attempts. Then, randomly 25% of the students' goals for both raters were selected to code. IRR was measured by calculating Pearson Correlations and Cohen's Kappa for the total SMART score and each total subscale of the SMART-GEM goals rubric. Cohen's k was run to determine whether there was an agreement or disagreement between the two raters. Internal consistency of the overall measure was calculated using Cronbach's alpha, which demonstrated good internal consistency for total SMART goal scores and its characteristics (α = 0.808), indicating that the subscales are reasonably correlated, and the rubric reliably assesses SMART goal characteristics.

Further, the total SMART goal score showed moderate agreement between the raters ($k$ = 0.58, percent agreement = 65%, $r$ = 0.96). Total Specific score demonstrated higher agreement ($k$ = 0.69, percent agreement = 87%, $r$ = 0.88), Measurable score showed substantial agreement ($k$ = 0.76, percent agreement = 83% $r$ = 0.88), Attainable score indicated moderate agreement ($k$ = 0.73, percent agreement = 91%, $r$ = 0.91), Relevance score suggested perfect agreement ($k$ = 1, percent agreement = 100%, $r$ = 1), and lastly, Timeframe score exhibited high agreement ($k$ = 0.90, percent agreement = 96%, $r$ = 0.96). These findings highlight varying levels of agreement between the raters, with strong positive correlations observed for total SMART score, Specific, Measurable, Attainable, Relevance, and Timeframe variables.

**Procedures**

In both studies (Strait et al., 2012b; 2017), student participants were randomly assigned to treatment or control groups. All participants completed pre-and post-treatment outcome measures related to varying academic behaviors and attitudes. Unfortunately, these measures were inconsistent across the studies, so they were not included or analyzed in this study. In both studies, participants were assigned to a treatment group and participated in a single session of the SCU at the end of the third quarter of the academic year (Strait et al., 2012b; 2017), and participants in the control group participated in school as usual. Before treatment, all SCU providers received training on integrating MI skills throughout the semi-structured SCU interview protocol. The following sections provide details regarding similarities and differences in the SCU treatment and training across the Strait et al., 2012b and 2017 studies.

**Treatment Condition**

The SCU (Strait et al., 2012b; Strait et al., 2017; studentcheckup.org) included a pre-interview survey and a 45-to-60-minute semi-structured interview that guided students through four phases: a) Introduction, b) Self-Assessment c) Summary and Feedback, and d) Change Plan Development and Commitment. Specifically, before the interview, each participant completed a pre-interview survey about their school attitudes, academic enabling and maladaptive behaviors, and current and desired grades. SCU providers then referred to each student's pre-interview survey during the student's interview. The introduction phase of the interview involved discussing the purpose of the meeting and addressing the limits of confidentiality. During the self-assessment phase, the provider used preset open-ended questions to help students self-evaluate their academic-related values and goals and compare their academic behaviors to their middle school peers (Strait et al., 2019). Data from the pre-interview survey anchored many of the self-assessment questions (e.g., You rated the importance of making good grades a 10, why did you choose that number? You reported watching TV for 7 hours a day, how does that make your grades worse?). During the feedback phase, the SCU provider summarized the previously discussed self-assessment discussion and any related change talk (i.e., values, goals, current behavior, and ambivalence; Strait et al., 2017). Finally, as part of the change plan development phase, the SCU provider gave participants the option to complete a goal worksheet and sign a public commitment poster reading, "If I can be academically responsible, then so can you. I am committed to my academic plan and career" (p. 8). Both studies followed these SCU procedures. However, there were some variations between the two studies' use of the SCU. Specifically, in the paraprofessional study (Strait et al., 2017), participants completed a goal progress worksheet two weeks after the SCU session. The goal progress worksheet included the participants' first session academic goal, their quarterly grades for each class (i.e., ELA, math, and science), and questions related to goal attainment, satisfaction with grades, and two open-ended questions asking students to list three good things that would happen if they reached their goal and three reasons why they could reach their goal. Participants in the original SCU study did not complete this worksheet. Other differences included school location (i.e., rural school vs. small urban school) and service provider educational background (i.e., graduate vs. undergraduate students).

## Training

Service providers in both studies (Strait et al., 2012b; 2017) received training for basic MI skills and training in the specific SCU protocol; however, the training format and time varied across the studies (Strait et al., 2019). Service providers from the original SCU study (Strait et al., 2012b) were graduate providers with prior MI skills training and engaged in a single 90-minute-long training session, particularly for the SCU. In contrast, in the Strait et al. (2017) study, service providers were undergraduate providers without prior MI skills training. Each service provider was required to pass a written MI-knowledge test and an in vivo role-play fidelity competency test with 90% or higher accuracy and participate in four training sessions (each approximately 2 to 3 hours, about 12 hours of training altogether) that covered MI basic skills and the SCU protocol (Strait et al., 2019; see also StudentCheckup.org for a free [revised] version of the SCU manual).

## Ethical Consideration

Before beginning data analyses, the current project's application was reviewed and approved by the Committee for the Protection of Human Subjects (CPHS), UHCL's Institutional Review Board (IRB). Also, to secure confidentiality and anonymity, all participant identifying information was removed from their transcripts and goal worksheet and assigned an identity code (e.g., ID: 1, 2, 3, and 4), which was used during data analysis and when reporting the results. Additionally, procedures involving human participants conducted in both studies (i.e., Strait et al., 2012b; 2017) followed the ethical standards of the University of South Carolina's and Arkansas State University's IRB in addition to the 1964 Helsinki Declaration and its following amendments or similar ethical standards. Moreover, parental informed consent and child assent were attained for each participant.

## Data Analyses

Descriptive statistics were used to summarize student-grade outcomes and quality of goals (i.e., reporting mean, SD, and skewness/kurtosis). The categorical variables Gender (0 = male, 1= female), ethnicity (0 = white, 1 = black, 2 = other; with white set as the reference group), and grade level (6 = sixth grade, 7 = seventh grade, 8 = eighth grade) were dummy coded for the regression analysis and added as covariates in all regression models if these were determined to correlate with the outcomes of interest. Chi-square tests were used to test pre-treatment equivalence of categorical variables, including gender, ethnicity, and grade level. Independent t-tests were used to examine the pre-treatment equivalence of academic grades in math, science, and English language arts across the two treatment groups. In addition, the data for missing values were inspected, and the percentage of missing data for each variable was reported (Table 2). Restricted maximum likelihood estimates (REML) were used to estimate the parameters of all hierarchical linear models, which accounted for missing data.

Multiple linear regression was used to answer all research questions. Data were examined to ensure that the linear regression assumptions were met. Pearson Correlations was conducted for all variables to test for multicollinearity. Plots of outcome residuals from each model demonstrated whether errors were independent of each other, and histograms showed the distribution of residuals.

**Research Question 1: Does service providers' educational background influence post-treatment grade outcomes when compared to a school-as-usual control group and controlling for pre-treatment grades?**

Assuming clustering of students within classrooms (i.e., students grouped by classroom/teacher), a two-level hierarchical linear model was used to estimate the influence of the provider's educational background on post-treatment grade (i.e., 4th quarter grades) outcomes after controlling for pre-treatment grades (i.e., an average of the first three-quarters grades) and significant covariates. Specifically, for each subject (i.e., math, ELA, and science), a two-level hierarchical model was conducted that included two dummy coded provider background variables (e.g., *Under*: 0 = control or graduate provider, 1 = undergrad provider; *Grad*: 0 = control or undergraduate provider and 1 = graduate provider) allowing for comparisons of students in the control group (i.e., the reference group in the model) to students with a graduate student provider and students with an undergraduate provider (Table 8.1). A second model was then conducted with a new set of dummy coded variables for providers' educational backgrounds (i.e., *Control*: 0 = undergrad or graduate providers, 1 = control group; *Under*: 0 = control group or graduate providers, 1 = undergraduate providers) that compared students with graduate providers (i.e., reference group) to students with undergraduate providers. This model also retested the comparison between students with graduate providers and the control group; however, those findings are only reported in the first model (Table 8.2).

A teacher variable was also added as a level 2 random effect to control for clustering within classes. In addition, for each subject (i.e., math, ELA, and science), the model was ran twice, changing the reference group of the treatment variable to allow for pairwise comparisons between the three groups (i.e., no provider vs. undergraduate, no provider vs. graduate, and graduate vs. undergraduate). The level 1 model is depicted in the following equation:

$$\text{Model 1: } Y_{post\_grade} = B_0 + B_1 X_{pre\_grade} + B_2 X_{Under} + B_3 X_{Grad} + B_4 X_{covariates} + e_i$$

$$\text{Model 2: } Y_{post\_grade} = B_0 + B_1 X_{pre\_grade} + B_2 X_{Control} + B_3 X_{Under} + B_4 X_{covariates} + e_i$$

**Research Question 2: Does the total SMART score predict middle school students' academic performance?**

Using only data from students who received SCU, a two-level hierarchical linear model was used to examine the influence of total SMART score (overall goal quality) on 4th quarter grades after controlling for pre-treatment grades and the level 2 random effects of the teacher. The level 1 model is depicted in the following equation:

$$Y_{post\_grade} = B_0 + B_1 X_{pre\_grade} + B_2 X_{goal\_quality} + B_3 X_{covariates} + e_i$$

This type of hierarchical linear model was used for each academic subject (i.e., math, ELA, and science).

**Research Question 3: Which goal characteristics are the most predictive of post-treatment grade outcomes?**

A hierarchical linear regression analysis was used to identify which goal characteristics (i.e., Specificity, Measurability, Attainability, Relevance, and Timeframe of goals) had the most influence on 4th-quarter grades after controlling for pre-treatment grades. Started with the following equation, which only included the pre-treatment grades and significant covariates:

$$Y_{post\_grade} = B_0 + B_1 X_{pre\_grade} + B_2 X_{covariates} + e_i$$

Then, goal Specificity, Measurability, Attainability, Relevance, and Timeframe (in this order) was sequentially entered as independent variables into the model. The significance of the variables' contribution to the overall model was individually assessed by using an F-Test to compare it to the previous model (Draper & Smith, 1998). Since the order of the goal variables appears to be chronologically credible, the variables were entered into the model based on how the SMART goal theory was developed (i.e., Specific, Measurable, Attainable, Relevance, and Timeframe; Doran, 1981 as cited in Lawlor & Hornyak, 2012). Specifically, Specificity was entered as the first variable into the model since it is the primary criterion for setting a high-quality goal and achieving improved results (Locke et al., 1981). Notably, for a goal to be Measurable, Attainable, Relevance, and Timely, it is first necessary to be specific. Further, numerous authors in the goal-setting literature also identify goal specificity/clarity as an essential initial factor in goal achievement and support the rest of SMART goal factors in the order mentioned above (i.e., Austin & Vancouver, 1996; Doran, 1981 as cited in Lawlor & Hornyak, 2012; Hu & Liden, 2011; Locke & Latham, 1990, 2002; Locke et al., 1989; Schunk, 2003). A two-tailed test was used to estimate the significance of each goal characteristic on the final model. To calculate the unique variance explained by each variable, the $R^2$ of each model was subtracted from the $R^2$ of the previous model. The following equation shows an example of the final model if all the goal characteristics are significantly important and contribute to student grade outcomes:

$$Y_{post\_grade} = B_0 + B_1 X_{pre\_grade} + B_2 X_{goal\_specifity} + B_3 X_{goal\_measureability} + B_4 X_{goal\_attainability} + B_5 X_{goal\_relatability} + B_6 X_{goal\_time\text{-}orientation} + B_7 X_{covariates} + e_i$$

**Research Question 4: Does the service provider's educational background (graduate vs. undergraduate students) influence the total SMART score and specific SMART goal characteristics?**

First, after controlling for significant covariates, a multiple linear regression model was used to estimate the influence of the service provider's educational background (0 = undergraduate, 1 = graduate) on total SMART scores (overall goal quality). The graduate provider’s educational background was used as the reference group, and the undergraduate provider's educational background was used as the comparison group of the models. The following equation represents the model:

$$Y_{overall\_goal\_quality} = B_0 + B_1 X_{provider\_type} + B_2 X_{covariates} + e_i$$

Then, a logistic regression was used for the Timeframe SMART goal variable, given that it was a binary variable. Since each goal characteristic was ordinal (e.g., 0 = no/absent, 1 = yes/full presence), ordered logistic regression analyses was used to estimate the influence of the service provider's educational background (1 = undergraduate, 2 = graduate) on each goal characteristic (i.e., Specificity, Measurability, Attainability, and Relevance. For example, the following equation was used to investigate the impact of the service provider's educational background on goal specificity:

$$Y_{goal\_specifity} = B_0 + B_1 X_{provider\_type} + B_2 X_{covariates} + e_i$$

**Research Question 5: Does the total SMART goal quality mediate the relationship between service provider educational background (graduate vs. undergraduate students) and grade outcomes?**

These analyses aimed to test whether the total SMART score (overall goal quality) mediated the relationship between service providers' educational background (0 = undergraduate, 1 = graduate) and grade outcomes. Specifically, the hypothesis that a service provider's educational background indirectly affects grades through a casual chain illustrated in Figure 2 was tested (i.e., the composite pathway of *a* and *b*).

To measure the indirect effect, the product of the coefficients was calculated (Sobel, 1982) from path a and b (i.e., [Path $a$ $B_{provider\_type}$] * [Path $b$ $B_{mediator}$]) and tested their significance by using bootstrapping (Efron & Tibshirani, 1994) to calculate confidence intervals around the product of coefficients. For the path a model predicting total SMART score (overall goal quality), multiple linear regression analyses were conducted with provider type as the predictor variable. For the path b model predicting post-treatment grades, a regression equation that controlled for gender, ethnicity, and grade level was used and included provider type and total SMART goal score as predictors. The following two models provide examples of the regression models used to calculate the path a and b coefficients:

a) $Y_{mediator} = B_0 + B_1 X_{provider\_type} + B_2 X_{covariates} + e_i$

b) $Y_{post\_grade} = B_0 + B_1 X_{pre\_grade} + B_2 X_{mediator} + B_3 X_{provider\_type} + B_4 X_{covariates} + e_i$

# CHAPTER IV:

# RESULTS

## Preliminary Analysis

### Preliminary Analysis with Control Groups Included

Table 2 provides the N, means, median, range, skew, kurtosis, and percentage of missing data for pre- and post-treatment grade outcomes of participants in the treatment and control groups. Variables with skewed or kurtosis values less than -1 or greater than 1 were considered skewed or kurtotic, respectively (Gliner et al., 2016). Across all grade outcome variables, skew ranged from -1.47 to -0.58. Post-treatment grades for ELA (Skew = -1.22) and math (Skew = -1.47) were negatively skewed to the left, indicating that lower ELA and math scores serve as outliers that cause the mean of the scores to be less than the median and mode. Kurtosis values ranged from -0.11 to 3.47 across all variables. Kurtosis for post-treatment grades for math (kurtosis = 3.47) indicates that the distribution is leptokurtic, meaning that it has heavier tails and a more peaked shape on the positive tail of the distribution compared to a normal distribution which can imply that post-treatment math grades have more extreme values or outliers. Missing data across variables ranged from 1.0% to 2.1%. The variable with the highest percent of missing data was the post-treatment grades for math (2.1%) and ELA and science grades at 1.6%.

