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How Relational Instruction and Caring Learning Environments Relate to Mathematics Self-Concept: A Multilevel Investigation of the High School Longitudinal Study of Data

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HOW RELATIONAL INSTRUCTION AND CARING LEARNING ENVIRONMENTS

RELATE TO MATHEMATICS SELF-CONCEPT: A MULTILEVEL

INVESTIGATION OF THE HIGH SCHOOL LONGITUDINAL

STUDY OF DATA

by

Sandra J. Miles

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ABSTRACT

Improving Students' Mathematics Self-Concept Through Relational Instruction and Caring: A Multilevel Investigation of the High School Longitudinal Survey of 2009

by

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Students' self-concept for learning mathematics is an important construct in mathematics education as it relates positively to greater achievement and engagement in mathematics and positively predicts entry into a career in science, technology, engineering, or mathematics (STEM). Though the benefits of self-concept are strongly supported in the literature, there is little research which tries to identify specific components of mathematics self-concept or investigate the role teachers may play in strengthening their students' self-concept. This study investigates how relational instruction, and the creation of caring learning environments, contribute to the development of student mathematics self-concept, and how those factors influence students differently according to gender and race. I analyzed data from a nationally representative sample of over 22,000 students who participated in the High School Longitudinal Study, 2009. Using data from student surveys taken at three waves of data collection, student algebraic reasoning scores from the first two timepoints, and surveys from the student's mathematics teacher and parent(s) taken at the baseline year, I examined student trajectories for self-concept between 2009 and 2016. I then used multilevel modeling techniques to examine the influence of relational instruction and caring and supportive learning environments on student self-concept. Findings show that individual self-concept was very dynamic in high school and that the gender gap in self-concept grew while students were in high school. I found a positive association for student self-concept in ninth grade with caring and supportive learning environments and found that relational instruction positively influenced self-concept over time. An interaction between race and relational instruction supports the need for higher quality instruction among traditionally underserved populations to increase their self-concept in mathematics.

(175 pages)

PUBLIC ABSTRACT

Improving Students' Mathematics Self-Concept Through Relational Instruction and Caring: A Multilevel Investigation of the High School Longitudinal Survey of 2009

Sandra J. Miles

The purpose of this research is to look for ways mathematics teachers can increase their students' mathematics self-concept (i.e., achievement, confidence, and interest). Many students avoid taking upper-level mathematics classes or pursuing careers in science, technology, engineering, or mathematics (STEM). However, the need for STEM professionals in the workforce will increase in future years and there is a projected shortage of students who will be trained to fill the demand. This research proposes that mathematics teachers can actively work to improve their students' self-concept by providing a caring and emotionally supportive learning environment as well as providing instruction that builds students' conceptual understanding of mathematics instead of focusing on memorization of procedures and test preparation. To investigate the influence mathematics teachers have in building student mathematics self-concept, I analyzed survey data from the High School Longitudinal Study, 2009 (HSLS:09). The HSLS:09 study was sponsored by the National Center for Education Statistics and followed over 23,000 U.S. high school students for a period of seven years, beginning in ninth grade. The NCES gathered data describing students' achievement, attitudes, and perceptions about a variety of educational topics, including mathematics. I used these surveys, along with surveys from their ninth-grade mathematics teacher to examine the influence that providing conceptually focused mathematics instruction in a caring and supportive learning environment had on student self-concept. I found that the self-concept of female students decreased throughout high school while that of male students increased, and that both instruction and environment positively influenced self-concept. Additionally, I found the influence of conceptually focused instruction had a long-term influence and that it was especially important for Hispanic students. These results should be used to inform future professional development, pre-service teacher instruction, and curriculum development so educators can take a conscious, active role in providing instruction in mathematics which will build the mathematics self-concept of their students.

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CHAPTER I

INTRODUCTION

Research shows that self-concept is an important construct in mathematics education. Students who have strong self-concept in mathematics tend to demonstrate increased achievement (Arens et al., 2017), motivation (Seaton et al., 2014), and continued engagement with mathematics (Eccles & Wang, 2016). Conversely, students with low levels of self-concept exhibit lower levels of confidence and avoid situations that involve mathematics (Bong & Skaalvik, 2003; Hussain et al., 2017). Despite the observed benefits of a strong self-concept in mathematics, there is little research that investigates the influence teachers can have on strengthening their students' self-concept. The purpose of this study is to investigate the influence that (a) teaching mathematics for relational understanding and (b) creating a caring and supportive learning environment may have on the development of student self-concept.

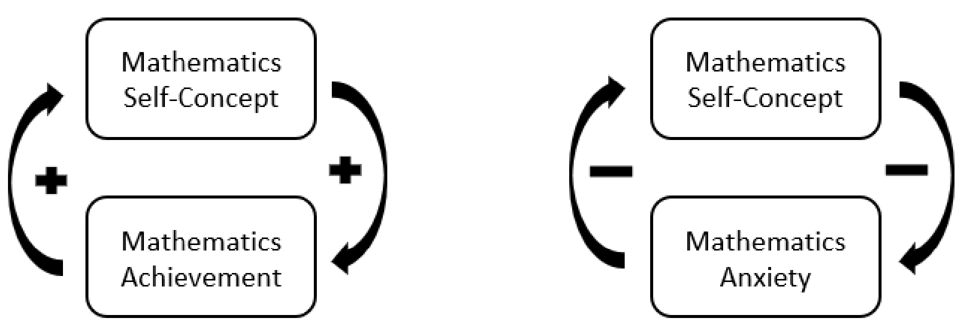
Background of the Problem

Self-concept has been an important construct in educational psychology for the past few decades (Arens et al., 2017; Marsh & Parker, 1984). It originated as a general construct that referred to an individual's self-perceptions formed through experience with and interpretations of their environment (Shavelson et al., 1976) but was later defined for mathematics specifically as "the beliefs, feelings, or attitudes regarding one's ability to understand or perform in situations involving mathematics" (Gourgey, 1982, p. 3). Mathematics self-concept includes both ability-based (cognitive) and emotion-based (affective) components (Bong & Skaalvik, 2003) and influences how a student feels about and interacts with mathematics.

Numerous studies demonstrate the positive connection between mathematics achievement and self-concept (Marsh & Parker, 1984; Parker et al., 2014; Trautwein et al., 2006; Van der Beek et al., 2017). As shown in Figure 1, this relationship is described as being reciprocal (Arens et al., 2017); so, not only does higher self-concept lead to increased achievement, but achievement also works to strengthen self-concept. The inverse relationship also exists where poor self-concept contributes to decreased achievement, which then leads to decreased self-concept. This relationship can be moderated by demographic factors (e.g., gender, Goldman & Penner, 2016), and environmental factors (e.g., relative school achievement, Chmielewski et al., 2013). Researchers also identified a similar, yet negative, reciprocal relationship between self-concept and mathematics anxiety; as self-concept increases, the level of mathematics anxiety decreases (Ahmed et al., 2012). Additionally, increased self-concept is associated

Figure 1

Illustration of the Reciprocal Relationships Between Self-Concept, Achievement, and Anxiety



with increased enjoyment in mathematics (Van der Beek et al., 2017) and is a strong predictor of entry into a science, technology, engineering, or mathematics (STEM) related career (Eccles & Wang, 2016; Goldman & Penner, 2016). These findings suggest that efforts to improve student self-concept may have a positive effect on students' affective experiences and continued engagement in mathematics.

Research shows there are discrepancies between levels of self-concept and achievement for some students. It is theorized students base much of their self-concept on evaluations of their past performance in mathematics (Bong & Skaalvik, 2003). However, as self-concept includes both frame of reference effects and relative comparisons with others (Möller et al., 2011, 2016), these performance evaluations may be subjective. One example of this is the Big Fish Little Pond Effect (Marsh et al., 2008) which posits that students in learning environments with high average achievement will have lower self-concepts than students with the same mathematical understanding in learning environments with low average achievement. These subjective evaluations may also contribute to the gender gap for self-concept. Female students generally report lower levels of self-concept than male students even when their performance and interest in mathematics is similar (Mejía-Rodríguez et al., 2021; Robnett & Thoman, 2017). Additionally, the self-concept of female students is more strongly related to their perception of teacher support than it is for male students while male students show a stronger association with learning goal structure than female students (E. M. Skaalvik & Skaalvik, 2013). These differences in self-concept may be explained by the subjective nature of self-evaluations.

An example of the influence of self-concept can be illustrated using the following example from an unpublished interview data set (Miles, 2020). In the data set, Brittany was one of eight undergraduate students who participated in interviews related to her experiences with mathematics. Brittany had low mathematics self-concept.[1] She described the way she felt about mathematics by saying, “I’m terrible at math…I don’t speak math…math is scary,” and then cited the fact that she counts on her fingers to multiply as evidence of her lack of abilities. However, later in the interview Brittany explained,

> If I knew the critical thinking of where I’m trying to get, and this is how you get there, I’m good at that and I can do that…If I turn it into a word problem…that’s the only way I get through it. (p. 6)

Though Brittany could apply critical thinking and reasoning to mathematics in context, she maintained a belief that she could not do mathematics because of her interpretation of what “doing mathematics” looks like. This example demonstrates one way that mathematics self-concept may be influenced by factors other than achievement, making it subject to students’ attitudes and perceptions about mathematics.

Given the subjective nature of student self-concept, it seems reasonable there would be ways to support students in developing stronger self-concepts. Education research has expanded over the years to include affective components (e.g., anxiety, interest, motivation) in addition to cognitive ones. Research on affective components in education shows attitudes, emotions, and beliefs of students are very influential on educational outcomes (Hannula et al., 2018; Middleton et al., 2017). The way a student

[1] Brittany scored in the bottom quartile on five different measures of self-perceptions in mathematics but had mean level achievement in her undergraduate quantitative reasoning course.

views themselves and their abilities has a significant impact on the way they engage in learning (Nagy et al., 2010; Ng, 2021; Tirri & Nokelainen, 2010) and can influence their interest, persistence, and achievement in learning mathematics (Trautwein et al., 2006). With all the associated positive outcomes, conducting research on avenues that may strengthen student self-concept in mathematics is vital.

This dissertation focuses on two possible avenues teachers can utilize to improve self-concept in their students, namely, through providing a) relational instruction and b) caring and supportive learning environments in mathematics. Relational instruction in mathematics is instruction that builds students' relational (conceptual) understanding. With relational instruction students understand "both what to do and why" (Skemp, 2012, p. 9). Along with relational instruction teachers can provide caring and supportive learning environments where they develop appropriate student/teacher relationships that (a) convey feelings of care and respect, (b) attend to students' physical, emotional, and academic needs, and (c) maintain high expectations while providing the supports students need to be successful (Hamre et al., 2013; Martin & Rimm-Kaufman, 2015; Sakiz et al., 2012). As teachers build caring and supportive learning environments and practice relational instruction, they can influence the way students view themselves and their abilities in mathematics resulting in strengthened self-concept.

Purpose of the Study

The purpose of this study was to investigate how relational instruction and the creation of a caring and supportive learning environment contribute to the development of student mathematics self-concept, and how those factors influence students differently according to various demographic factors. This dissertation used data from the High School Longitudinal Study, 2009 (HSLS:09, Ingels et al., 2011), which provided information from students, teachers, and parents to address this purpose. Identifying ways that educators can positively influence students' self-concept reveals an additional avenue for improving student engagement and achievement in mathematics. This dissertation shows that teachers can influence students' self-concept through their instructional practices, as well as through the environment they create in their classrooms.

Research Questions

Four research questions guided my investigation of mathematics self-concept in this dissertation. Question 1 was meant to model the growth trajectory for self-concept so that it could then be used to investigate the other questions. Questions 2 and 3 identified the potential effects of relational instruction and the creation of caring and supportive learning environments on self-concept. For these questions I include associated research and null hypotheses. Question 4 was exploratory and does not include a specific research hypothesis.

1. How does student mathematics self-concept change during students' secondary education years as measured on the HSLS:09?
2. How does an emphasis on relational instruction in mathematics influence change in student mathematics self-concept as measured on the HSLS:09 (Ingels et al., 2011)?

    H_0 – There is no significant difference in average level of mathematics self-concept for students whose ninth-grade mathematics teachers focus on relational instruction.

H_a – Students whose ninth-grade mathematics teachers focus on relational instruction will have significantly higher levels of mathematics self-concept than students whose teachers do not focus on relational instruction.

3. How do student perceptions of a caring and supportive learning environment influence change in student mathematics self-concept as measured on the HSLS:09 (Ingels et al., 2011)?

    H_0 – There is no significant difference in average level of mathematics self-concept for students who perceive their ninth-grade mathematics teachers as providing a caring and supportive learning environment.

    H_a – Students who perceive their ninth-grade mathematics teachers as providing a caring and supportive learning environment will have significantly higher levels of mathematics self-concept than students who do not have this perception.

4. Are there differences based on demographic factors such as gender and race?

Significance of the Problem

There is much research needed to improve our understanding of self-concept. Student perceptions of their own competence in mathematics contribute significantly to their self-concept (Bong & Skaalvik, 2003; Marsh et al., 2019) but it is still unclear exactly how those perceptions can be influenced by frames of reference, causal attributions, appraisals from significant others, attitudes about mathematics, and past affective experiences. In 2003, Bong and Skaalvik called for research that would separate "perceived competence components from other elements and [examine] the specific contribution of each major constituent" (p. 30), but research has not yet clarified the specific contributors to self-concept or exactly why it predicts entry into STEM fields. Some research suggests the perceived characteristics of a STEM career do not align with students' vision for their lives and that is what decreases their interest in STEM pathways

(Eccles & Wang, 2016). However, self-concept could also be influenced by specific attitudes and beliefs related to mathematics that students hold. Similarly, it may be influenced by affective experiences in mathematics classes or stereotypical gender beliefs about mathematics. Teachers have the power to influence these factors through instruction that places more emphasis on reasoning than memorization and by providing caring and supportive learning environments, but there is little research that investigates the influence these different factors have on self-concept. There is a need to clarify how these different factors influence students' mathematics self-concepts and the role educators play in developing and improving them in their students.

Kaskens et al. (2020) recommended teachers "attend more to the self-concepts of their students in general and their math self-concepts in particular" (p. 11). This dissertation seeks to inform our understanding of self-concept and suggest ways teachers can actively work to improve the self-concept of their students. The significant sample size of the HSLS:09 data provides an opportunity to investigate the influence teachers who focus on relational instruction or provide caring and supportive learning environments have on the self-concept of their students. These findings will contribute to teacher training and instructional practices that strengthen student mathematics self-concept, leading to increased achievement in mathematics and entry into STEM careers.

There is a need to encourage students in learning mathematics and prepare them for entry into mathematics related fields. As the world becomes more global and dependent on technology there will be a need for more individuals in STEM careers. The Bureau of Labor and Workforce Services (Fayer et al., 2017) reported the number of

STEM occupations grew by 10.5% between 2009 and 2015 while non-STEM occupations only grew by 5.2%. This growth is projected to continue with the greatest growth occurring in mathematical science (e.g., quantitative biology or data science) and computer occupations. In addition to preparing students to fulfill a future need in our society, preparing students for jobs in STEM will also help them have a better financial future since 93% of STEM occupations have wages above the national average.

A student with low self-concept may place limitations on themselves related to their future education, career, and even family life. Brittany illustrated this impact on her career goals when she said,

> I've always wanted to start my own business…I would love to create my own after school program…But…I would have to do all the programming and hire someone else to do all the business type stuff because I don't know how to figure out any of that. But I wish I could…I'll just work for somebody else forever. I don't want to be an entrepreneur. It's too hard. It's too much math. (Miles, 2020, p. 13)

For Brittany, her low self-concept even influenced her decisions on dating and marriage. She said, "Even with dating I'm like, 'Are you good at math? Because one of us has to be and it's not gonna be me" (p. 1). Brittany's comments illustrate how influential self-concept can be for students even after they complete their K-12 education. With all the research that demonstrates the importance of self-concept in helping students in their educations and future careers, it would benefit students greatly if teachers could work to strengthen their students' self-concept for mathematics.

Summary of Research Study Design

To investigate the influence of relational instruction and creating a caring and supportive learning environments on student self-concept, I conducted a secondary data analysis (Johnston, 2014) applying multilevel modeling techniques on longitudinal data (Singer & Willett, 2003). The study utilized quantitative data from the HSLS:09 collected from a large nationally representative sample at three timepoints. The large data set allowed for complex statistical analyses and examination of the self-concept trajectory in various demographic groups. Data came from student, parent, and mathematics teacher questionnaires. The data analysis included descriptive statistics, growth curve modeling, building and evaluating a series of models utilizing full likelihood estimation and model fit comparisons, and examining interactions utilizing simple slopes. These techniques allowed me to identify the amount of variation in student mathematics self-concept that was related to relational instruction and caring and supportive learning environments. Further, they identified differences based on gender and race to see how students from certain demographic groups benefitted more than others from these teacher-level variables.

Delimitations

There are two related constructs or issues related to the study of student mathematics self-concept that I intentionally chose to omit from this study. The first is the construct of self-efficacy. Self-efficacy is like self-concept in that it describes a student's beliefs about their abilities in mathematics (Pajares, 1996) but research has repeatedly demonstrated discriminant validity between the two constructs (Huang, 2012; Lent et al., 1997). Self-concept has different theoretical contributors and predictive abilities when compared to self-efficacy, but the scope of this dissertation does not include a detailed comparison of the two constructs. Due to their collinearity, self-efficacy was not included in the models for this study as it would account for much of the same variation as self-concept. However, due to the similar nature of these two self-perceptions some research related to self-efficacy is applicable to a discussion of self-concept and the development of the theoretical argument put forth in this dissertation so it will be included in the literature review.

The second intentional constraint on this dissertation is that the examination of variation in self-concept that is attributed to race was only considered from an intra-country perspective. The cultural and social implications of different racial groups can vary greatly between countries. The discussion of race in this project is only meant to describe its influence for students in the U.S. and not be generalized to other countries.

Glossary of Terms

The following is a list of terms used in this study and how they are being defined.

Attributions of success – the perceived causes that an individual perceives as leading to a successful outcome (Marsh et al., 1984).

Big Fish Little Pond Effect - "predicts that students have lower academic self-concepts (ASC) when attending schools where the average ability levels of other students is high compared to equally able students attending schools where the school-average ability is low" (Marsh et al., 2008, p. 320).

Caring learning environments - a learning environment with appropriate student/teacher relationships that (a) convey feelings of care and respect; (b) attend to students' physical, emotional, and academic needs; and (c) maintain high expectations while providing the supports students need to be successful (Hamre et al., 2013; Martin & Rimm-Kaufman, 2015; Sakiz et al., 2012)

Frame of Reference Effects – When evaluating their self-concept students "compare their perceived competence in one area with their peers' ability in the same area (i.e., external, social comparison) as well as with their own academic ability in the other areas (i.e., internal, self-comparison" (Bong & Clark, 1999, p. 142).

Level one growth plots – Plots that show the change in a dependent variable over time for each individual – used to verify the shape of a proposed model before analyses (Singer & Willett, 2003).

Mathematics Self-Concept – "the beliefs, feelings or attitudes regarding one's ability to understand or perform in situations involving mathematics" (Gourgey, 1982, p. 3).

Q-Q plots/normality tests – Ways to determine whether a variable is normally distributed. Common normality tests include the Shapiro-Wilks and the Kolmogorov-Smirnov tests (B. H. Cohen, 2008). The quartile-quartile plot is a visual test for evaluating normality.

Relational instruction – Instruction that focuses on helping students to "understand both what to do and why" (Skemp, 2012, p. 9).

Self-concept – a person's self-perceptions formed through experience with and interpretations of their environment (Shavelson et al., 1976).

CHAPTER II

LITERATURE REVIEW

The purpose of this study was to investigate how relational instruction and the creation of caring learning environments contribute to the development of student mathematics self-concept, and how those factors influence students differently according to race and gender. Though some of the variables that contribute to a student's self-concept are not subject to direct influence from educators (e.g., parental reinforcement), instructional practices and the school learning environment are more open to influence from teachers, staff, and administrators. Thus, it is important to understand the influence of these contextual factors so educators can work to enhance student self-concept. This research investigates how instructional and environmental factors that educators have influence over have the potential to positively influence students' self-concept.

This chapter presents the framework which forms the foundation for the current study and a review of related empirical research. First, I discuss literature related to self-concept: its association between self-concept and other educational outcomes, and its development. I then outline literature focused on relational instruction in mathematics along with the importance of creating caring and supportive classroom environments, and how they contribute to students' self-concept. Finally, I describe the conceptual framework used to interpret and analyze the research described.

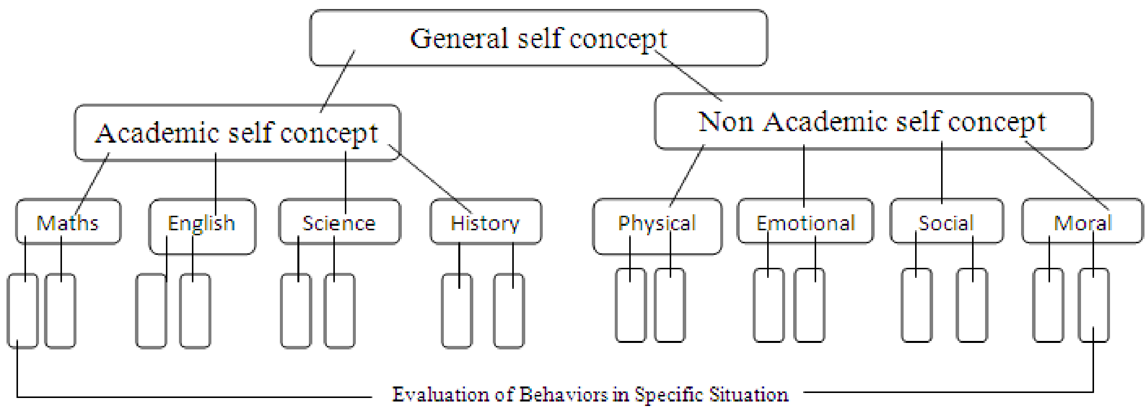
Description of Self-Concept

Self-concept is a structured, multidimensional, and hierarchical construct that expresses a persons' perceptions of their abilities interpreted within their social environment (Marsh et al., 2019). It is an individual's evaluation of their abilities in relation to internal and external frames of reference, reinforcement and evaluations of others, causal attributions, and attitudes related to the subject under consideration (Bong & Skaalvik, 2003; Marsh et al., 2019). Self-concept is a key focus of this study due to its significant influence on student motivation and engagement in mathematics. Students with higher levels of self-concept are more likely to learn mathematics at a deeper level and take more mathematics classes than students with lower self-concept (McInerney et al., 2012; Parker et al., 2014). Given the positive influence of self-concept, it is an important construct to understand and to develop in students.

Shavelson et al. (1976) describe a nested, hierarchical model of self-concept where various mutually exclusive dimensions of self-concept are situated within others. As seen in Figure 2, general self-concept is at the top of the hierarchy and is composed of both academic and nonacademic self-concepts. Academic self-concept subdivides into different subject matter areas, or domains, one of which is mathematics. Shavelson's model suggests that within each of these domains, self-concept could be further subdivided, but he does not specify the categories it would divide into. Most research in education considers academic self-concept or self-concept for a specific domain. For this dissertation study, self-concept will refer to the domain-level measure of mathematics self-concept which describes the "beliefs, feelings or attitudes regarding one's ability to understand or perform in situations involving mathematics" (Gourgey, 1982, p. 3). As described, self-concept measures a student's confidence for doing mathematics as well as the feelings they have about mathematics.

Figure 2

Model of Self-Concept Showing its Hierarchical, Nested Structure (Shavelson et al., 1976)



When an individual evaluates their self-concept, they consider their abilities in relation to internal and external frames of reference, reinforcement and evaluations of others, causal attributions, and their attitudes towards mathematics (Bong & Clark, 1999; Bong & Skaalvik, 2003; Shavelson et al., 1976). An individual uses internal frames of reference when they compare their performance in mathematics with that in other subjects (Marsh, 1990). They use external frames of reference when they compare their performance in mathematics with the performance of their peers (Marsh et al., 2019; Trautwein et al., 2006). The different evaluative and comparative criteria students use when evaluating their self-concept make self-concept a subjective construct but may also provide avenues by which self-concept can be strengthened.

Students' self-concept also incorporates verbal and nonverbal *reinforcements* or evaluations of others (Harter, 1988). This information is received through both verbal and non-verbal sources. Reinforcement can be either positive or negative and can be communicated through grades and feedback on assignments, responses to questions or comments the individual makes related to mathematics, the mathematics related stereotypes they hear expressed, or the degree to which others validate their knowledge (i.e., asking them to help with homework or verify answers). Positive messages from influential adults will result in higher levels of self-concept, while negative messages will serve to decrease an individual's self-concept.

The a*ttributions of success* an individual makes also influences their self-concept (Marsh & Parker, 1984). With each success or failure an individual experiences they identify factors to which they can attribute it. Failure can be attributed to external sources (e.g., the difficulty of the task or bad luck), or internal sources (e.g., a lack of effort or a lack of ability) (Cortes-Suarez & Sandiford, 2008). In a mathematics classroom, if a student attributes failure to external sources they are less likely to internalize that failure in a way that decreases their self-concept. Similarly, if a student attributes a successful experience in mathematics to their own abilities or effort, they are more likely to internalize it in a way that strengthens their self-concept (Marsh et al., 1984). Marsh et al. found a strong correlation between ability attributions in mathematics and self-concept such that students with strong self-concepts are more likely to attribute successes to their own abilities and efforts while attributing failure to outside sources. Thus, instruction that allows students to use mathematical reasoning to solve problems independently will facilitate successful experiences that students can attribute to their own efforts and understanding, thereby increasing their self-concept.

Finally, an individual's attitudes towards mathematics can influence their mathematics self-concept. Individuals who find mathematics interesting, useful, and applicable to their lives tend to have higher self-concepts (Marsh et al., 2005; Wang et al., 2021; Xu, 2018). However, attitudes are not universally included in descriptions of self-concept. Marsh and O'Neill (1984) included attitudes like interest and enjoyment as items measuring self-concept on the Self-Descriptive Questionnaire but other descriptions of self-concept do not make the same inclusion (Bong & Skaalvik, 2003), leaving researchers to include a separate measure of attitudes in their studies (Lazarides & Ittel, 2012). Though attitudes about mathematics influence self-concept, they are not always included in self-concept measurement instruments. Therefore, there is a lack of understanding in how influential attitudes are or whether changing students' attitudes can change their self-concept.

