CLASSROOM LEARNING ENVIRONMENT AND GENDER: DO THEY EXPLAIN MATH SELF-EFFICACY, MATH OUTCOME EXPECTATIONS, AND MATH INTEREST DURING EARLY ADOLESCENCE?

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Abstract

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Despite initiatives to increase and broaden participation in science, technology, engineering, and mathematics (STEM) fields, women remain underrepresented in STEM. While U.S. girls and women perform as well as, if not better, than boys and men in math, research results indicate that there are significant declines in girls' math self-efficacy, interest, and ambition as early as middle school. These decreases are associated with awareness of negative stereotypes viewing math as a predominately male domain. The classroom is one context for developing self-efficacy beliefs and gender-role stereotypes. The purpose of this quantitative study is to examine the role that students' perceptions of the academic and emotional support provided by their math teacher has on adolescents' math self-efficacy, math outcome expectations, and math interest. Social Cognitive Career Theory provides a theoretical framework for the study. Researchers collected data used for this study through a larger study (NSF grant #0624724). Data was collected from 230 students in sixth, eighth, and 10th grade to answer the research questions. Items from the Beliefs, Belong, and Behavior Survey provide measures for students' perceptions of Math Learning Environment, Math Self-Efficacy, Math Outcome Expectations, and Math Interest. The results of the study found that the relationships among math learning environment, specifically students' perceptions of the academic and emotional support provided by their math teacher, and the other SCCT variables were as predicted by the modified SCCT model. Students' perceptions of the academic and emotional support provided by their math teacher influences their math self-efficacy, math outcome expectations, and math interest. There were gender differences observed in the fit the modified SCCT model. Learning environment influenced the expected outcomes of taking advanced math courses differently for boys and girls. There were also gender differences in students' perceptions of teacher support, math self-efficacy, math outcome expectations, and math interest, with the greatest differences found between sixth grade girls and the other gender-grade groups. Finally, there was a relationship between girls' perceptions of the effect that taking math courses would have on relationships and their math interest, a relationship not observed in boys. Implications for researchers and practitioners are provided.

This dissertation is dedicated to my children, grandchildren, and parents. Without you, I would not be where I am standing today. I love you with all my heart!

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APPROVAL OF THE DISSERTATION

This dissertation, Classroom learning environment and gender: Do they explain math self-efficacy, math outcome expectations, and math interest in early adolescence?, has been approved by the Graduate Faculty of the Curry School of Education in partial fulfillment of the requirements for the degree of Doctor of Philosophy.

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CHAPTER 1

INTRODUCTION

In this chapter, I present the overview of a study that examines the role of the math learning environment on early adolescents' math self-efficacy, math outcome expectations, and math interest. I provide an argument presenting the rationale for this study. This chapter also presents the statement of the problem and the need, purpose, and significance of this study. Finally, I present the research questions and define the constructs of the study.

Background

For the U.S. to maintain global economic stability, national security, and future economic prosperity, there must be a continuous supply of highly trained scientists, technicians, engineers, and mathematicians as well as a scientifically and technically literate population (Farrel & Kalil, 2010; Obama, 2009). This workforce need is simultaneous with the growth of occupations in science, technology, engineering, and mathematics (STEM). The Bureau of Labor Statistics [BLS] estimates a 10% rise in overall employment opportunities from 2008 to 2018 (Bartsch, 2009). During this period, BLS expects STEM jobs to increase by over 22% (Lacey & Wright, 2009). For science and engineering, 2016 projected job openings will represent a greater proportion (43.9%) of present employment than all other occupations (33.7%) (National Science Board [NSB], 2010). To meet this growing need, policies such as America COMPETES Reauthorization Act of 2010 (Committee on Science and Technology, 2010) and

"Educate to Innovate" Campaign for Excellence in Science, Technology, Engineering & Math Education (Obama) aim to broaden participation and cultivate a diverse, scientifically literate citizenry.

Women remain a large untapped pool of potential American scientists, engineers, mathematicians, and technicians (Committee on Equal Opportunities in Science & Engineering [CEOSE], 2009). In 2009, females comprised 51% of the U. S. population and 47.4% of the U.S. workforce (BLS, 2010b; United States Census Bureau [USCB], 2007). However, women comprised 41% of biological and life scientists, 20% of computer software engineers, programmers, and mathematicians, and only 11% of engineers (BLS, 2009; NSF, 2009). In spite of programs intended to increase the number of women in STEM, women remain underrepresented in STEM occupations (CEOSE; NSF, 2008a). The systemic and institutional forces against encouraging and promoting promising women is increasingly costly given the current and projected shortages in the number of skilled U.S. workers in STEM (Beaton, Tougas, Rinfret, Huard, & Delisle, 2007; Carnevale, Smith, & Strohl, 2010a, 2010b).

Given that girls display similar abilities in math as do boys (Dalton, Ingels, Downing, & Bozick, 2007; Halpern et al., 2007a; 2007b), the underrepresentation of women in STEM is incongruent. The National Assessment of Education Progress 2008 data for fourth and eighth graders revealed no gender differences in math performance (National Assessment Governing Board [NAGB], 2007, 2010; Rampey, Dion, & Donahue, 2009). Girls in the U.S. are also performing as well as, if not better, than boys in high school math (Kenney-Benson, Patrick, Pomerantz, & Ryan, 2006; Rampey et al.).

Yet at each successive educational level, females are more likely than males to opt out of STEM subjects (Frome, Alfeld, Eccles, & Barber, 2006).

Although females earn over half of the bachelor's and master's degrees conferred in the U.S. (NSF, 2008b; USCB, 2007), women are less likely to choose careers in traditionally male STEM domains (NSF, 2008a; Watt, 2006) and more likely than males to drop out if they do enter those fields (Mau, 2003). Given the growing importance of STEM, gender-sensitive educators and counselors should understand the factors associated with this decrease in female participation in math and math-intensive educational programs.

Knowledge of the early factors that may keep women from equitably participating in math-related academic and career fields will help counselors, counselor educators, other educators, and researchers develop research-based interventions to help girls and women to choose predominantly male STEM fields. This, in turn, will promote gender equity, broaden career options for a large portion of our citizens, and improve the effectiveness of interventions to assist girls and women with their career development and decision-making (Betz & Hackett, 1981, 1997; Borman & Guido-DiBrito, 1986; Coogan & Chen, 2007; Lent & Brown, 2006).