To identify pre-treatment equivalence, a series of one-way ANOVAs (Tables 4.1 & 4.2) were conducted to test the relationship between graduate providers, undergraduate providers, and the control group (i.e., no providers). The results of the ANOVAs indicated that gender and grade-level were not significantly related to any predictor mediator or outcome variable (see Table 4.1). However, a statistically significant difference existed between pre-treatment grade outcomes for ELA, $F(2, 186) = 3.74$, $p =$

.03, and math F(2, 186) = 3.16, *p* = .05. In addition, an ANOVA indicated that there was also pre-treatment inequivalence for ethnicity, F(2, 186) = 7.15, *p* = .001. Table 4.2 provides means and standard deviations of students' academic grades by the assigned treatment condition and study site. A Tukey post-hoc test (see Table 5) showed that there was a significant difference between pre-treatment ELA grades for students with an undergraduate provider (*M* = 82.58) compared to students with no providers (*M* = 86.42), *p* = .04 and students with graduate providers (*M* = 87.07), *p* = .04 (Table 2). Similarly, there was a significant difference in math pre-treatment grades for students with undergraduate providers (*M* = 81.21) compared to students with graduate providers (*M* = 86.30), *p* = .04 (see Table 5). All regression analyses were conducted with and without controlling for grade level, gender, and ethnicity, but it did not affect the conclusions. However, only outcomes of models that control for these demographics are reported, as this is consistent with Strait and colleagues' (2012b) original data analyses.

**Preliminary Analyses for Treatment Groups Only**

Since research questions 2 through 4 only use data from the treatment groups, Table 3 provides the N, means, median, range, skew, kurtosis, and percent of missing data for pre- and post-treatment grade outcomes and goal quality for only participants who were randomly assigned to the MI conditions in both studies. Across all variables involving the treatment groups, the skew ranged from -1.76 to 1.62. The timeframe goal characteristic score (skew = 1.62) was positively skewed. Conversely, goal relevance (skew = -1.49), total SMART score (skew = -1.76), and post-treatment grades for ELA (skew = -1.32) were negatively skewed. Kurtosis ranged from -0.10 to 2.43 across all variables. Kurtosis for ELA grades (kurtosis = 2.43) and goal relevance (kurtosis = 1.25) indicate a leptokurtic distribution. Missing data for treatment groups ranged from 0% to

3.3% across variables. Post-treatment grades for math (3.3%) had the highest percentage of missing data.

For data involving the treatment groups from the two studies, chi-square tests between the two provider types (Table 6) were used to test pre-treatment equivalence of categorical demographic variables, including gender, ethnicity, and grade level. Chi-square tests indicated pre-treatment equivalence for gender and grade level (see Table 6). There was no pre-treatment equivalence for ethnicity, $\chi 2$ (2, $n$ = 90) = 13.75, $p < .001$. Specifically, participants interviewed by graduates (i.e., Strait et al., 2012b) had significantly more African American students and fewer white participants than participants interviewed by undergraduates (i.e., Strait et al., 2017 study). We tested all models with and without grade-level, gender, and ethnicity included as a covariate, but it did not impact the findings; however, only outcomes that controlled for these covariates were reported, as this is consistent with Strait and colleagues' (2012b) past analyses.

An independent samples t-test (Table 6) was used to examine the pre-treatment equivalence of academic grades in ELA, science, and math for participants either interviewed by graduates or undergraduate providers. The results showed pre-treatment equivalence for pre-treatment grades in science. However, participants interviewed by graduate providers (Strait et al., 2012b) had significantly higher pre-treatment grades in comparison to participants interviewed by undergraduate providers in math, $t(89) = -2.50$, $p < .01$, and ELA, $t(89) = -2.58$, $p < .01$. To control for pre-treatment differences, pre-treatment grades were incorporated in all models that examined the effect of provider education-level on grade outcomes.

**Assumptions and Missing Data**

Multilevel and multiple regression models were examined to test whether regression assumptions were met. Multicollinearity was a concern. Pearson Correlations were conducted for all the predictor variables (Specific, Measurability, Attainability, Relativity, Timeframe, total SMART score, and pre-treatment grades for ELA, math, and science) to test for multicollinearity (Table 7). Per Tabachnick and Fidell (2013), correlation coefficients higher than .70 between predictor variables could indicate multicollinearity. The Pearson correlation revealed several high correlations between the predictor variables (Table 7). Specifically, the Specific characteristic was highly correlated with Measurable, Attainable, Relevance, and total SMART goal variables. Similar high correlations were shown among the Measurable, Attainable, Relevance, and Total SMART score, with correlation coefficients ranging from .71 to .94, all significant at the .01 level. Hence, multicollinearity among these variables could be confirmed based on these high correlations. Considering these findings for the Specific, Measurable, Attainable, and Relevance, caution should be exercised when interpreting the regression analysis results where all these variables are included (i.e., research question 3).

Plots of outcome residuals from each model demonstrated whether errors were independent of each other, and histograms showed the distribution of residuals (note: interpretation of these plots are discussed with the results subsection for each research question). Restricted maximum likelihood estimates (REML) were used in all multilevel models and mediation models to account for missing data in parameter estimation. Pairwise deletion was used for hierarchical regression analyses (i.e., research question 3), logistic and ordinal regression, and multiple regression models.

## Research Question 1

### Service Provider Educational Background Influence on Post-treatment Grades

Two-level hierarchical linear models (Table 8.1) were used to investigate the influence of the provider's educational background (dummy coded) on post-treatment grades after controlling for pre-treatment grades and demographic covariates; Teachers were included as a level 2 random effect to account for clustering within classes. Importantly, for each subject, to test the amount of clustering within classrooms, Intraclass Correlation Coefficients (ICC) were calculated from intercept and residual variance estimates from two-level models that only include pre-treatment grades as a predictor and post-treatment grades as a dependent variable (Wu et al., 2012). The ICCs were 0.00 for math, 0.07 for ELA, and 0.20 for science. Because the ICC for math was less than 0.01, we ran a multiple regression model for this outcome based on the level 1 regression equation and used bootstrapping with 1,000 simulations to estimate standard error and p-values. The two-level hierarchical models were run for all other subjects. We also report the results for the two-level model for math in addition to the bootstrapped version. Visual inspection of the histograms and scatter plots (figures 1 & 2; Appendix B provides examples of residuals histograms and plots; plots not included are available by contacting the author via email) of the residual for the multilevel models appeared to indicate that the assumptions of normality, linearity, distribution of residuals, and homoscedasticity were all satisfied.

The hierarchical model that compared ELA post-treatment grades for students in the control group (no-provider) to students with graduate providers and students with undergraduate providers revealed that students in the control group had significantly higher post-treatment ELA grades in comparison to the students with undergraduate providers, $\beta = -.30$, $t(187) = -2.14$, $p = .03$; however, students with graduate providers had marginally (i.e., $p < .10$) significant higher post-treatment ELA grades in comparison to students in the control group, $\beta = 0.22$, $t(187) = 1.80$, $p = .07$. Additionally, the model with graduate students as the reference group showed that students with undergraduate providers had statistically significantly lower post-treatment grades than students with graduate providers, $\beta = -0.52$, $t(178) = -3.28$, $p = .001$.

The multilevel models predicting math outcomes received a boundary fit warning, indicating that the random effect was not needed because the null ICC indicated no statistically significant difference in post-treatment math grades between students with no providers and students with undergraduate providers. However, students with graduate providers showed a non-significant trend (i.e., 88.8% chance effect is greater than 0) toward having higher post-treatment math grades than those in the control group, $\beta = 0.19$, $t\,(177) = 1.60$, $p = .11$, and students with undergraduate providers had marginally statistically significant lower post-treatment grades in math than those with graduate providers, $\beta = -\ 0.29$, $t\,(177) = -\ 1.84$, $p = .07$. After removing the random effect from our models and using bootstrapping to estimate standard errors, the results showed that students with graduate providers had significantly higher post-treatment math grades than those without providers, $\beta = 0.198$, $SE = 0.100$, $z = 1.98$, $p = .05$. Students with undergraduate providers had significantly lower post-treatment math grades than students with graduate providers, $\beta = -0.31$, z = -1.95, $p = .05$. There was no significant difference in math grade outcomes between the control group and students with undergraduate providers.

The first hierarchical model for science revealed no statistically significant difference in post-treatment science grades between students with no provider and students with graduate or undergraduate providers. The second model for science with graduate providers as the reference group showed no statistically significant difference in post-treatment science grades between students with graduate and undergraduate providers (Table 8.2).

## Research Question 2

### Does SMART Goal Quality Predict Middle School Students' Academic Performance

After controlling for pre-treatment grades, a two-level hierarchal linear model was conducted to examine the relationship between the total SMART goal score and middle school students' academic performance (Table 9). Post-treatment grades were included as the outcome variable, pre-treatment grades as the control variable, and total SMART goal score as the predictor variable. Similar to research question one, the Teacher variable was added as the random effect variable to control for clustering within classes. Gender, ethnicity, and grade-level were also included as covariates in the model. The plot of the model residuals suggested that the assumptions of homoscedasticity and normality approached acceptable levels. However, the histogram of the residuals showed some negative skewness, and plots of residuals to predicted values showed some slight fanning of the residuals, indicating a risk of non-constant variance, particularly for post-treatment grades in English. Because of this, readers should interpret these with some caution.

The hierarchical model showed that the total SMART goal score had a statistically significant negative relationship with post-treatment ELA grades, $\beta$ = - 0.23, $t$ (88) = -2.66, $p$ = .01, suggesting that as the overall SMART-ness of goals (i.e., total SMART goal score) set by the students increased, the students' post-treatment ELA grades decreased. Nevertheless, the total SMART goal score did not statistically significantly impact math or science post-treatment grades (Table 9).

## Research Question 3

### Which Goal Characteristics Are the Most Predictive of Post-treatment Grade Outcomes

A hierarchical linear analysis was conducted to examine the influence of SMART goal characteristic total scores (Specific, Measurable, Attainable, Relevance, and

Timeframe) on post-treatment grades in ELA, math, and science, after controlling for pre-treatment grades, gender, ethnicity, student grade level, and clustering within teacher classroom. Like research question 2, results should be interpreted with caution due to some skewness of residuals and the risk of heteroscedasticity. Table 10.1, 10.2, and 10.3 show the results of the two-level hierarchical linear regression model.

For ELA (Table 10.1), the total specific SMART goal characteristic was added as a predictor for the first model. The results showed the model fit significantly improved compared to the base model, which only included pre-treatment ELA grades and demographic variables, $\chi2(1) = 5.72$, $p = .02$. The model revealed that Specific SMART goal characteristic had a statistically significant negative effect on post-treatment ELA grades, $B = - 1.98$, $t(88) = - 2.32$, $p = .02$, 95% CI [-3.66, -0.07], indicating that students with lower scores on the Specific SMART goal characteristic tended to have higher ELA post-treatment grades. The final regression model, including fixed and random effects, accounted for approximately 40.5% of the variance in post-treatment grade outcomes, $R^2 = 0.405$, $F(10, 80) = 5.72$, $p < 0.05$. Adding the Specific characteristic to the base model, which only included students' pre-treatment grades, gender, ethnicity, and grade-level, contributed 3.5% ($\Delta R^2 = 0.035$) to the explained variance, indicating its predictive power for post-treatment grade outcomes. This change in R-squared suggests that the Specific characteristic of goals was associated with an increase of 3.5% in the variance explained in post-treatment grade outcomes when compared to the base model without the specific variable. However, none of the other SMART goal characteristics (i.e., Specific, Measurable, Attainable, Relevance, and Timeframe) significantly improved the model fit or explained variance when added to the model, nor had any statistically significant impact on post-treatment ELA grades. The Specific SMART goal characteristic did not stay significant after controlling for all the SMART goal characteristics, $p > .05$, likely due to multicollinearity.

For post-treatment math outcome (Table 10.2), the inclusion of total Relevance SMART goal characteristic marginally improved model fit compared to the previous model that only included pre-treatment math grades, demographic variables, and the total Specific, Measurable, and Attainable variables. The chi-square test indicated a non-significant trend towards improving the model when the adding total Relevance, $\chi2(1) = 2.52$, $p = .11$. The change in $R^2$ for the inclusion of the total Relevance characteristic was small, contributing only 1.2% to the explained variance in the post-treatment grade outcomes ($\Delta R^2 = 0.0119$). This change in $R^2$ suggests that, despite the non-significant increase in model fit, the Relevance characteristic of goals was associated with a modest increase in the variance explained in post-treatment grade outcomes when compared to the prior model without the total Relevance variable. Similarly, including the Timeframe variable marginally improved the model fit and explained variance compared to the previous model, $\chi2(1) = 2.98$, $p = .08$. The change in $R^2$ for adding the Timeframe SMART goal characteristic was marginally significant but small, contributing approximately 4% to the explained variance in post-treatment math grade outcomes ($\Delta R^2 = 0.0404$); this suggests that the Timeframe SMART goal variable has a greater impact on post-treatment math grade outcomes compared to the Relevance goal characteristic. The final model revealed that the total Attainable SMART goal characteristic showed a non-significant trend towards a negative effect on post-treatment grades, B = -3.78, $t(87) = -1.53$, $p = .13$, 95% CI [-8.75, 0.90]. In contrast, the Relevance SMART goal characteristic had a marginally significant positive effect on post-treatment math grades, B = 4.95, $t(87) = 1.90$, $p = .06$, 95% CI [0.07, 10.07]. Additionally, the Timeframe characteristic displayed a non-significant trend towards a negative relationship with math grade outcomes B = -3.31, $t(87) = 1.60$, $p = .12$, 95% CI [-7.24, 0.90]. For the final model, the fixed effects explained approximately 50.9%, and the fixed and random effects accounted for approximately 55.0% of the variance in the response variable.

For science (Table 10.3), none of the SMART goal characteristics (i.e., Specific, Measurable, Attainable, Relevance, or Timeframe) yielded a statistically significant relationship on science post-treatment grades ($p > 0.1$). Moreover, the inclusion of SMART goal characteristics did not result in improved model fit or significantly improve the amount of variance explained.

## Research Question 4

### Does Service Provider's Educational Background Influence the total SMART score and Specific SMART Characteristics

A linear regression model examined the relationship between the provider's educational background (graduate vs. undergraduate providers) and total SMART score, controlling for Gender, Ethnicity, and Grade level. The results showed that the provider's educational background did not significantly predict the total SMART score (Table 11.1). A logistic regression model was also conducted to investigate the relationship between the provider's educational background and total SMART goal Timeframe characteristics. The results indicated that the provider's educational background did not significantly predict the total SMART goal Timeframe (Table 11.2).

Ordinal regression models were conducted using SPSS to explore the relationship between the provider's educational background and total Specific, Measurable, Attainable, and Relevant SMART goal characteristics (Tables 11.3.a to 11.3.d). The analysis highlighted a potential quasi-complete separation in the data, indicating a substantial overlap among the predictor variables, thus hindering the estimation of reliable relationships. Additionally, the maximum likelihood estimates, commonly used for parameter estimation, were unavailable in this case. Despite these issues, the GENLIN procedure continued to generate results based on the available data. However, it is important to note that the validity of the model fit is uncertain due to the challenges, which implies that the reliability and accuracy of the obtained results should be interpreted with caution. The results revealed no statistical significance between the provider's educational background and Measurable, Attainable, or Relevant SMART goal characteristics. However, the analysis showed a positive, marginally significant relationship between the provider's educational background on the total specific SMART goal characteristic. Specifically, the analysis showed that having an undergrad provider was associated with higher total Specific goal scores, B = 0.81, $SE = 4.71$, $Z = 1.73$, and $p = .08$.