Mathematics self-concept is a complex construct that asks individuals to do more than just evaluate their objective abilities. It considers frames of reference, reinforcements from others, and attributions of success that give meaning to perceived success and failure (Bong & Skaalvik, 2003). Self-concept explains how an individual feels about their mathematics abilities, but it does not necessarily indicate a desire to work in a mathematics related field. Just as an individual may understand the mechanics behind how a car operates and can fix it when it breaks down, students can understand and be confident in their ability to solve problems using mathematics without considering themselves professionals in a mathematics field. This is what mathematics self-concept describes – an individual's evaluative perceptions of their ability to understand and use mathematics.

Current Directions in Research on Self-Concept

Self-concept is studied with two general objectives. The first objective is to examine relationships to other academic outcomes: achievement, student goals and mindset beliefs, or continued study in science, technology, engineering, and mathematics (STEM) fields. The second objective is to identify trends in student self-concept related to demographic factors like age, gender, and socioeconomic status, and to examine the way culture and environment may alter its effect. Past research supports the idea that self-concept is an important construct due to its positive and multifaceted association with students' mathematics learning (Ahmed et al., 2012; Parker et al., 2014; E. M. Skaalvik & Hagtvet, 1990), but little research considers self-concept as a dependent variable or looks for ways to strengthen it. Past research also suggests that self-concept may develop differently for different student populations (e.g., female or black students; Evans et al., 2011), but relevant research used large international samples comparing homogenous student groups in different countries. In this situation it is impossible to know how to interpret these differences. This dissertation study goes beyond the current research as it examines the trajectory of self-concept for different student populations within the U.S. and investigates the specific influence that relational instruction and caring learning environments have on it.

How Self-Concept Relates to Achievement

One of the most common academic outcomes studied alongside self-concept is student achievement. Achievement can be described in different ways but for this dissertation achievement will describe both student performance and understanding in mathematics. Research has repeatedly shown that domain level self-concept is strongly related to achievement within the same domain (Marsh, 1992; Parker et al., 2014; Van der Beek et al., 2017) but the way the relationship functions has been unclear. At times self-concept is found to be affected by achievement (Eccles & Wang, 2016) and at other times achievement is found to be affected by self-concept (Marsh et al., 2005). A reciprocal effects model (REM) (E. M. Skaalvik & Hagtvet, 1990) has been validated repeatedly in the literature (Arens et al., 2017; Seaton et al., 2014). This model posits a cyclical relationship where achievement and self-concept both affect one another so that high achievement strengthens a student's self-concept in mathematics which then serves to increase future achievement. Inversely, low achievement reinforces negative self-concept, contributing to decreased achievement in the future.

Findings from International Studies

Due to this theorized relationship between self-concept and achievement many researchers have conducted studies to identify patterns in the development of self-concept (Goldman & Penner, 2016; Marsh et al., 2005, 2008; Seaton et al., 2014). By discovering patterns, researchers hope to discover ways to strengthen student self-concept. Many of these studies utilize large scale survey research designs (see Lee & Stankov, 2018; Yoshino, 2012). International assessments like the Program for International Student Assessment (PISA) and Trends in International Mathematics and Science Study (TIMSS) provide large samples of students from across the globe that enable researchers to look for patterns and trends in many different cultural subgroups.

Goldman and Penner (2016) conducted an analysis of the 2007 TIMSS data to look for differences in eighth-grade student self-concept. They found U.S. students generally had lower mathematics self-concept than students in Sweden, but there was a greater gender gap in Sweden than in the United States. By running identical regression models for each of the countries in their sample, they found significant gender differences in 26 countries. In most of these countries male students had greater mathematics self-concept than female students, but in Malaysia, Norway, Romania, Russia, and Ukraine, it was reversed; female students had stronger self-concept than males. Within the United States there was no significant difference in self-concept between male and female students. This finding conflicts with past research that showed male students had stronger self-concept for mathematics than female students (Eccles & Wang, 2016). One interpretation of this discrepancy in the literature is that the gender gap in mathematics self-concept among U.S. students is decreasing. However, the quantity of self-concept research has decreased in recent years among U.S. researchers, being replaced with constructs like self-efficacy or expectancy value. Though self-concept is still actively included in international research it is uncommon to see it studied in strictly U.S. samples. Further research, both within the U.S. and internationally, is needed before a general claim can be made that the gender gap in self-concept is decreasing.

In addition to the main effect of gender on student self-concept, researchers also investigated different moderation effects related to self-concept. In addition to the gender gap previously discussed, Goldman and Penner (2016) found that gender moderated the relationship between achievement and self-concept. In some countries, achievement had a stronger effect on self-concept for female students than it did for male students. However, as the level of gender equality in the country increased, the gender gap in mathematics self-concept decreased. Goldman and Penner (2016) suggest this decrease in the gender gap for self-concept is due to female students in more egalitarian countries being free to choose a career based on the "gendered identities that they have internalized" (p.415), but there is little research to confirm this hypothesis. The research does demonstrate again the subjective nature of self-concept and how gender can influence it both directly and through interaction with other factors.

The Big Fish Little Pond Effect

Incorporating external frames of reference into self-concept contributes to the Big Fish Little Pond Effect (BFLPE, Marsh et al., 2019; Marsh & Parker, 1984). The BFLPE suggests that the effect of achievement on self-concept is moderated by the academic environment the student is in. For instance, a student in a high achieving school, or an advanced classroom with high achievers, is more likely to have decreased levels of self-concept, despite their own high achievement (Marsh et al., 2019). Seeing all the high achievers around them weakens their self-concept as they evaluate their abilities in comparison with their peers. Conversely, a student that has been tracked into a low achieving school or classroom is more likely to have an elevated level of self-concept since they are comparing their abilities with other low achievers. This effect has been observed by multiple researchers (Marsh et al., 2008, 2019; Marsh & Hau, 2003; Trautwein et al., 2006) and has the strongest negative effect for average achieving students in high achieving classrooms (Trautwein et al., 2006). However, these same studies reported that students in advanced, or high achievement, classrooms tended to have stronger self-concept than those in the average or lower track classrooms. This indicates that while the BFLPE predicts environmentally produced variation to self-concept among students at the same achievement level, it does not predict significant changes to self-concept among students across different achievement levels.

While there is a general consensus among researchers that self-concept is positively related to mathematics achievement, there are a variety of moderating variables that change the way this relationship functions. These moderators effectively designate the classroom environment as an external frame of reference that can significantly influence the perceived importance of mathematics and a student's evaluation of their abilities.

How Self-Concept Relates to Attitudes and Emotions in Mathematics

As self-concept incorporates both cognitive and affective judgements, it is important to consider how self-concept relates to affective components in mathematics education. Research strongly supports the idea that students' emotions and attitudes significantly affect their motivation and ability to learn (Pekrun & Schutz, 2007; Wigfield & Eccles, 2000) so it is important for research to consider the relationship between self-concept and non-cognitive outcomes. Some of the outcomes discussed in the research along with self-concept are anxiety, interest, and enjoyment.

Mathematics anxiety is a negative emotion that significantly impedes a student's ability to learn mathematics (Ahmed et al., 2012). Van der Beek et al. (2017) used exploratory factor analysis to show mathematics self-concept and mathematics anxiety are negatively related constructs. They also found students with low self-concept reported less enjoyment of mathematics. Students who do not enjoy or find interest in mathematics are likely to become bored in mathematics class. Boredom and anxiety are both negative emotions that correlate with the use of shallow learning strategies and decreased achievement in mathematics (Ahmed et al., 2013). This suggests that increasing student mathematics self-concept will decrease the level of negative emotions students feel while learning mathematics and increase achievement.

Research has shown strong associations between affective and emotional constructs, like interest or anxiety, and self-concept. Using path analysis, Ahmed et al. (2012) found support for a reciprocal, two-way relationship between self-concept and anxiety meaning that self-concept affected anxiety which then, in turn, affected self-concept. However, the association from self-concept to anxiety was twice as strong as the association from anxiety to self-concept suggesting that self-concept has a stronger influence on anxiety. Other research found that the relationship between self-concept and emotions in mathematics was stronger than the relationship between self-concept and achievement (Van der Beek et al., 2017). This demonstrates a link between self-concept and affective constructs in education and suggests benefits from strengthening student self-concept.

Self-Concept and Additional Educational Constructs

Another area of study related to self-concept investigates the relationship between self-concept and student learning goals. Student learning goals can be categorized into four types using two criteria. The first criterion distinguishes mastery goals from performance goals. Mastery goals are goals that focus on developing abilities. They are related to having an incremental (or growth) mindset and strongly predict achievement in mathematics (Liu, 2021). Mastery-approach goals are goals where the student is trying to increase their learning while mastery avoidance goals would describe a student who wants to avoid learning or avoid a potential change in paradigm. Performance goals are more concerned with a desire to have others think positively about one's abilities and are related to having an entity (or fixed) mindset. The second criterion considers whether a student is trying to approach or avoid an outcome. Performance-approach goals describe goals related to getting good grades or recognition while performance-avoidance goals are adopted by students who are trying to keep from being the lowest performing student. Students who adopt performance-avoidance goals may be concerned with getting high grades, but only because they want to avoid any negative consequences. Generally, students who adopt mastery approach goals engage more and use deeper learning strategies.

Hussain et al. (2017) found a strong negative relationship between self-concept and mastery avoidance goal orientation, and a moderate positive correlation between self-concept and mastery goal orientation. Students who have strong self-concept in mathematics tend to have goals focused on learning and internalizing the mathematics they are exposed to. Due to the comparative nature of self-concept, a connection to performance related goals is also expected. Because self-concept involves comparison to others, students are likely to have goals that position them to receive recognition or keep them from being perceived as low achieving. However, Hussain et al. found that the correlation between performance goals and self-concept was not as strong as the correlation between mastery goals and self-concept. Thus, students with strong self-concept are more likely to set learning goals based on personal growth and gaining knowledge, which will likely lead to increased achievement (Liu, 2021). This research supports the need for strengthening student self-concept to encourage adoption of mastery goals and improve achievement.

This link between learning goals, mindset, and self-concept is not surprising. When a student has a strong self-concept, they are more confident in their ability to overcome challenges and be successful in mathematics. Self-concept includes more than just being able to reproduce mathematics previously demonstrated. It suggests that students understand mathematics well enough to adapt their knowledge to unique situations and use what Lithner (2008) refers to as creative reasoning. This research does suggest an important link between students' implicit theories of intelligence and the development of self-concept. Students who endorse a fixed mindset are not likely to be responsive to practices or interventions designed to alter self-concept. Though learning goals and mindset are not constructs being examined in this study, the research discussed further demonstrates the importance of strengthening student self-concept to improve mathematics education.

How Self-Concept Relates to Further Engagement in STEM

Multiple researchers have found mathematics self-concept to be a powerful predictor of entrance into a STEM field (Eccles & Wang, 2016; Goldman & Penner, 2016; Parker et al., 2014). Self-concept is often compared to other predictive self-beliefs, like self-efficacy, but research suggests that selection of a STEM major in college, or a STEM career is predicted by self-concept and not by self-efficacy (Parker et al., 2014). Goldman and Penner found that a career involving mathematics was predicted by self-concept and that self-concept included both achievement and interest in mathematics. It is important to identify the elements of self-concept that contribute to a student's desire to enter STEM fields to ensure that educators are not creating or perpetuating barriers that keep students from STEM.

As previously mentioned, not all measures of self-concept include interest as part of their scale. Bong and Skaalvik (2003) note that some researchers include interest and enjoyment as part of self-concept while other researchers consider these separate constructs. Further research that investigates the link between self-concept and interest would be valuable in clarifying self-concept and illuminating why it predicts entry into STEM fields. Can students only develop strong self-concepts for mathematics if they have an innate interest in the subject? If so, can interest in mathematics be increased through developing relational understanding, and will that also improve self-concept? This is one area where the research is still unclear and further investigation would be beneficial.

Achievement, the number of math courses taken, and socioeconomic level all predict entrance into STEM fields (Eccles & Wang, 2016), but self-concept has been shown to be an even stronger predictor (Parker et al., 2014). Additionally, self-concept predicts student achievement more than standardized tests (Trautwein et al., 2006) or socioeconomic status (SES) (Gervasoni et al., 2012) and is significantly related to more positive emotions in mathematics classrooms (Van der Beek et al., 2017), use of deeper learning strategies, and mastery goal orientations (Hussain et al., 2017). Because self-concept contributes to deeper learning, more positive emotions, improved achievement, and entry into STEM fields, it is essential that researchers continue to study this complex construct to develop interventions and instructional practices that will serve to increase student self-concept for mathematics.

Relational Instruction

In this dissertation study the term *relational instruction* is used to indicate instruction focused on building the relational understanding of mathematics for students. Relational understanding is described as “knowing both what to do and why” (Skemp, 1976, p. 9). It is contrasted with instrumental understanding which is having “possession of such a rule, and the ability to use it” (Skemp, 1976, p. 9). Other terms used in mathematics education research to describe the same dichotomy are conceptual and procedural knowledge (Rittle-Johnson & Alibali, 1999), and creative and algorithmic reasoning (Jonsson et al., 2014). In this dissertation study all three semantic pairs will be included in the discussion of research and singularly referred to as relational or instrumental understanding. Research on relational understanding considers its relationship to achievement, and the role of instruction in its development. This section of the review discusses research focused on the benefits and development of relational understanding in mathematics and how it may relate to self-concept.

How Instruction to Build Relational Understanding Relates to Achievement

When students engage in learning designed to develop relational understanding it can improve their achievement, decrease future cognitive effort, and help them develop the ability to explain their solution strategies, identify their own mistakes, and reformulate their solutions (Jonsson et al., 2014, 2016; Norqvist, 2018; Selman & Tapan-Broutin, 2018). However, other research suggests that gains to achievement are associated with instruction that is teacher-led, emphasizes memorization of formulas and procedures, and does not concern the teacher with illustrating connections between mathematics and daily life (Eriksson et al., 2019; Mosimege & Winnar, 2021). Many teachers believe that effective instruction includes a mixture of student-led and teacher-led activities (Khan et al., 2016), but the current research does not describe what that combination should look like.

In a qualitative case study investigating geometry learning (Selman & Tapan-Broutin, 2018), a small group of seventh-grade girls in Turkey used interactive Geometry software to learn about symmetry transformations. The research was based on the constructivist Theory of Didactical Situations (Brousseau, 2006) which outlines a five-phase process for learning. The researchers had the students engage with the computer assisted geometry lesson over two days. The lesson was designed to help them discover their own knowledge and understanding. The students engaged in forming and testing conjectures and were able to informally explain ideas related to symmetry transformations. This lesson illustrated an effective way to help students develop relational understanding.

In two studies in northern Europe, identical sets of mathematical tasks were presented to students using three different approaches. Each approach required students to use one of three types of reasoning based on Lithner's (2008) framework for mathematical reasoning (Jonsson et al., 2014, 2016; Norqvist, 2018). The imitative reasoning (IR) group required students to recall a memorized fact or formula to solve the problem. The algorithmic reasoning (AR) group required students to apply a learned process or algorithm to a problem that they had not seen before, and the creative reasoning (CR) group required students to develop their own strategy or derive their own formula to solve the problem. The CR group had the highest performance on the exam one week later. Further, students in the CR group required less cognitive effort when taking the exam when compared with the AR group. These findings align with other research which showed that teaching for relational understanding had a positive effect on student achievement while teaching that focused on procedural proficiency had a negative effect (Yu & Singh, 2018). When students develop relational understanding, they have increased achievement because they are able to reason through novel problems instead of having to rely on memorized procedures.

In contrast to the previous studies, Eriksson et al. (2019) examined data from multiple waves of the TIMSS to investigate the relationship between instructional practices and achievement. They considered student reports of how often their teachers gave lecture-style presentations, related mathematics to their daily lives, or had them memorize formulas and procedures, and analyzed how well each frequency predicted scores on the TIMSS mathematics achievement score. They found that lecture-style instruction in Sweden had a consistently positive relationship with achievement, but that relationship was only significant in 2007 ($\beta = 18.68$, $SE = 4.64$, $p < .001$) and 2011 ($\beta = 24.19$, $SE = 7.80$, $p < .001$). The relationship was not significant in 2003 or 2015. Memorization of procedures was not measured in 2003 but was significant in the three later waves ($\beta = 16.77\text{-}24.99$, $SE = 6.36 – 8.11$, $p < .01$). Both practices are generally more associated with developing instrumental understanding in mathematics. Conversely, application of mathematics to daily life generally works to develop relational understanding, but Eriksson et al. found that it consistently had a negative association with achievement. Though this effect was not as strong ($\beta = -11.39 – -14.69$, $SE = 5.84 – 10.81$), it was a surprising result when considering the direction of the relationship. Though these results were specific to Sweden, the patterns remained when all the international TIMSS countries were included in the analysis.

In another study analyzing TIMSS data, Mosimege and Winnar (2021) looked at topic-specific achievement in over 12,000 South African students. They found that students in an algebra class whose teachers had them solve problems without providing direct guidance scored an average of 38 fewer points when compared to students who had more teacher guidance ($p < .01$). They found similar findings in analyses of students studying geometry, numbers, and data and chance. Students taught by teachers who provided more guidance during problem solving tasks had higher scores than those whose teachers provided less guidance.

There could be a few explanations for these contradictory findings. First, the samples from the studies came from different countries. Students in Sweden and Finland showed improved achievement when forced to complete tasks without teacher guidance while students in South Africa demonstrated higher achievement when they received guidance from their teachers. These findings may indicate cultural differences related to how students learn, the role of a teacher, or the role of struggle and persistence in learning. It is likely that students who are not regularly required to struggle during mathematics instruction may become confused and frustrated with this type of instructional strategy, resulting in decreased performance. Those same students, however, may use the guidance from teachers to help them make connections and think more deeply about mathematics. Understanding the educational norms in each country would illuminate possible explanations for the discrepancy. The conflicting results in these studies suggest the need for further research that investigates the relationship between relational instruction and student achievement, and how culture might mediate that relationship.

Other reasons for the contradictory findings may be related to the measure of achievement used, or the temporal connection between the study and the measure of achievement. Sometimes achievement is measured using an assessment that clearly aligns with a recent intervention (Jonsson et al., 2014; Norqvist, 2018) and at other times it is measured by student engagement and participation in a discovery-based lesson (Selman & Tapan-Broutin, 2018). The TIMSS studies (Eriksson et al., 2019; Mosimege & Winnar, 2021) measured relationships between general teaching practices that were not explicitly tied to specific mathematics topics, nor associated with a specific time interval. It is possible that these variations in temporality or alignment between instruction and the measure of achievement influence the results when measuring achievement. These variations in achievement measures may contribute conflicting messages when students evaluate their self-concept. Further research is necessary to delineate the different effects instructional practices have on short-term content-specific achievement as well as more general long-term achievement and how students incorporate the results of different achievement measures into their self-concept evaluations.

Though the northern European studies (Jonsson et al., 2014, 2016; Norqvist, 2018) analyzed content-specific results over a short term, the studies suggest positive long-term benefits for achievement. Results of the studies suggest that if students successfully complete tasks requiring creative reasoning, they have greater retention of the material and an ability to easily recreate what they had done in the practice session (Jonsson et al., 2014, 2016; Norqvist, 2018). Students in the CR group could quickly produce a needed formula while students in the AR group tried to recall a formula they had previously used but did not understand. When students develop a relational understanding of mathematics, they understand relationships in mathematics and can use mathematics creatively to solve problems.

The goal of most educational reforms is to improve achievement for all students, but research has not yet reached a consensus on how to do this. At times reforms which increase rigor in mathematics instruction create difficulties for students who have a history of low achievement (Clotfelter et al., 2015), while at other times low achieving students show the greatest improvement when a focus on college readiness increases rigor (Edgerton & Desimone, 2018). To clarify this apparent contradiction in the literature, Allensworth et al. (2021) suggested that researchers consider how past achievement moderates the relationship between instructional practices and student performance. To clarify how teachers' instructional and supportive practices affect students differentially according to past mathematics achievement, the statistical models used to answer RQ2 included covariates to measure both past performance and understanding.

Instruction that focuses on developing relational understanding may help equalize instructional quality among different groups of students. For students taught with reliance on memorization of algorithms, achievement was more strongly associated with innate cognitive abilities than for students who had to rely on conceptual understanding of relationships (Jonsson et al., 2014; Norqvist, 2018). Students in the CR group were building relational understanding and showed less variation due to cognitive abilities, though the groups were purposefully designed to represent similar levels of cognition. This suggests building relational understanding may minimize differences in achievement and provide better instruction for students who have not shown high previous aptitude for mathematics.

How Relational Instruction May Influence Self-Concept

There are potential positive and negative effects on students' self-concept when instruction focuses on building relational understanding. A potential benefit is that students develop deeper understanding and greater flexibility in using mathematics. A potential drawback is that students may experience more struggle and frustration with relational instruction. These negative affective experiences could contribute to a decrease in self-concept.

Productive Struggle in Mathematics

There is a great deal of research related to productive struggle in learning mathematics, but most of the research investigates its effect on achievement, with less focus on affective or emotional effects. Some results, however, present evidence that students who receive instruction designed to build relational understanding of mathematics experience more struggle during the learning process. In Norway, students who learned through tasks requiring creative reasoning initially struggled and required more time to complete the practice problems (Jonsson et al., 2014; Norqvist, 2018). This struggle could lead to decreased self-concept in multiple ways. First, the negative emotions that students experience while engaged in productive struggle may become associated with mathematics and cause them to view their relationship with mathematics negatively. Second, students may incorporate the struggle in their frame of reference evaluations and decide that since they do not experience the same struggle in another class, or they experience more struggle than another student, they are less competent in mathematics.

One area of current research pertains to the role of struggle in mathematics education and different strategies used to alleviate it. In accordance with previous research (Renkl, 1999), Norqvist et al. (2018) tried to alleviate struggle while maintaining instructional quality by adding conceptual explanations to worked examples of algorithmic problems. However, they did not find an increase in students' achievement or a decrease in the amount of cognitive strain required to complete the exam. Their findings indicated that providing worked examples is not enough to get students thinking deeply about mathematics or reduce the amount of struggle students experience.

Kapur (2014) described the benefits of productive struggle in mathematics. He compared the achievement and cognitive strain between students who received a lecture related to standard deviation before or after engaging in problem solving. He found that the students in the productive failure group, who engaged in problem solving before the lecture, attained the same level of instrumental understanding as the direct instruction group, but outperformed the direct instruction group on relational understanding (d = 2.00). However, these students also reported greater mental effort during both the problem-solving phase (d = 1.70) and the lecture phase (d = 1.66). When students experience similar situations of high cognitive strain in mathematics, they may interpret them as a lack of ability which would negatively affect their self-concept.

Skemp (1976) suggested that when students have relational understanding in mathematics, they experience greater achievement. The other research cited in this section (Jonsson et al., 2014; Kapur, 2014; Norqvist, 2018) indicates that students who develop relational understanding have better retention and flexibility with mathematics, and they experience fewer negative emotions related to mathematics learning. However, there is also evidence to suggest that relational instruction may lead to increased anxiety and frustration (Jonsson et al., 2014). Though I do not measure anxiety in this dissertation, I investigate the interaction between relational instruction and supportive and caring learning environments to see how they work together to influence student self-concept. The caring and supportive learning environment should mitigate the potential negative effects of instruction that builds relational understanding.

Caring and Supportive Learning Environments

A third factor that likely contributes to students' self-concept is the degree to which they feel cared for and supported in their learning environment. Many researchers have studied how students are affected by having caring, supportive teachers (Kashy-Rosenbaum et al., 2018; Ruzek et al., 2016; Sakiz et al., 2012; Yıldırım, 2012). Because of the demonstrated importance of caring teachers, the School Center for Advanced Study of Teaching and Learning developed the Classroom Assessment Scoring System™ (CLASS™) (Pianta et al., 2008) to evaluate the quality of classroom instruction. This observational assessment tool has been used repeatedly in research on mathematics education (Allen et al., 2013; Virtanen et al., 2018) and includes a measure of emotionally supportive classrooms. It is based on Self-Determination Theory (SDT, Ryan & Deci, 2000) and measures teacher/student interactions that affect a student's feelings of competence, belonging, and autonomy. This section of the literature review presents research related students having a caring and supportive learning environment and how it may influence their self-concept.

According to Hamre et al. (2013), an emotionally supportive environment is one with warm, caring relationships where the teachers are sensitive to students' behavioral, affective, and academic needs, while also being respectful of students' perspectives and ideas. Similarly, Martin and Rimm-Kaufman (2015) stated that caring is expressed as teachers are sensitive, genuinely kind, and aware of students' interests and needs. Other research has suggested that students want teachers who care and hold them to high expectations (Sakiz et al., 2012). Sakiz et al. also found teacher behavior that communicates caring was positively associated with students' feelings of belonging (see also Ruzek et al., 2016), as well as increased enjoyment and confidence in academics while being negatively associated with hopelessness. Based on this research I hypothesize that positive emotional outcomes in a mathematics classroom improve student engagement and achievement in school (Ahmed et al., 2013; Martin & Rimm-Kaufman, 2015) and likely contribute to increased self-concept.

How Caring and Supportive Learning Environments Relate to Achievement

Research suggests that teachers who provide a caring and supportive learning environment may help improve their students' achievement. A cross-country analysis of 2012 PISA data (OECD Publishing, 2013) showed that emotional support from teachers had a weak, yet significant, positive correlation with student mathematics achievement ($r = .13$, $p < .001$) and significantly predicted achievement even when controlling for student country and sex (Oda et al., 2021). In another study, researchers used hierarchical linear modeling (HLM) and found that the degree of emotional support high school students received from their homeroom teacher significantly predicted their grade point average ($b = 3.33$, $SE = 1.34$, $p < .05$) (Kashy-Rosenbaum et al., 2018). When students feel emotionally supported by their teachers, they show increased achievement.

Though the effects are moderate, they suggest that emotionally supportive teachers may have a positive influence on achievement. However, they leave questions concerning the strength of the effect. The measure of emotional support in the Oda et al.

(2021) study asked students to consider the emotional support they received from “most teachers” (p. 47). Thus, the study reported how a general feeling of care from all teachers influenced mathematics achievement. Kashy-Rosenbuam et al. (2018), however, reported how a single teacher’s level of emotional support influenced general academic achievement. Research is needed that examines the specific effect a caring and supportive environment in a mathematics classroom has on student self-concept.

Given the research related to emotions is correlational, we cannot say that positive emotions contribute to improved academic achievement. Ruzek et al. (2016) pointed out that although research has repeatedly connected student motivation and engagement with teacher emotional support, the nature of the relationship has not been explained. It may be that students in the Oda et al. (2021) study were assigned to homeroom classes based on their past performance, or their current schedule, which would bias the results. However, there are several reasons why it is reasonable to argue the emotional support students receive from teachers will contribute to increased achievement. First, as students feel supported, they are more likely to be attentive and engage in the learning process (Murdock & Miller, 2003; Noddings, 2012). Second, when students struggle or make mistakes, they are more willing to seek help from their teachers and correct errors or misconceptions (E. M. Skaalvik & Skaalvik, 2013). Finally, if students feel emotional support from their teachers, it will decrease the influence of negative emotions related to learning mathematics (Kashy-Rosenbaum et al., 2018). When experienced, these negative emotions increase cognitive strain and create a barrier to learning so if they are reduced, students can put more cognitive energy into understanding mathematics relationally.