Educational and Career Choice

The career options available to individuals are closely associated with their educational choices (Eccles, 2007). Because a bachelor's degree is required for entry into many professional and technical fields, including STEM (BLS, 2010a, 2010b, 2010c), pursuing postsecondary education expands the range of available career options (Carnevale et al., 2010a, 2010b). Studies using data from the *National Education*

Longitudinal Study of 1988 [NELS:88] found that students' post-high school academic and career choices are strongly shaped by their pre-high school educational aspirations (Lee & Rojewski, 2009; Rojewski, 2005) and their middle and high school course choices (Akos, Lambie, Milsom, & Gilbert, 2007; Shulruf, Keuskamp, & Brake, 2010; Trusty, 2004). By eighth grade, students' educational aspirations were predictive of their career and academic choices two years after high school (Kim & Rojewski, 2002; Rojewski & Kim, 2003; Van Bui, 2005). By early high school, students often have formulated and have potentially narrowed their academic and career aspirations (Akos et al.; Lee & Rojewski, 2009; Liben, Bigler, & Krogh, 2001; Rojewski, 2005; Rojewski & Kim; Trusty, 2004; Schoon, Ross, & Martin, 2007; Trusty & Niles, 2003; Weisgram, Bigler, & Liben, 2010).

Thus, by the eighth grade, middle school math course choices have expanded or narrowed student access to the full range of STEM and other educational opportunities (Trusty, 2004). Studies suggest that students' educational choices and subsequent career plans are significantly associated with mathematics course trajectories (Atanda, 1999; Riley, 1997; Trusty, 2004). Specifically, students' eighth-grade math ability influences math course taking in high school. This, in turn, predicts bachelor's degree completion and choice of STEM college majors over other majors (Trusty, Robinson, Plata, and Ng, 2000), with these effects stronger for women than men (Trusty, 2002; 2004). NELS: 88 analyses indicate that 12th-grade students who took eighth-grade algebra were more likely to apply to a four-year college than students who did not take eighth-grade algebra (Atanda, 1999).

Researchers observed this trend for students taking eighth-grade algebra and at all subsequent levels of high school math. Of those students who took eighth-grade algebra, 72% of those who subsequently took advanced high school math, 59% who took middle-level math, and 53% who took low-level math applied to college. Of those students who took algebra after eighth grade, however, only 42% of those who subsequently took advanced high school math, 29% who took middle-level math, and 24% who took lower-level math applied to college (Atanda, 1999). Given evidence that students' early academic choices in math have implications for students' future college success and career choices (Akos et al., 2007; Shulruf et al., 2010), early adolescence, especially the middle school years, is a pivotal period in STEM-related career decision-making (Akos et al., 2007; Brown & Lent, 2006).

Adolescent Development

These pivotal career decision-making processes during the middle school years take place during a developmental period marked by dramatic academic, physical, cognitive, and psychosocial changes (Eccles, 2009; Eccles et al., 1989). As early adolescents transition from elementary to middle school, substantial changes occur in their academic and social environment (Bandura, 2006; Cook, MacCoun, Muschkin, & Vigdor, 2008; Eccles et al., 1989). Concurrently, the appearance of secondary sex characteristics signals the end of childhood and increases the personal importance of socialized gender-specific activities and appearance (Alsaker & Flammer, 2006; Susman & Dorn, 2009).

Emerging formal operational (abstract) thinking allows early adolescents to engage in analytical reasoning, to envision the future, and to reflect on other's points of view (Elkind, 1967; Erikson, 1968; Inhelder & Piaget, 1958; Lehalle, 2006). Finally, through the psychosocial task of identity formation, early adolescents experiment with and begin to establish self in relation to others, school, and the world of work (Erikson, 1968; Schwartz, 2001, 2008; Yeager & Bundick, 2009). Young people's negotiation of these developmental changes can have emotional, social, career, and academic implications.

Career Decision Making and Interest Development

One important dimension of adolescent development is the formation of an occupational or career identity (Blustein, Devenis, & Kidney, 1989; Erikson, 1968; Nauta & Kahn, 2007). Central to the process of career formation are current and past learning experiences (Krumboltz, 1996, 2009; Lent, Brown, & Hackett, 1994). These experiences, which are ongoing and occur in all arenas, shape career-relevant behaviors and influence adolescents' perceptions of their academic and career competencies, interests, values, worldviews (Lapan, 2004; Mitchell & Krumboltz, 1996; Gottfredson, 2006), and aspirations (Shapka, Domene, & Keating, 2006). Through learning experiences, young people discover their academic and career interests and their place in the world of work. They also acquire the skills, values, beliefs, personal traits, and problem-solving strategies that guide academic and career preferences, decision-making skills, academic choice, and career selection (Krumboltz, 1996, 2009).

These learning experiences and their associated activities are important factors in the identity or career development process. From an early age, children form perceptions about the world of work as they observe it within the context of family and community (Gottfredson, 1981; Krumboltz, 1996, 2009; Trice, 1991; Weisgram, Bigler, & Liben, 2010). Children begin to form interests and gravitate toward preferred activities. They begin to categorize and assign attributes to occupations based on their understanding of the appropriateness of careers. Over time, children eliminate from consideration those career fields they believe are incongruent with their developing identity, including possible incongruence with their gender identity. Gottfredson (1981, 1996) refers to this process as *circumscription*. Because gender is central to personal and career development, the gendered nature of occupations, as understood by children, expands or limits their career aspirations (Gottfredson & Lapin, 1997).

By age six (Liben, Bigler, & Krogh, 2001) or four (Trice & Rush, 1995), before or soon after most U.S. children begin required schooling, they can differentiate careers by gender, categorizing certain jobs as suitable for girls and others for boys (Bigler & Liben, 1992; Gottfredson, 1981, 1996; Helwig, 2001; Weisgram, Bigler, & Liben, 2010). At the same time, selective learning opportunities and the outcome of learning experiences (Bandura, 1997, 2009; Lent, Hackett, & Brown, 1996) unintentionally or intentionally perpetrate or dispel these career gender stereotypes (Bandura, 1986, 1997; Lent, 2005). Parents, peers, and now teachers reinforce children for pursuing or avoiding certain activities. For example, girls may be encouraged to participate in gender-appropriate activities. Sometimes they receive different reinforcement for their performance in classroom or group activities than boys (Bandura, 1986; Gottfredson & Lapin, 1997; Lent, Hackett, & Brown, 1996). This, in turn, influences the development of interest in certain types of activities, continuing to broaden or narrow potential career paths (Lent, 2005; Lent et al., 1994).