## Research Question 5

### Does total SMART Goal Quality Mediate the Relationship Between Service Provider Educational Background and Grade Outcomes

A mediation analysis (Figure 3) using the lavaan package in R tested whether the educational background of service providers had an indirect effect on student post-treatment grades in ELA, math, and science through total SMART goal quality (Table 12).

The results did not indicate a mediating relationship for the ELA, math, and science post-treatment grade outcomes. Specifically, the results of the model for post-treatment grades in ELA showed that, in comparison to graduate student providers, students with undergraduate providers had statistically significant lower post-treatment grades in ELA, $B = -5.96$, $SE = 2.31$, $Z = -2.57$, $P = .01$ (Figure 4). The effect of the provider's educational background on the Total SMART Goal score (path a) was not statistically significant, indicating that the service provider's educational background did not significantly predict SMART goal quality. The relationship between Total SMART goal and post-treatment grades (path b) in ELA was statistically significant, B = - 0.71, *SE* = 0.29, *Z* = - 2.47, *P* = .01, indicating that higher SMART goal quality was associated with lower post-treatment ELA grades. However, the indirect effect (*a*b)* was not statistically significant, B = 0.16, *SE* = 0.52, Z = 0.31, *P* > .05, suggesting that SMART Goal quality did not mediate the relationship between the service provider's educational background and ELA post-treatment grades.

The results of the mediation analysis revealed that the provider's educational background had a significant statistically negative relationship with post-treatment grades in math, B = - 3.29, *SE* = 1.62, *Z* = - 2.03, *P* = .04 (Figure 5), suggesting that there is an association between students with undergraduate providers and lower post-treatment math grades. The provider type was not significantly related to the Total SMART score, and the Total SMART score was not significantly related to post-treatment math grades. Relatedly, the indirect effect of the provider on math grades through SMART scores was not statistically significant (Table 12).

The direct effect, representing the provider's educational background, had a statistically significant negative relationship with post-treatment grades in science, B = - 5.20, *SE* = 1.33, *Z* = - 3.91, *P* = .001 (Figure 6), indicating that students with undergraduate providers were associated with lower post-treatment science grades. The provider type was not statistically significantly related to the Total SMART score, and the Total SMART score was not significantly associated with post-treatment science grades. Hence, the indirect effect of the provider on science grades through SMART scores was not statistically significant (Table 12).

# CHAPTER V:
# DISCUSSION

The primary purpose of the proposed study was to utilize extant data from two randomized control trials (Strait et al., 2012b; Strait et al., 2017) to identify factors that contributed to the efficacy of SBMI on academic grades. The factors of interest included SBMI providers' educational background (e.g., less than a college degree or college graduate) and characteristics of goals set by students during SBMI. Specifically, this study examined: a) the effects of setting SMART goals on middle school students' academic grades, b) the effects of SBMI providers' educational background on middle school students' academic grades, c) the effects of SBMI providers 'educational background on setting SMART goals, and d) the relationship between providers' educational background, SMART goals, and middle school students' post-treatment academic grades. The study's results inform researchers and practitioners about variables that can strengthen or weaken the effects of SBMI. The following section discusses these results, study limitations, and guidance for future research.

## Research Question 1: Service Provider Type on Grade Outcomes

The findings from this study suggested that the providers' educational background significantly impacts students' post-treatment grades in ELA and math. In particular, students with graduate providers, who had prior training in MI skills, achieved higher post-treatment ELA and math grades than students with undergraduate providers. Students with graduate providers also showed a non-significant trend toward having higher post-treatment math grades than those with no providers. While this result did not reach statistical significance ($p$ = .11), the probability that the effect is greater than 0 is high (88.8%), indicating that the observed trend could be of practical significance. It may suggest a potential advantage for students who work with graduate providers, warranting further investigation in future studies. Ultimately, these results further support Strait and colleagues' (2017) hypothesis that the SCU may be more effective when implemented by providers with higher college education levels and prior experience in delivering academic and mental health interventions to youth.

Furthermore, the results revealed that having no provider was associated with higher post-treatment grades in science and ELA compared to students with an undergraduate provider. This finding raises the potential for iatrogenic effects if providers lack appropriate educational and applied experiences and support. Thus, ongoing professional development and support for service providers are vital. However, on-going support is difficult in single-session interventions and, thus, researchers interested in diffusing mental health tasks to paraprofessionals could consider multi-session brief interventions that could allow for on-going and proactive support and supervision of paraprofessionals. By strengthening skills and keeping up with best practices, providers can mitigate potential iatrogenic effects and deliver more effective interventions. Future research should focus on developing comprehensive training programs to ensure high-quality interventions and improved academic outcomes.

Importantly, in the original SCU study (2012b), graduate providers underwent a 90-minute training session focused on the SCU. In contrast, undergraduate providers in the 2017 study underwent four training sessions, totaling approximately 12 hours, covering MI skills and the SCU protocol. The undergraduate providers also completed a competency test to ensure proficiency in MI knowledge and skills and a goal progress worksheet two weeks post-SCU session, which graduate providers did not complete. The additional goal progress worksheet could be considered an increased 'dosage' of goal-setting intervention. Discussing and describing progress to the undergraduate providers might have boosted the students' motivation. Also, the potential reinforcement from goal progress worksheet could have positively or negatively influenced the students' goal progress and outcomes. Hence, further research would be beneficial to confirm these effects. Ultimately, despite the longer and more intensive training undergraduate providers received, students with graduate providers achieved higher post-treatment grades in ELA and math. Considering the results, this suggests that the training for undergraduate providers might not have been adequate to reach the level of competence demonstrated by graduate providers. Researchers and program developers should consider whether this is a training depth or breadth issue. It is possible the longer undergraduate training briefly covered a lot of topics related to MI without enough depth or emphasis on the skills needed to carry out the SCU. It is also possible training provided enough depth in vital skills, but these aspects of the training were clouded by unneeded training content.

As discussed in the limitations section, other contextual factors associated with each study's site might also be responsible for these differences (e.g., location of studies, backgrounds of participants). Nonetheless, this study builds on Strait and colleagues' original (2012b) and paraprofessional (2017) studies by combining the control groups from these studies and comparing the outcome differences between the groups. This likely minimizes the direct effect of these potential factors as the control group consisted of participants from both study sites and the statistical analyses controlled for pre-treatment grades and clustering within classrooms. Future researchers should examine whether ethnicity may serve as moderator between the treatment effect and post-treatment outcomes.

**Research Question 2: Total SMART Goal Quality on Grade Outcomes**

The second research question of this study aimed to investigate the relationship between SMART goal quality and middle school students' academic performance.

Contrary to the initial hypothesis and previous research findings, the results revealed an unexpected and significant negative relationship between the total SMART goal score and post-treatment ELA grades. These findings imply that as the total SMART goal score increased, there was a tendency for post-treatment ELA grades to decrease. However, it is important to note that the total SMART goal score did not significantly impact post-treatment grades in math or science, as indicated in Table 9. These findings provide valuable insights into the role of SMART goal quality on middle school students' academic performance. The observed negative relationship between the total SMART goal score and post-treatment ELA grades suggests that the effectiveness of SMART goal setting may vary across different academic domains. This finding implies that the impact of SMART goals on academic performance may not be consistent across all subjects.

To gain a deeper understanding of this domain-specific relationship, further research is needed to explore the underlying factors that influence the observed negative relationship between SMART goal quality and post-treatment ELA grades. The limited variance in the scores may have influenced the relationship between SMART goal quality and post-treatment ELA grades. Specifically, the median of the total score approached the ceiling, indicating that most students scored highly on the goal sheet. Moreover, the negative skewness of the scores suggests that outliers were predominantly on the extreme-low end of the scale. This lack of variance can be attributed to the structured nature of the goal sheets used by participants in Strait and colleagues' 2012b and 2017 studies, which may have constrained the range of responses and goals set by the students. One way to increase the variability in how the goal sheet is scored would be to introduce a broader range of categories for goal setting, encompassing different academic and personal growth areas (e.g., core subjects, study habits, class participation, or other academic skills). This approach could essentially motivate students to set goals that are more aligned with their desires/values and generate a more comprehensive array of goals, which can then allow necessary changes (e.g., adding additional sub-criterion that can capture individual differences between the students' goals) to the rubric itself to increase scoring variability.

Further, the raters in this study evaluated the students' goals for overall Specificity and Relevance to their overall school success, not related to individual subjects. For example, a goal like "get a B in my classes" could have been evaluated but was not subject-specific, like, "I want to get a B in science." Future researchers could consider evaluating the quality of SMART goals set for each student's academic subject rather than only evaluating students' general academic success. By tailoring the SMART goal rating to each academic subject, essentially, the evaluation could be more nuanced and subject-specific.

Moreover, scoring non-goal sheet completers as 0 may have influenced the relationship. Likely, students who chose not to complete a goal sheet had specific reasons for doing so, and these reasons may not have been random. Factors such as confidence in their ability to achieve goals without the goal sheet or satisfaction with their current grades and academic behaviors could have influenced their decision. By assigning a score of 0 to non-completers, their absence of goals may have skewed the overall relationship. Additionally, it is worth considering that students with more academic needs may have included more information on their goal worksheets. This could be because they had more behaviors that required change to achieve their goals. Consequently, their goal sheets might have reflected a higher specificity and comprehensiveness level than students with fewer academic needs. This discrepancy in goal content could have influenced the observed relationship between SMART goal quality and academic performance.

While SMART goal setting is often mentioned in Motivational Interviewing (MI) for change plan development, it is essential to note that the most common predictor of change in an MI conversation is change talk, specifically plans and commitment to change. Conner and Norman (2022), in their study, emphasize the importance of recognizing the intention-behavior gap and the role of intention strength in facilitating behavior change. Specifically, not just forming intentions, but also the strength and commitment behind these intentions. Although SMART goals are related to plans, they may serve as a necessary but insufficient condition for facilitating change. Therefore, researchers should consider coding the goal sheets for specific change-talk elements, such as commitment and action plans.  These might include expressions of commitment, desire, ability, reasons, and need (the DARN-C components of change talk; Miller & Rollnick, 2013), along with specific action plans. This approach would offer a more holistic view of the individual's readiness for change and their likelihood of turning their intentions into action. Alternatively, in future studies, recording sessions and utilizing the Motivational Interviewing Treatment Integrity (MITI; Miller, 2020) code could be beneficial for analyzing both provider behavior and the elicited change talk. By incorporating a more comprehensive assessment of change talk, researchers can gain deeper insights into the effectiveness of SMART goal setting within the context of MI interventions.

Ultimately, it is crucial to acknowledge the limited variance in scores, the potential influence of scoring non-goal sheet completers as 0, and the need to consider the role of change talk in future studies. By addressing these considerations, researchers can further enhance their understanding of the relationship between SMART goal quality and middle school students' academic performance within the framework of educational interventions.

### Research Question 3: SMART Goal Characteristics on Grade Outcomes

When considering unique SMART goal characteristics, this study found that SMART goal characteristics varied in how well they predict grades for each subject. Notably, none of the SMART goal characteristics for science yielded statistically significant relationships or improved model fit. However, the Specific SMART goal characteristic for ELA significantly improved the model fit. Interestingly, lower scores predicted higher post-treatment grades in ELA. This unexpected finding could suggest that the outcome might be greater than the sum of its parts, as the combination of SMART goal characteristics likely plays a pivotal role in eliciting meaningful results that individual goal characteristics might not achieve independently.

Furthermore, this could indicate that adopting flexible and less narrowly defined goals in ELA could facilitate a broader engagement with the subject, ultimately improving students' academic performance. In essence, setting Specific goals that are generalized across various settings could lead to more opportunities for reinforcement and overlearning, which could lead to the development of stronger habits that can replace older, less effective ones. Despite the notable impact of the Specific characteristic on ELA, other SMART goal characteristics did not significantly contribute to the model predicting ELA post-treatment grades. These findings emphasize the complexity and nuanced nature of goal setting and its impact on academic performance.

In math, the Attainable and Relevance SMART goal characteristics displayed non-significant trends toward an effect on post-treatment grades. Lower attainable scores were associated with higher post-treatment grades, which might suggest that setting challenging goals can increase student motivation to strive harder. This finding supports and aligns with Locke and Latham's (2002) study, which suggests that challenging goals lead to higher performance than easy goals, creating higher motivation and effort.

Relatedly, higher relevance scores were associated with a trend towards higher math grades, implying that students perform better when their goals and plans appear connected to school success. The construct of relevance also aligns with the third-wave approaches like Acceptance and Commitment Therapy (ACT), where the individuals are encouraged to identify their core values and set goals aligned with them (Harris, 2019). In this study, the higher relevance scores might suggest that students are setting goals that have meaningful connections to their school success. When the students perceive their goals as relevant and personally meaningful, they become more interested, leading to increased motivation and effort to achieve them.

The Timeframe characteristic also showed a non-significant trend towards a negative relationship to math grades. This raises questions about whether the timeliness of goals, particularly for math, optimizes students' academic success. However, it is essential to also consider the rubric in comparison to the goal worksheet's structured components. Specifically, the Timeframe rubric criteria were based on one "yes" or "no" question: "The goal includes the Timeframe within which the outcome should be achieved?" While the current goal sheet used in the SCU does ask students to provide a date and time for when they will start implementing their plan, it does not prompt students to set a time by which their goal should be accomplished. Hence, most students in this study scored a 0 on this item. It is advisable for future research to update the goal sheet by adding a target date for goal achievement. These results highlight differences in how SMART goals relate to post-treatment grades across subjects. Further investigation is needed to decipher the factors causing these variations and provide clarity on the findings.

### Research Question 4: Provider Type on SMART Goal Characteristics and Overall Quality

Research question four investigated whether the service provider's educational background (graduate vs. undergraduate) influences the overall quality and specific characteristics of SMART goals. The results indicated no significant relationship between the service provider's educational background and the total SMART score or most SMART characteristics (Measurable, Attainable, Relevant, and Timeframe). However, a marginally significant positive relationship was observed between students with an undergraduate provider and higher total Specific scores, suggesting that the educational background of the service providers might have some impact on the specificity of goals. As previously mentioned, it is crucial to consider the limitation regarding coding no-change plan completers as 0s in the analysis. This method could skew the results or fail to capture the nuances in the data. For example, it did not differentiate between high-performers who made no changes and those unengaged in the goal-setting process. Moreover, no student with a graduate service provider scored 1 on the Specific characteristic – scores were either higher or 0s. This bimodal distribution might suggest an underlying factor falsely correlating provider type with the Specific characteristic.

### Research Question 5: SMART Goal Quality Does Not Mediate Relationship Between Provider Type and Grade Outcomes

This study's final aim was to examine whether total SMART goal quality mediated the relationship between service providers' educational background and ELA, math, and science grade outcomes. The research question investigated the potential mediating role of SMART goal quality in explaining the relationship between provider educational background and academic grades. Based on the hypothesized theory, it was expected that differences in the quality of SMART goals would mediate between provider educational background and grade outcomes. Specifically, it was anticipated that higher educational backgrounds among service providers would be associated with higher SMART goal quality, positively influencing academic grade outcomes in ELA, math, and science. However, the results of the mediation analysis did not support this hypothesis. Ultimately, SMART goal quality did not mediate the relationship between the providers' educational background and post-treatment grades. These findings suggest that other factors beyond SMART goal quality may be influencing the relationship between provider background and academic outcomes.