Additional evidence for the beneficial effects of teacher emotional support can be seen by looking at interaction effects. For students with high levels of confidence in mathematics teacher caring did not have as strong of an effect as it did on students with low levels of confidence (Lewis et al., 2012; Martin & Rimm-Kaufman, 2015). Similarly, when comparing the effects of teacher caring between English fluent students and English learners, researchers found that teacher caring had a stronger effect for students who were learning English than for students who spoke English fluently (Lewis et al., 2012). For English learners a 1.0 standard deviation increase in teacher caring predicted an increase of 1.043 standard deviations in mathematics achievement. This result is supported by other research which found that mathematics achievement for students categorized as high risk was substantially influenced by the teacher level of caring, and that the level of caring mitigated the negative effect of being labeled at-risk (Muller, 2001). Though main effects of teacher caring are often judged to be insignificant (Lewis et al., 2012; Muller, 2001), these studies suggest positive results due to how the caring environment moderates other variables. When teachers provide caring and emotionally supportive learning environments for students, they can improve the achievement of students who face other cognitive, social, and affective disadvantages. In this dissertation study I examine the effect that student perceptions of the learning environment their mathematics teacher creates had on student self-concept.

Caring and Supportive Learning Environments Promote Positive Affective Experiences

In addition to positive associations with achievement, providing students with caring and emotionally supportive learning environments positively relates to additional beneficial affective outcomes that may influence self-concept. Emotionally supportive environments help to increase student engagement and feelings of autonomy (Ruzek et al., 2016; E. M. Skaalvik & Skaalvik, 2013). They also have a negative association with harmful emotions such as mathematics anxiety (Oda et al., 2021) and academic hopelessness (Sakiz et al., 2012). Caring and emotionally supportive environments that increase student engagement while decreasing negative emotional experiences should strengthen student self-concept by increasing achievement and providing more positive affective experiences in mathematics classes. This claim is supported by E. M. Skaalvik and Skaalvik, who found that emotionally supportive teachers were more likely to have students with strong self-concept (see also Oda et al., 2021). Teachers who provide caring and supportive mathematics learning environments may serve to strengthen students' self-concept for mathematics though both cognitive and affective relationships. The statistical models in RQ #3 allowed me to examine how creating a caring and supportive learning environment influenced student self-concept both directly and through its interaction with relational instruction.

How Messages of Caring and Support Influence Self-Concept

Though most individuals who enter the teaching profession are likely to claim they care for their students, that message is not always transmitted to those they teach. In a study looking at the interrelationships between self-concept and perceived instructional quality among secondary mathematics students, researchers found that only about 10% of students rated their teachers as providing high quality interactions, one aspect of which included social support (Lazarides & Ittel, 2012). In fact, half of the students perceived their interactions with their teacher as being low quality. In the following paragraphs I discuss research which illuminates different ways teachers may convey caring and support to their students and how they may influence self-concept.

The way teacher messages of caring and support contribute to self-concept can be influenced by teachers' beliefs about intelligence. When teachers endorse entity (fixed) beliefs of intelligence, they attribute student success to factors outside of the student's control (Rattan et al., 2012). They tend to relate poor grades to lack of intelligence rather than student effort or their own teaching practices and make these judgements after only one low test score. Rattan et al. found teachers had lower expectations for the students they considered low achieving and attributed continued low performance to a lack of ability. When teachers view their students as having an inadequate level of intelligence, the messages of support and caring they send may be detrimental to student self-concept.

Teachers' beliefs about intelligence influence the way they discuss poor performance with their students (Rattan et al., 2012). Rattan et al. found that teachers with entity (fixed) beliefs felt the most appropriate response to failure was to console their students for their lack of aptitude and try to make them feel better by suggesting "not everyone can be good at every subject." (p. 731) Students who received this type of feedback had lower expectations for their future performance. Conversely, when teachers who endorsed incremental (growth) beliefs of intelligence discussed failure with their students they reviewed problems the student faced and developed strategies for improving performance in the future. These teachers maintained high expectations for their students and continued to put effort into helping them learn. When students receive this type of support they experience more enjoyment and confidence in learning mathematics (Gervasoni et al., 2012). While both groups of teachers were trying to be supportive, the messages from teachers who held incremental beliefs of intelligence expressed confidence in the student. These messages are more likely to increase the student's self-concept. Conversely, the lack of confidence communicated by teachers with entity beliefs is more likely to discourage students and contribute to low self-concept.

In addition to the obvious ways students receive messages of caring (e.g., listening or showing interest in non-academic events in the student's life) messages of caring and support can come through other interactions. Students feel increased caring and support when teachers work to meet their academic needs while being respectful of their unique perspectives (Hamre et al., 2013), acknowledging and respecting their interests (Martin & Rimm-Kaufman, 2015), and maintaining high expectations (Sakiz et al., 2012). Though the influence of these components on self-concept has not been tested empirically, theory related to self-concept suggests that each would have a strengthening effect. Respecting students' unique interests and perspectives will allow teachers to validate students' individual mathematical processes and help students see how mathematics applies to their lives. Maintaining high expectations, when coupled with academic support, will help students be successful and give them confidence that they are able to understand mathematics. As students develop confidence and see mathematics as relevant to their lives, they will have stronger self-concept.

Demographic Differences

The main dependent variables in this dissertation are relational instruction and caring and supportive learning environments. However, research suggests that the way students evaluate their self-concept may be influenced by demographic characteristics like race and gender. Very little research investigates demographic differences in self-concept though differences have been observed according to gender (Evans et al., 2011; Goldman & Penner, 2016; S. Skaalvik & Skaalvik, 2004), and race (Dasgupta et al., 2022; Evans et al., 2011). With the demographic diversity that exists in classrooms it is important to understand how demographic factors play a role in the way students develop their self-concept.

Though little exists in self-concept literature to explain the role of demographic characteristics in the way students evaluate their self-concept, the related construct of self-efficacy may provide insight. Differences related to gender and race were observed in studies on mathematics self-efficacy (Huang, 2013; Usher, 2009; Usher & Pajares, 2006). Mathematics self-efficacy tends to be higher in male students than female students even when their performance in mathematics is similar. Additionally, Zeldin et al. (2008) found that adult women placed more emphasis on observation and verbal feedback of others when evaluating their self-efficacy while men placed more emphasis on past achievement. This research suggests that gender influences how students evaluate their self-perceptions.

Gender can also interact with the main study variables to influence student self-concept. Lazarides and Ittel (2012) found female students twice as likely to describe their mathematics teachers as exhibiting low quality interactions than male students. They also found female students more likely to feel their teachers were not willing to take time to speak to their students. These findings suggest that there might be different gender effects related to instruction as well as students feeling that they have a caring and supportive learning environment.

Research suggests that race also influences the way students evaluate their self-perceptions. Huang (2013) suggested that self-efficacy is influenced by the socialization practices of different cultures. Though he did not find empirical evidence for this hypothesis, it is likely that cultural socialization will influence self-concept since it includes subjective evaluation components that self-efficacy does not. Some research has found race-based differences in self-concept, but it was observed when comparing different homogeneous samples (Yoshino, 2012). In a more recent study of 2,939 adolescents, Dasgupta et al. (2022) found Black, Latinx, and Native American students had greater benefits to self-concept than white students when they understood how mathematics related to their societies and when they felt a greater sense of belonging in their classes. In this dissertation study I look at the effects of race on relational instruction and perceptions of a caring and supportive learning environment to see how they influence self-concept.

Another demographic factor that may influence students' self-concept is SES. Some scholars suggest that academic gaps which appear to be racially defined might be more appropriately attributed to SES than race (Gray-Little & Hafdahl, 2000; Ravitch, 2016). Much of the research which supports the BFLPE compares student populations in different schools or tracks, each with distinctly different levels of achievement. Because school assignment and placement into higher academic tracks are often correlated with SES, the observed BFLPE may be confounded by SES as well. It is important to distinguish the effect of SES from other demographic variables to develop interventions that increase student self-concept. As such, I included SES as a control variable in the multilevel models to separate its influence from the influence of race.

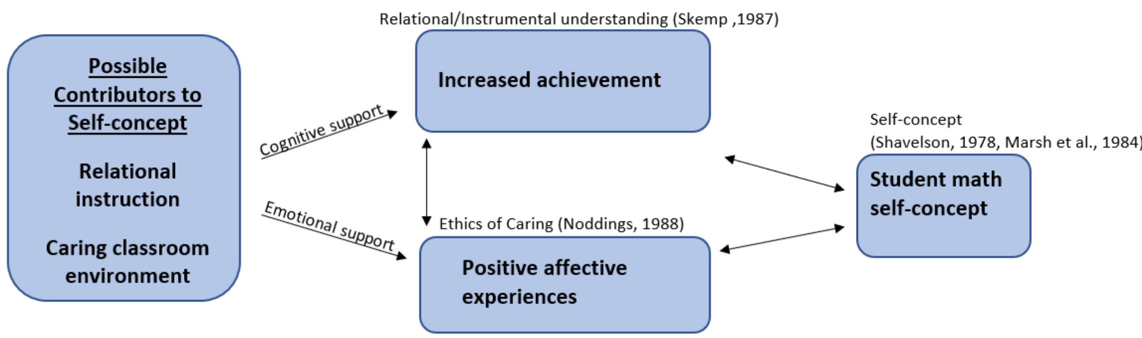
The findings and suggestions in the research support the continued need to investigate demographic differences in how students evaluate their self-concept. If we know how different student populations interpret messages related to their self-concept, then we will be able to better tailor environmental and instructional conditions to increase student learning and achievement. To illuminate how demographic factors influence student self-concept and how they interact with relational instruction and student perceptions of a caring and supportive learning environment, the models for RQ #4 will include interactions between the main predictors (i.e. relational instruction and the creation of caring and supportive learning environments), race, and gender.

Conceptual Framework

This section explains the conceptual framework describing the theoretical foundation supporting this research. It presents a theoretical argument linking the instructional emphases of mathematics teachers and the classroom environment with the development of self-concept. This framework draws on theories related to: (a) relational understanding of mathematics, and (b) ethics of caring. The theoretical relationships which explain how instructional and environmental factors may contribute to students' self-concept are shown in Figure 3.

Figure 3

Conceptual Framework



Explanation of Theoretical Constructs

The first theoretical construct underlying the conceptual framework is the theory of relational/instrumental understanding in mathematics (Skemp, 1976, 2012). This theory is frequently used in mathematics education research and provides a framework for discussing different types of mathematical knowledge or understanding. In his book *The Psychology of Learning Mathematics* (Skemp, 2012), Richard Skemp described the difference between relational and instrumental knowledge using the analogy of navigating a new city. An individual can be given step-by-step directions that allow them to successfully reach their destination, but if a road is closed, the individual may find themselves helplessly lost. This is analogous to a student with instrumental, or procedural, understanding of mathematics. However, if the individual instead has a map and understands how to use it, then they will be able to find alternate routes to their destination without getting lost. This second scenario is analogous to a student who has developed relational, or conceptual, understanding and uses their mental schemes (maps) to help them engage more flexibly in mathematics. The development of relational understanding contributes to increased flexibility, recall, transfer, enjoyment, and achievement in mathematics learning (Skemp, 1976). In this study achievement in mathematics includes both performance and understanding as relational instruction should result in both. The development of relational understanding in mathematics should strengthen students' self-concept as it allows them to think flexibly and creatively with mathematics with a higher level of understanding.

The second theoretical component is ethics of caring (Noddings, 1988). Noddings proposed a relationship between the carer (teacher) and the cared for (student) that would function as a mechanism for teaching ethical behavior. She explained that teachers should "treat students with respect and consideration and encourage them to treat each other in a similar fashion" (Noddings, 1988, p. 223). She claimed that this caring relationship is built on dialogue and an understanding of students' background knowledge and experiences. Later researchers expanded on Nodding's theory when they found that caring teachers improved academic motivation, and thereby performance, of students in mathematics (Lewis et al., 2012; Muller, 2001; Murdock & Miller, 2003; Noddings, 2012; Valenzuela, 2010). In summary, they found that students "prefer to be cared for before they care about school" (Valenzuela, 2010, p. 342). If students feel emotionally cared for and supported by their mathematics teachers, the frequency and severity of negative affective experiences while learning mathematics should decrease, leading to a stronger self-concept.

Interrelationships Between the Constructs

The conceptual framework is based on a set of premises which suggest relationships between teachers' instructional emphases, classroom and school caring, and self-concept. First, this research presumes the activities and instructional techniques a mathematics teacher employs can strongly influence whether students develop relational or instrumental understanding in mathematics (Chapin et al., 2009; Stephens et al., 2015; Van de Walle et al., 2015). Activities that focus on connecting mathematics concepts (Stephens et al., 2015), having students explain their reasoning (Chapin et al., 2009), or engaging students in problem solving (Van de Walle et al., 2015) will help students to construct mental schema associated with relational understanding. If students develop relational understanding their self-concept should increase because they develop the ability to think flexibly with mathematics, see mathematics as more connected to their individual lives, and experience increased enjoyment and success.

The second premise guiding this research is that students who feel that they are cared for and belong in their mathematics learning environment will engage more deeply in learning, and have fewer negative emotions related to mathematics. Many students experience stress, discouragement, or frustration when learning mathematics (Ahmed et al., 2012, 2013). Additionally, students experience uncertainty, sadness, and disappointment related to situations outside of the classroom which can create barriers to their motivation and learning (Joëls et al., 2006). However, when students perceive that their teachers care about them, respect them, and provide positive emotional support they feel an increased sense of belonging, and greater academic enjoyment (Sakiz et al., 2012). Based on E. M. Skaalvik and Skaalvik (2013) who found that students with caring teachers had deeper learning goals and put greater effort into learning, I hypothesized that if students felt a sense of belonging in their mathematics classrooms, they would be more engaged in the learning process and have increased motivation to do their best. Taken together, a caring and emotionally supportive learning environment should contribute to both cognitive and affective improvements that would then translate into an increase in student self-concept.

The third premise, shown by the double headed vertical arrow in the conceptual framework, is that a reciprocal relationship exists between students' cognitive and affective experiences in mathematics. This suggests that improvements in students' understanding of mathematics will increase their positive affective experiences, and vice versa. In the framework there are also double-headed arrows indicating similar reciprocal relationships between self-concept and cognitive or affective experiences. As self-concept increases, it will contribute to further increases in understanding and positive affective experiences.

The framework described above provides a theoretical and conceptual basis for describing how the relational instructional practices of mathematics teachers and the caring, supportive environment they help create for students can have a positive effect on students' self-concept. In the current study I examine these relationships through the following research questions.

1. How does student mathematics self-concept change during students' secondary education years as measured on the HSLS:09?
2. How does an emphasis on relational instruction in mathematics influence change in student self-concept for mathematics as measured on the HSLS:09

(Ingels et al., 2011)?

3. How do student perceptions of a caring learning environment influence change in student self-concept for mathematics as measured on the HSLS:09 (Ingels et al., 2011)?

4. Are there differences based on demographic factors such as gender and race?

Conclusion

The research reviewed in this paper presents evidence which suggests that self-concept can be affected through teachers' use of instructional activities that focus on building relational understanding in mathematics and the creation of emotionally caring and supportive environments. However, since self-concept has rarely been the main outcome of interest in studies on teacher/student interactions, the current study investigates the influence of relational instruction, and caring environments on student self-concept. Additionally, since research points to both cultural and gender differences in how self-concept perceptions are formed, this research investigates how relational instruction and caring environments may affect various student groups differently.

CHAPTER III

METHODS

The purpose of this study was to investigate how relational instruction and the creation of a caring learning environment contribute to the development of student mathematics self-concept, and how those factors influence students differently according to race and gender. To investigate these relationships, I conducted a secondary analysis of data from the High School Longitudinal Study of 2009 (HSLS:09) to answer the previously outlined research questions. The extensive data provided in the HSLS:09 allowed for the identification of trends and relationships in student self-concept that have previously been undiscovered due to limitations of sample size.

Research Design

The design of this study was a quantitative secondary data analysis using multilevel regression techniques on longitudinal survey data. In secondary data analysis a researcher analyzes data that was collected by another individual or entity (Johnston, 2014). Secondary analysis of the HSLS:09 data was beneficial for this study as the large nationally representative sample (a) provided statistical power for multilevel modeling techniques and (b) allowed for examination of variation in the development of self-concept among different student populations.

Regression is an inferential statistical method that allows a researcher to examine the relationships of multiple predictor variables on a single outcome (Montgomery et al., 2021). According to Rabe-Hesketh and Skrondal (2008), the purpose of multilevel modeling is to “model the relationship between a response variable and a set of explanatory variables … [which] involves units of observation at different ‘levels’” (p.1). When variables of interest are found at different nested levels, or clusters (i.e., individuals, classrooms, and schools), the use of standard regression models can lead to ecological or atomistic fallacies, and inaccurate standard errors. Ecological fallacies occur when aggregated level 2 data is interpretated in regards to lower level variables and atomistic fallacies are made when analyses of level 1 variables are used to make inferences at a higher level (Hox, 2010). Multilevel modeling overcomes these issues as it accounts for dependence of observations at each level and attributes unexplained variability to the different levels. Multilevel modeling was appropriate for this dissertation as it accounted for clustered variation due to students having a shared school environment.

One additional reason a multilevel model was appropriate for this research is the longitudinal nature of the dependent variable. Longitudinal data are data that are collected at multiple time points on the same participants (Diggle et al., 2002). The repeated observation data are necessary for studying change over time (Singer & Willett, 2003) and can be viewed as clustered data for inclusion in a multilevel model (Rabe-Hesketh & Skrondal, 2008). Longitudinal data allows for examination of both within-subjects and between-subjects change (Baltes & Nesselroade, 1979; Singer & Willett, 2003). The longitudinal data found in the HSLS:09 allowed me to examine how student self-concept changes over time, the duration of the influence of the predictor variables on student self-concept, and how these findings change according to student demographics.

Data Source

The data for this analysis came from the restricted-use dataset from the HSLS:09 study. The HSLS:09 is an extensive longitudinal study sponsored by the National Center for Educational Statistics (NCES) designed to investigate the transition of students from high school, through any post-secondary education, into adulthood and long-term careers. The unit of analysis in the HSLS:09 study is individual students which means the data set can only be used to investigate dependent variables at the student level. The NCES administered initial baseline year (BY) surveys to the sample of students in their ninth-grade year, and gathered follow up survey data during students' junior year (11th grade) in 2012 (F1) and three years after graduation from high school in 2016 (F2) (Ingels et al., 2011). In addition to the student surveys, parents, teachers, school counselors, and school administrators completed surveys in 2009 to provide further contextual information. The HSLS:09 measured student achievement, attitudes, beliefs, experiences, and practices related to education, with an emphasis on mathematics and science.

The data for this dissertation came from student surveys at multiple waves, along with teacher surveys in the 2009 baseline year. The data was downloaded as a data frame and formatted for use in the R statistical software. A separate Excel file was provided which listed all the included variables, their data file designation, and the data collection instrument that they came from. The HSLS:09 data set contains thousands of variables. The variables applicable to this dissertation provide demographic information (i.e., gender, race, and SES), measures of student achievement (i.e., class grades and standardized exam scores), student perceptions of their mathematics teacher (e.g., "My math teacher treats students with respect"), and student perceptions of their abilities in mathematics (i.e., "I consider myself a math person"). The dataset also contains data from the math teacher survey which includes variables related to instructional foci in mathematics (e.g., math teacher's "emphasis on connecting math ideas").

Procedures

The HSLS:09 was administered by the NCES. The initial surveys took place in the fall of 2009 with follow-up surveys occurring Spring 2012, and February 2016. The deidentified HSLS:09 data are housed at the NCES website and freely available for download. However, for this dissertation I needed access to additional variables that contain linking or identifying information which can only be accessed following an extensive approval process and licensure from the US Department of Education. I gained access to these school identifiers through the license and access granted to Dr. Mario Suarez, one of my dissertation committee chairs. After completing the required training from the Institute of Education Sciences (IES) and submitting a notarized non-disclosure agreement, I was added to Dr. Suarez's license as an approved researcher. As an approved researcher, I ran all analyses under Dr. Suarez's supervision, in his office, on a secure computer which did not connect to the internet.

Participants

The HSLS:09 used a nationally representative sample of over 23,000 ninth-grade students from more than 944 schools across the United States. The study used a two-stage stratified random sampling process (Ingels et al., 2011), first identifying and selecting eligible schools to participate and then randomly selecting ninth-grade students from within the schools. Schools were categorized according to the following three criteria: (a) school type (i.e., public, private - Catholic, private – other), (b) region of the U.S. (i.e., Northeast, Midwest, South, West), and (c) locale (i.e., city, suburban, town, rural). These criteria were used to create 48 different sampling strata from which schools could be randomly selected to create a nationally representative sample of schools. Once the school sample was selected, between 20 and 50 students were selected from each school using a stratified systematic sampling procedure with sampling strata defined by student race or ethnicity. For this dissertation I analyzed pertinent data from the full HSLS:09 student sample. However, missing data and survey attrition resulted in a final analytical sample that was smaller than the original HSLS:09 sample. Demographic information for the final analytical sample can be seen in Table 1. In compliance with requirements from the Department of Education, all sample sizes were rounded to the nearest 10.

Table 1

Demographic Information for the Sample

Race	# Males	% of total sample	# Females	% of total sample
White	6,250	24.8	6,010	23.9
Hispanic	2,020	8.0	1,980	7.9
Black	1,400	5.6	1,250	5.0
Asian	1,060	4.2	1,040	4.1
> 1 Race	1,000	4.0	950	3.8
Native American/Alaskan/Hawaiian/Pacific Islander	150	.6	130	.5
No race reported	980	7.6	940	3.7
Totals	12,860		12,300	

Note. N = 25,160.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study, 2009 (HSLS:09), "Baseline Year, Student Survey, 2009."

Data Analysis

The analysis for this dissertation occurred in three phases. In the first phase, I created a data set that included only the variables needed for my analysis and prepared the data for analysis by creating new composite variables and transforming the data set into long form. The statistical packages in R for analyzing longitudinal data require data to be organized in long form, where everyone has multiple rows in the data set (Singer & Willett, 2003). In the second phase, I ran exploratory analyses to describe the main variables of interest and investigate the trajectory for self-concept to answer the first research question. Finally, I built multi-level statistical models to answer the final three research questions. Table 2 provides a summary of the research questions, the source of the data for each question, and the types of data analyses that will be conducted.

Variables

All variables used in the analysis came from the HSLS:09 data. Some were scales created by the NCES while others were created for this dissertation by combining individual items to generate new scales to measure the new predictor variables. Descriptions of the variables used in the study are listed below. Most of the HSLS:09 items used to create the new predictor variables were Likert-type items measured on a four-point scale. Though Likert scales are discrete scales, studies have shown that Likert-type scales with five or more response options can be treated as continuous in statistical analyses (Sullivan & Artino, 2013). Further, researchers observed that 4-point scales produced the same statistical values as higher point scales, even among elementary

Table 2

Summary of Research Questions, Data Sources, and Method of Analysis

Research questions	Data source	Data analysis
1. How does student mathematics self-concept change during students' secondary education years?	HSLS:09 data Student baseline year, 1st and 2nd follow up instruments. Math teacher instrument	Descriptive statistics Longitudinal growth curve modeling (Singer & Willett, 2003)
2. How does an emphasis on relational instruction in mathematics influence change in student self-concept for mathematics as measured on the HSLS:09 (Ingels et al., 2011)?	HSLS:09 data Student baseline year, 1st and 2nd follow up instruments. Math teacher instrument	Confirmatory factor analysis (Levine, 2005) 3-level MLM regression model (Gelman & Hill, 2006; Hox, 2010; T. Snijders, 1996; T. A. Snijders & Bosker, 2011)
3. How do student perceptions of a caring and supportive learning environment influence change in student self-concept for mathematics as measured on the HSLS:09 (Ingels et al., 2011)?	HSLS:09 data Student baseline year, 1st and 2nd follow up instruments. Math teacher instrument	3-level MLM regression model (Gelman & Hill, 2006; Hox, 2010; T. Snijders, 1996; T. A. Snijders & Bosker, 2011)
4. Are there differences based on demographic factors such as gender, race, SES, and parent education level?	HSLS:09 data Student baseline year, 1st and 2nd follow up instruments. Math teacher instrument Parent instrument	3-level MLM regression model with interactions (Gelman & Hill, 2006; Hox, 2010; T. A. Snijders & Bosker, 2011) Plots of simple slopes (Aiken et al., 1991; Gelman & Hill, 2006)

Note. HSLS:09 = High School Longitudinal Survey, 2009. MLM = Multi-level model. All analyses will be conducted in RStudio (Version 4.1.1) using the packages *levaan,* and *lme4*.

school children (Adelson & McCoach, 2010; Leung, 2011). However, for best methodological practices, I adjusted the commands in the statistical software to maximize the accuracy of the variable values and allow me to treat them as continuous in the multi-level models. The adjustments are described in the upcoming data structure and analysis techniques section.

Standardizing and mean centering variables allows for easier interpretation of results when variables are measured on different scales and should always be done when interaction terms will be included (Gelman & Hill, 2006). Given that recommendation, I standardized all continuous variables to have $\bar{X} = 0$ and $SD = 1$. A description of the variables included in this analysis, along with their associated HSLS:09 source is included in Table 3.