By early adolescence, young people begin to integrate their perceptions of self and of work. Based on prior learning experiences, if not revised, early adolescents have already eliminated those careers that are inconsistent with their perceptions of appropriate gender roles (Gottfredson, 1981, 1996). Furthermore, they now are gaining an awareness of distinctions in the social class, ability-level, and prestige of various careers, which further narrows their set of acceptable careers. Therefore, by the time middle school students (ages 11-14) explore academic and career preferences, they have already begun to narrow their set of acceptable academic and career options to exclude those perceived as unfit for their gender or as lacking prestige (Helwig, 2001; Gottfredson, 2005, 2006).

Moving into the environment of middle school, early adolescents reestablish their sense of academic efficacy, social connectedness, and social status formed in elementary school (Bandura, 2006a). During this transition, students report decreases in self-esteem, sense of belonging, numbers of relationships (Byrnes & Ruby, 2007; Eccles, 2008), perceptions of academic competence (Jacobs, Lanza, Osgood, Eccles, & Wigfield, 2002; Schunk & Pajares, 2002), motivation (Wigfield, Eccles, Mac Iver, Reuman, & Midgley, 1991), and academic performance (Cook, MacCoun, Muschkin, & Vigdor, 2008). Importantly, caring and supportive student-teacher relationships appear to positively influence students' academic motivation, academic effort, positive social behavior, and well-being (Furrer & Skinner, 2003; Reddy, Rhodes, & Mulhall, 2003; Wentzel, 2002; Wentzel, Battle, Russell, & Looney, 2010). This relationship may also be critical for the career development process (Ciani, Ferguson, Bergin, & Hilpert, 2010).

The educational environment plays a major role in maintaining or challenging this set of acceptable academic and career options (Bandura, 2006a, 2006b). Indeed, one of the arenas for negotiating multiple developmental changes is school (Erikson, 1968; Roeser, Eccles, & Sameroff, 2000). Classroom learning experiences provide students with a social context for testing the appropriateness and social acceptability of academic and career aspirations (Good & Aronson, 2008; Gottfredson & Lapin, 1997) They also provide students with social validation of their skills and cognitive competencies (Bandura, 1997). Learned and often unconscious perceptions developed in this context continue to narrow or expand academic and career options (Betz, 2004; Lent et al., 1994; Low & Rounds, 2007; Trusty, 2002, 2004; Trusty & Niles, 2003, 2004). This, in turn, influences the process by which early adolescents develop personal, academic, and career interests, attitudes, and aptitudes (Bandura, 1994; Krumboltz, 1996, 2009; Schultheiss, Palma, & Manzi, 2005; Weisgram, Bigler, & Liben, 2010).

Learning experiences, as mentioned previously, also form the foundation for the development and acquisition of academic and career interests (Lent, Brown, & Hackett, 1994; Lent, 2005; Schaub & Tokar, 2005). As children and adolescents engage in academic and career-related activities, feedback on their performance shapes their sense of competence, or self-efficacy, and their expectations of the outcomes of performing these behaviors (Brown & Bigler, 2005; Ciani, Ferguson, et al., 2010; Lent et al., 1994; Lent, Hackett, & Brown, 1996). Through this process, children and those in early adolescence develop an emerging pattern of likes, dislikes, interest, or disinterest for these activities (Lent & Brown, 2006). Students developing interest, high self-efficacy, and positive outcome expectations for a particular activity are likely to engage more often in and practice the activity, which in turn facilitates revision of self-efficacy and outcome expectations related to this activity (Lent & Brown, 2006; Lent et al., 1994; Özyürek, 2005; Usher, 2009).

This process of practicing an activity and revising self-efficacy and outcome expectations occurs throughout the lifespan. Some researchers consider it most malleable until late adolescence, or early adulthood, at which point educational and career interests tentatively stabilize (Lent & Brown, 1996; Rojewski, 2005; Rojewski & Kim, 2003). Other researchers suggest that career interests stabilize before this, in early adolescence (Low, Yoon, Roberts, & Rounds, 2005; Low & Rounds, 2007; Tracey Robbins & Hofsess, 2005). It may be that career interests are relatively stable from early adolescence (age 12) until after late in high school, then become less stable in late adolescence and early adulthood (age 18-22) as adolescents are exposed to new experiences (Low & Rounds, 2007). While exposure to new learning experiences expands interests during this transitional time, remaining in environments similar to earlier environments tends to limit the scope of interest expansion. Entering adulthood, personal attributes, educational choices, and life commitments further limit the scope and frequency of these experiences, and interests stabilize again (Low & Rounds; Low et al., 2005). Taken together, these findings suggest that interventions to increase gender equity in STEM must begin early (Low & Rounds, 2007). They further imply that the middle school years are a critical period in the development of self-efficacy, outcome expectations, and learning experiences, the social cognitive variables that shape subsequent academic and career interest.

Social Cognitive Career Theory

Social Cognitive Career Theory [SCCT] (Lent, Brown, & Hackett, 1994, 2000) provides a framework that integrates these career-related factors into a comprehensive model of career development, from interest, to goal-behavior, to choice, to persistence. SCCT focuses on the interactional dynamics of person, environment, and behavior, which together influence the processes of (a) developing academic and career interests, (b) making and revising academic and vocational plans, and (c) achieving academic and career objectives (Lent & Brown, 2006). In this model, individuals develop interest in those activities in which they feel efficacious (i.e., have higher levels of self-efficacy) and for which they expect positive outcomes (Bandura, 1986; Lent et al., 1994). Some of these interests elicit corresponding goals, which then influence career choice behaviors and further influence interests (Lopez, Lent, Brown, & Gore, 1997).

Self-efficacy is at the heart of Bandura's Social Cognitive Theory (1977a, 1977b, 1986, 1997, 2005) and SCCT (Lent et al., 1994). Academic and career choice behaviors are strongly influenced by self-efficacy, the perceptions of one's ability to successfully perform a given task or behavior (Bandura, 1986). Self-efficacy determines the amount of effort people expend on an activity, their perseverance when confronting obstacles, and their resiliency when facing challenges (Bandura, 1977b; Schunk, & Pajares, 2002). When people believe that their actions can produce desired results, they have more motivation to act or to persevere in the face of difficulties.