The results highlight the need to further explore additional factors that could explain the observed associations. Future research should investigate other potential mediators or moderators that may play a role in the relationship between providers' educational backgrounds and student grade outcomes.  For example, competing intentions could be a factor to consider. Essentially, a student might have a goal to excel in academics but also wishes to spend time with friends, play sports, or pursue hobbies. These competing intentions can interfere with Achieving their primary goal and understanding these factors can contribute to the development of more comprehensive interventions and strategies to improve academic performance in middle school-aged children.

Another factor could for future research to check ethnicity as a moderator. Incorporating ethnicity as a moderator in future research could offer essential insights into the effectiveness of SBMI and goal setting. Ethnicity can impact educational experiences and goal attainment due to cultural values, resource accessibility, and potential bias. Understanding these factors can help tailor more culturally-sensitive and effective interventions. However, other potential moderators like socioeconomic status, family educational background, and individual psychological factors could also be considered for a more comprehensive understanding of influences on academic performance.

## Limitations and Strengths

A limitation of this study is that it relies on archival data and employs a quasi-experimental design. Specifically, while participants were randomly assigned within each study to receive the SCU or school as usual, random assignment was not applied to the provider type. Participants in the original SCU study had graduate-level providers, and the paraprofessional study had undergraduate providers. This absence of variation in provider type within the studies raises the possibility that other study-specific characteristics, such as school site characteristics (e.g., differences in grading, rural vs. small urban), might explain the differences in outcomes based on provider type. However, this project's first research question clarifies site differences by comparing the two provider types to participants who had no providers, which comprised a mix of both studies' control groups. Furthermore, this limitation does not impact research questions measuring the direct effects of goal characteristics on academic grade outcomes.

As previously mentioned, this study also faced a dilemma in handling coding for participants in the treatment group who opted not to complete a goal sheet. This decision can have implications for the results, particularly with whether these students should be classified as missing data or assigned a score of 0 for SMART scores. Another concern is the small sample size, which limits the power to detect significant small effects, and restricts the generalizability of the findings. Moreover, conducting a large number of analyses could increase the likelihood of finding significant results by chance. Although applying Bonferroni corrections to p-values could mitigate this, it might reduce the statistical power further. Given these limitations, the findings of this study should be viewed with some caution. It is crucial for future research to address these limitations by utilizing larger sample sizes, ensuring the random assignment of provider types, and using robust statistical techniques to account for heteroscedasticity.

This study's strengths lie in its ability to identify potential variables that may have contributed to previous replication failures (Strait et al., 2017 study) and provide valuable insights for program developers and practitioners. By understanding the factors that strengthen or weaken treatment efficacy, practitioners can make informed decisions and adopt the most effective practices when using MI with students. This includes selecting qualified providers (e.g., selecting providers with graduate-level training in psychology or education), tailoring interventions to specific academic domains and student goals (e.g., provide skills training to related to students' goals that were developed by MI; Hart et al., 2021), and providing sufficient, efficient, and on-going training and supervision to treatment providers (McQuillin et al., 2013; Hart et al., 2021).

**Limitations and Considerations Involving the SMART Goal Scoring System**

While this study offers notable insights into the relationship between SMART goal characteristics and post-treatment grades, discussing some inherent issues and areas for improvement in the current SMART goal-scoring system is essential. The data's skewness concerning SMART goal outcomes and residuals, combined with limited variance (where most participants had higher scores, but a few had consistently low scores), could have impacted the interpretation of the results. Hence, it is crucial to address the implication the limited variance has on the data analysis. The limited variance in the SMART goal scores might have resulted from the SMART-GEM Rubric measurement's inability to differentiate the subtle discrepancies in goal quality among participants. The clustering of higher scores indicates that the SMART goal rubrics that were used might have failed to capture the variation in the quality of goals set by students, which would result in reduced discrimination between moderate and high-quality goals, as most goals might have been rated similarly, hence leading to a ceiling effect. The consistently low scores could have also indicated a floor effect for participants whose goals were poorly aligned with the SMART goal rubric criteria.

To better measure the quality and relevance of students' goals and the efficacy of SBMI, a more refined SMART goal rubric could be developed. The expanded rubric could potentially involve more nuanced criteria and scaling, making it more sensitive to variations in the quality of the goals set, which could lead to a broader distribution of scores, crucial for conducting robust statistical analyses. In particular, moving from a broad school-based approach to a more subject-specific approach could help to capture the nuances in goal quality more effectively. For example, a student might have different goals and strategies for math than for English Language Arts, and this subject-specific approach to goal setting could be a more effective strategy for improving academic performance. There could also be value in maintaining a broader, more holistic approach to goal setting that considers the overall school experience, including factors like social interactions and extracurricular activities.

It may also be helpful to use a more differentiated scoring system rather than a simple sum of answers to dichotomously scaled questions. A scaling system that captures the gradual transition in goal quality could be beneficial. Incorporating a Goal Attainment Scaling (GAS) system into future MI studies could also be helpful in understanding the direct and indirect effects of SBMI. GAS is a method that measures the degree to which a person's specific goals are achieved during an intervention. Including GAS measures could allow researchers to understand whether MI’s impact on academic grades is partially accounted for through goal attainment. It would also be interesting to understand the relationship between goal quality and goal attainment on MI treatment outcomes. GAS could make the current SMART goal rubric more personalized, sensitive to changes, standardized, and outcome focused. Ultimately, this could improve the rubric's overall utility and precision in evaluating students' goal setting and attainment, regardless of whether the goals are subject-specific or more broadly based.

## Conclusion

In conclusion, this study shed light on potential factors influencing the efficacy of SBMI on academic grades, explicitly focusing on the educational background of SBMI providers and the characteristics of SMART goals set by middle school students. The findings suggested that students with graduate providers achieved higher post-treatment ELA and math grades than undergraduate providers or no providers. The study also revealed a complex relationship between SMART goal quality and academic performance. The study also revealed a complex relationship between SMART goal quality and academic performance, with the negative impact of SMART goals on post-treatment ELA grades, potentially suggesting subject-specific variations and running counter to goal-setting theories. Relatedly, the existing limitations in the current SMART goal-scoring system suggest a need to refine the SMART goal rubrics, allowing for a more detailed analysis of goal quality. Most importantly, the findings did not support the mediating role of SMART goal quality between providers' educational level background and students' post-treatment grade outcomes, indicating that variations in goal-setting quality did not explain the relationship between the type of provider and post-treatment grades. Furthermore, it underscores the complexity of the intervention, highlighting that the efficacy of SBMI might be influenced by many factors and is not solely contingent on the quality of goal setting or provider background. Ultimately, the results of this study emphasized the need for further research to explore underlying factors of efficacious MI interventions and address the limitations of this study. This study contributes to understanding variables influencing SBMI efficacy and guides future research to enhance educational interventions and strategies for SBMI with middle school students and related fields/settings.

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APPENDIX A:

TABLES

**Table 1**

*Sociodemographics of Participants for Each Study*

| Baseline characteristic | Original SCU (Strait et al., 2012) *n* = 103 | | Paraprofessional (Strait et al., 2017) *n* = 88 | | Full Sample | |
|---|---|---|---|---|---|---|
| | *N* | % | *n* | % | *n* | % |
| Gender | | | | | | |
| Female | 51 | 50 | 61 | 69 | 112 | 58 |
| Male | 52 | 50 | 27 | 31 | 79 | 42 |
| Ethnicity | | | | | | |
| White | 34 | 33 | 50 | 58 | 84 | 44 |
| Black | 60 | 58 | 35 | 40 | 95 | 50 |
| Other | 9 | 9 | 2 | 2 | 11 | 6 |
| Grade Level | | | | | | |
| 6th grade | 55 | 54 | 41 | 48 | 96 | 50 |
| 7th grade | 22 | 21 | 27 | 31 | 49 | 26 |
| 8th grade | 26 | 25 | 19 | 21 | 45 | 24 |
| Provider Type | | | | | | |
| Grad | 5 | 100 | 0 | 0 | 5 | 100 |
| Under | 0 | 0 | 11 | 100 | 11 | 100 |

*Note*. *N* = 191. Participants are listed in the racial category they reported.

**Table 2**

*Descriptive Statistics for Pre-and Post-Grade Outcomes of Participants Across Treatment and Control Groups*

| Measure | *n* | *Min* | *Max* | *M* | *SD* | *Mdn* | *Skew* | *Rku* | % Missing |
|---|---|---|---|---|---|---|---|---|---|
| Pre-Grades | | | | | | | | | |
| ELA Pre | 189 | 57.00 | 100 | 85.73 | 8.70 | 87.33 | -0.63 | -0.11 | 1.0 |
| Math Pre | 189 | 57.67 | 100 | 84.30 | 9.92 | 85.33 | -0.58 | -0.28 | 1.0 |
| Science Pre | 189 | 59.00 | 99.00 | 84.94 | 9.01 | 86.00 | -0.66 | -0.03 | 1.0 |
| Post-Grades | | | | | | | | | |
| ELA Post | 188 | 45.00 | 100 | 87.22 | 10.36 | 90.00 | -1.22 | 1.56 | 1.6 |
| Math Post | 187 | 32.00 | 100 | 85.14 | 10.50 | 87.00 | -1.47 | 3.47 | 2.1 |
| Science Post | 188 | 60.00 | 100 | 88.37 | 8.71 | 89.00 | -0.84 | 0.53 | 1.6 |

**Table 3**

*Descriptive Statistics for Pre- and Post-Grade Outcomes of Participants in the Treatment Groups*

| Measure | *n* | *Min* | *Max* | *M* | *SD* | *Mdn* | *Skew* | *Rku* | % Missing |
|---|---|---|---|---|---|---|---|---|---|
| SMART Goal | | | | | | | | | |
| Specific | 90 | 0 | 3 | 2.18 | 1.09 | 3 | -1.12 | -0.14 | 2.2 |
| Measurable | 90 | 0 | 2 | 1.43 | 0.78 | 2 | -0.94 | -0.70 | 2.2 |
| Attainable | 90 | 0 | 2 | 1.52 | 0.74 | 2 | -1.19 | -0.09 | 2.2 |
| Relevance | 90 | 0 | 2 | 1.66 | 0.74 | 2 | -1.76 | 1.25 | 2.2 |
| Timeframe | 90 | 0 | 1 | 0.19 | 0.39 | 0 | 1.62 | 0.63 | 2.2 |
| Total SMART | 90 | 0 | 10 | 6.98 | 3.14 | 8 | -1.49 | 0.87 | 2.2 |
| Pre-Tx Grades | | | | | | | | | |
| ELA Pre | 91 | 64.00 | 100.0 | 84.99 | 8.52 | 85.33 | -0.40 | -0.53 | 1.1 |
| Math Pre | 91 | 57.67 | 99.67 | 83.94 | 9.97 | 85.00 | -0.47 | -0.35 | 1.1 |
| Science Pre | 91 | 61.67 | 99.00 | 84.39 | 8.90 | 86.67 | -0.65 | -0.25 | 1.1 |
| Post-Tx Grades | | | | | | | | | |
| ELA Post | 90 | 45.00 | 100 | 86.60 | 10.37 | 89.00 | -1.32 | 2.43 | 2.2 |
| Math Post | 89 | 64.00 | 100 | 85.26 | 10.36 | 87.00 | -1.03 | 0.86 | 3.3 |
| Science Post | 90 | 61.00 | 100 | 87.46 | 9.23 | 88.00 | -0.79 | 0.33 | 2.2 |

**Table 4.1**

*ANOVA Test for Pre-treatment Equivalence Comparing Graduate Providers, Undergraduate Providers, and the Control Group (i.e., No Provider)*

| Measure | Sum of Squares | *df* | Mean Square | *F* | *p* |
|---|---|---|---|---|---|
| ELA Pre | 550.69 | 2 | 275.34 | 3.74* | 0.03* |
| Math Pre | 607.41 | 2 | 303.70 | 3.16* | 0.05* |
| Science Pre | 56.71 | 2 | 28.35 | 0.35 | 0.71 |
| Gender | 1.03 | 2 | 0.51 | 2.15 | 0.12 |
| Ethnicity | 4.52 | 2 | 2.26 | 7.15* | 0.00* |
| Grade Level | 0.98 | 2 | 0.49 | 0.72 | 0.49 |

* $p < .05$.

**Table 4.2**

*Means and Standard Deviation of Students Grades by Group and Study Location*

| Measures | | *N* | *M* | *SD* |
|---|---|---|---|---|
| ELA Pre | Treatment-2017 | 42 | 82.58 | 8.41 |
| | Treatment-2012 | 49 | 87.07 | 8.13 |
| | Control-2012 | 53 | 88.46 | 7.79 |
| | Control-2017 | 45 | 84.01 | 9.51 |
| | Total | 189 | 85.73 | 8.70 |
| ELA Post | Treatment-2017 | 41 | 81.63 | 11.03 |
| | Treatment 2012 | 49 | 90.76 | 7.70 |
| | Control-2012 | 53 | 90.08 | 9.18 |
| | Control-2017 | 45 | 85.11 | 11.12 |
| | Total | 188 | 87.22 | 10.36 |
| Math Pre | Treatment -2017 | 42 | 81.21 | 10.41 |
| | Treatment -2012 | 49 | 86.29 | 9.02 |
| | Control-2012 | 53 | 86.53 | 8.85 |
| | Control-2017 | 45 | 82.39 | 10.71 |
| | Total | 189 | 84.3 | 9.92 |
| Math Post | Treatment-2017 | 40 | 81.83 | 11.74 |
| | Treatment-2012 | 49 | 88.06 | 8.18 |
| | Control-2012 | 53 | 86.6 | 8.58 |
| | Control-2017 | 45 | 83.18 | 12.58 |
| | Total | 187 | 85.14 | 10.50 |
| Science Pre | Treatment-2017 | 42 | 84.17 | 9.12 |
| | Treatment-2012 | 49 | 84.58 | 8.79 |
| | Control-2012 | 53 | 84.84 | 9.04 |
| | Control-2017 | 45 | 86.16 | 9.27 |
| | Total | 189 | 84.94 | 9.01 |
| Science Post | Treatment-2017 | 41 | 84.68 | 8.63 |
| | Treatment-2012 | 49 | 89.78 | 9.16 |
| | Control-2012 | 53 | 90.42 | 8.35 |
| | Control-2017 | 45 | 87.78 | 7.79 |
| | Total | 188 | 88.37 | 8.71 |

**Table 5**

*Pair-wise Comparisons Using Tukey HSD Post-hoc Test*

| Measure | Comparison | Groups | *MD* | *SE* | *p* | 95% CI | |
|---|---|---|---|---|---|---|---|
| | | | | | | *LL* | *UL* |
| ELA Pre | No Provider | Under | 3.84* | 1.58 | 0.04* | 0.10 | 7.57 |
| | No Provider | Grad | -0.65 | 1.50 | 0.90 | -4.20 | 2.89 |
| | Under | Grad | -4.49* | 1.80 | 0.04* | -8.75 | -0.23 |
| Math Pre | No Provider | Under | 3.43 | 1.81 | 0.14 | -0.85 | 7.70 |
| | No Provider | Grad | -1.66 | 1.72 | 0.60 | -5.71 | 2.39 |
| | Under | Grad | -5.09* | 2.06 | 0.04* | -9.96 | -0.21 |
| Science Pre | No Provider | Under | 1.28 | 1.67 | 0.72 | -2.66 | 5.22 |
| | No Provider | Grad | 0.86 | 1.58 | 0.85 | -2.87 | 4.60 |
| | Under | Grad | -0.42 | 1.90 | 0.97 | -4.91 | 4.07 |

*Note*. CI = confidence interval*; MD* = mean difference, *SE* = standard error, *LL* = lower limit, UL = upper limit.