Self-Concept

The dependent variable in this study is mathematics self-concept and is based off the NCES created MTHID variable. The MTHID variable is a two-item scale found in the first two waves of data collection. It was created using the items, "I see myself as a math person," and "Others see me as a math person." These items were combined using principal components analysis (PCA) weighted by the STUDENT1 and STUDENT2 weighting variables (Ingels et al., 2011). Though the MTHID scale is not included in the data for the second follow up, the same two individual items were included on the 2016 survey, therefore I used a similar process to create new variables for use in my analyses. Self-concept refers to the way an individual sees themselves but can be affected by perceived evaluations from others (Bong & Skaalvik, 2003). As such, these two HSLS:09 items complement each other to describe a total measure of mathematics self-concept. I used these two items at each time point to create the variables *self-concept 1*, *self-concept 2,* and *self-concept 3* where higher values are associated with higher levels of self-concept. Cronbach's alpha is a measure of internal consistency and can be used as a measure of scale reliability (Cronbach, 1951). The NCES reports that each scale showed good reliability with $\alpha_{\text{self-concept 1}} = .84$ and $\alpha_{\text{self-concept 2}} = .87$ (Ingels et al., 2011). The

Table 3

Description and Source of Composite Variables

Composite variable	Description	HSLS:09 instrument	HSLS designation	Item wording
Dependent variable				
Self-concept 1	*HSLS scale* - Students describe how much they consider themselves (and others consider them) a "math person."	Student BY	X1MTHID	Scale created from the following two items.
Self-concept 2		Student F1	X2MTHID	
Self-concept 3		Student F2	S4MPERSON1	I see myself as a math person.
			S4MPERSON2	Others see me as a math person.
Primary predictor variables				
Relational instruction	Teacher describes how much emphasis they place on building student relational understanding of mathematics.	Math Teacher BY	M1CONCEPTS	emphasis on teaching math concepts.
			M1PROBLEM	emphasis on developing problem solving skills.
			M1REASON	emphasis on reasoning mathematically.
			M1IDEAS	emphasis on connecting math ideas.
			M1LOGIC	emphasis on logical structure of mathematics.
			M1EXPLAIN	emphasis on effectively explaining math ideas.
Teacher caring	Student perceptions of how their math teacher treats students	Student BY	S1MTCHVALUES	… values/listens to students' ideas.
			S1MTCHRESPCT	…treats students with respect.
			S1MTCHFAIR	…math teacher treats every student fairly.
			S1MTCHCONF	…thinks all student can be successful.
			S1MTCHMISTKE	…thinks mistakes OK if students learn.
			S1MTCHTREAT	…treats some kids better than others.
			S1MTCHMFDIFF	…treats males/females differently.

Note. BY = Baseline year (2009); F1 = First follow-up (2012); F2 = Second follow-up (2016).

SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study, 2009 (HSLS:09), "Baseline Year, Student Survey, 2009," "Baseline Year, Mathematics Teacher Survey, 2009," "First Follow-up, Student Survey, 2012," & "Second Follow-up, 2016."

reliability for self-concept 3 was calculated during phase two of the analysis and also showed good reliability $\alpha_{\text{self-concept 3}} = .90$.

Time

The HSLS:09 study measured self-concept at three separate time points. An analysis of longitudinal data requires the inclusion of a time variable. For this study, the time variable was calculated by subtracting 2009 from the year the wave of the survey was administered. This means that the time value for data recorded during the baseline year (BY) was 2009 – 2009 = 0, the time value for data collected in the first follow up (F1) was 2012 – 2009 = 3, and the time value for data collected in the second follow (F2) up was 2016 – 2009 = 7. This method of transforming the time variable allowed for easier interpretation as the variable indicated the number of years since ninth grade. One of the main objectives of this dissertation is to investigate the effect of predictor variables that were measured in the ninth grade, so it makes sense to consider the timing of the dependent variable as beginning from the introduction of those predictors.

Relational Instruction

I included two new variables in my analysis to investigate the influence that teachers have on the development of their students' self-concept. The first of these two variables was called *relational instruction* and relied on data from the mathematics teacher questionnaire. The ninth-grade mathematics teachers of all participants completed surveys that asked about their attitudes and practices related to teaching mathematics. The teachers responded to multiple items asking them to rate the level of instructional emphasis they placed on things like problem solving skills or speedy and accurate computations. The complete list of items is in Appendix A. I identified items that theory suggests can contribute to instruction which builds relational understanding (e.g., reasoning mathematically and connecting math ideas) to create the relational instruction variable. I validated their inclusion in a single scale using confirmatory factor analysis (CFA; Levine, 2005). Once validated, I used factor scores from an additional CFA as individual values for this variable. Higher values on the relational instruction variable indicate instructional goals more likely to promote relational understanding of mathematics.

Caring and Supportive Learning Environment

The second composite variable examined the influence of the learning environment on students' self-concept. I created a scale to measure the degree to which students experience a caring and supportive learning environment in their mathematics classroom. This scale measures student perceptions of the environment created by their mathematics teachers. The HSLS:09 contains seven items on the student BY instrument which ask students to rate their agreement with statements like "My math teacher treats students with respect" and "My math teacher thinks all students can be successful." Like the items for relational instruction, these items were examined and validated using CFA. Once the selection of items for the new scale was validated, I extracted and standardized the factor scores from an additional CFA to use as individual scores on the *teacher caring* variable.

Level 3 Identification Variable

The HSLS:09 has a nested data structure where time is nested within students which are nested within classrooms. Ideally, the third level of the models would be a classroom or teacher level. However, for multilevel regression analysis it is recommended to have at least 100 groups at the highest level with a minimum of 10 participants in each group (Hox, 2010; Lee & Hong, 2021). Though more than 100 teachers are included in the data set, they do not typically have that many HSLS:09 sample students in their classes. Because the students and their corresponding mathematics teachers are clustered within the same school, I chose instead to define the third level of the multilevel models as schools. This level 3 grouping variable accounted for the shared variance between students that was a result of being at the same school. This is a statistically effective grouping variable for the analyses because there are 944 schools included in the data set with an average of 23 students at each school.

Control Variables

I included multiple control variables (or covariates) in the analyses so the models could better identify the amount of variation in self-concept that is truly related to relational instruction and caring and supportive learning environments. The inclusion of demographic covariates also allowed me to identify how the predictor variables influenced self-concept differently for different student subpopulations. The following is a list of predictor variables taken from the student and parent BY instruments that were used as controls in my analyses.

- *SES* – Taken from items on the parent BY survey, the X1SES_U variable provides a measure of relative student SES based on locale of the student's school. It includes components that measure parent education and occupation, as well as family income, and accounts for differences based on the school locale. Recent research suggests that observed racial gaps in student mathematics achievement may be related to SES instead of race (Ravitch, 2016). Student SES is included in this study to ensure that any variation attributed to race or gender in the models is accurately attributed and not a result of student SES.

- *Gender* – The X1SEX variable is a dichotomous variable measured in the baseline year surveys. Though it is a dichotomous variable, it is based on the way an individual views themselves, so I refer to it as gender in this dissertation. Responses from the student, parent, and school provided sampling roster were compared to check for consistency. If an inconsistency was found, the HSLS:09 team manually coded the variable based on review of the student's first name. The gender variable was included to look for possible gender-based differences in how the main predictor variables influence self-concept.

- *Race* - Student race/ethnicity on the HSLS was recorded in the BY study using the X1RACE variable. Data are based mainly on responses from the student survey but if that information was missing the race/ethnicity information came from the school sampling roster or the parent survey. The HSLS dataset reports eight different categories for race/ethnicity. To provide greater statistical power, I consolidated some of the categories resulting in the following six categories: White, Black, Hispanic, American Indian/Pacific Islander, Asian, and more than one race. The race variable was included to look for possible interaction effects between race and the main predictor variables.

- *Math Grade (8)* – Measured in the BY student survey, the S1M8GRADE variable reports the final grade the student earned in their most advanced eighth-grade mathematics class. Grades are reported as letter grades with possible responses of A, B, C, D, "Below D," and "Class was not graded" (Ingels et al., 2011). This variable provides a measure of students' previous success in school mathematics which contributes to student self-concept (Bong & Clark, 1999; Bong & Skaalvik, 2003). The inclusion of this variable allowed me to see if the main predictor variables had positive effects regardless of a student's past experiences in mathematics.

- *MathScore* – The HSLS:09 variables X1TXMTH and X2TXMTH report a norm referenced measure of student mathematics achievement taken during students' ninth-grade year and during the first follow up. In addition to the survey measuring attitudes, experiences, and educational goals, students completed an algebraic reasoning assessment that measured their understandings across the six domains of algebraic content and four algebraic processes shown in Table 4. All students took the same first segment of the test then those results were used to route them into one of three second stage tests with varied levels of difficulty. The results from this assessment were

> compiled to create a continuous, norm-referenced measure of achievement that describes student achievement relative to the entire sample of ninth graders. Most of the research studying self-concept investigates its link with achievement, but the purpose of this research is to examine the influence of relational instruction and a caring learning environment on self-concept. Including this measure of achievement clarifies whether changes in self-concept can be attributed to the main predictor variables or if they appear to be tied to achievement. Because students did not complete the algebraic reasoning assessment at the third timepoint it could not be included in the models as a level 1 variable. Therefore, I averaged values on the two HSLS:09 variables to create a level 2 variable which describes students' average performance on the algebraic reasoning assessment over the two years.

Table 4

Summary of Content on the Algebraic Reasoning Assessment

Content domains	Processes
Language of algebra	Demonstrating algebraic skills
Proportional relationships and change	Representing algebraic ideas
Linear equations, inequalities, and functions	Performing algebraic reasoning
Nonlinear equations, inequalities, and functions	Solving algebraic problems
Systems of equations	
Sequences and recursive relationships	

Data Structure and Analysis Techniques

In this section I outline the various statistical analysis techniques used in analysis. This includes an initial factor analysis to create composite variables, growth curve modeling to examine the self-concept trajectory, and multilevel modeling to examine the influence of the predictor variables. Occasionally, I had to make slight analytical changes or additions in response to findings from the preliminary analyses. Additional details explaining these specific changes and the findings which necessitated them will be included in the results section.

Because the main predictor variables are composite variables created from items in the HSLS:09 data set, I used CFA to validate their inclusion into a single scale. CFA can test to see if multiple items measure the same construct (Levine, 2005). This statistical procedure can be used when (a) multiple items are being used to measure a single construct, (b) there is a theory-based a priori idea of the item relationships, and (c) each scale item has a linear relationship with the scale total (or average). Traditional factor analysis techniques rely on variables being measured on a continuous numeric scale (Linting et al., 2007). Because the HSLS:09 items only included four Likert-type categories the CFA will be modified by including the “ordered=TRUE” argument to account for non-linear, ordinal data. I ran a series of two factor CFAs which included the items for both relational instruction and teacher caring.

Inter-item correlations provide a measure of how scores on one item of a scale correlate with all the other items on the scale, giving an overall measure of how well the individual items are measuring the same content (R. J. Cohen et al., 1996). Inter-item correlations should fall between .20 and .40. An inter-item correlation weaker than .20 indicates the items are not measuring the same overarching construct and an inter-item correlation stronger than .40 suggests the included items may be repetitive and not fully describing the construct. Before running the models, I calculated the inter-item correlations for the items to be included in each model to evaluate the strength of the new composite variables.

After running the models, I evaluated multiple fit indices to determine the fit of the items into one scale (Hu & Bentler, 1995). Goodness of fit indices can either measure absolute fit, fit adjusted for model parsimony, or incremental fit, and all three types should be included in an analysis (Brown, 2006). The standardized root mean square residual (SRMR) is a measure of absolute fit. It evaluates the likelihood of a model without consideration of complexity or comparison to other models. SRMR values closer to zero indicate a stronger model with anything less than .08 considered good. The root mean square error of approximation (RMSEA) is like an absolute fit statistic, but it penalizes complex models, encouraging researchers to balance accurate measurement with model parsimony. As with the SRMR, values closer to zero indicate better fit with anything less than .06 considered good. The comparative fit index (CFI) and the Tucker-Lewis index (TLI) are both comparative fit indices that evaluate a model in comparison with a more restricted baseline model. Like the RMSEA, the TLI also includes a penalty for model complexity. Values on the CFI and TLI indices that approach one indicate better fit with anything above .95 considered strong. The two factor CFA served to validate the distinction between these two variables and indicate the proper combination of items to construct the composite variable most accurately.

Once the items were validated in the two factor CFA, I ran two additional CFA models to create the new variables. Each set of items verified in the first CFA were included in one of two separate one-factor CFA models. The purpose for these models was to provide scores on the variables for everyone in the data set. Because the items were measured on a four-point Likert scale, creating variable values using the sum or average of the individual items could result in biased variable values (Rhemtulla et al., 2012). These straightforward approaches assume that the difference between *strongly* *disagree* and *disagree* is equal to the difference between *disagree* and *agree*. Further, they assume that *strongly agree* is equivalent to four times *strongly disagree*, which is not a reliable assumption. Instead of using means or sums I extracted factor scores from each of the later CFAs to create individual variable scores (DiStefano et al., 2019). The factor scores are linear combinations of the measured items which take into account the amount of shared variance between the measured item and the factor. The CFA produced standardized scores that place everyone on the newly created factor. To further reduce bias which may be due to the factors being correlated I used a Ten Berges correction (Logan et al., 2022). This correction should be used when factors might be correlated and results in scores with minimal bias. These corrected scores were the values for the new continuous variables which were used in the multilevel model analysis. I only used CFA models to validate the two new variables and provide non-biased values for those variables. Once the variables were created, the CFA portion of the analyses was complete.

The structure of the data and the specific research questions to be investigated in this dissertation require the use of multilevel modeling techniques. The HSLS:09 variables I examined have a nested structure where the repeated measurements are nested within individuals which are nested within schools. My analyses involved multiple cycles, first looking at how self-concept changes over time, then examining the influence of the predictor variables on the self-concept trajectory, and finally, looking at interactions with race and gender.

The first research question asks how students' mathematics self-concept changes during their secondary education years. To answer this question, I looked at the means and standard deviations of self-concept at all time points. I created plots that showed the growth trajectories of 12 different random subsamples of 50 students each, along with an average change trajectory for the entire subsample (Singer & Willett, 2003). I plotted average trajectories with the data divided by subgroups determined by gender and race to see if the average growth trajectories were noticeably different for different student groups.

The second and third research questions investigate the influence of relational instruction and a caring or supportive learning environment on student self-concept. To investigate these questions, I estimated a series of multilevel models using either restricted (REML) or full (ML) maximum likelihood estimation. I used REML when calculating intraclass correlation coefficients to examine the amount of variation at each level of the model. However, following the advice of Singer and Willett (2003), I used ML estimation when comparing models that differed in fixed effects in addition to variance components. This estimation technique allowed me to compare the models in my study as covariates were added to assess the new model fit. I built a series of models examining both random slopes and random intercepts. In traditional regression, data from all students is aggregated so all students are given the same intercept, or base level self-concept, and variations in self-concept are attributed to predictor variables consistently for all students. Using a random slopes and random intercepts model allows everyone in the analysis to have their own intercept and slope as predicted by the level two variables to see how the predictors influence the growth of self-concept. I evaluated model fit by examining the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). The AIC and BIC are relative goodness of fit indices which can be used to evaluate models that have different predictor variables (Singer & Willett, 2003). Both criteria penalize non-parsimonious models, and the BIC has an additional consideration for sample size. In very large samples the improvement to a model that comes from adding a new predictor variable must be great to get a better BIC score. For both the AIC and BIC smaller values indicate a better model. In addition to the AIC and BIC, I considered the deviance statistic when evaluating models that had the same predictor variables but differed in the random components. The deviance statistic is based on the log-likelihood statistic (LL) and found by the formula $deviance = -2\,[LL_{Current\ model} - LL_{Saturated\ model}]$. As with the AIC and BIC, lower values of the deviance statistic indicate better fitting models.

The final research question investigates how gender and race interact with teacher caring and relational instruction to influence the self-concept trajectory. To look for these effects I ran the final models again with an additional interaction term. I first modeled interactions between race and the two predictor variables in two separate models and then replaced race with student gender to test the second set of interactions. When an interaction term showed statistical significance, I analyzed its meaning using plots of simple slopes (Aiken et al., 1991; Gelman & Hill, 2006). This technique allows for visual comparison of the regression lines across different student groups. I plotted regression lines by either gender or race for each of the significant interaction terms to compare differences in the variable relationships. All analyses were carried out in R Studio 4.3.1

(R Core Team, 2023) using the packages lavaan (Yves, 2012) and lme4 (Bates et al., 2015). I also used the package sjPlot (Lüdecke, 2023) to create the model comparison table for the MLM.

The Models

I started the multi-level model (MLM) analysis by running a three-level unconditional model that did not include any predictor variables. This model identified the amount of variability found at each of the three levels and provided a baseline to compare with later models. If the amount of variability at a given level is large, predictors can be added to try and explain the source of the variability. In this model the intercept represented the average level of self-concept for all students in the study in the fall of their ninth-grade year. The equations for each level in the model were as follows:

Level 1: $Selfconcept_{tij} = b_{0ij} + b_{1ij}(time_{tij}) + e_{tij}$ (1)

Level 2: $b_{0ij} = \beta_{00j} + \zeta_{0ij}$

$b_{1ij} = \beta_{10j} + \zeta_{1ij}$

Level 3: $\beta_{00j} = \gamma_{000} + u_{00k}$

$\beta_{10j} = \gamma_{100} + u_{10k}$

Equations 2 and 3 can be substituted in to give a composite equation:

$$Selfconcept_{tij} = \gamma_{000} + \gamma_{100}(time_{tij}) + u_{00k} + \zeta_{0ij} + u_{01k}(time_{tij}) + \zeta_{1ij}(time_{tij}) + e_{tij} \quad (2)$$

This equation predicts the self-concept at time *t* for individual *i* with teacher *j*. When the value of the time variable is zero, the equation simplifies to $Selfconcept_{tij} = \gamma_{000} + u_{00k} + \zeta_{0ij} + e_{tij}$. The γ_{000} term is the intercept for all students and represents the average self-concept for all individuals in all classrooms over time. The terms e_{tij}, ζ_{0ij}, and u_{00k}

represent the deviations from the intercepts at levels one, two, and three respectively. The deviations are assumed to be normally distributed around zero with common unexplained variance denoted by σ^2 at level one, τ_b at level two, and τ_β at level three. These values can be used to calculate the proportion of unexplained variability at each level using the following equations (Hox, 2010):

Level one: $\frac{\sigma^2}{\sigma^2+\tau_b+\tau_\beta}$ *(3)*

Level two: $\frac{\tau_b}{\sigma^2+\tau_b+\tau_\beta}$ *(4)*

Level three $\frac{\tau_\beta}{\sigma^2+\tau_b+\tau_\beta}$ *(5)*

The second model was an unconditional growth model (Singer & Willett, 2003). This model only included the level 1 predictor of time and indicated the change in self-concept for everyone that was due to time. The next set of models were conditional models that included the individual level predictors measured on the ninth-grade student survey. The first set of these models included the five control variables of SES, gender, race, MathGrade(8) and MathScore and provided a baseline model for comparison. The next models added the predictor of teacher caring followed by the predictor of relational instruction. These variables were added one at a time to allow calculation of the amount of additional variation explained by their inclusion. These models had random intercepts and random slopes for everyone predicted by the level two predictors. They also included a random intercept or random slope for schools. The equations for the first two levels of the final model without interactions was:

Level 1: $Selfconcept_{tij} = b_{0ij} + b_{1ij}(time_{tij}) + e_{tij}$

Level 2: $b_{0ij} = \beta_{0j} + \beta_{1j}(SES_{ij}) + \beta_{2j}(gender_{ij}) + \beta_{3j}(race_{ij}) + \beta_{4j}(MathGrade8_{ij}) +$ *(6)*

$\beta_{5j}(MathScore_{ij}) + \beta_{6j}(TeacherCaring_{ij}) + \beta_{7j}(Relational\_Instruction_{ij}) + \zeta_{0ij}$

$b_{1ij} = \beta_{10j} + \beta_{11j}(SES_{ij}) + \beta_{12j}(gender_{ij}) + \beta_{13j}(race_{ij}) + \beta_{14j}(MathGrade8_{ij}) +$ *(7)*

$\beta_{15j}(mathscore_{ij}) + \beta_{16j}(TeacherCaring_{ij}) + \beta_{17j}(Relational\_Instruction_{ij}) + \zeta_{1ij}$

Because three of the level-2 covariates are categorical variables a separate beta coefficient had to be estimated for each level of the variable, resulting in a total of 34 betas estimated. That means that at level-3 there were 34 equations that each took the following form:

$$\beta_{ij} = \gamma_j + u_j \quad (8)$$

All models that included covariates also included cross level interactions with time, but the only interactions that I investigated were those between the main predictor variables (i.e., TeacherCaring and Relational_Instruction) and the demographic variables (i.e., race and gender). The interaction terms identified differences in the effect of the main predictor variables that were related to student race and gender.

To investigate the interactions within level two variables, I ran the final model two more times including the interaction between teacher caring and gender first, followed by the interaction between teacher caring and race. Due to the complexity of the models, these interactions are difficult to interpret within the entire model, so the purpose of the models was to identify statistically significant interactions. Once identified I used plots of simple slopes (Aiken et al., 1991; Gelman & Hill, 2006) to illustrate and explain the meaning of each significant interaction.

When analyzing multi-level models, it is important to look at the variance components that describe the residual variation at each level of the model. In the first level of the model the residual is described by $e_{tij} \sim N(0, \sigma_\varepsilon^2)$ meaning the level 1 residual is normally distributed around a mean of zero and a variance σ_ε^2. This variance explains how much the level-1 residuals deviate from each individual's true change trajectory. The level-2 and level-3 residuals are described by the following equations:

$$\begin{pmatrix}\zeta_{0i}\\ \zeta_{1i}\end{pmatrix} \sim N\left[\begin{pmatrix}0\\0\end{pmatrix}, \begin{pmatrix}\tau_{00}^2 & \tau_{01}\\ \tau_{10} & \tau_{11}^2\end{pmatrix}\right] \text{ - Level 2} \quad (10)$$

$$\begin{pmatrix}u_{0k}\\ u_{1k}\end{pmatrix} \sim N\left[\begin{pmatrix}0\\0\end{pmatrix}, \begin{pmatrix}\varphi_0^2 & \varphi_{01}\\ \varphi_{10} & \varphi_1^2\end{pmatrix}\right] \text{ - Level 3} \quad (11)$$

In these equations τ_{00}^2 and τ_{11}^2 express the amount of between student variability in the random intercept and random slope. The level-3 values of φ_0^2 and φ_1^2 express the amount of variability in the random intercept and random slope that is due to differences between schools. The other terms at each level explain the amount of covariance between the random slope and random intercept at each level, but they were not a major focus of my analysis.

Assumptions

Running multi-level models with longitudinal data involves making assumptions in relation to the structural portion of the models as well as the stochastic portion (Anderson, 2012; Singer & Willett, 2003). Structurally, a researcher dictates the general shape of the proposed level one model (i.e., linear, logarithmic, polynomial) and specifies the relationship between the growth parameters and the predictor variables.

Stochastically, it is assumed that (a) the residuals of the dependent variable are normally distributed at level one (Singer & Willett, 2003; Snijders, 1996), (b) level two and three residuals have a multivariate normal distribution, and (c) residuals between levels are independent (Anderson, 2012).

Singer and Willet (2003) suggested that it is neither efficient or plausible to check every model for each assumption and proposed the following strategies to ensure assumptions are not violated.

1. Plot level one growth plots with an OLS-estimated change directory superimposed to verify the shape of the proposed model.
2. Create plots to compare each level two predictor with OLS estimates of the individual growth parameters.
3. Create Q-Q plots or run normality tests to check for normality of the raw residuals at each level.

Because the HSLS:09 data set only measures self-concept at three timepoints, only a linear model could be tested. However, I followed the above recommendations to ensure that the residuals were distributed normally and that the residuals at each level were independent from each other.

Threats to Validity/Reliability

In any longitudinal study attrition and missing data create a serious threat to validity. However, the threat is mitigated in the HSLS:09 dataset because this was the first-year student surveys and assessments were administered by the NCES electronically. This data collection method allowed for continued collection even when students had left or switched schools, resulting in less missing data at the student level. The HSLS:09

dataset also includes a variety of analytic weights to account for missing data and make statistical analyses generalizable to the study population. In my multi-level analyses, I included a composite weight, created for longitudinal analyses, which utilizes both student and mathematics teacher data (W3W1MATHTCH) in order to adjust for missing data and increase generalizability.

The main limitations of this research are due to the use of secondary data. Because the HSLS:09 survey was not specifically designed with the intent of studying how teacher behaviors influence students' mathematics self-concept, it does not include every item that would be desired to measure the composite variables of self-concept, relational instruction, and teacher caring. However, the wealth of data contained in the HSLS:09 data set and the large samples of minority students make the benefits of this research outweigh the limitations. The research outlined will help identify how teachers can contribute to the development of positive mathematics self-concept for their students. Additionally, the large representative sample allows me to look at self-concept among different student populations which have, in the past, been inaccurately treated as homogeneous.

CHAPTER IV

RESULTS

The objective of this dissertation was to determine how relational instruction and the creation of a caring learning environment contribute to the development of student mathematics self-concept, and how those factors influence students differently according to various demographic factors. To achieve this objective, I followed a multi-stage statistical analysis approach using confirmatory factor analysis and multilevel modeling techniques to analyze data from the High School Longitudinal Study of 2009 (HSLS:09). I ran all statistical analyses in RStudio (version 4.4.1) using the lavaan and lme4 packages. In this chapter I present results from each phase of the analysis. First, I will describe the steps I took to prepare the dataset and my approach to missing data. Then, I present results related to the CFA and the creation of composite variables measuring relational instruction and caring and supportive learning environments. Finally, I present results from the multilevel model analysis in accordance with each of the four research questions.

Before beginning any analyses, I had to prepare the data set. The HSLS:09 items included several different response categories for missing or incomplete data. I changed any responses that were categorized as “Unit non-response,” “Item legitimate skip/NA,” “Missing,” or “Item not administered: abbreviated interview” to “NA” so the R software would consider them missing data and not skew the results. I examined the missing data and observed that missing cases varied based on data type, data collection instrument, and wave of data collection. Descriptive student level data (i.e., gender, SES, parent education level) had the lowest frequency of missing data with anywhere between 0-13% missing. As expected with data collected over an extended period, the percentage of missing data on items measuring student self-concept increased with each wave of data collection such that there was 15% missing at the baseline year, 20% missing in 2012, and 38% missing from the 2016 data. The items taken from the baseline student survey which were used to measure a caring classroom environment had 24%-25% missing, and the data taken from the baseline mathematics teacher survey which measured relational instruction had 44%-46% missing. The National Center for Education Statistics team that designed and conducted the HSLS:09 used multiple imputation techniques to create sampling weights which can be used to correct for missing data in the data set (Ingels et al., 2011). Because I used those weights in my analyses, I did not make further adjustments to accommodate missing data.

After considering the missing data I turned my attention to the Likert-type items in the data set. The Likert categories in the HSLS:09 data set were set so that a score of one signified the highest level of agreement. To make the meaning of the scores more intuitive I reversed the Likert values so a score of one corresponded with *Strongly Disagree* and a score of four corresponded with *Strongly Agree.* However, several of the Likert-type items in the data were worded such that higher values indicated more negative responses (i.e., My math teacher treats some kids better than others) so I reverse coded these items so higher values on items consistently indicated more favorable perceptions. Additionally, Likert-type items that asked teachers to rate the degree of emphasis they placed on things like practicing speedy computations or teaching procedures indicate instructional foci more strongly associated with instrumental (procedural) learning. Therefore, these items were also recoded so teachers who placed stronger emphasis on instrumental (procedural) instructional goals would have lower values on the relational instruction variable. All recoded items are indicated in the complete list of items in Appendix A. Once the data set was prepared, I began the confirmatory factor analysis (CFA) to create the composite variables for teacher caring and relational instruction.