Beliefs about the outcome of performing these activities also influence academic and career choice behaviors (Bandura, 1986; Lent et al., 1994). Individuals are more likely to choose a career they believe offers positive outcomes and will tend to avoid careers they anticipate will produce negative outcomes (Bandura, 1986, 1989, 1997). Expecting a career option to have positive outcomes is not sufficient for pursuing a certain career. Self-efficacy tends to be more powerful an influence than outcome expectations (Tang, Pan, & Newmeyer, 2008) for many groups, but not for all (Alliman-Brissett & Turner, 2010; Byars-Winston, 2008). Individuals tend to avoid careers if they believe that they cannot succeed (Bandura, 1986, 1997; Lent et al., 1994), regardless of the expected outcomes. Conversely, highly self-efficacious, well-skilled people may choose not to engage in behaviors consistent with their high levels of self-efficacy in an academic or career path if they believe there will be negative outcomes, such as social constraints, disincentives, or performance restrictions (Bandura, 1986, 1997; Flores, Navarro, & DeWitz, 2008; Lent, Brown, & Hackett, 2000; Lent et al., 2001). Although an integral part of social cognitive theory, few studies focus on outcome expectations (Fouad & Guillen, 2006; Lent, Sheu, et al., 2008).

Self-efficacy, outcome expectations, and interests do not exist at the same levels across varying domains. Instead, they are personal self-appraisals and judgments linked to distinct realms of functioning (Bandura, 1997, 2005; Betz & Hackett, 2006; Lent et al., 1994). Higher levels of self-efficacy in one domain result in more positive outcome expectations in that domain. Together, higher levels of self-efficacy and more positive outcome expectations lead to and reinforce interests in the same domain (Lent et al., 1994). However, self-efficacy and outcome expectations do not operate alone in shaping vocational interest, choice, and performance. Individual traits and context, including gender (Lent & Brown, 1996), socioeconomic status, and schooling (or education) (Bandura, 1977b, 1997) all influence career interest, choice, and performance.

Because gender affects the learning experiences and feedback to which a person is exposed, SCCT provides a foundation for focusing on the psychological and social effects of gender on education and career interests (Evans & Diekman, 2009; Lent & Brown, 1996, 2006; Schaub & Tokar, 2005). Social-cultural environment and available opportunity structures strongly shape career development, especially that of girls and women (Lent et al., 1994; Lent & Brown, 1996; Tokar, Thompson, Plaufcan, & Williams, 2007). Access to opportunities, parents' and teachers' gender role attitudes, and classroom learning activities that are reinforced differently for girls than boys directly influence girls' career-related self-efficacy, outcome expectations, and subsequent interest in traditionally male fields such as math (Hackett & Betz, 1981; Good & Aronson, 2008; McKown & Weinstein, 2003). The effect of gender on career interest, choice, and performance in a given domain operates largely through self-efficacy and outcome expectations as well as the differential gender-based learning experiences shaping these beliefs (Lent et al., 1994; 2000). Given the research supporting the importance of math to STEM career (Akos et al., 2007; Shulruf et al., 2010; Trusty, 2004), I will examine the domain-specific constructs of Math Self-Efficacy, Math Outcome Expectations, and Math Interest for this study.

Social Cognitive Career Theory and the Domain of Mathematics

Math self-efficacy strongly predicted the choices made by and the persistence of females pursuing STEM fields (Schoon et al., 2007; Usher & Pajares, 2009; Zeldin & Pajares, 2000). Specifically, math self-efficacy is associated with girls' and women's interest and success in STEM fields (Byars-Winston & Fouad, 2008; Hackett & Betz, 1989; Pajares, 2005; Plant, Baylor, Doerr, & Rosenberg-Kima, 2009; Rottinghaus, Larson, & Borgen, 2003), academic and career-related behaviors (Hackett, 1985; Hackett & Lent, 1992; Lent, Sheu, et al., 2008), and career attainment (Schoon et al.). Because lower levels of math self-efficacy may lead to avoidance of math-related behaviors, math self-efficacy is significant in the career choices of people from groups prone to underestimate their capabilities or to perceive constraints in their accessible career options (Betz, 2004; Hackett & Betz, 1981; Lent et al, 2000). This particularly applies to girls and their current underrepresentation in math (Betz, 2004).

Stereotypic beliefs that, in math, females are not as competent as males, coupled with the underrepresentation of women in STEM fields may discourage young women from pursuing these fields (Plant et al., 2009). Furthermore, women's self-efficacy regarding their math ability and their actual objectively measured ability may be vastly different. Elementary school boys and girls reported equal confidence in their math ability (Linver & Davis-Kean, 2005). However, early adolescent girls reported lower math self-efficacy, even when their skills were equal to or better than boys' skills (Huguet & Régner, 2007, 2009; Jacobs et al., 2002; Linver & Davis-Kean; Thiessen, 2007). Given the relationship between math self-efficacy and math-related academic and career choices (Nagy, Trautwein, Köller, Baumert, & Garrett, 2006, Nagy et al., 2008), the ramifications of this erosion in girls' math self-efficacy beliefs during the early adolescent school years may resonate throughout their academic and professional careers (Good et al., 2003).

While math self-efficacy influences math outcome expectations, both math self-efficacy and math outcome expectations influence the development of math interest (Brown & Hackett, 1994; Byars-Winston & Fouad, 2008; Fouad & Smith, 1996; Lent &

Brown, 2006). Research provides evidence that the indirect relationship of math self-efficacy to math interest as mediated by math outcome expectations, as well as the direct effect of math outcome expectations on math interests (Navarro, Flores, & Worthington, 2007) were stronger for middle school boys than girls (Fouad & Smith). These results support Lent et al.'s (1994) premise that math outcome expectations directly predicts math interest when girls or women expect negative outcomes from math-related activities, even if they have high math self-efficacy (Betz and Voyten, 1997; Fouad & Guillen, 2006).

Girl's lower math self-efficacy and math outcome expectations correspond to significant declines in girls' interest for math (Eccles, 2007; Linver & Davis-Kean, 2005). Even when girls and boys had similar prior math courses and math achievement levels, high school boys reported higher success and expected success in math, and were more likely to plan a career in a math-based field than girls (Watt, 2006, 2008). Conversely, girls believed math was a more difficult undertaking, perceived themselves having less talent, and held lower expectations of success at math (Watt, 2006). These findings suggest that factors other than math performance account for girls' lower levels of math self-efficacy.