* $p < .05$.

**Table 6**

*Pretest Equivalence Chi-Square and T-Tests (Treatment Groups Only)*

| Measures | Original SCU (Strait et al., 2012) $n$ = 50 | | Paraprofessional (Strait et al., 2017) $n$ = 42 | | $t(89)$ | $p$ |
|---|---|---|---|---|---|---|
| | *M* | *SD* | *M* | *SD* | | |
| Grades | | | | | | |
| ELA Pre | 87.08 | 8.13 | 82.58 | 8.41 | -2.58 | 0.01 |
| Math Pre | 86.29 | 9.02 | 81.21 | 10.41 | -2.47 | 0.01 |
| Science Pre | 84.58 | 8.79 | 84.17 | 9.12 | -0.22 | 0.83 |
| | *n* | | *n* | | $X^2$ | |
| Gender | | | | | 0.14 | 0.71 |
| Female | 32 | | 29 | | | |
| Male | 17 | | 13 | | | |
| Ethnicity | | | | | 13.75* | 0.00 |
| White | 14 | | 28 | | | |
| Black | 31 | | 14 | | | |
| Other | 3 | | 0 | | | |
| Grade Level | | | | | 3.61 | .16 |
| 6th Grade | 23 | | 21 | | | |
| 7th Grade | 12 | | 15 | | | |
| 8th Grade | 15 | | 6 | | | |

$^{**}p \leq .01$; $^{*}p \leq .05$; † $p \leq .1$.

**Table 7**

*Correlations for Pre-treatment Grades and SMART Goal Characteristics*

| Variables | n | M | SD | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Specific | 90 | 2.18 | 1.09 | _ | | | | | | | | |
| 2. Measurable | 90 | 1.43 | 0.78 | .68** | _ | | | | | | | |
| 3. Attainable | 90 | 1.52 | 0.74 | .82** | .66** | _ | | | | | | |
| 4. Relevance | 90 | 1.66 | 0.74 | .85** | .71** | .85** | _ | | | | | |
| 5. Timeframe | 90 | 0.19 | 0.39 | 0.16 | .24* | 0.12 | .23* | _ | | | | |
| 6. Total SMART | 90 | 6.98 | 3.14 | .93** | .84** | .90** | .94** | .32** | _ | | | |
| 7. ELA Pre | 91 | 84.99 | 8.51 | 0.02 | -0.05 | 0.01 | 0.08 | -0.14 | -0.001 | _ | | |
| 8. Science Pre | 91 | 84.41 | 8.92 | -0.17 | -0.19 | -.22* | -0.16 | -0.13 | -.21* | .67** | _ | |
| 9. Math Pre | 91 | 83.93 | 8.94 | -0.16 | -0.15 | -0.19 | -0.18 | -0.11 | -0.20 | .65** | .70** | _ |

**Correlation is significant at the 0.01 level (2-tailed).

*Correlation is significant at the 0.05 level (2-tailed).

**Table 8.1**

*RQ #1: Hierarchical Regression Results for Service Providers' Educational Background on Post-treatment Grades*

| Construct | Fixed Effect | | | | Random Effect Variance Component | | |
|---|---|---|---|---|---|---|---|
| Parameter | B | SE | *t* | *p* | $\sigma^2$ | $\tau$ | *Pr(>χ²)* |
| **ELA** | | | | | | | |
| Intercept | 0.00 | 0.12 | -0.01 | 0.99 | 0.00 | 0.48 | |
| Pre-Grade | 0.65 | 0.06 | 11.72 | 0.00*** | | | |
| Grad | 0.22 | 0.12 | 1.80 | 0.07† | | | 0.001** |
| Under | -0.30 | 0.14 | -2.14 | 0.03** | | | |
| Gender | | | | | | | |
| Male | 0.08 | 0.11 | 0.73 | 0.46 | | | |
| Ethnicity | | | | | | | |
| Black | -0.06 | 0.11 | -0.58 | 0.56 | | | |
| Other | -0.17 | 0.25 | -0.68 | 0.50 | | | |
| Grade Level | | | | | | | |
| 7th Grade | -0.29 | 0.12 | -2.31 | 0.02** | | | |
| 8th Grade | 0.31 | 0.13 | 2.42 | 0.02** | | | |
| **Math** | | | | | | | |
| Intercept | 0.02 | 0.11 | 0.16 | 0.87 | 0.00 | 0.46 | |
| Pre-Grade | 0.67 | 0.06 | 11.33 | 0.00*** | | | |
| Grad | 0.19 | 0.12 | 1.59 | 0.11 | | | 0.17 |
| Under | -0.10 | 0.14 | -0.72 | 0.47 | | | |
| Gender | | | | | | | |
| Male | 0.19 | 0.11 | 1.77 | 0.08† | | | |
| Ethnicity | | | | | | | |
| Black | -0.07 | 0.11 | -0.62 | 0.54 | | | |
| Other | -0.21 | 0.24 | -0.87 | 0.39 | | | |
| Grade Level | | | | | | | |
| 7th Grade | -0.22 | 0.12 | -1.82 | 0.07† | | | |
| 8th Grade | -0.24 | 0.14 | -1.74 | 0.08† | | | |
| **Science** | | | | | | | |
| Intercept | 0.18 | 0.18 | 1.00 | 0.33 | 0.12 | 0.41 | |
| Pre-Grade | 0.70 | 0.06 | 11.98 | 0.00*** | | | |
| Grad | 0.08 | 0.13 | 0.60 | 0.55 | | | 0.57 |
| Under | -0.12 | 0.14 | -0.86 | 0.39 | | | |

| Construct | Fixed Effect | | | | Random Effect Variance Component | | |
|---|---|---|---|---|---|---|---|
| Parameter | B | SE | *t* | *p* | $\sigma^2$ | $\tau$ | $X^2$ |
| Gender | | | | | | | |
| Male | -0.18 | 0.11 | -1.59 | 0.11 | | | |
| **Science** | | | | | | | |
| Intercept | 0.18 | 0.18 | 1.00 | 0.33 | 0.12 | 0.41 | |
| Pre-Grade | 0.70 | 0.06 | 11.98 | 0.00*** | | | |
| Grad | 0.08 | 0.13 | 0.60 | 0.55 | | | 0.57 |
| Under | -0.12 | 0.14 | -0.86 | 0.39 | | | |
| Gender | | | | | | | |
| Male | -0.18 | 0.11 | -1.59 | 0.11 | | | |
| Black | -0.12 | 0.11 | -1.09 | 0.28 | | | |
| Other | 0.05 | 0.24 | 0.23 | 0.82 | | | |
| Grade Level | | | | | | | |
| 7th Grade | 0.08 | 0.24 | 0.33 | 0.74 | | | |
| 8th Grade | -0.05 | 0.22 | -0.25 | 0.81 | | | |

*Note.* No Provider Group is Selected as the Reference Group in the Model.

****p = 0.0; **p ≤ .01; *p ≤ .05; † p ≤. 1.*

**Table 8.2**

*RQ #1: Hierarchical Regression Results for Service Providers' Educational Background Influence on Post-treatment Grades*

| Construct Parameter | Fixed Effect B | SE | *t* | *p* | Random Effect Variance Component σ $^2$ | τ | $X^2$ |
|---|---|---|---|---|---|---|---|
| **ELA** | | | | | | | |
| Intercept | 0.22 | 0.15 | 1.46 | 0.14 | 0.00 | 0.48 | |
| Pre-Grade | 0.65 | 0.06 | 11.72 | 0.00** | | | |
| No Provider | -0.22 | 0.12 | -1.80 | 0.07† | | | 0.001** |
| Under | -0.52 | 0.16 | -3.28 | 0.00*** | | | |
| Gender | | | | | | | |
| Male | 0.08 | 0.11 | 0.73 | 0.46 | | | |
| Ethnicity | | | | | | | |
| Black | -0.06 | 0.11 | -0.58 | 0.56 | | | |
| Other | -0.17 | 0.25 | -0.68 | 0.50 | | | |
| Grade Level | | | | | | | |
| 7th Grade | -0.29 | 0.12 | -2.31 | 0.02* | | | |
| 8th Grade | 0.31 | 0.13 | 2.42 | 0.02* | | | |
| **Math** | | | | | | | |
| Intercept | 0.21 | 0.15 | 1.41 | 0.16 | 0.00 | 0.46 | |
| Pre-Grade | 0.67 | 0.06 | 11.33 | 0.00*** | | | |
| No Provider | -0.19 | 0.12 | -1.59 | 0.11 | | | 0.17 |
| Under | -0.29 | 0.16 | -1.84 | 0.07† | | | |
| Gender | | | | | | | |
| Male | 0.19 | 0.11 | 1.77 | 0.08† | | | |
| Ethnicity | | | | | | | |
| Black | -0.07 | 0.11 | -0.62 | 0.54 | | | |
| Other | -0.21 | 0.24 | -0.87 | 0.39 | | | |
| Grade Level | | | | | | | |
| 7th Grade | -0.22 | 0.12 | -1.82 | 0.07† | | | |
| 8th Grade | -0.24 | 0.14 | -1.74 | 0.08† | | | |
| **Science** | | | | | | | |
| Intercept | 0.26 | 0.21 | 1.22 | 0.23 | 0.12 | 0.41 | |
| Pre-Grade | 0.70 | 0.06 | 11.98 | 0.00*** | | | |
| No Provider | -0.08 | 0.13 | -0.60 | 0.55 | | | 0.57 |
| Under | -0.20 | 0.19 | -1.08 | 0.28 | | | |

| Construct | Fixed Effect | | | | Random Effect Variance Component | | |
|---|---|---|---|---|---|---|---|
| Parameter | B | SE | *t* | *p* | $\sigma^2$ | $\tau$ | $X^2$ |
| Gender | | | | | | | |
| Male | -0.18 | 0.11 | -1.59 | 0.11 | | | |
| Ethnicity | | | | | | | |
| Black | -0.12 | 0.11 | -1.09 | 0.28 | | | |
| Other | 0.05 | 0.24 | 0.23 | 0.82 | | | |
| Grade Level | | | | | | | |
| 7th Grade | 0.08 | 0.24 | 0.33 | 0.74 | | | |
| 8th Grade | -0.05 | 0.22 | -0.25 | 0.81 | | | |

*Note*. The graduate providers' group is selected as the model's reference group in the model.

***$p$ = 0.0; **$p \leq .01$; *$p \leq .05$; † $p \leq .1$.

**Table 9**

*RQ #2: Hierarchical Regression Results for Effects of Total SMART Goal Score on Post-Treatment Grades*

| Construct | Fixed Effect | | | | Random Effect Variance Component | | |
|---|---|---|---|---|---|---|---|
| Parameter | B | SE | *t* | *p* | $\sigma^2$ | $\tau$ | $X^2$ |
| **ELA** | | | | | | | |
| Intercept | -0.10 | 0.19 | -0.51 | 0.62 | 0.01 | 0.61 | |
| Pre-Grade | 0.59 | 0.09 | 6.31 | 0.00*** | | | |
| Gender | | | | | | | |
| Male | -0.12 | 0.19 | -0.60 | 0.55 | | | |
| Ethnicity | | | | | | | |
| Black | 0.14 | 0.18 | 0.82 | 0.42 | | | |
| Other | 0.85 | 0.58 | 1.47 | 0.15 | | | |
| Grade Level | | | | | | | |
| 7th Grade | -0.21 | 0.21 | -1.01 | 0.35 | | | |
| 8th Grade | 0.68 | 0.23 | 2.96 | 0.01* | | | |
| Total SMART Score | -0.23 | 0.09 | -2.66 | 0.01** | | | 0.01 |
| **Math** | | | | | | | |
| Intercept | -0.09 | 0.18 | -0.47 | 0.65 | 0.03 | 0.50 | |
| Pre-Grade | 0.71 | 0.09 | 7.57 | 0.00*** | | | |
| Gender | | | | | | | |
| Male | 0.17 | 0.18 | 0.96 | 0.34 | | | |
| Ethnicity | | | | | | | |
| Black | 0.02 | 0.16 | 0.13 | 0.90 | | | |
| Other | -0.39 | 0.53 | -0.74 | 0.46 | | | |
| Grade Level | | | | | | | |
| 7th Grade | 0.03 | 0.21 | 0.14 | 0.89 | | | |
| 8th Grade | -0.04 | 0.24 | -0.15 | 0.88 | | | |
| Total SMART Score | 0.00 | 0.08 | 0.06 | 0.95 | | | 0.97 |
| **Science** | | | | | | | |
| Intercept | -0.03 | 0.24 | -0.13 | 0.90 | 0.15 | 0.42 | |
| Pre-Grade | 0.75 | 0.09 | 8.58 | 0.00*** | | | |
| Gender | | | | | | | |
| Male | -0.13 | 0.17 | -0.76 | 0.45 | | | |
| Ethnicity | | | | | | | |
| Black | 0.01 | 0.15 | 0.04 | 0.97 | | | |
| Other | 0.17 | 0.51 | 0.33 | 0.75 | | | |
| Grade Level | | | | | | | |
| 7th Grade | 0.32 | 0.29 | 1.10 | 0.29 | | | |
| 8th Grade | 0.35 | 0.29 | 1.23 | 0.23 | | | |
| Total SMART Score | -0.04 | 0.07 | -0.56 | 0.58 | | | 0.57 |