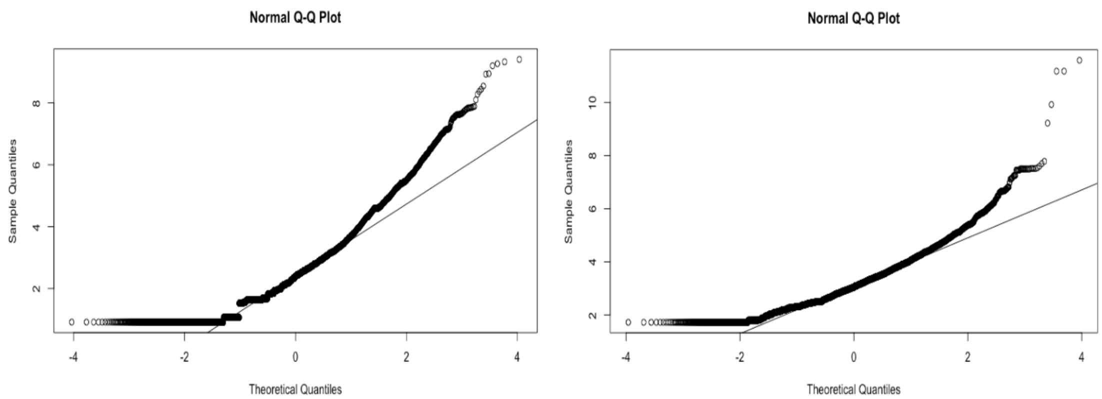
CFA and Variable Creation

Factor analysis assumes that variables are normally distributed (Brown, 2006) so I ran Mardia's test for multivariate normality using the psych package in R. This test evaluates multivariate skew and kurtosis and conducts a significance test for normality. I ran separate analyses using complete observations for the items related to teacher caring and the items related to relational instruction. The results of the Mardia tests showed statistical significance for the teacher caring items (skew=8.65, $p < .0001$; kurtosis=129.3, $p < .0001$) as well as the relational instruction items (skew = 13.25, $p < .0001$; kurtosis=171.03, $p < .0001$). These results, along with the QQ-plots shown in Figure 4, which plot the expected values of a normal distribution versus the Mahalanobis distance for the items, indicated the data was not multivariate normal. To correct for this violation of multivariate normality I used robust standard errors in all my analyses.

Confirmatory factor analysis (CFA) allowed me to determine which HSLS:09 observed items should be included in the composite variables that would be used to

Figure 4

QQ-plots for Teacher Caring Items (left) and Relational Instruction Items (right)



SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study, 2009 (HSLS:09), “Baseline Year, Student Survey, 2009” & “Baseline Year, Mathematics Teacher Survey, 2009.”

measure teacher caring and relational instruction. Because the HSLS:09 did not directly measure student perceptions of a caring learning environment or the degree to which a mathematics teacher emphasizes relational instruction, those constructs can only be measured by combining multiple observed variables which describe elements of the overarching construct. It was likely that some of the observed items would need to be eliminated and CFA allowed me to test different models to determine which items should be excluded when creating the composite variable.

I began by examining correlations between the items included in each of the HSLS:09 question blocks related to the constructs of TeacherCaring and Relational_Instruction. The correlations between items in the TeacherCaring block ranged from .24 (*teacher makes math interesting* and *teacher thinks mistakes okay as* *long as student learns*) to .79 (*teacher treats all students fairly* and *teacher treats all students with respect*). The correlations between items in the Relational_Instruction block were not as strong, ranging from .10 (*focus on algorithms* and *focus on making math interesting*) to .59 (*focus on problem solving* and *focus on reasoning*).

I created three nested models using the observed items from the HSLS:09 dataset where each succeeding model was a subset of the previous model. The first model contained all eight items included in the relevant HSLS:09 question block for teacher caring and 11 of the 13 items from the HSLS:09 block asking about teachers' instructional emphases. I chose not to include two items where teachers indicated the amount of emphasis placed on preparing students for future study in mathematics or business/industry applications. Preparing students for future study in mathematics or focusing on industry applications can be done in conceptual *or* procedural ways, so I did not think the items strongly indicated either relational or instrumental instruction and therefore excluded them from the analysis.

The second model excluded items that did not seem theoretically related to the construct, (i.e., emphasis on teaching the history of mathematics) but did include items which were either positively or negatively related to the construct. I included the negative items (i.e., emphasis on developing computational skills) to see if they created a stronger model. I thought it possible that a teacher's relational instruction could be measured by seeing what they chose not to emphasize along with what they chose to emphasize. For example, if a teacher gave very little emphasis to developing computational skills it may indicate a tendency toward teaching that builds relational understanding. This second model included five positive items and two negative items for teacher caring as well as six positive items and four negative items for relational instruction.

The third model was the theorized model and included only the items hypothesized to describe or positively contribute to the relevant construct. I hypothesized that creating composite variables using only the positive items directly related to the construct would create the strongest measure. This third model included five items which described elements of creating caring classroom environments and six items which described instruction that develops relational understanding in mathematics. I compared all models using the comparative fit index (CFI), the Tucker-Lewis index (TLI), the root mean square residual (SRMR), and the root mean square error of approximation (RMSEA). Comparison of all four fit indices indicated which combination of observed items would create the strongest scales to measure the caring learning environment and relational instruction. The items included in each model along with the inter-item correlations and associated model fit statistics are seen in Table 5.

I fit the models using an adjustment for ordinal data with robust standard errors to account for the violation of multivariate normality. According to all fit criteria listed above, Model 3 is the strongest model because it is the only model that meets the requirements for good model fit on all four fit indices (CFI > .95, TLI > .95, RMSEA < .06, SRMR < .08). The inter-item correlation for relational instruction fell within the ideal range for creating a scale variable (.20 – .40) but the inter-item correlation for the teacher caring variable was higher than ideal.

Table 5

Confirmatory Factor Analysis Models for Variable Creation

Variable	Model 1	Model 2	Model 3
Teacher Caring			
s1mtchvalues	X	X	X
S1mtchrespct	X	X	X
S1mtchfair	X	X	X
S1mtchconf	X	X	X
S1mtchmistke	X	X	X
S1mtchtreat_r	X	X	
S1mtchdiff_r	X	X	
S1mtchintrst	X		
Inter-item correlation	.52	.54	.65
Relational Instruction			
M1problem	X	X	X
M1concepts	X	X	X
M1reason	X	X	X
M1ideas	X	X	X
M1explain	X	X	X
M1logic	X	X	X
M1compskills_r	X	X	
M1algorithm_r	X	X	
M1test_r	X	X	
M1compute_r	X	X	
M1history	X		
Inter-item correlation	.08	.07	.38
Robust Model Fit Statistics			
CFI	.837	.838	.980
TLI	.815	.813	.975
RMSEA	.111	.118	.059
SRMR	.066	.071	.021
N	10420	10490	10740

Note. Per NCES requirement, all sample sizes are rounded to the nearest ten.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study, 2009 (HSLS:09), “Baseline Year, Student Survey, 2009,” & “Baseline Year, Mathematics Teacher Survey, 2009.”

This suggests there are additional elements of a caring learning environment that are not represented in this scale, and I will discuss this result later. For the purposes of this dissertation, the strong fit indices support the use of the five teacher caring items to create a variable describing the creation of a caring and supportive learning environment and the six relational instruction items to create a variable describing the degree to which a teacher emphasizes instruction which builds relational understanding.

The parameter estimates shown in Table 6 indicate the contribution each observed item makes to the composite variable. When considering the variable measuring caring and supportive learning environments, a one standard deviation increase in the composite variable is associated with a .73 to .95 standard deviation increase on each of the

Table 6

Final Items for the Composite Variables

Composite variable	Observed item (HSLS Designation)	Estimate (Robust SE)	Variance
Caring and Supportive Learning Environment	...values and listens to students' ideas (S1MTCHVALUES)	.878 (.003)	.229
	…treats students with respect (S1MTCHRESPCT)	.954 (.002)	.090
	…treats every student fairly (S1MTCHFAIR)	.916 (.002)	.162
	…thinks every student can be successful (S1MTCHCONF)	.834 (.004)	.305
	…thinks mistakes are okay as long as all students learn (S1MTCHMISTKE)	.739 (.005)	.454
Relational Instruction	…emphasis on teaching math concepts (M1CONCEPTS)	.595 (.012)	.647
	…emphasis on problem-solving skills (M1PROBLEM)	.807 (.007)	.349
	…emphasis on reasoning mathematically (M1REASON)	.891 (.005)	.206
	…emphasis on connecting math ideas (M1IDEAS)	.774 (.007)	.401
	…emphasis on effectively explaining math ideas (M1EXPLAIN)	.706 (.007)	.502
	…emphasis on logical structure of mathematics (M1LOGIC)	.681 (.007)	.536

Note. All estimates and variances are standardized. All estimates statistically significant ($p < .001$).

Number of observations used is approximately 10,740.

$df = 43$.

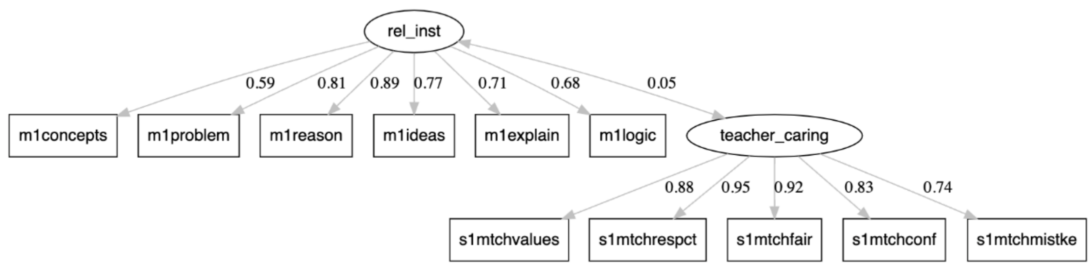
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study, 2009 (HSLS:09), "Baseline Year, Student Survey, 2009" & "Baseline Year, Mathematics Teacher Survey, 2009."

indicator variables. The relationships on the relational instruction variable are not quite as strong but a one standard deviation increase in relational instruction is associated with an increase of approximately .60 to .89 standard deviations on the indicator variables. Interestingly, the "teaching students mathematical concepts" item was the weakest item on the scale, showing only an increase of .60 standard deviations. This lower parameter estimate is unexpected because relational instruction, by definition, involves focusing on concepts, but I will provide possible explanations for this in the discussion. Despite having the lowest parameter estimate, the idea of teaching students mathematical concepts has a strong theoretical connection to relational instruction so I kept the item as part of the composite variable. The residual variances for each of the observed items are relatively large, suggesting substantial variation in how students with the same value on the composite scale responded to the individual items. A diagram depicting the final model with standardized factor loadings is shown in Figure 5. The bidirectional arrow between relational instruction and teacher caring indicates a reciprocal relationship between the two predictor variables. This means that an increase in teacher caring is associated with a slight increase in relational instruction and that an increase in relational instruction is similarly associated with an increase in teacher caring.

I created the variables for caring environment and relational instruction by extracting factor scores from individual one-factor CFAs and applying a Ten Berges correction to reduce bias. Because the variables are measured on different scales, I standardized them to improve interpretation of the multilevel model outputs. I created the new variables by matching the

Figure 5

Factor Loadings for Items Included in the Relational Instruction and Teacher Caring Variables



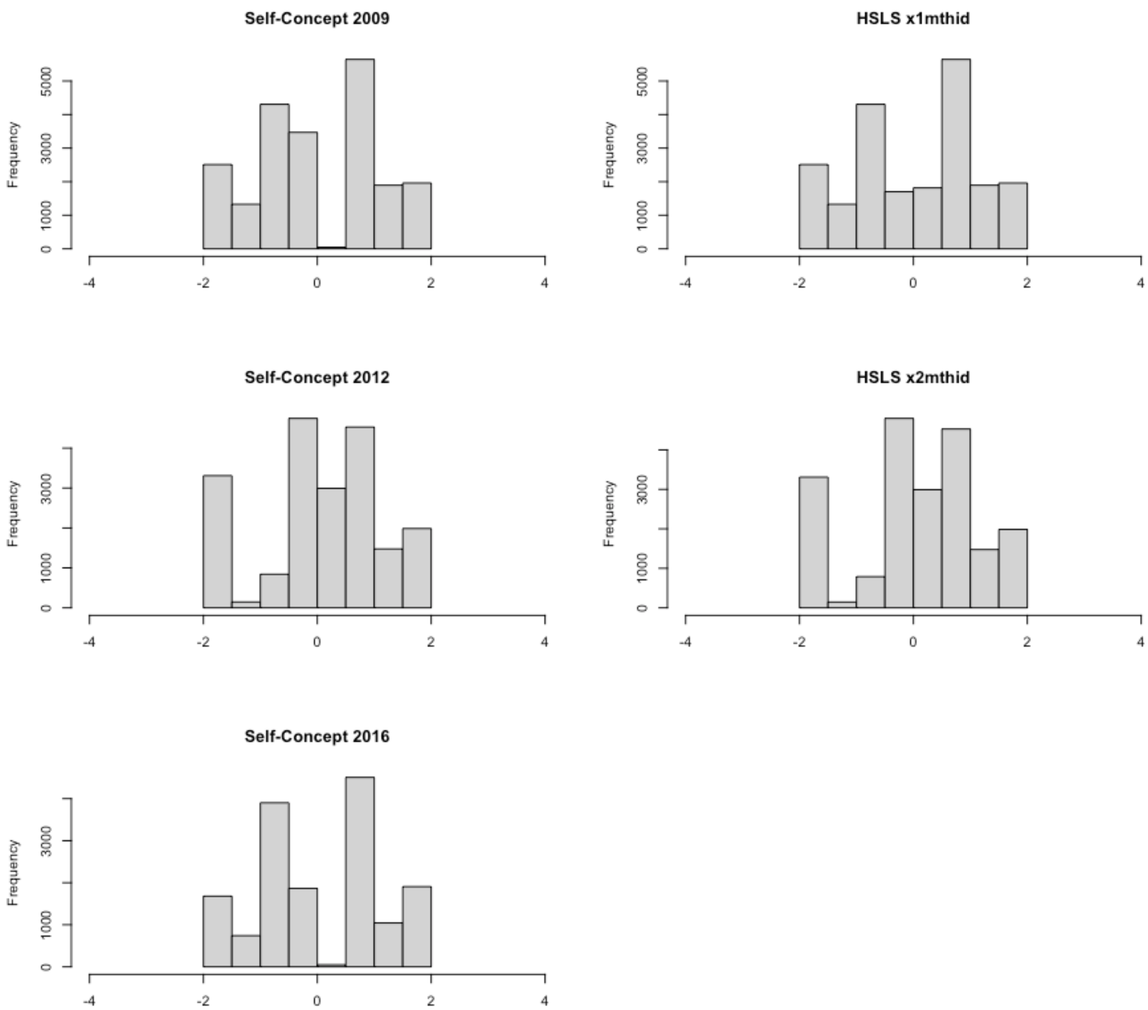
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study, 2009 (HSLS:09), "Baseline Year, Student Survey, 2009" & "Baseline Year, Mathematics Teacher Survey, 2009."

extracted factor scores to the main data set using student identification numbers. Descriptive details for each variable will be described later.

I used principal components analysis (PCA) to create the self-concept variables at each timepoint. To test the validity of this method I compared the new variables to the HSLS:09 created variables of x1mthid and x2mthid. Figure 6 shows the distribution of each self-concept variable along with the distribution of the two mthid variables. The distributions of the new self-concept variables were very similar to the distributions of the mthid variables and the variables for self_concept1 and self_concept2 strongly correlated with the variables of x1mthid and x2mthid ($\sigma_1 > .99$, $\sigma_2 > .99$). The information in Table 7 further illustrates the statistical similarities between the two sets of variables. Because this procedure created variables that were statistically like the HSLS:09 variables, I followed the same process to create the variable for self-concept3 at the third timepoint and used the newly created variables (self-concept1 and self-concept2) in my analyses instead of the HSLS:09 variables (x1mthid and x2mthid). A statistical description of self-concept3 is also included in Table 7.

Figure 6

Histograms Comparing HSLS:09 "mthid" Variables with New Self-Concept Variables



SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study, 2009 (HSLS:09), "Baseline Year, Student Survey, 2009," "First Follow-up, Student Survey, 2012," & "Second Follow-up, 2016."

Table 7

Statistical Comparison of HSLS:09 "mthid" Variables and New Self-Concept Variables

Variable	*n*	$\bar{X}$	*s*	Med	Min	Max	Range	Skew	Kurtosis	SE
X1mthid	21160	.04	1	.03	-1.73	1.76	3.49	-.15	-.74	.01
Self-concept1	21160	0	1	-.01	-1.76	1.72	3.48	-.15	-.73	.01
X2mthid	20020	.05	1.02	.12	-1.54	1.82	3.36	-.01	-.86	.01
Self-concept2	20020	0	1	.07	-1.57	1.74	3.31	0	-.86	.01
Self-concept3	15690	0	1	-.05	-1.80	1.65	3.45	-.10	-.73	.01

Note. Per NCES requirement, all sample sizes are rounded to the nearest 10.

SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study, 2009 (HSLS:09), "Baseline Year, Student Survey, 2009," "First Follow-up, Student Survey, 2012," & "Second Follow-up, 2016."

Descriptions of All Variables

This section includes a statistical description of each variable used in the multilevel analysis. The dependent variable (self-concept) and the two main predictors (relational instruction and teacher caring) were all continuous, as were the control variables for socio-economic status (SES_U) and norm referenced mathematics achievement (MathScore). The remaining variables were categorical.

Self-Concept

Student mathematics self-concept (SC) was measured at three timepoints using the items, "I see myself as a math person," and "Others see me as a math person." Students answered on a scale from 1 (*Strongly* agree) to 4 (*Strongly* disagree) so I reverse coded the items so that higher values indicate stronger levels of agreement. Cronbach's alpha for the items in each self-concept variable showed strong internal reliability ($\alpha_{self\text{-}concept\ 2009}$ = .84, $\alpha_{self\text{-}concept\ 2012}$ = .88, and $\alpha_{self\text{-}concept\ 2016}$ = .90). Statistical descriptions as outlined previously in Table 7 and Figure 6 show that the variables are not exactly normal, but multi-level modeling does not require input or outcome variables to be normally distributed so this is not a problem. The greatest gap between students with high and low self-concept occurred in 2009 (range = 3.49) and the smallest gap was in 2012 (range = 3.31).

Teacher Caring

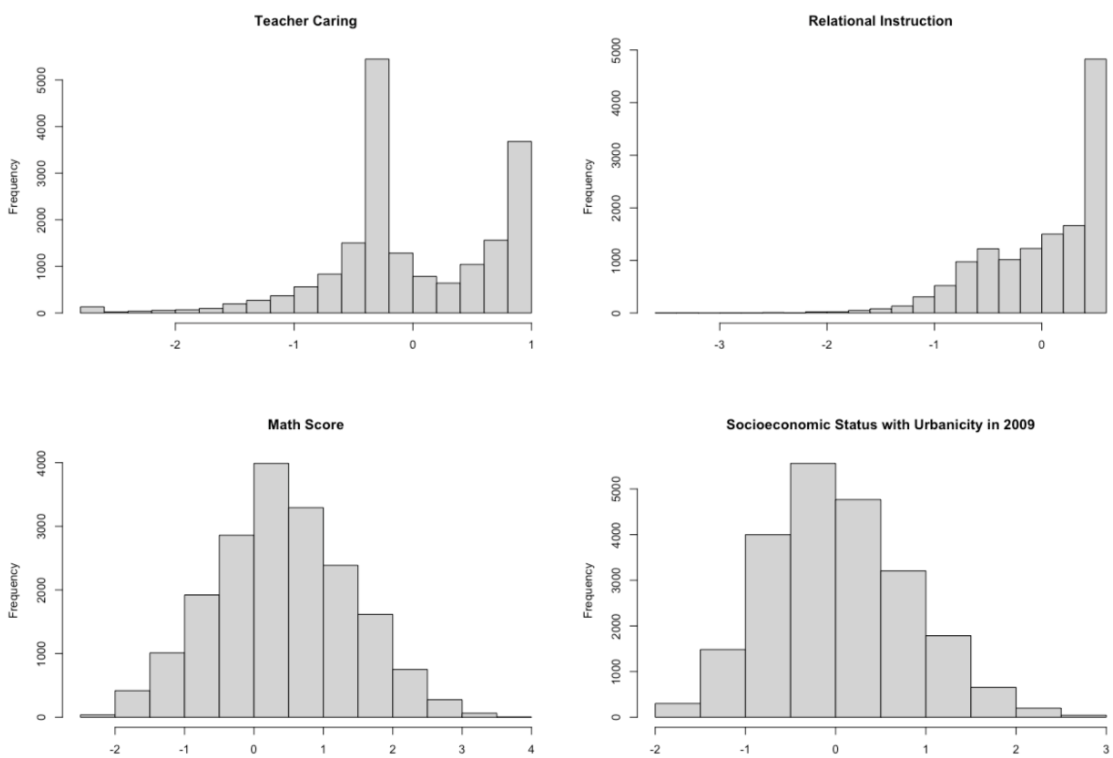
The teacher caring variable (N = 18580) measures student perceptions of the learning environment in their ninth-grade mathematics class. High values on this variable signify perceptions that a teacher (a) values and listens to students' ideas, (b) treats students with respect, (c) treats every student fairly, (d) believes every student can be successful, and (e) helps students understand that mistakes are okay if students learn. The items on this variable show strong internal reliability (α = .90) and variable values ranged from -2.60 to .90 with $\bar{X}$ = 0 and SD = .70. As seen by the histogram in Figure 7, this variable was negatively skewed (skew = -.58 with kurtosis = .72) suggesting most students felt their mathematics teachers did at least a fair job at creating caring environments. The students who had very negative perceptions and did not feel their teachers provided a caring environment were outliers.

Relational Instruction

The relational instruction variable (N = 13,580) measures the amount of emphasis mathematics teachers place on instruction which develops relational (conceptual) understanding in mathematics. High scores on this variable indicate a teacher who tries to

Figure 7

Histograms of the Four Continuous Independent Variables



SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study, 2009 (HSLS:09), "Baseline Year, Student Survey, 2009," "Baseline Year, Parent Survey, 2009," & "Baseline Year, Mathematics Teacher Survey, 2009."

(a) teach concepts, (b) develop problem-solving skills, (c) effectively explain ideas in mathematics, (d) connect mathematical ideas, (e) reason mathematically, and (f) teach the logical structure of mathematics. Though teachers rated the amount of emphasis they gave to each topic on a scale from 1 (*No* emphasis) to 4 (*High emphasis*) the labels for four of the items were combined in the HSLS:09 data set to create a new scale from 1 (*Little or no* emphasis) to 3 (*High* emphasis). The items show strong internal reliability ($\alpha = .79$) and scores on this variable ranged from -3.59 to .60 with $\bar{X} = 0$ and *sd* = .56. This indicates most mathematics teachers considered themselves as having a fairly strong focus on relational instruction. This variable was also negatively skewed (skew = -.96; kurtosis = .71) with extreme values representing teachers who gave little emphasis to relational instruction.

Socio-economic Status (SES)

The HSLS:09 variable of SES (*N* = 21,990) I used was a continuous composite variable that accounted for parent education level, occupation, income, as well as school locale. The variable was normally distributed (skew = .36, kurtosis = -.06) with a mean of .03, standard deviation of .79, minimum value of -1.92 and maximum value of 2.98. The histogram in Figure 7 shows a slight positive skew with extreme values representing students with higher SES.

Math Score

The MathScore variable (*N* = 18,620) records students' mean performance on the 2009 and 2012 HSLS:09 algebraic reasoning assessments. Just like the two original variables, the average scores are normally distributed (skew = .09, kurtosis = -.24) with a mean of .42 and standard deviation of .99. The correlations between the average variable and the scores from the two individual years are strong ($r_{2009} = .92$, $r_{2012} = .95$) suggesting students tended to have similar performance on the two assessments. Since the performance tends to be similar on both assessments, the use of an average score should provide an accurate way to control for student achievement in mathematics.

Gender/Race

The demographic variables of gender and race were student reported categorical variables provided in the HSLS:09 data. Gender was a dichotomous variable, and the race variable was condensed down to the six categories shown previously in Table 1.

Grade in Eighth-Grade Mathematics Class

Students in the HSLS:09 study self-reported the highest letter grade they received in their eighth-grade mathematics class. There were approximately 7730 students who reported getting As, 7820 who reported getting Bs, 3680 who reported getting Cs, 1030 who reported getting Ds, and 570 who reported getting below a D. Approximately 170 additional students indicated being in classes where they did not receive a grade. Overall, approximately 75% of the students who completed a graded mathematics class in eighth grade received a B or higher.

Research on self-concept suggests it is related to achievement and strengthened through successful experiences with mathematics (Marsh, 1992; Van der Beek et al., 2017). The norm referenced MathScore variable and the MathGrade8 variable can both be interpreted as indicators of students' achievement and successful experiences with mathematics, so I calculated Spearman correlations using complete observations between (a) students' eighth-grade mathematics grade and their self-concept in the fall of ninth grade, and (b) between students' scores on the algebraic reasoning assessment and their self-concept in ninth grade. There was a moderate positive correlation ($r = .40$) with grade in mathematics which means students with higher grades in their eighth-grade mathematics class were more likely to have stronger self-concepts in mathematics at the start of their freshman year. There was a similar moderate positive correlation between the 2009 algebraic reasoning assessment score and students' self-concept in ninth grade ($r = .42$). These results suggest a moderate positive relationship between students' achievement in mathematics and their self-concept.

Table 8 shows the correlations between the main study variables. The correlations between all measures of self-concept were moderately strong with the strongest correlation found between the second and third timepoints. The correlations show a positive but weak association between self-concept and the variables for caring teacher and relational instruction. This association is strongest at the first timepoint and then decreases as time passes. The correlations also show a moderate positive association between self-concept and the Math Score variable which is in harmony with current research.

Table 8

Descriptive Statistics and Spearman Correlations for Continuous Study Variables

Variable	*n*	*M*	*SD*	1	2	3	4	5	6	7
1. SES	21990	0	1	1						
2. MathScore	18620	.42	.99	.43	1					
3. Teacher Caring	18580	0	.70	.05	.09	1				
4. Relational Instruction	13580	0	.56	.14	.24	.06	1			
5. SC 1	21160	0	1	.13	.44	.19	.12	1		
6. SC 2	20020	0	1	.14	.45	.10	.10	.58	1	
7. SC 3	15690	0	1	.07	.37	.06	.08	.49	.61	1

Note. Per NCES requirement, all sample sizes are rounded to the nearest 10.

SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study, 2009 (HSLS:09), "Baseline Year, Student Survey, 2009," "Baseline Year, Parent Survey, 2009," "Baseline Year, Mathematics Teacher Survey, 2009," "First Follow-up, Student Survey, 2012," & "Second Follow-up, 2009."