The prevailing stereotype that women are less competent in higher-level math than men appears to affect girls negatively in early adolescence (Good, Aronson, & Harder, 2008). Beginning in middle school, the stereotype that women are intellectually inferior to men in math can result in decreased levels math achievement and performance (Neuville & Croizet, 2007). As early as first grade (Cvencek, Meltzoff, & Greenwald, 2011), the association of math as a male domain can interact with situational cues and activate gender stereotypes, potentially reducing girls' and women's math self-efficacy, math interest (Good, Dweck, & Rattan, 2008; Huguet & Régner, 2007; Kiefer & Sekaquaptewa, 2007a; b), and math performance (Good et al., 2008; Steele & Aronson, 1995).

Classroom Learning Environment

The environment where math learning occurs is an important factor in the development of math self-efficacy (Fast, et al., 2010; Friedel, Cortina, Turner, & Midgley, 2010; Patrick et al., 2007) and subsequent math interest (Bandura, 1997; Ciani, Ferguson, Bergin, & Hilpert, 2010; Fraser & Kahle, 2007). For early adolescents, the classroom is one of the two primary settings where they develop cognitive competencies and acquire the knowledge and problem-solving skills essential to participate effectively in society (Bandura, 1994, 1997). As students master these skills, they develop a growing sense of their intellectual self-efficacy. However, factors beyond formal instruction and personal performance affect the development of their intellectual self-efficacy (Bandura, 1997; 2000; Ciani, Ferguson, et al., Fraser & Kuhle). Researchers found that the social and psychological context in which learning occurs can also affect students' achievement and attitudes (Fraser, 1978, 1998; LaRocque, 2008; Moos. 1979) as well as their academic self-efficacy (Dorman, 2001; Dorman & Adams, 2004; Dorman, Fisher, & Waldrip, 2006; Fast et al., 2010; McMahon, Wernsman, & Rose, 2009; Patrick, Ryan, & Kaplan, 2007).

Classroom learning experiences, such as teachers' interpretations of students' successes and failures and social comparison with peers' performances influence students' perceptions of their academic and career self-efficacy (Bandura, 1997; 2000;

Brown & Bigler, 2005; Ciani, Middleton, Summers, & Sheldon, 2010; Senko & Miles, 2008). Furthermore, teachers often inadvertently reinforce gender stereotypes, particularly during the middle school years (Good et al., 2003). Through these learning experiences, early adolescents construct and internalize beliefs about self, their abilities, and interests, and the values about self and others, including gender-stereotypes (Bandura, 1989; Eccles et al, 1989; Eccles, 2008). These socially constructed beliefs may potentially result in girls having lower self-efficacy and interest in math than boys. Given the aforementioned role of school socializing agents, such as teachers, in influencing the development of self-efficacy, student's perceptions of the classroom, including their sense of teacher connection, are critical relational dimensions of their learning environment.

While studies have examined the influence of learning environment on self-efficacy in science classrooms (Pearson & Fraser 2006; Wolf & Fraser, 2008; Wolf, Fraser, & Aldridge, 2006) and high school mathematics classes (Chionh & Fraser, 2009; Dorman, 2001; Dorman & Adams, 2004); few studies have examined the relationship of psychosocial classroom learning environment on the math self-efficacy of U. S. middle school students. Furthermore, no studies have examined learning environment and math outcome expectations of this group. Given research suggesting that classroom learning environment influences self-efficacy (Dorman & Fraser, 2009; McMahon, Wernsman, & Rose, 2009; Fan, Lindt, Arroyo-Giner, & Wolters, 2009) and the internalization of gender stereotypes (Bandura, 1997; Leaper & Brown, 2008; Brown & Bigler, 2005), there is a need for further research of the learning environment, specifically, students' sense of support from their teacher and social cognitive variables related to early math interest.

Statement of the Problem

The role of the math learning environment appears to be crucial to girls' interest in and pursuit of STEM learning and careers. Despite initiatives to increase and broaden participation in STEM, the percentage of students pursuing math-related academics is shrinking (NSB, 2010; OSTP, 2006) and women remain underrepresented in STEM fields (NSB). Despite the lack of significant gender differences in children's, adolescents' (NAGB, 2010; Kenney-Benson et al., 2006; Rampey et al., 2009), and adults'(Ceci, Williams, & Barnett, 2009) math aptitude and achievement, research results suggest significant declines in girls' math self-efficacy, interest, and aspirations as early as middle school (Linver & Davis-Kean, 2005; Linver, Davis-Kean, & Eccles, 2004; Watts, Eccles, & Durik, 2006). Furthermore, these decreases are associated with awareness of negative stereotypes viewing math as a predominately-male domain (Huguet & Régner, 2007). These dynamics have strong potential to decrease females' math interest and performance as early as the sixth grade (Good et al., 2008). The significant declines in girls' math self-efficacy and math interest occurring in middle school, and a contrasting maintenance of math performance (grades and achievement test scores), underscore the need for early intervention. The critical period for addressing math self-efficacy, math outcome expectations, and learning experiences in order to influence levels of math interest appear to be the middle school years. However, we know relatively little about the role of the math learning context and early math interest of middle school girls and boys.

Purpose

The purpose of this study is to examine the association of sixth, eighth, and 10th participants' perceptions of the math learning environment with math self-efficacy, math outcome expectations, and math interest. Specifically, I will research the math classroom as a context for developing gendered math self-efficacy beliefs and gender stereotypes (Lent, Lopez, et al., 2008). I will use quantitative data to examine a modified SCCT model to test the predictive power of math learning environment to explain math self-efficacy and math outcome expectations, and the predictive power or math learning environment, math self-efficacy and math outcome expectations to explain math interest.

Need for the Study

There is a need for research examining the role of classroom learning environment on the development of math interest in early adolescent girls. Math self-efficacy beliefs formed in the classroom during the pivotal period of middle school set the foundation for future academic decisions. These decisions have significant implications for subsequent career options. The knowledge gained by investigating the learning environment and its role in math interest can help career, school, and mental health counselors, as well as educators and others who work with youth, understand the factors that influence early STEM career development. This, in turn, will allow for the development of research-based interventions to help girls and women gain greater representation in predominantly male STEM fields (Gainor, 2006). These early learning experiences play a powerful and long-lasting role in girls' and women's math self-efficacy and outcome expectations (Lent & Brown, 2006). By verifying the early factors that keep women from equitably participating in math-related academic and career fields, this research will also help counselors, counselor educators, educators, and researchers promote gender equity and thus advance social justice.