***$p$ = 0.0; **$p \leq .01$; *$p \leq .05$; † $p \leq .1$.

**Table 10.1**

*RQ#3: Hierarchical Regression Results for Effects of SMART Goal Characteristics for ELA*

| Model ELA | Variable | B | 95% CI for B LL | UL | SE B | t | P | $R^2$ | $\Delta R^2$ |
|---|---|---|---|---|---|---|---|---|---|
| M 0 | (Intercept) | 23.90 | 4.03 | 43.76 | 10.14 | 2.36 | 0.02 * | 0.3704 | - |
| | Pre-grade | 0.73 | 0.50 | 0.97 | 0.12 | 6.14 | 0.00 *** | | |
| | Gender-Male | -1.38 | -5.46 | 2.71 | 2.08 | -0.66 | 0.51 | | |
| | Ethnicity-Black | 1.57 | -2.11 | 5.24 | 1.87 | 0.84 | 0.41 | | |
| | Ethnicity-Other | 7.58 | -4.60 | 19.76 | 6.21 | 1.22 | 0.23 | | |
| | Grade Level-7 | -3.05 | -7.26 | 1.15 | 2.14 | -1.42 | 0.16 | | |
| | Grade Level-8 | 5.46 | 0.88 | 10.05 | 2.34 | 2.34 | 0.02* | | |
| M 1 | (Intercept) | 26.65 | 7.16 | 46.14 | 9.94 | 2.68 | 0.01 ** | 0.4054 | 0.0349 |
| | Pre-grade | 0.74 | 0.52 | 0.97 | 0.12 | 6.40 | 0.00 *** | | |
| | Gender-Male | -1.52 | -5.50 | 2.46 | 2.03 | -0.75 | 0.46 | | |
| | Ethnicity-Black | 1.80 | -1.78 | 5.38 | 1.83 | 0.98 | 0.33 | | |
| | Ethnicity-Other | 9.41 | -2.55 | 21.37 | 6.10 | 1.54 | 0.13 | | |
| | Grade Level-7 | -2.36 | -6.49 | 1.78 | 2.11 | -1.12 | 0.27 | | |
| | Grade Level-8 | 6.81 | 2.20 | 11.42 | 2.35 | 2.90 | 0.01 ** | | |
| | Specific | -1.98 | -3.66 | -0.31 | 0.86 | -2.32 | 0.02 * | | |
| M 2 | (Intercept) | 28.57 | 8.71 | 48.43 | 10.13 | 2.82 | 0.01** | 0.4093 | 0.0039 |
| | Pre-grade | 0.73 | 0.50 | 0.96 | 0.12 | 6.17 | 0.00 *** | | |
| | Gender-Male | -1.16 | -5.21 | 2.89 | 2.06 | -0.56 | 0.58 | | |
| | Ethnicity-Black | 1.69 | -1.90 | 5.28 | 1.83 | 0.92 | 0.36 | | |
| | Ethnicity-Other | 9.68 | -2.30 | 21.65 | 6.11 | 1.58 | 0.12 | | |
| | Grade Level-7 | -2.18 | -6.33 | 1.97 | 2.12 | -1.03 | 0.31 | | |
| | Grade Level-8 | 6.88 | 2.27 | 11.49 | 2.35 | 2.93 | 0.00 ** | | |
| | Specific | -1.25 | -3.47 | 0.96 | 1.13 | -1.11 | 0.27 | | |
| | Measurable | -1.56 | -4.64 | 1.52 | 1.57 | -0.99 | 0.32 | | |
| M 3 | (Intercept) | 28.56 | 8.53 | 48.58 | 10.22 | 2.80 | 0.01 ** | 0.4066 | - 0.0027 |
| | Pre-grade | 0.73 | 0.50 | 0.96 | 0.12 | 6.11 | 0.00 *** | | |
| | Gender-Male | -1.16 | -5.24 | 2.91 | 2.08 | -0.56 | 0.58 | | |
| | Ethnicity-Black | 1.66 | -1.96 | 5.28 | 1.85 | 0.90 | 0.37 | | |
| | Ethnicity-Other | 8.97 | -4.06 | 22.01 | 6.65 | 1.35 | 0.18 | | |
| | Grade Level-7 | -2.17 | -6.37 | 2.03 | 2.14 | -1.01 | 0.35 | | |
| | Grade Level-8 | 6.95 | 2.27 | 11.63 | 2.39 | 2.91 | 0.01 * | | |
| | Specific | -0.95 | -4.06 | 2.16 | 1.59 | -0.60 | 0.55 | | |
| | Measurable | -1.46 | -4.68 | 1.77 | 1.64 | -0.89 | 0.38 | | |
| | Attainable | -0.66 | -5.29 | 3.98 | 2.36 | -0.28 | 0.78 | | |
| M 4 | (Intercept) | 28.60 | 8.36 | 48.85 | 10.33 | 2.77 | 0.01 ** | 0.4043 | - 0.0023 |
| | Pre-grade | 0.73 | 0.50 | 0.97 | 0.12 | 6.04 | 0.00 *** | | |
| | Gender-Male | -1.18 | -5.29 | 2.93 | 2.10 | -0.56 | 0.58 | | |
| | Ethnicity-Black | 1.53 | -2.13 | 5.19 | 1.87 | 0.82 | 0.42 | | |
| | Ethnicity-Other | 9.26 | -3.96 | 22.48 | 6.74 | 1.37 | 0.17 | | |
| | Grade Level-7 | -2.19 | -6.49 | 2.12 | 2.20 | -1.00 | 0.35 | | |
| | Grade Level-8 | 7.13 | 2.31 | 11.96 | 2.46 | 2.90 | 0.02* | | |
| | Specific | -0.62 | -3.99 | 2.76 | 1.72 | -0.36 | 0.72 | | |
| | Measurable | -1.27 | -4.66 | 2.13 | 1.73 | -0.73 | 0.47 | | |
| | Attainable | -0.13 | -5.46 | 5.20 | 2.72 | -0.05 | 0.96 | | |
| | Relevance | -1.33 | -7.06 | 4.39 | 2.92 | -0.46 | 0.65 | | |

| Model | Variable | B | 95% CI for B | | SE B | t | P | $R^2$ | $\Delta R^2$ |
|---|---|---|---|---|---|---|---|---|---|
| ELA | | | LL | UL | | | | | |
| M 5 | (Intercept) | 29.37 | 7.61 | 49.73 | 10.61 | 2.77 | 0.01 ** | 0.4084 | 0.0041 |
| | Pre-grade | 0.73 | 0.48 | 0.98 | 0.12 | 5.82 | 0.00 *** | | |
| | Gender-Male | -1.12 | -5.44 | 2.82 | 2.12 | -0.53 | 0.60 | | |
| | Ethnicity-Black | 1.42 | -2.31 | 5.36 | 1.89 | 0.75 | 0.46 | | |
| | Ethnicity-Other | 9.31 | -4.42 | 23.09 | 6.81 | 1.37 | 0.18 | | |
| | Grade Level-7 | -2.17 | -6.18 | 2.50 | 2.25 | -0.97 | 0.37 | | |
| | Grade Level8 | 7.14 | 2.33 | 12.60 | 2.51 | 2.85 | 0.02 * | | |
| | Specific | -0.60 | -3.91 | 2.84 | 1.74 | -0.35 | 0.73 | | |
| | Measurable | -1.27 | -4.87 | 2.24 | 1.75 | -0.73 | 0.47 | | |
| | Attainable | -0.24 | -5.67 | 5.23 | 2.76 | -0.09 | 0.93 | | |
| | Relevance | -1.23 | -7.43 | 5.01 | 3.01 | -0.41 | 0.68 | | |
| | Timeframe | -0.49 | -5.10 | 4.13 | 2.42 | -0.20 | 0.84 | | |

***p = 0.0; **p ≤ .01; *p ≤ .05; † p ≤ .1.

**Table 10.2**

*RQ#3: Hierarchical Regression Results for Effects of SMART Goal Characteristics for Math*

| Model | Variable | *B* | 95% CI for B | | *SE* | *t* | *P* | *R²* | *ΔR²* |
|---|---|---|---|---|---|---|---|---|---|
| Math | | | LL | UL | | | | | |
| M0 | (Intercept) | 22.27 | 6.06 | 38.49 | 8.28 | 2.69 | 0.01* | 0.5019 | - |
| | Pre-grade | 0.74 | 0.55 | 0.93 | 0.10 | 7.65 | 0.00*** | | |
| | Gender-Male | 1.78 | -1.80 | 5.36 | 1.83 | 0.97 | 0.33 | | |
| | Ethnicity-Black | 0.21 | -3.07 | 3.49 | 1.67 | 0.13 | 0.90 | | |
| | Ethnicity-Other | -4.06 | -14.81 | 6.70 | 5.49 | -0.74 | 0.46 | | |
| | Grade Level-7 | 0.32 | -3.91 | 4.55 | 2.16 | 0.15 | 0.89 | | |
| | Grade Level-8 | -0.35 | -5.07 | 4.36 | 2.41 | -0.15 | 0.89 | | |
| M1 | (Intercept) | 22.34 | 5.54 | 39.14 | 8.57 | 2.61 | 0.01* | | |
| | Pre-grade | 0.74 | 0.55 | 0.93 | 0.10 | 7.59 | 0.00*** | 0.4987 | - 0.0032 |
| | Gender-Male | 1.78 | -1.82 | 5.38 | 1.84 | 0.97 | 0.34 | | |
| | Ethnicity-Black | 0.23 | -3.07 | 3.53 | 1.68 | 0.14 | 0.89 | | |
| | Ethnicity-Other | -4.01 | -14.92 | 6.91 | 5.57 | -0.72 | 0.47 | | |
| | Grade Level-7 | 0.35 | -3.94 | 4.64 | 2.19 | 0.16 | 0.88 | | |
| | Grade Level8 | -0.32 | -5.15 | 4.51 | 2.46 | -0.13 | 0.90 | | |
| | Specific | -0.03 | -1.60 | 1.54 | 0.80 | -0.04 | 0.97 | | |
| M2 | (Intercept) | 21.41 | 4.44 | 38.38 | 8.66 | 2.47 | 0.02* | 0.4984 | - 0.0003 |
| | Pre-grade | 0.75 | 0.55 | 0.94 | 0.10 | 7.63 | 0.00*** | | |
| | Gender-Male | 1.57 | -2.09 | 5.24 | 1.87 | 0.84 | 0.40 | | |
| | Ethnicity-Black | 0.40 | -2.91 | 3.71 | 1.69 | 0.24 | 0.81 | | |
| | Ethnicity-Other | -4.02 | -14.97 | 6.93 | 5.59 | -0.72 | 0.47 | | |
| | Grade Level-7 | 0.29 | -3.93 | 4.51 | 2.15 | 0.14 | 0.89 | | |
| | Grade Level8 | -0.26 | -5.03 | 4.50 | 2.43 | -0.11 | 0.92 | | |
| | Specific | -0.51 | -2.54 | 1.52 | 1.04 | -0.49 | 0.63 | | |
| | Measurable | 1.01 | -1.82 | 3.84 | 1.44 | 0.70 | 0.49 | | |
| M3 | (Intercept) | 21.72 | 4.59 | 38.85 | 8.74 | 2.49 | 0.02* | 0.4975 | - 0.0009 |
| | Pre-grade | 0.75 | 0.55 | 0.94 | 0.10 | 7.58 | 0.00*** | | |
| | Gender-Male | 1.60 | -2.08 | 5.28 | 1.88 | 0.85 | 0.40 | | |
| | Ethnicity-Black | 0.30 | -3.03 | 3.64 | 1.70 | 0.18 | 0.86 | | |
| | Ethnicity-Other | -5.61 | -17.56 | 6.35 | 6.10 | -0.92 | 0.36 | | |
| | Grade Level-7 | 0.29 | -4.03 | 4.61 | 2.20 | 0.13 | 0.90 | | |
| | Grade Level8 | -0.18 | -5.05 | 4.69 | 2.48 | -0.07 | 0.94 | | |
| | Specific | 0.15 | -2.69 | 2.99 | 1.45 | 0.10 | 0.92 | | |
| | Measurable | 1.23 | -1.70 | 4.17 | 1.50 | 0.83 | 0.41 | | |
| | Attainable | -1.37 | -5.64 | 2.90 | 2.18 | -0.63 | 0.53 | | |

| Model | Variable | $B$ | 95% CI for B | | $SE$ | $t$ | $P$ | $R^2$ | $\Delta R^2$ |
|---|---|---|---|---|---|---|---|---|---|
| Math | | | LL | LU | | | | | |
| M4 | (Intercept) | 20.42 | 3.14 | 37.70 | 8.82 | 2.32 | 0.02* | 0.5094 | 0.0119 |
| | Pre-grade | 0.75 | 0.56 | 0.95 | 0.10 | 7.61 | 0.00*** | | |
| | Gender-Male | 1.53 | -2.12 | 5.17 | 1.86 | 0.82 | 0.41 | | |
| | Ethnicity-Black | 0.29 | -3.05 | 3.63 | 1.71 | 0.17 | 0.87 | | |
| | Ethnicity-Other | -7.57 | -19.62 | 4.48 | 6.15 | -1.23 | 0.22 | | |
| | Grade Level-7 | 0.10 | -4.51 | 4.70 | 2.35 | 0.04 | 0.97 | | |
| | Grade Level8 | -0.77 | -5.88 | 4.34 | 2.61 | -0.30 | 0.77 | | |
| | Specific | -0.68 | -3.70 | 2.35 | 1.54 | -0.44 | 0.66 | | |
| | Measurable | 0.54 | -2.47 | 3.54 | 1.53 | 0.35 | 0.73 | | |
| | Attainable | -3.44 | -8.30 | 1.42 | 2.48 | -1.39 | 0.17 | | |
| | Relevance | 4.30 | -0.78 | 9.38 | 2.59 | 1.66 | 0.10† | | |
| M5 | (Intercept) | 22.01 | 2.75 | 40.31 | 8.74 | 2.52 | 0.01* | 0.5094 | 0.0404 |
| | Pre-grade | 0.73 | 0.54 | 0.95 | 0.10 | 7.46 | 0.00*** | | |
| | Gender-Male | 1.62 | -1.88 | 5.02 | 1.84 | 0.88 | 0.38 | | |
| | Ethnicity-Black | 0.31 | -2.94 | 3.72 | 1.68 | 0.19 | 0.85 | | |
| | Ethnicity-Other | -6.69 | -18.75 | 5.66 | 6.09 | -1.10 | 0.28 | | |
| | Grade Level-7 | 0.26 | -4.28 | 5.01 | 2.26 | 0.11 | 0.91 | | |
| | Grade Level8 | -0.94 | -6.21 | 4.10 | 2.53 | -0.37 | 0.72 | | |
| | Specific | -0.84 | -3.67 | 2.34 | 1.53 | -0.55 | 0.59 | | |
| | Measurable | 0.81 | -2.31 | 3.76 | 1.53 | 0.53 | 0.60 | | |
| | Attainable | -3.78 | -8.75 | 0.89 | 2.47 | -1.53 | 0.13 | | |
| | Relevance | 4.95 | 0.07 | 10.07 | 2.61 | 1.90 | 0.06† | | |
| | Timeframe | -3.31 | -7.24 | 0.90 | 2.09 | -1.58 | 0.12 | | |