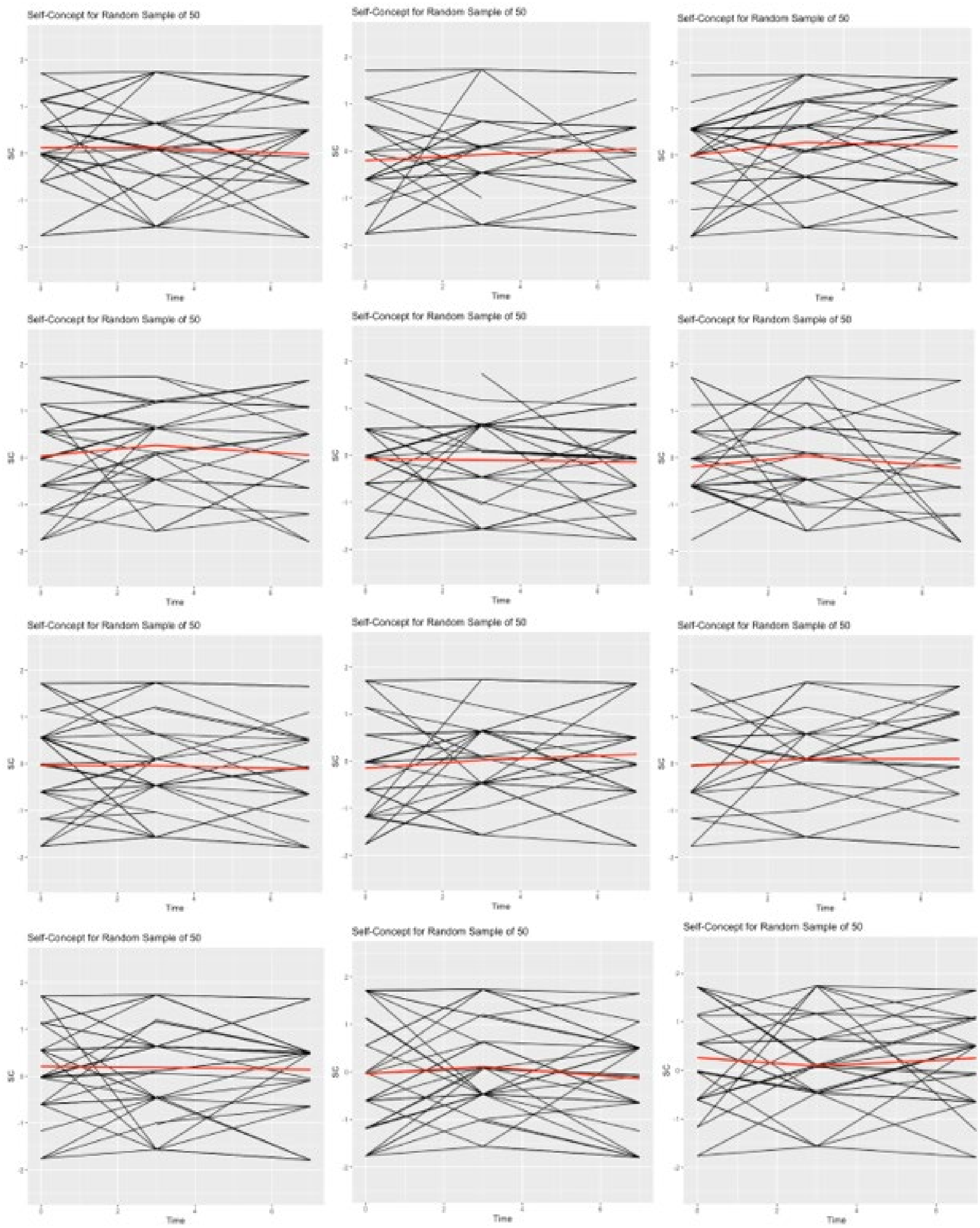
RQ1: Examining the Self-Concept Trajectory

Having completed the CFA and created variables to measure relational instruction and caring and supporting learning environments, I was ready to begin examining the trajectory of self-concept. I began by creating individual growth plots to compare to the growth of averages and visualize the direction of the self-concept trajectory. Because of the size of the dataset, a single plot of all participants would be unclear, so I plotted trajectories for random subsets of 50 participants. I resampled the data twelve times, creating new plots of 50 random participants each time, which are shown in Figure 8. In each plot, the black lines show individual change trajectories for the 50 subjects while the red line shows the average self-concept trajectory for the 50 subjects together. From the plots it is apparent that self-concept does not have a consistent trajectory. For many students the junior year (when wave 2 of the data was collected) marks a change point. Though the mean trajectory does not show substantial change, there was considerable variation in the individual trajectories. For some students, self-concept increased significantly between ninth and 11th grade and then decreased, while for others the opposite pattern is seen. These findings suggest that self-concept is not fixed when students enter high school but can be quite dynamic and illustrates the need for research which can determine the factors that exert the strongest influence on students' mathematics self-concept.

In addition to an aggregated average, I wanted to look at the growth trajectories with students subset into various demographic groups. Figure 9 shows the average trajectories of self-concept when comparing male and female students. On average, the

Figure 8

Growth Plots of Self-Concept with Curve of Averages for 12 Random Subsamples

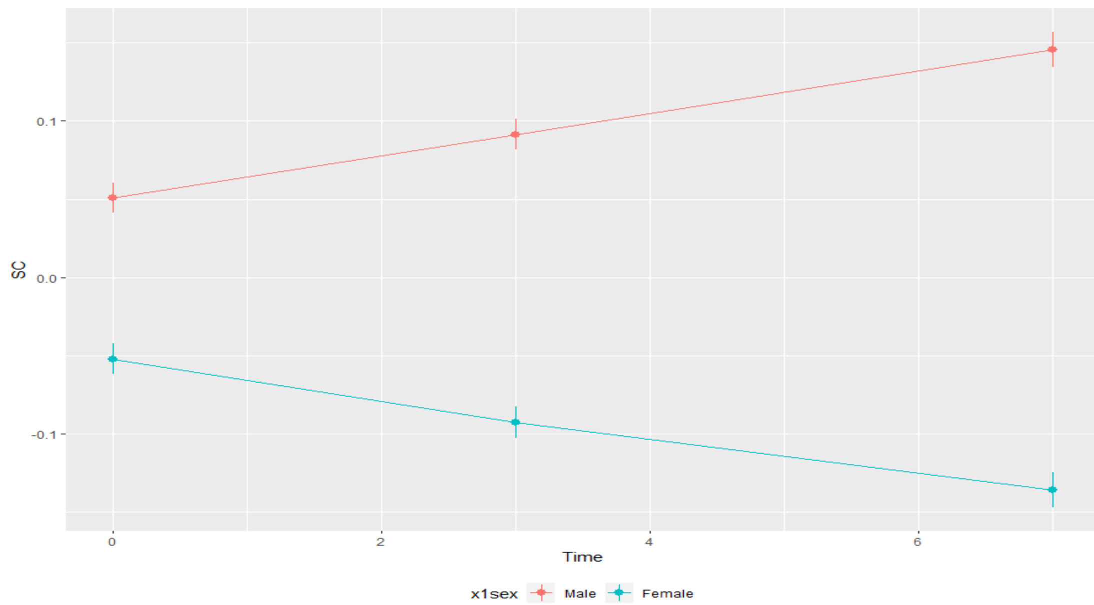


Note. The average trajectory for the random subsample is in red.

SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study, 2009 (HSLS:09), "Baseline Year, Student Survey, 2009," "First Follow-up, Student Survey, 2012," & "Second Follow-up, 2009."

Figure 9

Average Self-Concept by Gender

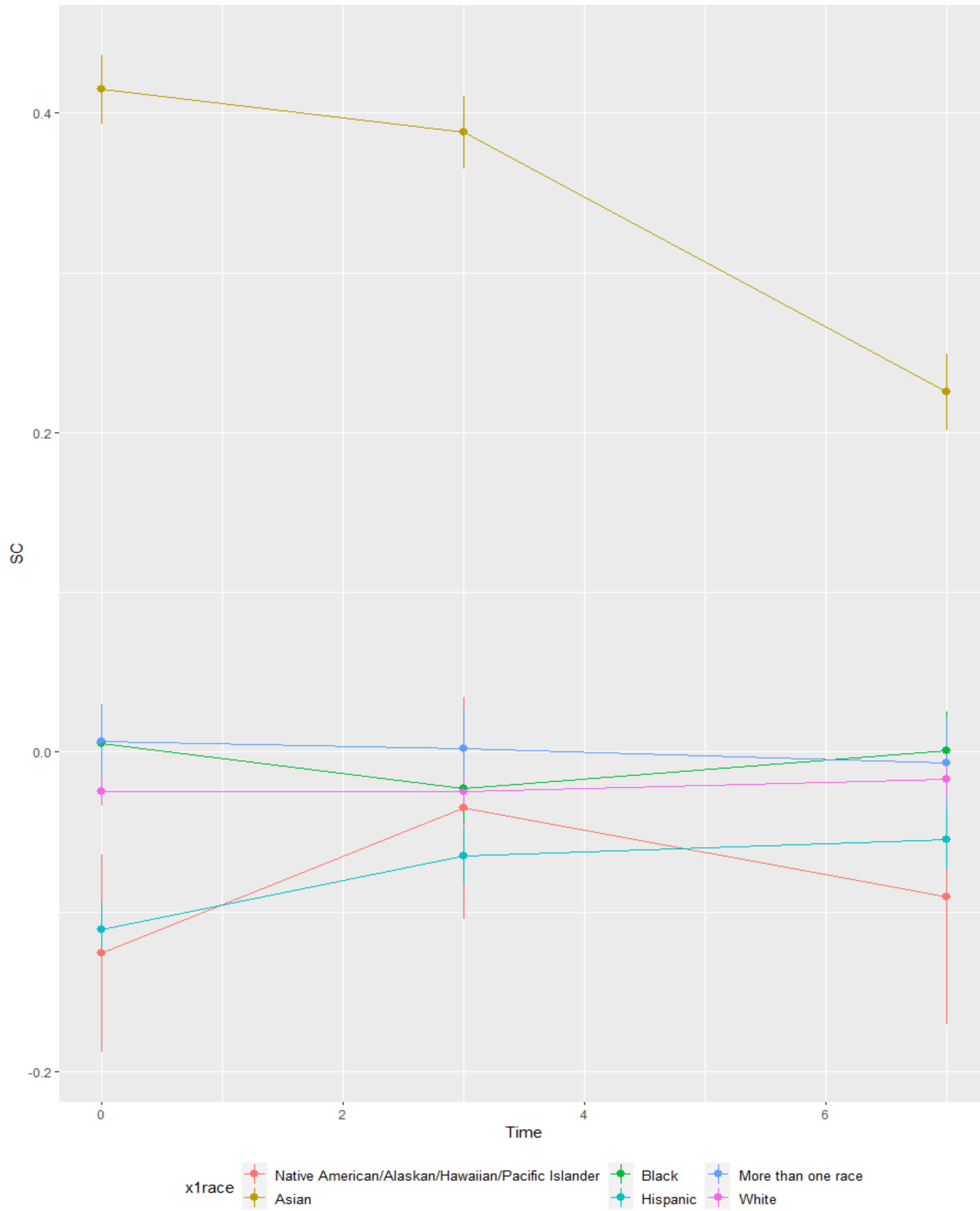


SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study, 2009 (HSLS:09), "Baseline Year, Student Survey, 2009," "First Follow-up, Student Survey, 2012," & "Second Follow-up, 2009."

self-concept of male students increased over time while that of female students decreased. Figure 10 shows the average self-concept trajectories of students when considered by racial identity. Asian students had much higher levels of self-concept at the start of high school when compared to all other racial groups, but their self-concept tended to decrease over time. The average trajectory for students who identified as Native American, Alaskan, Hawaiian, or Pacific Islander showed significant increase between 2009 and 2012 but then significant decrease between 2012 and 2016. This is a very heterogeneous group so it is not reasonable to draw any inferences from this observation. However, it suggests future research that takes a more nuanced approach would be beneficial. Black students showed an opposite average trajectory, first decreasing and

Figure 10

Average Self-Concept by Race



SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study, 2009 (HSLS:09), “Baseline Year, Student Survey, 2009,” “First Follow-up, Student Survey, 2012,” & “Second Follow-up, 2009.”

then increasing. However, the amount of change was smaller than that of Native American, Alaskan, Hawaiian, and Pacific Islanders with a total net change close to zero. The only other racial group which demonstrated noticeable change in the self-concept trajectory is Hispanic students. The average self-concept trajectory for students who identified as Hispanic increased across all time points. These results provide evidence supporting the idea that demographic factors, like race and ethnicity, can contribute increased variation in how students' self-concept develops. There are multiple possible explanations for this variance which will be discussed in the next chapter of this dissertation. However, these initial plots validate the inclusion of gender and race variables in the following multilevel model analysis.

The Multi-Level Models

To answer the final three research questions, I ran a series of multilevel models. I systematically added predictors to the models and compared model fit indices to determine which model best fit the data. Most models included both random slopes and random intercepts at the student level, allowing each student to have their own intercept and slope when predicting self-concept. At the third level, I compared models that included both random intercepts and random slopes with models which just included random intercepts. A random intercept at the school level would measure differences in the 2009 self-concept of students that result from being at different schools. A random slope at the school level would measure the variation in the slope of the self-concept trajectory that is a result of being at different schools. When predictors are included in the models, the random slopes and random intercepts measure variation which describes how well the predictor variables account for levels of self-concept when looking at individuals or schools.

The Unconditional Model

The first model (Model A) in my analysis was an unconditional intercepts-only model. This model did not include any predictors or random slopes but allowed for random intercepts at the individual and school levels. I ran this unconditional model as both a two-level and a three-level model to compare and see if the amount of variation due to students being nested within schools was large enough to warrant the three-level model. The AIC, BIC, and deviance statistics were all lowest with the three-level model, identifying it as the preferred model. To further validate using the three-level model, I ran a chi-squared test of significance which also indicated a statically significant improvement in using the three-level model ($\chi^2 = 50.021$, $p < .001$). The formula for this model was $Selfconcept_{tij} = \gamma_{000} + u_{00k} + \zeta_{0ij} + e_{tij}$ where γ_{000} represented the average self-concept for all students over time, ζ_{0ij} represented the deviation from the intercept at the student level, u_{00k} represented the deviation from the intercept at the school level*, and* e_{tij} reported the residual variance.

This unconditional intercepts-only model served as a baseline model and allowed me to use equations 3, 4, and 5 to calculate the intraclass correlation coefficients (ICCs) to determine the amount of variation found at each level of the model. The level 1 ICC was .413/1.003 = .411 which means 41.1% of the variation in self-concept was found at level 1. This describes the amount of variance in self-concept that was due to within subject change over time. The level 2 ICC was .571/1.003 = .569 which means 56.9% of the variation in self-concept was found at level 2. This between subject variation is due to individual level characteristics, or differences between students. The level 3 ICC was .019/1.003 = .019 which means only 1.9% of the variation in self-concept in this sample was found at level 3. This variation results from students being in different school environments. The high proportion of variance found at level 2 supported the need for a multilevel model and the inclusion of variables at the student level to help account for the variation.

I ran 14 models during the analysis and evaluated them using the AIC, BIC, and deviance statistics. For each model, Table 9 shows the structure of the model (fixed and random components) and the fit indices which I analyzed to identify the final model. I fit Model A using restricted maximum likelihood estimation (REML) but fit all succeeding models using full maximum likelihood estimation because they had different fixed effects (predictor variables). To ensure the results would be generalizable to the sample population, I weighted all variables using the HSLS analytic weight *w3w1mathtch*.

I ran chi-squared tests of significance using the anova function to compare models that included a random slope and intercept for schools with duplicate models that only included a random slope. For Models A, B, and C, the model that included a random slope at the school level showed statistical improvement over the random intercept only model ($\chi^2 = 16.04$, $df = 2$, $p < .001$). However, for the later models there was no statistically significant improvement from including a level 3 random slope, so evaluation of the models was based strictly on the fit indices.

Table 9

Summary of the Multi-Level Models with Model Fit Indices

Model components	A	B	B.0	C	C.0	D	D.0	E	E.0	F1	F2	G1	G2	H
Fixed Effects														
Time		X*	X*	X*	X*	X*	X*	X*	X*	X*	X*	X*	X*	X*
Gender				X*	X*	X*	X*	X*	X*	X*	X*	X*	X*	X*
Race				X*	X*	X*	X*	X*	X*	X*	X*	X*	X*	X*
SES				X*	X*	X*	X*	X	X	X	X	X	X	X
MathScore				X*	X*	X*	X*	X*	X*	X*	X*	X*	X*	X*
MathGrade8				X*	X*	X*	X*	X*	X*	X*	X*	X*	X*	X*
TC						X*	X*	X*	X*	X*	X*	X*	X*	X*
RI								X	X	X	X	X	X	X
Interactions														
TC:Gender										X				
TC:Race												X		
RI:Gender											X			
RI:Race													X*	
RI:TC														X
Random Effects														
Int|Student	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Slope|Student		X	X	X	X	X	X	X	X	X	X	X	X	X
Int|School	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Slope|School		X		X		X		X						
AIC	—	542706	542726	390055	390067	332239	332246	119954	119953	119956	119950	119968	119959	119955
BIC	—	542786	542788	390381	390375	332578	332567	120288	120271	120290	120284	120367	120358	120289
Deviance (-2LL)	—	542688	542712	389981	389997	332161	332171	119872	119875	119874	119868	119870	119861	119873

Note. TC-TeacherCaring, RI-Relational_Instruction.

*Denotes statistically significant effect of variable in random slope or intercept ($p < .01$).

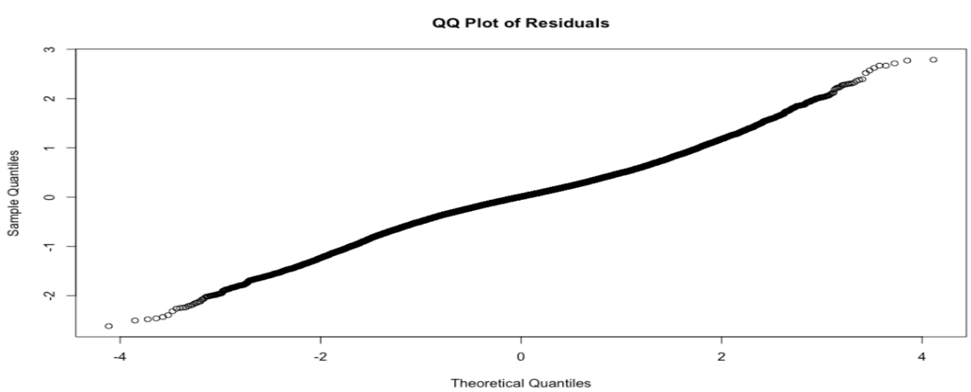
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study, 2009 (HSLS:09), “Baseline Year, Student Survey, 2009,” “Baseline Year, Parent Survey, 2009,” “Baseline Year, Mathematics Teacher Survey, 2009,” “First Follow-up, Student Survey, 2012,” & “Second Follow-up, 2009.”

There was substantial improvement in the AIC, BIC, and deviance statistics with the addition of all control variables and the two target predictors of teacher caring and relational instruction. The models that included interaction terms did not show significant improvement in the fit indices but model G2 had a statistically significant interaction between race and relational instruction. Though model G2 did not have the lowest values on the AIC and BIC, it did have the lowest deviance value (AIC = 119959, BIC = 120358, -2LL = 119861). The significant interaction and the low values on the fit indices provide statistical support for using model G2 as my final model and interpreting the influence of relational instruction and teacher caring using its parameters.

Before interpreting the model, I checked to be sure it met the assumptions that the residuals were independent and normally distributed. The QQ-plot in Figure 11 shows the residuals close to a normal distribution and the plot of residuals in Figure 12 shows no obvious pattern, which means the residuals are independent.

Figure 11

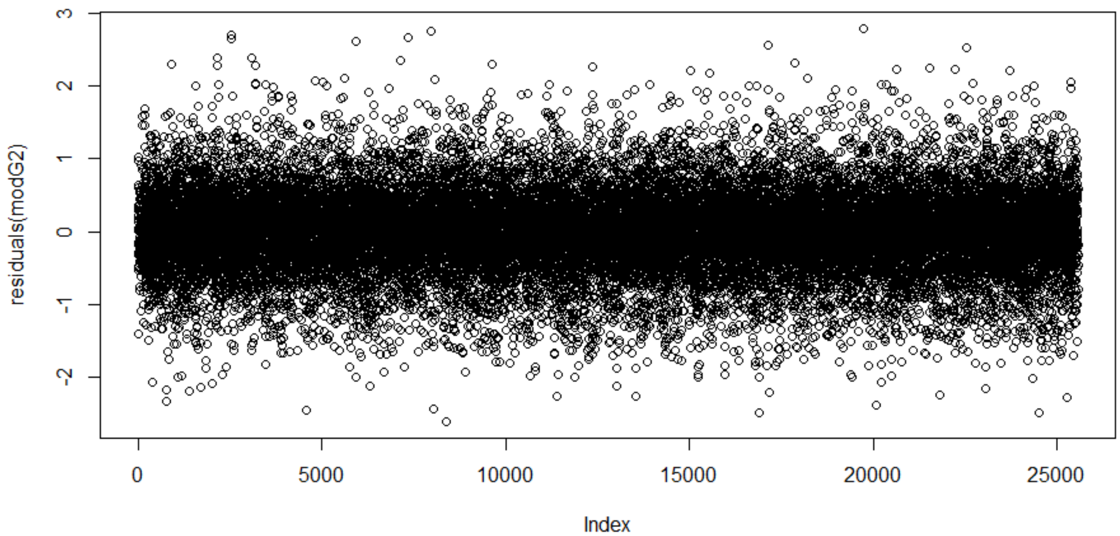
QQ-Plot to Check Normal Distribution of Residuals (modG2)



SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study, 2009 (HSLS:09), “Baseline Year, Student Survey, 2009,” “Baseline Year, Parent Survey, 2009,” Baseline Year, Mathematics Teacher Survey, 2009,” “First Follow-up, Student Survey, 2012,” & “Second Follow-up, 2009.”

Figure 12

Plot of Residuals (modG2)



SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study, 2009 (HSLS:09), "Baseline Year, Student Survey, 2009," "Baseline Year, Parent Survey, 2009," Baseline Year, Mathematics Teacher Survey, 2009," "First Follow-up, Student Survey, 2012," & "Second Follow-up, 2009."

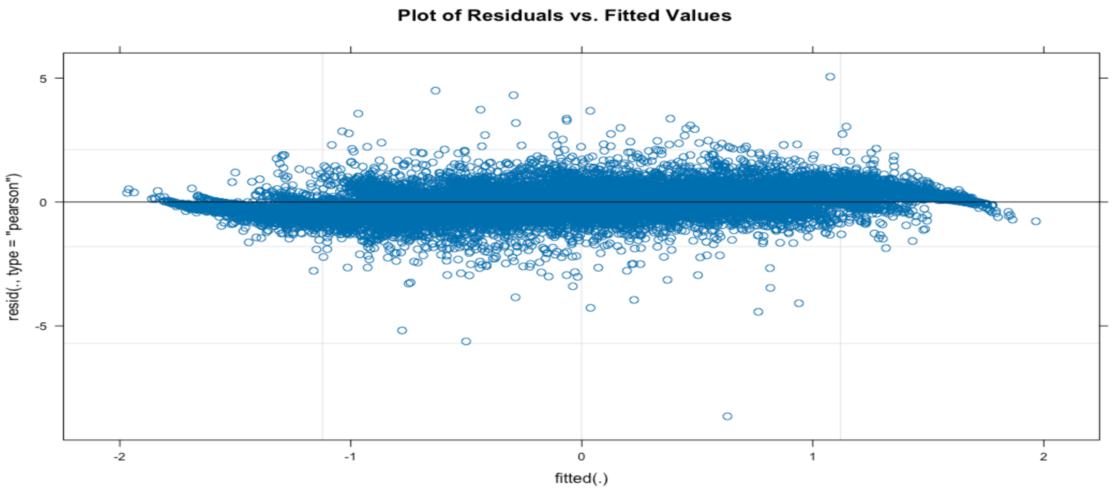
The plot in Figure 13 plots the residuals against the predicted values for the model. Since there is no visible pattern in the graph, the level 1 residuals appear to be homogeneously distributed which indicates good model fit. Because the diagnostic charts indicate the assumptions are met, I now interpret the model parameters to answer the final three research questions.

Interpreting the Final Model to Answer RQ2 – RQ4

Before specifically addressing the final three research questions, I explain some preliminary results seen in the models depicted in Table 10. As seen in the table, each of the independent variables appears multiple times. When the variable appears alone it represents the predicted contribution that variable makes to the intercept of an

Figure 13

Plot of the Residuals vs. Fitted Values for Final Model



SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study, 2009 (HSLS:09), "Baseline Year, Student Survey, 2009," "Baseline Year, Parent Survey, 2009," Baseline Year, Mathematics Teacher Survey, 2009," "First Follow-up, Student Survey, 2012," & "Second Follow-up, 2009."

individual's self-concept (SC) trajectory. Since the first wave of data collection was in 2009 the intercept represents a student's mathematics self-concept in the fall of their freshman year. The second time each variable appears in the model it is part of an interaction with time, so it signifies the contribution the variable makes to the change in self-concept over time, or the slope of the self-concept trajectory. Table 10 illustrates how each control variable had a statistically significant effect on both the ninth-grade self-concept (intercept) and the rate at which a student's self-concept changed over time (slope). Because the variables are reported in standard deviation units, I found the percent change attributable to each predictor by dividing the predictor estimate by the range of the self-concept variable (3.48). In the next section, I briefly explain the association between self-concept and each control variable included in the analysis.