Significance of the Study

Given the growing importance of math in expanding academic and career options, it is important to know the factors that lead to the selection or conscription of STEM careers (Simpkins, Davis-Kean, & Eccles, 2006). Math self-efficacy is a strong predictor of math interest and, for students in fourth through 12th grade, is associated with math learning environment, especially student-teacher interactions (McMahon, Wernsman, & Rose, 2009; Fan et al., 2009; Fast et al., 2010). There is a need for research that examines math learning environment as a primary context where self-efficacy and outcome expectations develop. While math outcome expectations influence math interest, particularly in girls (Fouad & Smith, 1996), it has received little attention in the SCCT literature in terms of its predictive power (Betz, 2007; Fouad & Guillen, 2006). There is a need for research to determine the role of math outcome expectations in girls' math interest. Examining contextual factors associated with math interest adds to the research literature on women's career development. This provides career, school, and mental health counselors information that will facilitate the correction of inaccurate perceptions, the development of new career decision-making skills, and the promotion new math-related learning opportunities. This, in turn, will facilitate a more equitable participation of girls and women in STEM.

Research Questions

In this study, I explore the relationships among math self-efficacy, math outcome expectations, math learning environment, math interest of girls and boys in sixth, eighth, and 10th grades. Specifically, I will examine the fit of the data to a modified model of Social Cognitive Career Theory (SCCT, Lent, Brown, & Hackett, 1994). The following research questions guide this investigation:

Research Question 1

Are there differences in Math Self-Efficacy, Math Outcome Expectations, Math Learning Environment, and Math Interest among boys and girls in Grades 6, 8, and 10 by gender and grade level?

Research Question 2

Does Math Learning Environment explain a significant amount of the variance in Math Self-Efficacy for boys and girls in Grades 6, 8, and 10?

Research Question 3

Does Math Learning Environment explain a significant amount of the variance in Math Outcome Expectations for boys and girls in Grades 6, 8, and 10?

Research Question 4

Do Math Self-Efficacy and Math Outcome Expectations explain a significant amount of the variance in Math Interest of boys and girls in Grades 6, 8, and 10?

Research Question 5

Does the data fit the modified model of SCCT for girls and boys in grades 6, 8, and 10?

Research Question 6

Is the modified model of SCCT invariant across gender for participants in Grades 6, 8, and 10?

Definitions of Terms

I examine four constructs in my study: Math Self-Efficacy, Math Outcome Expectations, Math Learning Environment, and Math Interest. Following are the definitions of these constructs as used in this study.

Math Self-Efficacy

Math Self-Efficacy is the level of belief in one's capability to perform math tasks or to succeed at math activities (Bandura, 1997).

Math Outcome Expectations

Math Outcome Expectations are the perceived levels of positive results of performing math-related activities and behaviors (Bandura, 1986, 1989).

Math Learning Environment

Math Learning Environment includes two components: math classroom climate and math teacher connection. Classroom climate is the perceived level of warmth, respect, and enjoyment in the student-teacher relationship (Fast et al., 2010; Fraser, 1998; McMahon, Wernsman, & Rose, 2009; Moos, 1979; Patrick et al., 2007). In this study, Math Classroom Climate is the perceived quality of interpersonal relationship with the math teacher. Teacher connection is the perceived level of teacher responsiveness to students' emotional and academic needs (Fraser, 1998; McMahon, Wernsman, & Rose, 2009; Moos, 1979; Patrick et al., 2007). In this investigation, Math Teacher Connection is the perceived level of the math teacher's responsiveness.

Math Interest

Math Interest is the level of liking associated with mathematics activities (Lent & Brown, 1994; 2006).

Organization of the Study

This study explores the role of Math Learning Environment on sixth, eighth, and 10th grade participants' Math Self-Efficacy, Math Outcome Expectations, and Math Interest. Chapter 1 provided the rationale for the study, the need, purpose, and significance of the study, the research questions, and the definition of terms. Chapter 2 presents a review of the literature on the theoretical foundations of the study, Math Interest, Math Self-Efficacy, Math Outcome Expectations, and Math Learning Environment. Chapter 3 provides the methodology for this research. I present the answers to the research questions and findings of the analyses in Chapter 4, and present discussion and implications of results in Chapter 5. In Chapter 5, I also discuss the limitations of the study and specific implications for counselors, counselor educators, theorists, researchers, and educators.

CHAPTER II

REVIEW OF THE LITERATURE

In this chapter, the researcher will present a review of the literature, providing the basis for examines the role of the math learning environment on early adolescents' math self-efficacy, math outcome expectations, and math interest. This chapter includes a literature review on the population, on the theoretical foundations of the study, and on the constructs Math Interest, Math Self-Efficacy, Math Outcome Expectations, and Math Learning Environment.

Educational Choices and Career Options in STEM

Early educational choices are increasingly related to the available career options in science, technology, engineering, mathematics (STEM), and other professional fields (Eccles, 2007). This is particularly true given the present levels of education needed to participate fully in the U.S. workforce (Carnevale, Smith, & Strohl, 2010a, 2010b). Because a bachelor's degree is now required for entry into many professional fields, including STEM (Bureau of Labor Statistics, [BLS], 2010a), a college education provides economic mobility and security for millions of Americans (St. Rose, 2010). Between 1973 and 2008, the percentage of jobs requiring at least a two-year college degree rose from 29% to 59%. BLS projections indicate that this share will increase from 59% to 63% over 2008 levels by 2018 (Carnevale et al.), with the greatest growth projected in STEM. By 2018, STEM jobs are expected to increase by over 22% compared to a 10% rise in overall employment opportunities (Bartsch, 2009; Lacey & Wright, 2009). At the same time, over 90% of workers with a high school education or less will likely be limited to the three career clusters: food and personal services, sales and office support, and blue-collar work (Carnevale et al., 2010b). Thus, even some college education, particularly in STEM, expands the range of available career options (BLS, 2010a; Trusty, Robinson, Plata, & Ng, 2000).