***p = 0.0; **p ≤ .01; *p ≤ .05; † p ≤ .1.

**Table 10.3**

*RQ#3: Hierarchical Regression Results for Effects of SMART Goal Characteristics for Science*

| Model Science | Variable | *B* | 95% CI for B LL | UL | *SE* | *t* | *P* | *R²* | *ΔR²* |
|---|---|---|---|---|---|---|---|---|---|
| M0 | (Intercept) | 21.35 | 6.44 | 36.25 | 7.61 | 2.81 | 0.01** | 0.4909 | - |
| | Pre-grade | 0.78 | 0.61 | 0.95 | 0.09 | 8.93 | 0.00*** | | |
| | Gender-Male | -1.25 | -4.27 | 1.78 | 1.54 | -0.81 | 0.42 | | |
| | Ethnicity-Black | 0.06 | -2.72 | 2.84 | 1.42 | 0.04 | 0.97 | | |
| | Ethnicity-Other | 1.33 | -7.90 | 10.55 | 4.71 | 0.28 | 0.78 | | |
| | Grade Level-7 | 2.84 | -2.46 | 8.13 | 2.70 | 1.05 | 0.31 | | |
| | Grade Level-8 | 3.07 | -2.10 | 8.24 | 2.64 | 1.17 | 0.26 | | |
| M1 | (Intercept) | 22.31 | 6.64 | 37.98 | 8.00 | 2.79 | 0.01** | 0.4886 | - 0.0023 |
| | Pre-grade | 0.78 | 0.60 | 0.95 | 0.09 | 8.73 | 0.00*** | | |
| | Gender-Male | -1.25 | -4.29 | 1.79 | 1.55 | -0.80 | 0.42 | | |
| | Ethnicity-Black | 0.08 | -2.72 | 2.88 | 1.43 | 0.06 | 0.96 | | |
| | Ethnicity-Other | 1.57 | -7.77 | 10.92 | 4.77 | 0.33 | 0.74 | | |
| | Grade Level-7 | 2.91 | -2.41 | 8.23 | 2.71 | 1.07 | 0.30 | | |
| | Grade Level8 | 3.19 | -2.03 | 8.40 | 2.66 | 1.20 | 0.24 | | |
| | Specific | -0.26 | -1.53 | 1.01 | 0.65 | -0.40 | 0.69 | | |
| M2 | (Intercept) | 22.48 | 6.53 | 38.44 | 8.14 | 2.76 | 0.01** | 0.4859 | - 0.0028 |
| | Pre-grade | 0.78 | 0.60 | 0.95 | 0.09 | 8.59 | 0.00*** | | |
| | Gender-Male | -1.22 | -4.31 | 1.88 | 1.58 | -0.77 | 0.44 | | |
| | Ethnicity-Black | 0.07 | -2.75 | 2.89 | 1.44 | 0.05 | 0.96 | | |
| | Ethnicity-Other | 1.59 | -7.81 | 10.99 | 4.80 | 0.33 | 0.74 | | |
| | Grade Level-7 | 2.92 | -2.42 | 8.26 | 2.73 | 1.07 | 0.30 | | |
| | Grade Level8 | 3.21 | -2.04 | 8.46 | 2.68 | 1.20 | 0.24 | | |
| | Specific | -0.19 | -1.86 | 1.49 | 0.85 | -0.22 | 0.83 | | |
| | Measurable | -0.16 | -2.46 | 2.13 | 1.17 | -0.14 | 0.89 | | |
| M3 | (Intercept) | 23.42 | 7.18 | 39.66 | 8.29 | 2.83 | 0.01** | 0.4812 | - 0.0047 |
| | Pre-grade | 0.77 | 0.59 | 0.95 | 0.09 | 8.37 | 0.00*** | | |
| | Gender-Male | -1.10 | -4.22 | 2.02 | 1.59 | -0.69 | 0.49 | | |
| | Ethnicity-Black | 0.05 | -2.78 | 2.88 | 1.44 | 0.04 | 0.97 | | |
| | Ethnicity-Other | 0.35 | -9.68 | 10.37 | 5.12 | 0.07 | 0.95 | | |
| | Grade Level-7 | 3.07 | -2.36 | 8.50 | 2.77 | 1.11 | 0.29 | | |
| | Grade Level8 | 3.40 | -1.93 | 8.74 | 2.72 | 1.25 | 0.22 | | |
| | Specific | 0.44 | -1.99 | 2.87 | 1.24 | 0.35 | 0.73 | | |
| | Measurable | 0.03 | -2.34 | 2.40 | 1.21 | 0.03 | 0.98 | | |
| | Attainable | -1.28 | -4.92 | 2.36 | 1.86 | -0.69 | 0.49 | | |

| Model | Variable | *B* | 95% CI for B | | *SE* | *t* | *P* | $R^2$ | $\Delta R^2$ |
|---|---|---|---|---|---|---|---|---|---|
| Science | | | LL | UL | | | | | |
| M4 | (Intercept) | 23.43 | 7.09 | 39.78 | 8.34 | 2.81 | 0.01** | 0.4785 | - 0.0027 |
| | Pre-grade | 0.77 | 0.59 | 0.95 | 0.09 | 8.31 | 0.00*** | | |
| | Gender-Male | -1.10 | -4.25 | 2.04 | 1.60 | -0.69 | 0.49 | | |
| | Ethnicity-Black | 0.06 | -2.79 | 2.91 | 1.45 | 0.04 | 0.97 | | |
| | Ethnicity-Other | 0.31 | -9.95 | 10.57 | 5.24 | 0.06 | 0.95 | | |
| | Grade Level-7 | 3.05 | -2.40 | 8.50 | 2.78 | 1.10 | 0.29 | | |
| | Grade Level8 | 3.38 | -2.04 | 8.79 | 2.76 | 1.22 | 0.23 | | |
| | Specific | 0.41 | -2.25 | 3.06 | 1.35 | 0.30 | 0.77 | | |
| | Measurable | 0.01 | -2.49 | 2.51 | 1.27 | 0.01 | 0.99 | | |
| | Attainable | -1.33 | -5.51 | 2.84 | 2.13 | -0.63 | 0.53 | | |
| | Relevance | 0.12 | -4.26 | 4.50 | 2.23 | 0.06 | 0.96 | | |
| M5 | (Intercept) | 23.81 | 6.75 | 40.59 | 8.49 | 2.80 | 0.01** | 0.4768 | - 0.0018 |
| | Pre-grade | 0.76 | 0.57 | 0.95 | 0.09 | 8.11 | 0.00*** | | |
| | Gender-Male | -1.05 | -4.08 | 2.33 | 1.62 | -0.65 | 0.52 | | |
| | Ethnicity-Black | 0.04 | -2.72 | 3.03 | 1.46 | 0.03 | 0.98 | | |
| | Ethnicity-Other | 0.37 | -10.13 | 10.97 | 5.27 | 0.07 | 0.94 | | |
| | Grade Level-7 | 3.05 | -2.89 | 8.68 | 2.82 | 1.08 | 0.30 | | |
| | Grade Level8 | 3.31 | -1.79 | 9.01 | 2.80 | 1.18 | 0.25 | | |
| | Specific | 0.41 | -2.08 | 3.10 | 1.36 | 0.30 | 0.76 | | |
| | Measurable | 0.05 | -2.47 | 2.57 | 1.29 | 0.04 | 0.97 | | |
| | Attainable | -1.43 | -5.90 | 2.66 | 2.16 | -0.66 | 0.51 | | |
| | Relevance | 0.22 | -4.15 | 4.61 | 2.27 | 0.10 | 0.92 | | |
| | Timeframe | -0.54 | -4.08 | 3.31 | 1.84 | -0.29 | 0.77 | | |

***$p = 0.0$; **$p \leq .01$; *$p \leq .05$; † $p \leq .1$.

**Table 11.1**

*RQ# 4: Linear Regression Model Predicting Total SMART Score*

| Variable | B | *SE* | *t* | *p* | 95% CI | |
|---|---|---|---|---|---|---|
| | | | | | LL | UL |
| Intercept | 5.95 | 0.86 | 6.92 | < .001*** | 4.24 | 7.66 |
| Gender | | | | | | |
| Male | 0.17 | 0.71 | 0.24 | 0.81 | -1.25 | 1.60 |
| Ethnicity | | | | | | |
| Black | 0.19 | 0.71 | 0.27 | 0.79 | -1.22 | 1.61 |
| Other | 1.83 | 2.29 | 0.80 | 0.43 | -2.73 | 6.40 |
| Grade Level | | | | | | |
| 7th Grade | 1.10 | 0.78 | 1.42 | 0.16 | -0.44 | 2.65 |
| 8th Grade | 2.09 | 0.85 | 2.46 | 0.02* | -0.40 | 3.78 |
| Undergraduate (1) | 0.12 | 0.72 | 0.16 | 0.87 | -1.32 | 1.60 |
| $R^2$ | - | - | - | 0.08 | - | - |
| Adjusted $R^2$ | - | - | - | 0.02 | - | - |
| F(6, 81) | - | - | - | 0.31 | - | - |

*Note*. *$p < .05$. ***$p < .001$. N = 88. $R^2 = .083$, Adjusted $R^2 = .015$, F(6, 81) = 1.22, $p = .305$; B = unstandardized regression coefficient; *SE* = standard error; t = t-value; p = p-value; CI = confidence interval; *LL* = lower limit; *UL* = upper limit. Provider Type (0 = grad, 1 = under).

**Table 11.2**

*RQ #4: Logistic Regression Model Predicting Binary Timeframe SMART Goal Factor*

| Variable | B | *SE* | *z* | *p* |
|---|---|---|---|---|
| Intercept | -1.49 | 0.73 | -2.05 | 0.04* |
| Gender | | | | |
| Male | 0.09 | 0.61 | 0.15 | 0.88 |
| Ethnicity | | | | |
| Black | -0.15 | 0.60 | -0.25 | 0.80 |
| Other | 1.25 | 1.55 | 0.81 | 0.42 |
| Grade Level | | | | |
| 7th Grade | 0.30 | 0.64 | 0.47 | 0.64 |
| 8th Grade | 0.20 | 0.71 | 0.29 | 0.77 |
| Undergraduate | -0.26 | 0.61 | -0.42 | 0.67 |

*Note*. *p < .05.

**Table 11.3.a**

*RQ #4: Ordinal Regression Models for the Specific SMART Goal Factor*

| Parameters | B | *SE* | *z* | *p* | 95% CI | |
|---|---|---|---|---|---|---|
| | | | | | LL | UL |
| Gender | | | | | | |
| Male | -0.06 | 0.45 | -0.12 | 0.90 | -0.94 | 0.83 |
| Ethnicity | | | | | | |
| Black | 0.73 | 0.46 | 1.57 | 0.12 | -0.18 | 1.64 |
| Other | 15.15 | 1.95e-07 | 7.77e+07 | < .001*** | 15.15 | 15.15 |
| Grade Level | | | | | | |
| 7th | 0.62 | 0.50 | 1.25 | 0.21 | -0.36 | 1.60 |
| 8th | 1.30 | 0.58 | 2.24 | 0.03* | 0.16 | 2.43 |
| Undergraduate | 0.81 | 4.71 | 1.73 | 0.08 | -0.109 | 1.74 |

*Note*. $N = 88$; B = coefficient; *SE* = standard error; $p$ = p-value. $P$ <.001 is reported as <.001.

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

**Table 11.3.b**

*RQ# 4: Ordinal Regression Models for Measurable SMART Goal Factor*

| Parameters | B | *SE* | *z* | *p* | 95% CI | |
|---|---|---|---|---|---|---|
| | | | | | LL | UL |
| Gender | | | | | | |
| Male | 0.39 | 4.60 | 8.52 | 0.39 | -0.51 | 1.30 |
| Ethnicity | | | | | | |
| Black | 0.07 | 4.70 | 1.41 | 0.89 | -0.85 | 0.99 |
| Other | 14.84 | 8.81 | 1.70 | <.001 | 14.84 | 14.84 |
| Grade Level | | | | | | |
| 7th | 0.85 | 5.46 | 1.56 | 0.12 | -0.22 | 1.92 |
| 8th | 0.91 | 5.74 | 1.58 | 0.11 | -0.22 | 2.03 |
| Undergraduate | 0.01 | 4.72 | 1.28 | 0.99 | -0.92 | 0.93 |

*Note*. B = coefficient; *SE* = standard error; *p* = p-value. *p* < .001 are reported as <.001.

**p* < .05. ****p* < .001. *N* = 88.

**Table 11.3.c**

*RQ #4: Ordinal Regression Models for Attainable SMART Goal Factor*

| Parameters | B | *SE* | *z* | *p* | 95% CI | |
|---|---|---|---|---|---|---|
| | | | | | LL | UL |
| Gender | | | | | | |
| Male | 0.000 | 0.51 | 0.000 | 1.00 | -1.00 | 1.00 |
| Ethnicity | | | | | | |
| Black | 0.14 | 0.51 | 0.28 | 0.78 | -0.86 | 1.15 |
| Other | -1.21 | 1.18 | -1.03 | 0.31 | -3.53 | 1.11 |
| Grade Level | | | | | | |
| 7th | 0.78 | 0.55 | 1.41 | 0.16 | -0.30 | 1.86 |
| 8th | 1.47 | 0.70 | 2.09 | 0.04 | 0.10 | 2.85 |
| Undergraduate | -0.02 | 0.52 | -0.03 | 0.97 | -1.03 | 0.99 |

*Note*. The graduate provider is the reference group. $N = 88$; B = Coefficient; $SE$ = standard error; $p$ = p-value. $p$ <.001 are reported as <.001.

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

**Table 11.3.d**

*RQ #4: Ordinal Regression Models for Relevance SMART Goal Factor*

| Parameters | B | *SE* | *z* | *p* | 95% CI | |
|---|---|---|---|---|---|---|
| | | | | | LL | UL |
| Gender | | | | | | |
| Male | 0.08 | 0.62 | 0.123 | 0.90 | -1.13 | 1.29 |
| Ethnicity | | | | | | |
| Black | 0.01 | 0.61 | 0.020 | 0.98 | -1.18 | 1.20 |
| Other | 18.08 | 3.15e-09 | 5.74e+09 | < .001*** | 18.08 | 18.08 |
| Grade Level | | | | | | |
| 7th | 0.77 | 0.66 | 1.168 | 0.24 | -0.52 | 2.06 |
| 8th | 18.30 | 1.25e-08 | 1.46+09 | < .001*** | 18.29 | 18.29 |
| Undergraduate | 0.06 | .61 | 0.10 | 0.90 | -1.13 | 1.26 |

*Note*. $N$ = 88; B = Coefficient; *SE* = standard error; $p$ = p-value. $p < .001$ are reported as <.001.

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

**Table 12**

*RQ#5. Summary of Model Fitted using Lavaan with Direct and Indirect Effects on Post-Treatment Grades*

| Variable | B | SE | *p* | 95% CI | |
|---|---|---|---|---|---|
| | | | | LL | UL |
| **ELA** | | | | | |
| Total SMART Score ~ Under (a) | -0.22 | 0.65 | 0.73 | -1.50 | 1.11 |
| Post Grade ~ Total SMART Score (b) | -0.71 | 0.29 | 0.01* | -1.32 | -0.13 |
| Indirect Effect (a*b) | 0.16 | 0.52 | 0.76 | -0.74 | 1.46 |
| **Math** | | | | | |
| Total SMART Score ~ Under (a) | -0.22 | 0.69 | 0.75 | -1.55 | 1.20 |
| Post Grade ~ Total SMART Score (b) | -0.04 | 0.28 | 0.89 | -0.70 | 0.44 |
| Indirect Effect (a*b) | 0.01 | 0.21 | 0.97 | -0.52 | 0.33 |
| **Science** | | | | | |
| Total SMART Score ~ Under (a) | -0.22 | 0.66 | 0.74 | -1.50 | 1.08 |
| Post Grade ~ Total SMART Score (b) | -0.14 | 0.20 | 0.48 | -0.57 | 0.25 |
| Indirect Effect (a*b) | 0.03 | 0.17 | 0.85 | -0.19 | 0.49 |

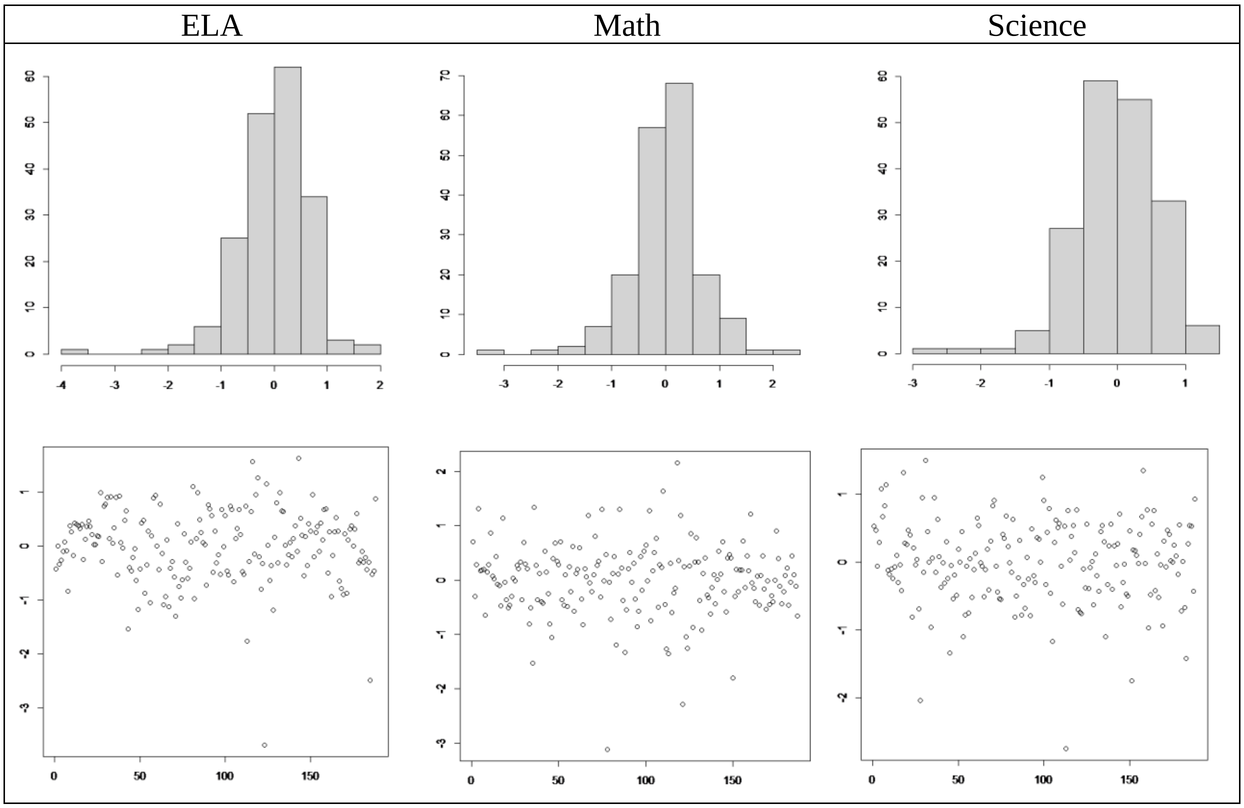
*Note*. Covariate estimates are not reported; *p*-values: * $p < .05$, ** $p < .01$, *** $p < .001$.