Table 10

All Parameter Estimates for Six Main Models

	Model A		Model B.0		Model C.0		Model D.0		Model E.0		Model G2.0	
Predictors	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*
(Intercept)	0.01	.01	0.02	.01*	0.21	.02***	0.20	.02***	0.19	.02***	0.19	.02***
Time			-0.00	.00**	-.02	.00***	-.02	.00***	-.02	.00***	-.02	.00***
SES					-0.10	.01***	-0.10	.01***	-0.11	.01***	-0.11	.01***
Gender [Female]					-0.13	.02***	-0.14	.02***	-0.15	.02***	-0.15	.02***
Math Grade 8 [B]					-0.39	.02***	-0.38	.02***	-0.37	.02***	-0.37	.02***
Math Grade 8 [C]					-0.69	.03***	-0.68	.03***	-0.67	.03***	-0.67	.03***
Math Grade 8 [D]					-0.79	.04***	-0.77	.04***	-0.77	.04***	-0.77	.04***
Math Grade 8 [Below D]					-0.88	.06***	-0.86	.06***	-0.86	.06***	-0.86	.06***
Math Grade 8 [Not graded]					-0.57	.09***	-0.53	.10***	-0.42	.12***	-0.42	.12***
Race [Native Am/Ala/Haw/PI]					0.15	.08	0.13	.09	0.10	.10	0.11	.11
Race [Asian]					0.12	.04***	0.11	.04**	0.11	.05*	0.11	.05*
Race [Black]					0.28	.03***	0.27	.03***	0.29	.04***	0.30	.04***
Race [Hispanic]					0.10	.02***	0.09	.03***	0.08	.03**	0.08	.03**
Race [>1 race]					0.05	.03	0.06	.03*	0.10	.04**	0.10	.04**
Math Score					0.37	.01***	0.36	.01***	0.36	.01***	0.36	.01***
Time × SES					-0.00	.00	-0.01	.00*	-0.00	.00	-0.00	.00
Time × Gender [Female]					-0.02	.00***	-0.02	.00***	-0.02	.00***	-0.02	.00***
Time × Math Grade 8 [B]					0.03	.00***	0.03	.00***	0.02	.00***	0.02	.00***
Time × Math Grade 8 [C]					0.05	.01***	0.05	.01***	0.05	.01***	0.05	.01***
Time × Math Grade 8 [D]					0.09	.01***	0.08	.01***	0.08	.01***	0.08	.01***
Time × Math Grade 8 [Below D]					0.09	.01***	0.09	.01***	0.08	.02***	0.08	.02***
Time × Math Grade 8 [Not graded]					0.04	.02*	0.03	.02	0.02	.03	0.02	.03
Time × Race [Native Am/Ala/Haw/PI]					0.00	.02	0.01	.02	0.04	.02	0.04	.02
Time × Race [Asian]					-0.02	.01*	-0.02	.01*	-0.02	.01	-0.01	.01
Time × Race [Black]					-0.01	.01	-0.01	.01	-0.01	.01	-0.01	.01

(*table continues*)

	Model A		Model B.0		Model C.0		Model D.0		Model E.0		Model G2.0	
Predictors	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*
Time × x1race [Hispanic]					0.00	.00	0.00	.01	0.01	.01	0.01	.01
Time × Race [> 1 race]					0.00	.01	-0.00	.01	-0.00	.01	-0.00	.01
Time × Math Score					0.01	.00**	0.01	.00***	0.01	.00**	0.01	.00**
Teacher caring							0.19	.01***	-.18	.01***	-.18	.01***
Time × Teacher caring							-0.03	.00***	-0.03	.00***	-0.03	.00***
RI									0.01	.02	-0.02	.02
Time × RI									-0.00	.00	0.01	.00
Race [Native Am/Ala/Haw/PI] × RI											0.06	.16
Race [Asian] × RI											0.04	.09
Race [Black] × RI											0.08	.06
Race [Hispanic] × RI											0.10	.05*
Race [> 1 race] × RI											.09	.06
(Time × Race [Native Am/Ala/Haw/PI]) x RI											-.02	.03
(Time × Race [Asian]) × RI											-.02	.02
(Time × Race [Black]) × RI											-.01	.01
(Time × Race [Hispanic]) × RI											-.02	.01*
(Time × Race [> 1 race]) × RI											-.04	.01**
Random effects												
σ^2	0.41		0.21		0.24		0.25		0.40		0.40	
$\tau_{00\ (student)}$	0.57		0.78		0.51		0.48		0.43		0.43	
(school)	0.02		0.02		0.01		0.01		0.01		0.01	
$\tau_{11\ (student \mid Time)}$			0.02		0.02		0.02		0.01		0.01	

Note. Native Am/Ala/Haw/PI = Native American/Alaskan/Hawaiian/Pacific Islander, RI=Relational instruction. Intercept refers to average self-concept trajectory for a white male student who received an A in their eighth-grade mathematics course and has mean level values of SES, MathScore, Relational instruction, and Teacher caring. For final model $N_{students}$ = 9500, $N_{schools}$ = 830.

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study, 2009 (HSLS:09), "Baseline Year, Student Survey, 2009," "Baseline Year, Parent Survey, 2009," "Baseline Year, Mathematics Teacher Survey, 2009," "First Follow-up, Student Survey, 2012," & "Second Follow-up, 2009."

Influence of the Control Variables

A student's gender had a statistically significant association with ninth-grade self-concept as well as the change in self-concept over time. In each model, female students had lower predicted self-concept in ninth grade when compared to male students by approximately 4.31% ($\beta = -.15$, $p < .001$), when keeping all other predictors constant. Additionally, the self-concept of female students decreased at a slightly faster rate than it did for male students ($\beta = -.02$, $p < .001$). These results indicate female students start high school with lower mathematics self-concept than their male counterparts and their self-concept decreases more quickly.

Students' race also had a statistically significant association with self-concept. Students who identified as Black, Hispanic, or Asian had higher predicted levels of mathematics self-concept in ninth grade when compared to their white peers. This difference was strongest for Black students ($\beta = .30$, $p < .001$) who had predicted levels of self-concept approximately 8.62% higher than white students in the final model. The influence of race was not seen when considering the slope of the self-concept trajectory for Black or Hispanic students and only showed significance for Asian students in models B and C. Once the variables for relational instruction and teacher caring were included, race no longer influenced the change in self-concept over time. There was no statistically significant influence on self-concept for students who identified as Native American, Alaskan, Hawaiian, or Pacific Islander. However, the sample for this group was small so it is likely there was not sufficient statistical power to detect an effect even if one existed. Additionally, combining so many racial groups resulted in a heterogeneous category that would not be theoretically reasonable to interpret so I chose not to make any inferences regarding this racial category. The racial category *more than one race* also had a statistically significant positive influence on student self-concept in ninth grade ($\beta = .10$, $p < .001$), but this effect was only seen in the later models that included teacher caring and relational instruction. It was not significant in Model C which only included the control variables. Due to the many ways students may consider themselves to be of more than one race, this category can also be difficult to interpret. The research does not suggest any common characteristics or shared experiences that would relate to all multiracial students. Further research would need to be done which could take a more detailed look at race to determine any possible relationship between self-concept and these more heterogeneous racial categories.

Student SES had a statistically significant relationship with self-concept in ninth grade ($\beta = -.11$, $p < .001$) but it did not significantly influence the change in self-concept over time. Surprisingly, the relationship between SES and self-concept was a negative one where students who came from higher SES homes had lower levels of self-concept. A one standard deviation increase on the SES scale was associated with a decrease in ninth-grade self-concept of about 3.16%.

In alignment with the correlations reported previously, the multi-level regression results show a significant predictive effect of the grade students received in their eighth-grade mathematics class and their ninth-grade self-concept. Students in all groups had predicted values of self-concept in 2009 significantly lower than students who received an A in their eighth-grade mathematics class and the effect increased as the grade dropped lower and lower. Students who had received a B in eighth grade had self-concept approximately 10.63% lower than those who received an A. Students who received a C, D, or below D had self-concept in 2009 approximately 19.25%, 22.13%, and 24.71% respectively lower than students who received an A the year before. A significant negative effect on ninth-grade self-concept was also associated with being in an ungraded class but the reason for students being in an ungraded class is unclear so these results are not interpretable in terms of influencing students' mathematics self-concept. Overall, the higher the grade a student received in their eighth-grade mathematics course, the higher their self-concept was at the start of ninth grade.

The grade a student received in their eighth-grade mathematics class also had a statistically significant influence on change in self-concept over time, but it was in the opposite direction. While keeping all other covariates constant, the lower the grade a student received in eighth grade, the more quickly their self-concept grew over time. Students who received lower than an A had predicted increases in their self-concept .57% - 2.30% more each year when compared to students who received an A. This result is not terribly surprising. It is reasonable that the greatest growth in self-concept would be predicted in students who started with the lowest self-concept. Students who had the most negative experiences in their eighth-grade mathematics class are likely to have more positive experiences in later years which would contribute to increased self-concept over time.

The second measure of student achievement, students' scores on the algebraic reasoning assessment, was also a statistically significant predictor of mathematics self-concept and had the strongest effect on students' self-concept in ninth grade (β = .36, $p <$ .001). Holding all other predictors constant, an increase of one standard deviation higher on the algebraic reasoning assessment was associated with approximately a 10.34% increase in self-concept in ninth grade. When considering the influence performance on the algebraic reasoning assessment had over time, there is a small but significant effect (β = .01, $p < .01$). In addition to having higher initial self-concept in ninth grade, students who scored one standard deviation higher on the algebraic reasoning assessment had their self-concept grow approximately .29% per year faster.

In accordance with the current literature, each of the control variables had a significant influence when predicting both initial levels of self-concept in ninth grade and the rate of change in self-concept over time. Because the control variables were all level-2 predictors, I examined the proportion of residual level-2 variance explained by including these predictors using the formula (Singer & Willett, 2003):

$$Pseudo\ R^2 = \frac{\tau_{00\ (Model\ B.0)} - \tau_{00\ (Model\ C.0)}}{\tau_{00\ (Model\ B.0)}} \qquad (12)$$

Applying this formula reveals that an additional 34.62% of the between-subjects variance was explained by the addition of these control variables. Therefore, including these variables while investigating the influence of relational instruction and the creation of a caring and supportive classroom environment will help isolate the influence these new variables have on student self-concept.

The Influence of Relational Instruction and a Caring Learning Environment

Model D added the level-2 variable of Teacher Caring which was a statistically significant predictor of student self-concept in ninth grade (β = .19, $p < .001$). This model explained an additional 38.46% of the between-subject variance when compared to the unconditional growth model which means this predictor alone explained approximately 3.84% of the between-subjects variance. Keeping all other variables constant, a one standard deviation increase in students' perceptions of having a caring and supportive mathematics teacher predicted an increase of approximately 5.46% in mathematics self-concept in the fall of ninth grade. However, this effect does not appear to be lasting because that same standard deviation increase in Teacher Caring in ninth grade was also associated with an additional .86% decline in self-concept each year after ninth grade (β = -.03, $p < .001$). Models F1 and G1 (not shown above) included interactions terms for student gender and Teacher Caring as well as student race and Teacher Caring but the interactions were not statistically significant. This indicates a student's perception of having a caring and supportive classroom environment had a similar effect for all students regardless of their gender or racial identity.

Model E added the level-2 variable of relational instruction. This variable did not show statistical significance, however, this model explained an additional 44.87% of the between-subject variance when compared to the unconditional growth model. This means that the addition of relational instruction as a predictor explained an approximately 6.41% of the between-subject variation. The decrease in unexplained variance, along with the sharp drop in all three fit indices suggest that relational instruction is in fact a significant predictor of self-concept. Statistical significance is often determined in statistical software by conducting Wald tests, but these are often inaccurate in longitudinal analyses where variables are allowed to violate the assumption of normality (Singer & Willett, 2003). The relational instruction variable used in this analysis was negatively skewed so the Wald test is not expected to be accurate. Therefore, I accepted relational instruction as statistically significant and continued with my planned outline, running models that included interactions with gender (Model F2) and race (Model G2). I did not find a significant interaction between gender and relational instruction but Model G2 revealed a statistically significant interaction with race in the random intercept ($\beta_{HispanicXRelational\_Inst}$ = .1, $p < .05$) and the random slope ($\beta_{HispanicXRelational\_InstXTime}$ = -.02, $p < .05$). Hispanic students whose ninth-grade teacher placed greater emphasis on relational instruction had a predicted self-concept in ninth grade about 2.87% higher than Hispanic students whose teachers only provided an average level of relational instruction.

A statistically significant interaction also occurred for students who identified as more than one race. For these students, relational instruction did not predict their self-concept in ninth grade, but their self-concept decreased over time by an additional 1.15% a year (β = -.04, $p < .01$). The interaction for both races is shown visually in Figure 14 but as previously discussed, any effects related to students having a multiracial identity is not interpretable so I limit my interpretation to students who identified as Hispanic. This chart shows how the relationship between relational instruction and race changes over time. In ninth grade, white students whose teachers placed greater emphasis on relational instruction had weaker predicted self-concept than white students whose teachers did not emphasize relational instruction, but the opposite trend is seen for Hispanic students. For Hispanic students, having a teacher who emphasized relational instruction predicted higher levels of self-concept. This pattern is repeated for Hispanic students during their junior year, but not for multi-racial students. For Hispanic students, having a teacher in ninth grade who emphasized relational instruction continued to predict higher levels of self-concept two and a half years later.

Figure 14

Plot Showing the Interaction Between Race and Relational Instruction Over Time

SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study, 2009 (HSLS:09), “Baseline Year, Student Survey, 2009,” “Baseline Year, Mathematics Teacher Survey, 2009,” “First Follow-up, Student Survey, 2012,” & “Second Follow-up, 2009.”

This positive trend does not continue into 2016 though. The graph of the third timepoint, which occurred two or three years after students left high school, shows an opposite result. At this timepoint relational instruction appears to positively predict self-concept for white students and negatively predict self-concept for Hispanic students. As this final timepoint occurs six years after leaving the mathematics class where relational instruction was measured, it is not reasonable to conclude relational instruction is continuing to have an effect. At this point in students' lives they are either continuing their education or have entered the workforce where other factors may be more influential in shaping their mathematics self-concept. Therefore, the relationship at the third timepoint should be considered critically and will not be discussed further in this dissertation.

The interaction with the most statistical strength relates to how relational instruction predicts self-concept for Hispanic students. The trend for Hispanic students was consistent across the first two timepoints suggesting that relational instruction had a positive influence on the mathematics self-concept of Hispanic students. Holding all other variables constant, Hispanic students whose mathematics teachers emphasized relational instruction had higher predicted levels of self-concept when compared to their Hispanic peers whose teachers did not emphasize relational instruction.

Interpreting the Random Effects

The fixed effects in the multi-level models contain the information relevant to answering the research questions posed in this dissertation. The random effects are not directly relevant to the research questions but were necessary to control for the clustered nature of the data. Though the random effects are not immediately relevant to answering the research questions, I briefly explain what they signify and any trends that appeared in the analysis.

The first random effect reported is σ^2 and represents the amount of unexplained variability at level 1. It explains how much an individual's predicted self-concept varies around their true change trajectory. This value was about .25 standard deviations until relational instruction was introduced as an independent variable at which point it jumped to .4 standard deviations. This is a high proportion of within person variability that could indicate the need for additional time-varying covariates at level 1 to help explain the within person variability.

The effects τ_{00} and τ_{01} represent the amount of between person variability in the random intercept and the random slope after controlling for all level-2 covariates and their interactions with time. Since $\tau_{00} = .43$ there is a substantial amount of between subject variability even after controlling for gender, race, SES, past achievement, perceptions of teacher caring and relational instruction. The amount of variability in the random slope is small ($\tau_{01} = .01$), which indicates students' true self-concept trajectories change very closely to the predicted rate. This means that although the covariates are not adequate for predicting a student's starting self-concept in ninth grade, they are fairly accurate at predicting how the self-concept will change over time.

Overall, the results of the CFA and multi-level analysis bring additional clarity to our understanding of mathematics self-concept and how it develops. The examination of the self-concept trajectory showed self-concept to be a dynamic construct which is subject to change throughout high school and moderated by student race and gender. These results set the stage for the multi-level model stage of the analysis which found a positive relationship between creating a caring and supportive learning environment and student self-concept for all student groups. Evaluation of model fit suggests relational instruction was also significant in predicting self-concept and further analysis revealed a significant interaction with race which showed that Hispanic students in the sample were more strongly influenced by having a mathematics teacher who taught in a way that focused on building relational understanding.

CHAPTER V

DISCUSSION

The purpose of this dissertation was to investigate how relational instruction and the creation of caring learning environments contributed to the development of student mathematics self-concept, and how those variables influenced students differently according to various demographic characteristics. The multi-stage analysis produced findings which clarified the nature of mathematics self-concept development, displayed a positive association with both caring and supportive learning environments and relational instruction, and revealed an interaction with race which suggests the self-concept of Hispanic students would especially benefit from teachers who place emphasis on relational instruction. In the following chapter I discuss the significance of each of these findings along with implications and suggestions for future research. However, before discussing the main findings I discuss interesting findings from the CFA analysis.

Findings from the CFA

Though not the focus of this research, the CFA results are worth mentioning because they provide insight into the main predictors of relational instruction and caring and supportive learning environments. The six items from the math teacher survey created a strong variable for measuring relational instruction. The coefficient alpha was high which indicated strong internal reliability, the inter-item correlation was in the ideal range for creating a scale variable, and the factor loadings for most items were high, which means the items strongly contributed to the composite variable. The item about placing emphasis on teaching mathematical concepts was the weakest with a factor loading of only .59 but that is well above the minimum factor loading value of .3 (Tavakol & Wetzel, 2020) so it still relates strongly to the composite variable.

There is a theoretical explanation that may explain why the teaching mathematical concepts item had the weakest factor loading. There is a current push in mathematics education to focus on teaching students concepts instead of just procedures (see NCTM, 2014; Rodríguez-Martínez et al., 2020; Russell et al., 2020). This emphasis is discussed in both popular and academic writing and has likely been a topic for many professional development programs (see Boaler, 2015; Stein et al., 2013). This emphasis could contribute to teachers being more likely to rate themselves as having a strong emphasis on teaching concepts, possibly contributing to an inflated value on the teaching mathematical concepts item which would cause it to not align with results on the other five items. This would happen if teachers rated themselves highly on teaching mathematical concepts even though they were less likely to emphasize other aspects of relational instruction. Another possible explanation for the weak factor loading on the teaching mathematical concepts item is that the idea of focusing on concepts is somewhat vague and abstract so teachers may not have known how to evaluate their emphasis. Though the lower factor loading on the teaching mathematical concepts item was surprising, it was still high enough to support its inclusion in the composite variable and the loadings on the other five items were strong enough to support the use of the relational instruction variable. Future research should be aware, however, of the possibility that self-reports by teachers of how much emphasis they put on teaching mathematical concepts may be influenced by ongoing conversations and contribute to inflated responses.

Though the teaching mathematical concepts item did not align as well as expected with the relational instruction variable, the other items on the scale all had strong factor loadings and provided an effective scale for measuring relational instruction. I have not been able to find an existing scale for measuring relational instruction and though the creation and validation of an official scale is beyond the scope of this dissertation, this composite variable can serve as a starting point in the development of such a scale. Aside from scale or variable creation, the results from the CFA help to operationalize the idea of relational instruction. Like conceptual teaching, relational instruction is a vague, abstract concept and even if teachers want to provide such instruction in their classes, they may struggle in knowing how to do that. The items in the composite variable suggest that if teachers focus on problem solving, connecting mathematical ideas, mathematical reasoning, the logical structure of mathematics, and explaining mathematical ideas, then they will be providing relational instruction. These less abstract, more observable ideas are easier to define, teach in professional development, observe, and incorporate into lesson plans. Though future research should work towards developing and validating an official scale to measure relational instruction, the findings in this dissertation provide not only a starting point for scale development, but also a more operationalized understanding of relational instruction which can be used to plan teacher training and professional development.

Findings Related to the Self-Concept Trajectory

The first research question in this dissertation concerns the trajectory of mathematics self-concept as students progress through high school and past graduation. One significant finding is that students' mathematics self-concept is dynamic and can change considerably throughout high school. This finding contradicts previously held beliefs that self-concept becomes stable around eighth grade and is not as prone to change in high school (Harter, 1990; Shavelson et al., 1976; Simmons & Blyth, 1987). This is important because the belief that self-concept becomes stable as students get older contributes to a failure to look for ways to strengthen self-concept in high school. This dissertation study was unique in that it mapped the self-concept trajectory over a period that covered students' entire experience in high school. Longitudinal research on self-concept is rare and students in elementary and middle grades are usually the target population (see Arens et al., 2017; Viljaranta et al., 2014). While preparing for this research, I was unable to find longitudinal studies which examined the self-concept of high school students. Understanding the dynamic nature of self-concept in the higher grades may act as a catalyst to place renewed focus on research designed to increase self-concept for students in mathematics classes from ninth through 12th grade. As students go through high school, they spend more time thinking about what they want to do as a career. Because self-concept is positively associated with enjoyment in mathematics (Van der Beek et al., 2017) and strongly predicts entry into STEM fields (Eccles & Wang, 2016; Goldman & Penner, 2016), a focus on improving mathematics self-concept among students at this time in their lives may encourage more students to pursue further study in mathematics related fields.

Although the data shows self-concept to still be dynamic in high school there is evidence that self-concept stabilizes over time. With repeated measurements it is typical that correlations are strongest when measures are separated by shorter amounts of time. Measurements that have a longer window of time between them typically have weaker correlations. However, this was not the case when examining self-concept. Though there was a smaller window of time between the first two timepoints, the correlation between those measures of self-concept was weaker than the correlation between the second two measures of self-concept, indicating less change between the second two time points. This supports the theory that students' self-concept is more dynamic in their younger teenage years but then becomes more stable as they approach adulthood (Harter, 1990; Marsh, 1990). However, though the results of this dissertation do indicate that change in self-concept decreases in magnitude as students get older, the direction of the change still fluctuates. This finding should not be taken as evidence that self-concept itself becomes more stable, or resistant to change, as students age. That is possible, but it is also possible that as students reach their later high school years their experiences in mathematics become more stable, maintaining the status quo. Tracking practices which separate students into perceived ability levels are common in U.S. schools and movement from a lower track into a higher one is extremely difficult. Unfortunately, the learning experiences at the various levels can differ considerably in such a way that experiences in a certain class could serve to reinforce students' current self-concept. The self-concept trajectories in this paper show a general convergence for different student groups after leaving high school. This could be interpreted as evidence that self-concept changes less in the later high school years partially because of the current educational practices that maintain the status quo. Then, following high school, self-concept adjusts because students' experiences change. Future research should consider how student experiences in different levels of mathematics classes differ in high school and how those differences influence student self-concept. It is important that educators are always working to strengthen student self-concept and never reinforcing negative student self-beliefs.

Findings Related to the Influence of Relational Instruction and Caring Learning Environments

Bong and Skaalvik (2003) called for further research which would identify contributors to self-concept, which are distinct from student perceptions of competence. In this dissertation I responded to their call in the second and third research questions, investigating the association between self-concept and relational instruction as well as the association between self-concept and the creation of caring and supportive learning environments. Both relational instruction and the creation of caring and supportive learning environments had positive relationships with self-concept for all students, meaning that students who experienced more caring and supportive learning environments, or had mathematics teachers who provided higher levels of relational instruction, were more likely to have higher levels of self-concept. This aligns with research which found that mathematics self-concept had stronger associations with emotions than with achievement (Van der Beek et al., 2017). A detailed understanding of the relationship between self-concept and caring and supportive learning environments cannot be determined from this dissertation. It may be that as students' self-concept increases, they experience the classroom environment in a way that increases their perception of a caring and supportive learning environment. Conversely, it could be that as teachers create a more caring and supportive learning environment, their students experience more support and success which leads to an increase in self-concept. I hypothesize a reciprocal relationship like the one observed between mathematics anxiety and self-concept (Ahmed et al., 2012). However, whereas Ahmed et al. found the pathway from self-concept to anxiety to be the more powerful of the two directions, I predict that student perceptions of having a caring and supportive learning environment will have a more powerful effect on self-concept while self-concept will only have a minor effect on students' perceptions of the learning environment. More research is needed to confirm the way the relationship between self-concept and caring and supportive learning environments functions, but these findings suggest the need for teachers to be deliberate in creating classroom environments where students feel listened to, respected, and treated fairly. This type of classroom environment will help to increase students' self-concept, which should then decrease the anxiety they experience when learning mathematics (Van der Beek et al., 2017) and improve achievement (Ahmed et al., 2013; Liu, 2021) and future engagement (Goldman & Penner, 2016) in mathematics.

Findings Related to Race and Gender

The final research question investigated the role of race and gender as moderators in the development of self-concept. The findings related to gender in this study are in harmony with findings in previous U.S. focused research, which found female students had decreased self-concept when compared to their male peers (Mejía-Rodríguez et al., 2021; S. Skaalvik & Skaalvik, 2004). However, the research in this dissertation goes a step further and shows that the gender gap in self-concept continued to grow throughout high school. The average self-concept for female students decreased over time while that of male students increased. This contrasts with findings of previous longitudinal research which also found that female students started with lower levels of self-concept but noted that the gap between gender groups remained constant over time (Nagy et al., 2010). This discrepancy may be related to how students of different races or ethnicities experience mathematics education, as the sample in the Nagy et al. study was predominantly white and White students showed the least variation in self-concept in this dissertation. However, more longitudinal research is needed which looks in depth at trends in self-concept related to gender. In addition, none of the predictor variables included in this analysis accounted for the gender discrepancy in self-concept so further research is needed to determine the mechanisms contributing to this gender gap. One possibility is that an individual's gender identity influences the way they experience and assimilate different situations that contribute to self-concept development. For example, Zeldin's (2008) findings that women considered the feedback of others when evaluating their self-efficacy while men considered past achievement, may also extend to self-concept. Another possibility is that gender-based stereotypes create barriers to female students seeing mathematics as a relevant or desirable part of their future (Eccles & Wang, 2016). This could create barriers to self-concept development even when students are successful in mathematics classes. Future research is needed to identify factors that create the gender gap in self-concept, so families and educators can enact changes that will close it.

This dissertation also took a more nuanced approach to investigating differences in self-concept development related to race. Previous comparative research has compared racially homogeneous samples in different countries to look differences by race (Yoshino, 2012). This dissertation focuses instead on a nationally heterogeneous population that has some shared culture. The significant interaction between Hispanic students and relational instruction is much more meaningful in this context. Hispanic students encounter various stereotypes that hinder their educational progress. One such stereotype is the misconception that they are intellectually lazy and do not value education (Marx, 2008; Valenzuela, 2010). The findings of this dissertation suggest that perceived deficiencies may be related to the type of instruction students receive, rather than the students themselves. Unfortunately, students who are English language learners or from minority groups are often categorized as low-achieving and are statistically less likely to be exposed to high-quality teaching (Haberman, 2010; Ladson-Billings, 2006). However, these same students exhibit significant academic improvement when enrolled in more challenging courses (Edgerton & Desimone, 2018). Additionally, Valenzuela noted that Latino(a) students attended classes and engaged in learning when they felt the class was relevant to them and they felt the teachers cared. Mathematics instruction that focuses on building relational understanding places more emphasis on problem solving and making connections, both of which make mathematics more relevant to students. In light of the previously described research, the findings from this dissertation point to the need to provide high-quality instruction which builds relational understanding to students at all levels and suggests that it may be especially important for helping Hispanic students be more engaged and successful in mathematics. In 2023, underrepresented minorities held only 16% of the positions in STEM fields that required a bachelor's degree (National Science Foundation & National Center for Science and Engineering Statistics, 2023). If providing relational instruction will improve Hispanic students' engagement in mathematics and increase their self-concept, it will encourage more Hispanic students to study STEM in college and thereby increase diversity in STEM professions.