Beyond career options, educational choices influence a person's employment opportunities and their potential standard of living. From 1992 to 2009, college-educated workers in the U.S. increased from 27 to 44 million workers, while the number of workers with a high school diploma or less slightly decreased (BLS, 2010a). At the same time, regardless of the state of the economy, there was an inverse relationship between educational level and unemployment. In 2009, the unemployment rate for college-educated workers was 10 points less than that of workers without a high school diploma and 5 points less than that of high school graduates.

Along with lower unemployment, BLS (2010a) statistics indicate that workers with a bachelor's degree make on average 1.8 times the salary of high school graduates and 2.5 times that of workers without a high school diploma. The projected range of available employment opportunities for these workers indicates that the wage gap will likely increase (Carnevale et al., 2010b). While workers with high school diplomas once could maintain a middle class standard of living, the three job clusters projected for these workers will tend to include lower-paying jobs with few benefits (Carnevale et al., 2010a). This potentially limits access to educational opportunities and advancement. In 1970, 74% of the middle class (yearly income between $30,000 and $79,000) had a high school education or less. By 2007, this percentage was 41%, and BLS predicts it to be

38% by 2018. However, in 2007, 61% of the middle class and 81% of upper-class workers (yearly income over $79,000) had college degrees (Carnevale et al., 2010b). Thus, a college education is increasingly important to provide an opportunity for a middle class standard of living and to meet future demands for an educated workforce.

Educational choices influence U.S. women's career choices and potential standard of living (St. Rose, 2010). For example, the increased number of women earning college degrees has resulted in overall greater equality between U. S. women's earnings and men's. In 1960, women earned 59 cents for every dollar earned by men. By 2009, women's wages rose to 77 cents for every dollar earned by men (Institute for Women's Policy Research [IWPR], 2010). However, in spite of these gains, for college-educated women, wage equity appears to decrease over time. Examining the wages earned by full time college-educated workers one year after graduation, women earned 20% less than men did. Yet ten years later, women earned 31% less than their male counterparts (Dey & Hill, 2007).

These wage gaps in part reflect differences in the choice of college major of women compared to men (St. Rose, 2010). In 2007, women earned 79% of the bachelor's degrees in education, but only 17% of the bachelor's degrees in engineering (Planty et al., 2009). One year after graduation, a full-time worker with a degree in education earned, on average, about 40% less than an engineer (Dey & Hill, 2007). Thus, while a college degree brings women closer to earning equal wages as men, the lower number of women in STEM limits the standard of living available to women (BLS, 2010b; Carnevale et al., 2010b; Trusty, Robinson, Plata, & Ng, 2000). Yet earlier educational decisions heavily influence these post-secondary choices.

Early Math Coursework and Future Educational Choices

Long before an individual makes the decision to select a college major or even apply to a college, the educational choices made early in the educational process have already "set the stage" for postsecondary choices. Results of studies using data from the *National Education Longitudinal Study of 1988* [NELS:88] suggest that students' post-high school educational and career choices are strongly shaped by their early (pre-high school) educational aspirations (Lee & Rojewski, 2009; Rojewski, 2005) and high school career aspirations (Schoon, Ross, & Martin, 2007). These aspirations, one's preferred ideal educational or career goals, are important to career development as they reflect self-assessment of competency and perceptions of available opportunities. These, in turn, prompt planning, guide learning, and direct choices (Lee & Rojewski). By the end of middle school, the educational aspirations held by eighth graders were predictive of their career and educational choices two years post high school (Rojewski & Kim, 2003). The educational aspirations of these students were stable over time and were the strongest predictor of their educational aspirations as 12th graders. In other research, career aspirations at age 16 were predictive of career attainment 14 to 17 years later (Schoon et al.). Early in high school, young people already have formulated and potentially narrowed their educational and career aspirations (Lee & Rojewski; Liben, Bigler, & Krogh, 2001; Rojewski, 2005; Rojewski & Kim; Schoon et al., 2007; Trusty, 2004; Trusty & Niles, 2003; Weisgram, Bigler, & Liben, 2010).

Research provides evidence of gender differences in the association between early STEM aspirations and later career attainment (Schoon, Ross, & Martin, 2007). Using data from the 1958 National Child Development Study ([NCDS] University of London) and the 1970 British Cohort Study [BCS70] University of London), Schoon et al. examined participants' STEM career aspirations at age 16 and later career attainment at ages 30 and 33 respectively. In both cohorts, early career aspirations predicted career attainment. In addition, students with STEM related career aspirations were more likely to attain a STEM related occupation than those expressing other interests. However, the odds ratios for girls were approximately two times that of boys. After controlling for social background factors, school experiences, and individual attainments at age 16, STEM related aspirations were stronger predictors for entering a STEM occupation among women than among men. These findings suggest that early formulation of STEM aspirations is an important factor for successful entry into STEM careers, particularly for adolescent girls (Schoon et al.).

In addition to students' educational aspirations, academic attainment, specifically middle and high school course-taking, strongly influences the likelihood of completing a bachelor's degree (Trusty, 2004). Results from studies using the NELS:88 data suggest that math courses taken in high school exerted the strongest influence on degree completion compared to all other subject areas (Trusty & Niles, 2003, 2004). Specifically, students' eighth grade math ability affected math course-taking in high school, which in turn affected bachelor's degree completion. Students enrolled in eighth grade algebra were more likely to take rigorous high school mathematics and science courses crucial to college entrance and later success in the labor force (Atanda, 1999; Riley, 1997; Trusty & Niles, 2004). Each additional advanced math course taken (e.g., algebra 2, trigonometry, pre-calculus, calculus) increased the odds of degree completion by 73% (Trusty, 2004). While taking intensive high school math courses has long-term implications for students' educational and career development, the trajectory toward intensive high school math that began in elementary school crystallizes in middle school (Trusty, Niles, & Carney, 2005). Thus, students' mathematics course trajectories during the middle school years have significant ramifications on their future career options.