APPENDIX B:

FIGURES

**Figure 1**

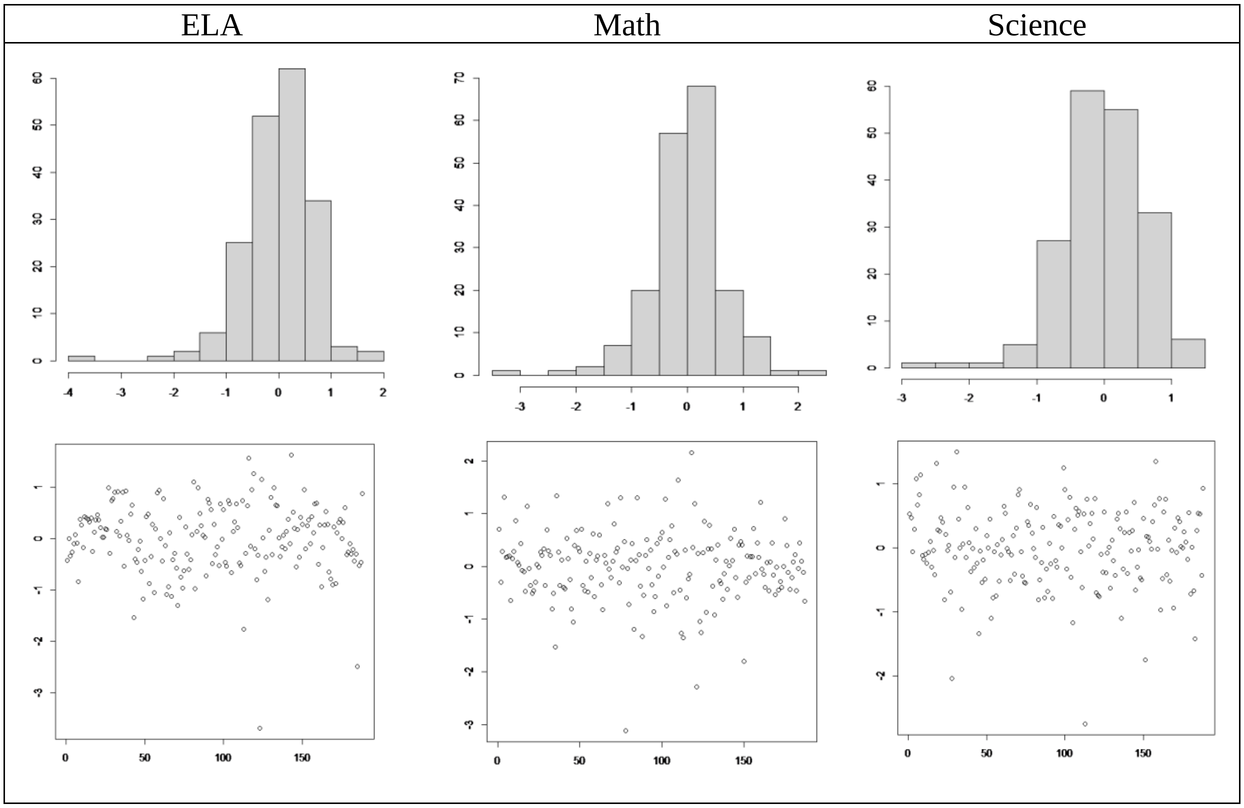
*RQ#1(Model 1): Histogram and Scatter Plot of Residuals for ELA, Math, and Science*




*Note.* Reference group is the Control group (no providers).

**Figure 2**

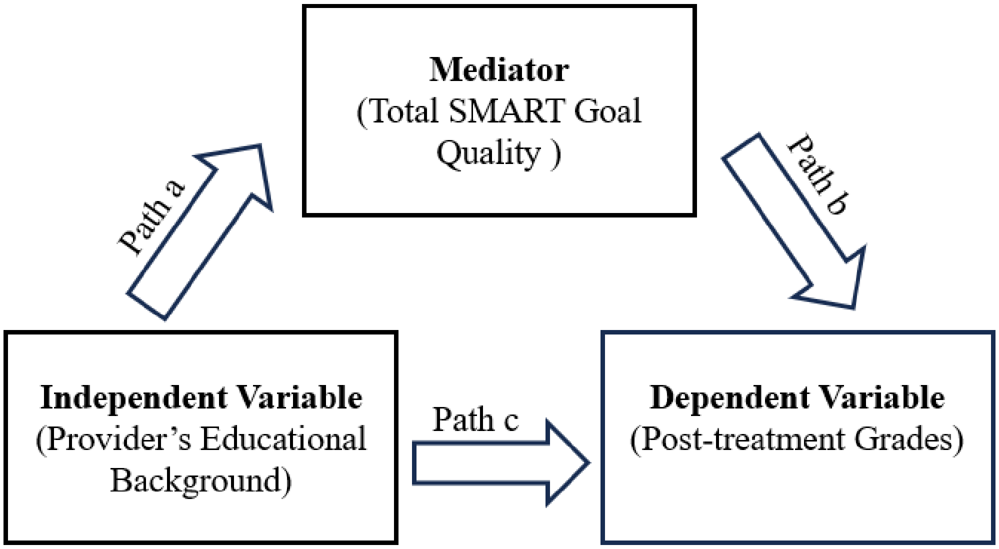
*RQ#1(Model 2): Histogram and Scatter Plot of Residuals for ELA, Math, and Science*




*Note*. Reference group is the graduate providers' group.

**Figure 3**

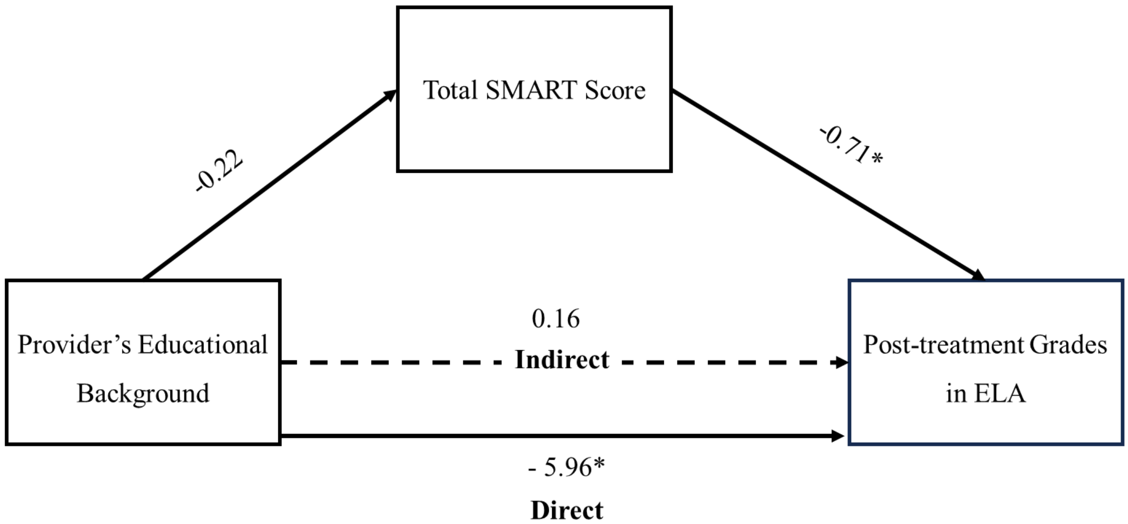
*Composite Pathway of a and b*




*Note*. Path c illustrates the direct effect of the providers' educational background on student grades, while paths a and b depict the indirect effect.

**Figure 4**

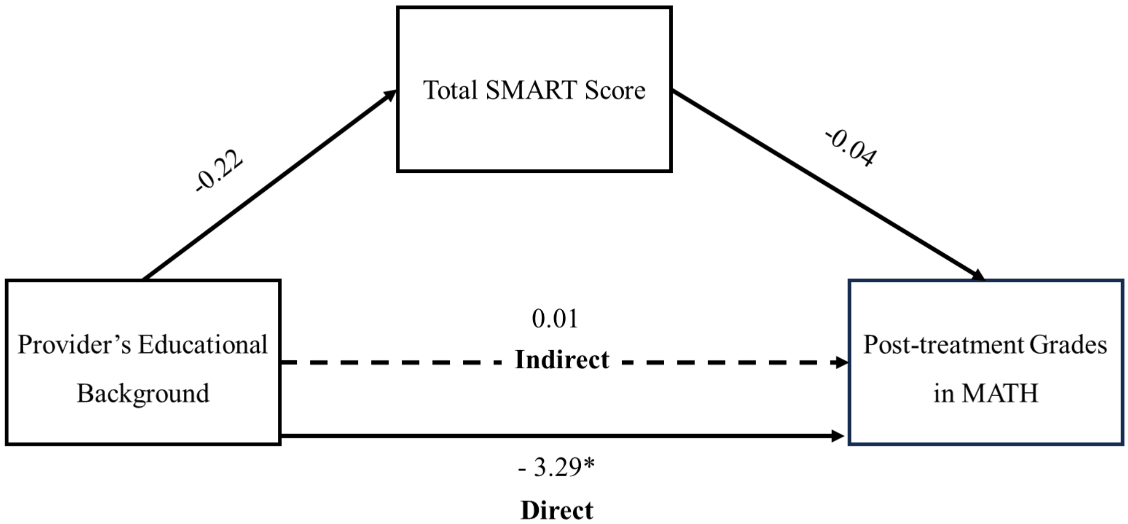
*ELA Mediation Analysis*




*Note.* Asterisks are for significant relationships, and the numbers are coefficients.

**Figure 5**

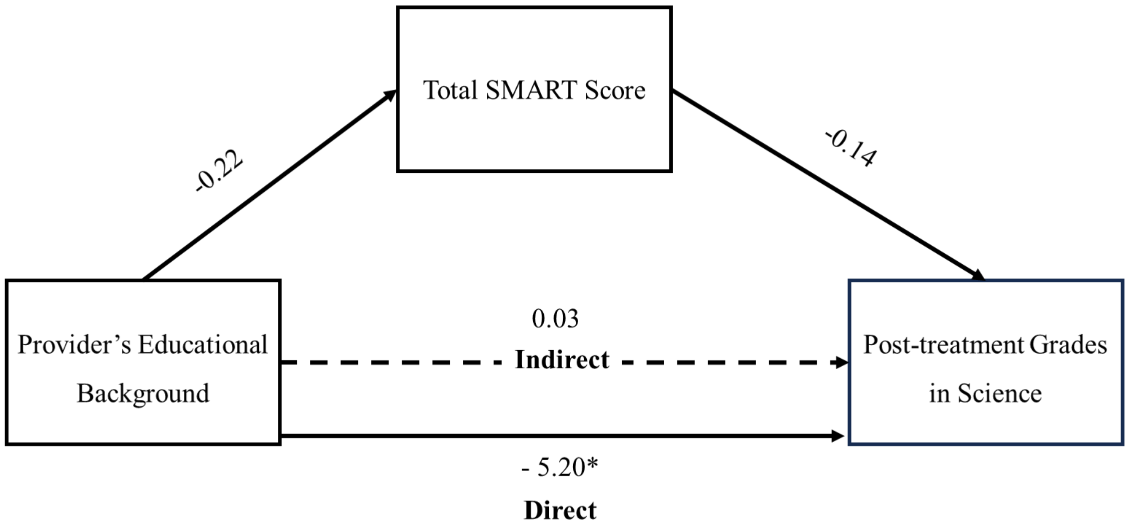
*Math Mediation Analysis*




*Note.* Asterisks are for significant relationships, and the numbers are coefficients.

**Figure 6**

*Science Mediation Analysis*




*Note.* Asterisks are for significant relationships, and the numbers are coefficients.

APPENDIX C:

REVISED SMART-GEM SCORE SHEET AND GRADING SCALE

| Domain | Criteria | Yes | No | Goal component |
|---|---|---|---|---|
| **Specific** | The goal describes in terms of observable behavior, what the student will be doing (Using a verb, e.g., 'the student will study'). | 1 | 0 | |
| | The goal includes conditions/plans that will help them obtain the goal (e.g., will study, will ask questions in class). | 1 | 0 | |
| | The goal includes the performance context (e.g., at home, library, in the classroom, or/and at school). | 1 | 0 | |
| **Measurable** | The goal states how achievement will be measured (e.g., outcome measurement, time, frequency). | 1 | 0 | |
| | The goal identifies the criteria for acceptable standard of outcome performance and should state how much, how fast, how long, how often or how accurate the expected goal outcome will be performed (e.g., every week, 4 days a week, 10 hours a week, with 90% accuracy, make passing or B grades, etc.). | 1 | 0 | |
| **Attainable** | The goal is within reason of the student's abilities and can be achieved (note: if student's ability is unknown compared to an average student's ability). | 1 | 0 | |
| | Describes *feasible* actions, interventions, and/or plans (e.g., complete weekly homework, sit near teacher, study) the student will use to achieve their goal. | 1 | 0 | |
| **Relevant** | The goal has a clear connection with school success. | 1 | 0 | |
| | Plans to achieve goals have a clear connection with school success. | 1 | 0 | |
| **Time-frame** | The goal includes the time-frame within which the outcome should be achieved (e.g., within 1 week, by date, end of the academic semester or year). | 1 | 0 | |

| Grade | Points | Criteria fulfilment |
|---|---|---|
| **A (1)** | 10 | Excellent goal. All domains have been addressed. This goal is useful. |
| **B (2)** | 8 | Good goal. Goal is useful most domains are addressed, but one. |
| **C (3)** | 6 | Average goal. The goal has limited usefulness. Up to two domains are not addressed. |
| **D (4)** | 5 or less | Poor goal. The goal is vague and not useful. Up to 3 domains have not been addressed. |