Though only significant for Hispanic students in this sample, Dasgupta et al. (2022) found similar positive results among Black, Latinx, and Native American students. Increased educational engagement has been seen in districts that offered ethnic studies programs that teach Hispanic students about their culture and the history of their culture in the U.S. (Bonilla et al., 2021). These programs validated the unique beliefs and heritage of various cultures and instilled a more positive sense of self in students. The findings in this dissertation suggest that a similar effect might be achieved in a mathematics classroom where students are taught to reason, problem solve, and communicate about mathematics. When students are expected to reason mathematically to find answers to real situations, it allows them to gain more confidence and see the relevance of mathematics in their lives – two characteristics which increase mathematics self-concept.

Limitations

Though the findings previously described help clarify how students' mathematics self-concept develops, there are limitations of this research which need to be acknowledged. One limitation of this dissertation project is that it is ultimately correlational research and cannot be used to define a causal relationship between the predictor variables and self-concept. Another limitation arises in the creation of the two composite variables. The HSLS:09 does not contain items that measure all aspects of the relational instruction or caring and supportive learning environment constructs. I was limited to those items that were available when creating the new variables and inter-item correlations indicate there may be additional elements that are necessary to fully describe the caring and supportive learning environments construct. Additional components of relational instruction may include teachers' emphasis on presenting multiple solution strategies or asking students to analyze various concept definitions. Caring and supportive learning environments may include students' perceptions of teachers being willing to provide help and answer questions or encouraging students to respect one another. Though additional items may be needed to exhaustively describe the composite variables, my goal was not to exhaustively describe relational instruction or caring and supportive learning environments. Ultimately, the included items were important components of those variables and gave a strong indication of whether a caring learning environment and instruction which builds relational understanding had an influence on self-concept, despite being only partially described.

A similar limitation results from the way self-concept is measured. The HSLS:09 only used two items to measure self-concept, and though these two items describe the core of mathematics self-concept, it is a more complex and multifaceted construct. A change in this HSLS:09 variable will not indicate whether students' perceptions of the nature of mathematics have changed or that they have developed more of an incremental (growth) mindset. The HSLS:09 contained items which measured mathematical mindset but they were only included at the second and third timepoints, so they were inappropriate to use in this analysis. However, the results of this study can still provide direction for future research which takes a more nuanced approach in investigating the specific facets of self-concept that are most affected by providing relational instruction and creating caring learning environments.

Other limitations arise from the way the HSLS:09 study was designed. Teacher caring and relational instruction were only measured at the first timepoint. This means the data can only be used to estimate the long-term influence of ninth grade teachers over time. To more accurately understand how a caring and supportive learning environment or relational instruction influences self-concept, the predictor variables must also be measured at multiple timepoints. Additionally, while the timespan of the HSLS:09 data is considerable, the fact that self-concept is only measured at three timepoints limits the possible shape which can be considered for the trajectory and leaves huge time gaps in the data. Longitudinal studies that measured the main predictors as well as self-concept, at smaller time intervals would be valuable in furthering our understanding of self-concept. Despite the limitations, the results of this dissertation are significant due to the availability of the large, nationally representative, HSLS:09 dataset and are beneficial because they provide an operationalized definition of relational instruction, identify demographic differences in the self-concept growth trajectory, and highlight the importance of positive classroom environments in strengthening students' self-concept and improving future achievement and engagement in mathematics.

Implications For Research

The findings from this dissertation propose several questions that should be studied in future research and highlight methodological issues that should be considered in future research on self-concept. In addition to the suggested research already mentioned, future research should investigate any connection between student emotions in mathematics and relational instruction. Does relational instruction lead to productive struggle for all students that will ultimately lead to success and increased confidence, or does it create situations full of frustration and increased despair for some? How can relational instruction be structured to minimize any negative experiences? Additionally, research should identify the sort of training prospective teachers need to teach in a way that builds relational understanding. Finally, there is little research that shows how students form their perceptions of teacher caring, so further research would be beneficial to identify behaviors and practices that increase student perceptions of caring and supportive learning environments.

The results in this dissertation also illustrate the need for future longitudinal research on self-concept. While the HSLS:09 provided valuable data which covered a significant window of time, the intervals between measurements were too long to accurately model the self-concept trajectory. Research spanning multiple years but with multiple data collection points within each year would allow for more accurate identification of change points in the data. Identification of these change points would help researchers to isolate factors which have significant influence on student self-concept. With those factors identified, professional development programs will be more effective at providing the knowledge and tools teachers need to strengthen their student mathematical self-concept.

These design limitations present implications for future NCES sponsored research. The HSLS:09 is the fifth longitudinal study sponsored by the NCES. As it is in its final stages, perhaps attention to the findings and limitations of this dissertation will guide development of future research which would allow for a more thorough investigation of how self-concept changes over time and its relationship to relational instruction and caring and supportive learning environments.

Another methodological consideration deals with the use of aggregated data. The drastic variation in individual trajectories suggests mean scores may be misleading when aggregating data on self-concept in statistical analyses. Most statistical research on self-concept considers mean scores in the analyses but the results in this dissertation show why that can be problematic. In each plot of self-concept trajectory, the aggregated mean change over time was minimal, despite the erratic nature of individual growth plots. However, when divided into groups by race or gender the average self-concept trajectories for each group varied significantly. Aggregating data may contribute to studies with null results and lead to erroneous conclusions. It is essential for researchers to understand that demographic factors moderate the way self-concept develops and examine different subpopulations of their sample independently to reveal these moderators and how they function.

Implications For Practice

This research provides guidance that addresses the recommendation that teachers attend to the self-concept of their student (Kaskens et al., 2020) as it demonstrates a link between student self-concept and the type of classroom environment teachers create. Students need to feel cared for and supported to improve learning and confidence. Teachers today face students with a variety of mental and emotional challenges. Whereas teachers in the past could focus solely on teaching content, today's teachers are trying to help students deal with anxiety, depression, pressures created through social media, troubled home lives and a whole barrage of other issues that create barriers to student learning. Unfortunately, many teachers are not trained in how to recognize or respond to these issues. Previous research has already demonstrated a link between student achievement and feeling cared for and supported at school (See Kashy-Rosenbaum et al., 2018; Oda et al., 2021; E. M. Skaalvik & Skaalvik, 2013), but the results of this dissertation show positive associations with an important self-belief.

Conclusion

This dissertation supports the idea that self-concept is more dynamic than previously theorized and that teachers have power to make a significant contribution to improving their students' mathematics self-concept. This self-belief is not solely tied to achievement and if we put more focus on instruction that improves self-concept then achievement will increase along with students' interest, persistence, and future engagement in STEM. The findings in this dissertation suggest that if teachers create a caring and supportive learning environment in their classroom, they will help positively strengthen the mathematics self-concept of their students, thereby improving learning. Additionally, a focus on instruction that builds relational understanding in mathematics may be instrumental in strengthening the mathematics self-concept of Hispanic students and ultimately increasing Hispanic representation in STEM occupations.

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APPENDICES

Appendix A

Items from the HSLS:09 Used to Create Composite Variables

Items from the HSLS:09 Used to Create Composite Variables

Self-concept: Student survey at three timepoints – 2009 (BY), 2012 (F1), 2016 (F2)

I see myself as a math person
Others see me as a math person

Relational Instruction: Mathematics teacher survey – 2009 (BY)

Think about the full duration of this [fall 2009 math course]. How much emphasis are you placing on each of the following objectives?

*Teaching math concepts
Teaching students mathematical algorithms or procedures (R)
Developing computational skills (R)
*Developing problem solving skills
*Reasoning mathematically
*Connecting math ideas
*Logical structure of mathematics
History and nature of math
*Effectively explaining math ideas
Speedy/accurate computations (R)
Preparing students for standardized tests (R)

*Items I believe will be included in the final variable following CFA analysis
Items marked with (R) were reverse coded for the analyses

Teacher Caring: Student survey – 2009 (BY)

How much do you agree or disagree with the following statements about [your math teacher]? Your math teacher…

*Values and listens to students' ideas
*Treats students with respect
*Treats every student fairly
*Thinks every student can be successful
*Thinks mistakes are okay as long as all students learn
Treats some kids better than other kids (R)
Treats males and females differently (R)
Makes math interesting

All items measured on a 4-point likert scale (1-strongly agree, 4-strongly disagree).
Relational instruction items (1-no emphasis, 4-heavy emphasis)
(R) – Item is reverse coded

Appendix B

Approval from the Institutional Review Board

Research
UtahStateUniversity

Certificate of Exemption

From: Ronald Gillam, Ph.D.
Chair, Institutional Review Board

Nicole Vouvalis, J.D.
Director of Human Research Protections

To: Katherine Vela
Date: 2023-07-25
Protocol #: 13481
Title: How Relational Instruction and Caring Learning Environments Relate to Mathematics Self-Concept

Your proposal has been reviewed by the Institutional Review Board and is approved under Exempt procedure(s) Exemption 4 (based on the Department of Health and Human Services (DHHS) regulations for the protection of human research subjects, 45 CFR Part 46, as amended to include provisions of the Federal Policy for the Protection of Human Subjects, January 21, 2019):

> Secondary research using identifiable private information or biospecimens, if publicly available, unidentifiable or de-identified, or involving only the investigator's use of identifiable health information when that use is regulated under HIPAA or FERPA.

This approval applies only to the proposal currently on file for the period of approval specified in the protocol. The expiration date matches your project completion date set in the Procedures section of your protocol. It is eligible for up to five years of exemption, at which point, it will be closed and a new exemption will need to be requested.

Any change affecting human subjects, including extension of the expiration date, must be approved by the IRB **prior** to implementation by submitting an Amendment request. Injuries or any unanticipated problems involving risk to subjects or to others must be reported immediately to the Chair of the Institutional Review Board. If Non-USU Personnel will complete work on this project, they may not begin until an External Researcher Agreement or Reliance Agreement has been fully executed by USU and the appropriate Non-USU entity, regardless of the protocol approval status here at USU.

Prior to involving human subjects, properly executed informed consent must be obtained from each subject or from an authorized representative, and documentation of informed consent must be kept on file for at least three years after the project ends. Each subject must be furnished with a copy of the informed consent document for their personal records.

Upon receipt of this memo, you may begin your research. If you have questions, please call the IRB office at (435) 797-1821 or email to irb@usu.edu. The IRB wishes you success with your research.

435.797.1821 | 1450 Old Main Hill | Logan, UT 84322 | MAIN 155 | irb@usu.edu | FWA#00003308

Appendix C

Notarized Affidavit of Nondisclosure

License
22110004

Affidavit of Nondisclosure

Graduate Student
(Job Title)

Utah State University
(Organization, State or Local Agency Name)

2805 Old Main Hill, Logan, UT 84322
(Organization or Agency Address)

(Date Assigned to Work with IES Data)

(NCES Database or File Containing Individually Identifiable Information*)

I, Sandra J. Miles, do solemnly swear (or affirm) that when given access to the subject IES database or file, I will not -

(i) use or reveal any individually identifiable information furnished, acquired, retrieved or assembled by me or others, under the provisions of Section 183 of the Education Sciences Reform Act of 2002 (P.L. 107-279) for any purpose other than statistical, research, or evaluation purposes specified in the IES survey, project or contract;

(ii) make any disclosure or publication whereby a sample unit or survey respondent (including students and schools) could be identified or the data furnished by or related to any particular person or school under these sections could be identified; or

(iii) permit anyone other than the individuals authorized by the Director of the Institute of Education Sciences to examine the individual reports.

(Signature)

[The penalty for unlawful disclosure is a fine of not more than $250,000 (under 18 U.S.C. 3571) or imprisonment for not more than five years (under 18 U.S.C. 3559), or both. The word "swear" should be stricken out when a person elects to affirm the affidavit rather than to swear to it.]

City/County of Cache Commonwealth/State of Utah.
Sworn to and subscribed before me this 21 day of February, 20 23. Witness my hand and official Seal.

CHELSEA RODRIGUEZ
NOTARY PUBLIC • STATE OF UTAH
COMMISSION NO. 727614
COMM. EXP. 10/28/2026

(Notary Public/Seal)

My commission expires 10/28/2026

* Request all subsequent follow-up data that may be needed. This form cannot be amended by NCES, so access to databases not listed will require submitting additional notarized Affidavits.

Form last revised 08/06/19

Appendix D

Approval to Work with Restricted HSLS Data

Certificate of Completion

Annual Licensee Training

This certifies that Sandra Miles has successfully completed all of the requirements of the Institute of Education Sciences restricted-use data security training for 2023.

2/18/2023
Date

You have successfully completed your annual licensee training. Click here to logout.

Return to Training

#22110004: Approve User

IESData.Security@ed.gov <IESData.Security@ed.gov>
To: Mario Suarez; Cc: IESData.Security@ed.gov

Thursday, April 6, 2023 at 12:20 PM

License Number: 22110004
Mario Suarez,

Your add user request for Sandra Miles has been approved.

EFFECTIVE IMMEDIATELY:
Until such time as ED Offices are fully reopened, all mail must be sent to: IES Data Security

IES Data Security, NCES, PCP 4165
400 Maryland Avenue SW
Washington, DC 20202
Office: 202-245-7674
IESData.Security@ed.gov

Appendix E

IES Disclosure Risk Review

Disclosure Risk Review Template

Please name this file DRR_LicenseNumber_Institution_AuthorName_YYMMDD.doc (e.g., DRR_123546_HortonUniversity_Seuss_220204.doc).
Also use that same file name as the subject of your email to IES_DRR@ED.GOV.

Part I. Review Request (to be completed by licensee)

Submitted by (licensee name):	Mario I. Suarez
License number:	**22110004**
Institution:	Utah State University
Title of the product being reviewed:	How Relational Instruction and Caring Learning Environments Relate to Mathematics Self-Concept: A Multilevel Investigation of the High School Longitudinal Study of 2009 Data
Dataset(s):	HSLS:09
Type of product being reviewed (presentation, dissertation, book chapter, journal article, etc.):	dissertation
Date submitted to IES_DRR@ed.gov:	02/26/2024
Notes/comments for IES DRR Team:	This is a re-submission after addressing past review comments

Part II. Review Findings (to be completed by IES DRR Team)

Received on:	02/14/2024 – initial 02/27/2024 – compliance
Due by:	02/28/2024 – initial 03/05/2024 – compliance
Reviewed on:	02/22/2024 – initial 02/28/2024 – compliance
IES DRR Team Findings:	_X_ No necessary changes identified. If this is not the final version of this information product, please reply to this email with the final digital copy in its entirety at your earliest convenience for attachment to your license file. OR ___ Necessary changes identified. Please see below, address changes, and resubmit for compliance review.

#	Page	Para	Line	Comment
1.	General			Authors using restricted license data files should include a source note at the bottom of all tables and figures. Guidance on source notes can be found in the following locations: (1) 2012 NCES Statistical Standards, Chapter 5, Standard 5-4-8 (on the web at https://nces.ed.gov/statprog/2012/pdf/Chapter5.pdf). Note that the examples provided should be preceded with the word "SOURCE:". (2) 2012 NCES Statistical Standards, Appendix B, "Tabular Notes" (on the web at https://nces.ed.gov/statprog/2002/appendixc8.asp#source).

Disclosure Risk Review Template

Please name this file DRR_LicenseNumber_Institution_AuthorName_YYMMDD.doc (e.g., DRR_123546_HortonUniversity_Seuss_220204.doc).
Also use that same file name as the subject of your email to IES_DRR@ED.GOV.

#	Page	Para	Line	Comment
				(3) 2005 IES Style Guide (on the web at https://nces.ed.gov/statprog/styleguide/pdf/styleguide.pdf). Search "source note" within the document. Page 56 is probably the most comprehensive and useful resource, and page H-12 provides additional examples. DRR 02/28: Change made.
2.	Table 11		Table note	Please round to the nearest 10 the number of students in the final model (N=9497 → N=9500). DRR 02/28: Change made.
3.				
4.				

RE: Disclosure Risk Review

ID

IES DRR <IES_DRR@ed.gov>

Wednesday, February 28, 2024 at 1:18 PM

To: Mario Suarez

DRR_22110004_Uta...
36.1 KB

Download • Preview

Good afternoon,

Attached, please find our re-review of the dissertation. No disclosure risks remain.

Thank you,

Claire Christman
Disclosure Risk Review Coordinator
IES_DRR@ed.gov

IES Institute of Education Sciences

550 12th Street SW, 4055
Washington, DC 20202

CURRICULUM VITAE

SANDRA MILES

Education

PhD in Education, Utah State University (May 2024)
Specialization: Curriculum & Instruction
Concentration: Mathematics Education and Leadership

M.Ed. in Elementary Education, Utah State University July 2020
Specialization: Curriculum & Instruction
Elementary Mathematics Education

BA in Secondary Education: Brigham Young University - Provo August 2003
Certification in Secondary Mathematics Education

Additional graduate level math classes taken at Utah State University (10 credits)
Math 5210 – Intro to Analysis Fall 2021
Math 6910 – Modern Research in Math/Statistics Fall 2021
Math 5810 – Intro to Probability Spring 2023
Math 6810 – DR Applied Mathematics Education Research Fall 2023
Math 6910 – DR Connecting Abstract Algebra to Secondary Education Spring 2024

Licenses and Certificates

Utah professional teaching license – Secondary education with a math level 4 secondary math endorsement. Expires 6/30/2028.

Professional Experience

Graduate Teaching & Research Assistant – Utah State University 2020 – present
School of Teacher Education and Leadership
Teach online and face-to-face classes in mathematics content and pedagogy for preservice K-8 teachers in the School of Teacher Education and Leadership.
Conduct research with university faculty on the development of student self-efficacy and identity in STEM fields.
Supervise pre-service teachers during field experiences: Conduct observations and provide feedback and support.

Adjunct math instructor –Brigham Young University- Idaho 2013-2016, 2017-2020
Department of Mathematics
Taught a quantitative reasoning course and participated in faculty collaboration related to course improvement.

Math Teacher –Madison Junior High (Rexburg, ID) 2016 - 2017
Taught Algebra I to 7th, 8th, and 9th graders
Created accelerated curriculum for advanced students, allowing them to complete two years of math in one.

Substitute Teacher – Madison School District (Rexburg, ID) 2015-2016, 2017-2019
Worked in classrooms from 2nd – 12th grade. Served as an emergency long term substitute for math teachers at the high school which required me to write lesson plans, grade assignments and assessments, and provide tutoring and feedback to students.

Family Teacher –Community Living Opportunities (Lawrence, KS) 2003 - 2013
Managed a group home for adults with developmental disabilities

Student Teacher – South Jordan Middle School (South Jordan, Utah) 2002 - 2003
Taught Algebra and Pre-Algebra to 6th, 7th, and 8th graders

Math Lab Tutor –Brigham Young University (Provo, Utah) 2001 - 2002
Tutored university students in math subjects ranging from College Algebra/Trigonometry to Advanced Calculus

Publications

Campbell, T. G., Miles, S., Kularajan, S. (under review). Geographical and methodological trends in ESM and JRME Over the Last Ten Years. *Educational Studies in Mathematics*.

Miles, S. (in press). Not everyone is the same: How demographic, contextual, and instructional factors contribute to mathematics identity in various student populations. *International Journal of Studies in Education and Science (IJSES).*

Miles, S. (under review). *Clarifying self-efficacy and self-concept: A mixed methods examination to improve measurement* [Unpublished Manuscript]. Department of Teacher Education and Leadership, Utah State University.

Miles, S. (2022). A science analogy for understanding mathematical structure. *Mathematics Teacher: Learning and Teaching Pre-K–12, 115*(12), 867-873.

Miles, S., Vela, K., (2022). Asking for help is a key to success: The relationship between student help seeking beliefs and mathematics self-efficacy. *School Science and Mathematics Journal*, *122*(7), 371-380.

Vela, K., Miles, S. (2022). The Relationship between self-efficacy and interest in a STEM career: A meta-analysis. In A.Z. Macalalag, I. Sahin, J. Johnson, & A. Bicer (Eds*.), Internalization of STEM Education* (pp.159-181). ISTES Organization.

Online Publications

Miles, Sandra J. (2022). *Neutralizing Reactions to Teach Identity and Inverses in Mathematics*. Online lesson plan for 6-8 grade. National Council of Teachers of Mathematics: Illuminations. Online: illuminations.nctm.org.

<u>University Teaching</u>

Utah State University, Logan, Utah (2020 – present)

<u>ELED 4056: Elementary Content Practicum</u>
Students apply instructional strategies in the curriculum areas of mathematics, science, and social studies under the guidance of cooperating classroom teachers and university faculty.

<u>ELED 4061: Teaching Elementary Mathematics I: Rational Numbers, Operations, and Proportional Reasoning</u>
Students develop pedagogical content knowledge in rational number, operations, and proportional reasoning for teaching grades preschool through grade 6. Understanding characteristics of instruction, assessments, and intervention are considered critically.

<u>ELED 4062: Teaching Elementary School Mathematics II: Number, Operations, and Algebraic Reasoning</u>
Students develop pedagogical content knowledge in number, operations, and algebraic reasoning for teaching grades preschool to grade six, including methods for designing and implementing mathematics instruction, assessment, remediation, and intervention.

<u>TEAL 5521: Mathematics for Teaching K-8: Numbers and Operations</u>
Course for prospective teachers that covers the content of numbers and operations to develop a comprehensive understanding of our number system and relate its structure to computation, arithmetic, algebra, and problem-solving.

<u>TEAL 5523: Mathematics for Teaching K-8: Algebraic Reasoning</u>
This course provides prospective teachers a deeper understanding of algebraic expressions, equations, functions, real numbers, and instructional strategies to facilitate the instruction of this content for elementary students.

<u>TEAL 6300 Workshop in Mathematics Education</u>
The course is an exploration of current topics and methods in mathematics education. Topics can include Common Core mathematics content, relevant mathematics in rural settings, and integration of mathematics and children's literature.

<u>TEAL 6551: Mathematics for Teaching K-8: Assessment and Intervention</u>
This course provides practicing teachers a deeper understanding of the various types of

assessment and their appropriate use for guiding instruction, intervention and evaluation of student learning.

Brigham Young University – Idaho, Rexburg, Idaho (2013 – 2016, 2017 – 2020)

FDMAT108/Math108X: Math for the Real World
Prepares students to understand, analyze, and solve real-life problems that require quantitative reasoning. Topics include the meaning of probabilities, how to read, critique, and apply basic statistical information; the use of mathematical models in describing, understanding, and making predictions about real world phenomena; and the mathematics of budgeting, loans, and investments.

Awards & Professional Recognition

School Science and Mathematics (SSMA) John Park Student Convention Award. Fall 2022. ($290)

Conference Presentations

Miles, S., Vela, K. N. (2024, April 11-14 – accepted). *How Video Role Models Combat STEM Stereotypes to Increase Identity Perceptions and STEM Dispositions for Female and Minority Students.* [Poster Presentation]. American Educational Research Association (AERA) Annual Meeting, Philadelphia, PA.

Miles, S., Vela, K. N. (2024, February 9). *Ideas for using AI to improve mathematics instruction in secondary education.* [Conference Presentation]. National Council of Teachers of Mathematics (NCTM) Regional Conference and Exposition, Seattle, WA, United States.

Miles, S., Vela, K. N. (2024, February 15). *Cultivating STEM Identity and Dispositions: The influential role of virtual STEM role models in high school.* [Conference Presentation]. Southwest Educational Research Association (SERA), Arlington, TX, United States.

Miles, S. (2023, October 27). *Not everyone is the same: How demographic, contextual, and instructional factors contribute to mathematics identity in various student populations.* [Paper Presentation]. International Conference on Social and Education Sciences (IConSES), Las Vegas, NV, United States.

Miles, S. (2023, April 11). *Creating a positive sense of place: Feelings of safety and autonomy in a refugee camp* [Poster Presentation]. Utah State University Student Research Symposium.

Miles, S. (2023, March 28). *How security and autonomy create a positive sense of place* *for refugees.* [Poster Presentation]. Utah State University Library Digital Humanities Symposium.

Parslow, M., Miles, S. (2023, March 25). *"The math I used, I learned that it really is used in most of your everyday activities you do." -An Integrated Math Activity*. National Science Teachers Association National Conference, Atlanta, GA, United States.

Vela, K. N., Parslow, M., Miles, S., Weber, D. (2023, January 31). *The beauty of planning a school garden.* Utah Council of Teachers of Mathematics, Provo, UT, United States.

Miles, S. (2022, October 29). *Clarifying constructs to improve research on mathematical confidence.* [Paper Presentation]. School Science and Mathematics Association Annual Convention, Missoula, MT, United States.

Miles, S. & Vela, K. N., (2022, February 24). *Asking for Help as a Key to Success: The Relationship Between Student Help Seeking Skills and Mathematics Self-Efficacy.* [Paper Presentation]. Southwest Educational Research Association Annual Meeting, New Orleans, LA, United States.

Miles, S. (2021, April 15). *What can I do about it? Teacher behaviors that strengthen students' mathematical identities* [Paper Presentation]. Utah State University Student Research Symposium, Virtual Conference.

Vela, K. N., & Miles, S. (2021, February 3-5). *The relationship between self-efficacy and academic achievement or interest in a STEM career: A meta-analysis* [Paper presentation]. Southwest Educational Research Association Annual Meeting, Virtual Conference.

Service

- Conference Reviewer
- School Science and Mathematics Association (SSMA), Fall, 2022 Convention.
- Southwest Educational Research Association (SERA): Division II: Instruction, Learning, and Cognition, 2022 Annual Meeting.
- Southwest Educational Research Association (SERA): Division III: Methodology, Measurement and Evaluation, 2022 Annual Meeting.
- American Educational Research Association (AERA): Research in Mathematics Education, 2022, 2023, 2024.

Journal Reviewer

Journal on Empowering Teacher Excellence (JETE)

Guest Lectures

Utah State University – ELED 2010 Algebraic Thinking and Number Sense for Elementary Education School Teachers (for Jacy Beck) (2022, January)
Utah State University– ELED 4062 Teaching Elementary School Mathematics II: Number, Operations, and Algebraic Reasoning (for Dr. Katherine Vela) (2021, April).

Additional Skills
Foreign Language
Spanish – I have 4+ years of Spanish instruction (approximately conversational)
Russian – I have 2+ years of Russian instruction (beginner)

Statistical Software
R/R Studio
Stata

Professional Affiliations
Member – American Educational Research Association (AERA) 2021 - current
Member – School Science and Mathematics Association (SSMA) 2022 - current
Member – American Mathematical Society (AMA) 2021 - current
Member – National Council of Teachers of Mathematics (NCTM) 2021 - current
Member – Southwestern Educational Research Association (SERA): 2020 – 2021, current