Level of completed math courses and eighth grade math achievement also predicted choice of science and math majors versus other majors in college (Trusty, Robinson, Plata, and Ng, 2000), with stronger effects for women than men (Trusty, 2002). Analyses of the NELS:88 data suggest that females' early math achievement positively affected the courses taken in math, which then positively influenced choice of science and math majors. Men's self-perceptions of their math skills and their degree of computer use in high school had strong effects on choice of science and math major. Neither self-perceptions of math skills nor computer use in high school had an effect for women (Trusty, 2002). Trusty also observed gender differences in the effect academically intensive high school science and math course taking had on the choice of science and math majors versus other majors in college (Trusty). For women, taking the three most rigorous high school math courses (trigonometry, pre-calculus, and calculus) predicted choice of STEM college major, whereas for men, taking physics was the sole predictor.

Researchers also report gender differences in the perceived value of reading and math performance on college major (Thiessen, 2007; Trusty, 2002; Trusty & Ng, 2000; Trusty et al., 2000). Analyses of the NELS:88 data indicated that across all Holland career types (Realistic, Investigative, Artistic, Social, Enterprising, and Conventional), men tended to use math achievement and women tended to use reading achievement as the basis for their initial postsecondary educational choices. In addition, men chose the Investigative-type STEM majors more frequently than did women (Trusty & Ng; Trusty et al.). Eighth-grade mathematics scores (Trusty et al.) and tenth grade perceptions of math achievement (Trusty & Ng) were the strongest predictors of major for men, while eighth-grade reading scores and tenth grade perception of English achievement strongly predicted choice of major for women (Trusty & Ng; Trusty et al., 2000). In fact, eighth grade math achievement was the lowest predictor of college major (within the Holland types) for women (Trusty et al.).

These results are consistent with analyses of data from the Canadian 2000 Youth in Transition Survey (YITS, Human Resources Development Canada, 2000). Women's language grades were consistently higher than men's scores (Thiessen, 2007). In math, women took as many advanced classes and performed as well or better than men. However, women rated themselves lower in their numeric skills. At the same time, females' language grade was negatively associated with their numeric skill self-assessment. The higher a woman's grade in language, the lower she assessed her numeric skill. For males, language grade had no effect on their numeric skill ratings. In almost all comparisons, men rated their numeric skills higher than did women at comparable performance levels. As females' language art skills increased, their math skill self-perception decreased. Males did not display this same phenomenon (Thiessen). These findings suggest that women's identification with language arts negatively influences their self-assessments of math achievement. This, in turn, predicts college major (STEM vs. non-STEM) and subsequent career choice.

Late Childhood and Early Adolescence Development

Young people make these pivotal math course-taking decisions during a developmental period marked by dramatic academic, physical, cognitive, and psychosocial changes (Eccles, 2009). As early adolescents begin to develop the academic and social competencies needed to make viable career, social, and romantic commitments (Erikson, 1968), they must navigate the transition from elementary to middle school, and from child to adolescent, with concomitant changes in their academic and social environment (Eccles et al., 1989).

At the same time, hormonal changes trigger rapid biological change, comparable in intensity to the fetal period and to infancy (Susman & Dorn, 2009). This rapid development has a dramatic effect on adolescent personality development (Bozhovich, 2004). During puberty, the most obvious changes are (a) the development of secondary sexual characteristics such as body and pubic hair, increased body fat and muscle, and increased breast and testes size and (b) the adolescent or pubertal growth spurt, culminating in the attainment of peak height velocity approximately 3 years after the onset of puberty (Rosenfeld & Nicodemus, 2003).

During this critical period, physical maturation increases the adolescent's sense of adultness, yet the lack of corresponding social, physical, and mental development limits their ability to satisfy their budding adult identity. The ensuing tension provides the stimulation necessary for the development of identity and personality (Bozhovich; Erikson, 1968). As adolescents struggle through the transition from childhood to adulthood, they tend to be overly preoccupied with their rapidly changing bodies. This often leaves them feeling uncertain, insecure, and anxious, particularly late developing males and early developing females (Alsaker & Flammer, 2006; Susman & Dorn).

During early adolescence, maturation in different areas of the brain occurs at differing rates (Casey, Getz, & Galvan, 2008), with girls attaining peak gray matter density one to two years before boys (Giedd et al., 2009). During this time, brain function development occurs in executive functions like delayed gratification (Steinberg, 2008; Steinberg et al., 2009) and the processing of reward and aversive stimuli begins to mature (Ernst & Mueller, 2008). Brain imaging studies suggest that adolescents may be more sensitive to reward, less sensitive to aversive stimuli, less able to inhibit responses, and more likely to disconnect future outcomes from current choices because their frontal cortex circuits, which regulate behavior, are immature compared to adults (Crews & Boettiger, 2009; Geier & Luna, 2009; Steinberg). This often results in greater impulsivity and sensation seeking during adolescence (Steinberg et al.). .

Cognitively, as they transition from concrete to formal operational thinking, early adolescents increasingly employ more complex information-processing strategies, and generate multiple solutions when problem solving (Inhelder & Piaget, 1958). As they develop the ability to consider both hypothetical and real outcomes and consequences of actions, early adolescents begin to operate in terms of possibilities for their future, reflect simultaneously on other's points of view rather than solely their own perspective, and navigate amongst these views (Erikson, 1968; Inhelder & Piaget, 1958; Lehalle, 2006). Early adolescents begin think to not only about their own thinking, but they also begin to visualize what other people are thinking. This ability creates the assumption that others, especially peers, watch and judge them (*adolescent egocentrism*). In addition, because they tend to think of themselves as unique and invincible, early adolescents tend to believe the *personal fable* that they are beyond the negative consequences of risky behavior (Elkind, 1967). This fable can leave the early adolescent unable to make connections between actions and consequences at a time when current decisions have far-reaching consequences into adulthood.

This level of cognitive development gives rise to self-examination as early adolescents recognize that their personalities are unique, while they also desire to be like their chosen role model (Erikson, 1968). This culminates in a drive for expression of self, self-affirmation, self-realization, and self-development. The personality structure that develops during adolescence is a self-definition that not only encompasses growing self-understanding, but also an understanding of their place in society and their purpose in life (Schwartz, 2008). This, when achieved, leads to a successful integration of multiple roles into a single, consistent identity (Bozhovich, 2004), and is the culmination of the fifth stage of psychosocial development (identity versus identity diffusion) (Erikson). This period is also a time when ego values and confidence accumulated in childhood are incorporated into this sense of identity (Hamachek, 1988). A defined personality therefore develops within an understood social reality, resulting in an identity that helps give direction, purpose and meaning to life (Bozhovich, 2004).

As early adolescents undergo these changes, they begin to gain an awareness of self in relation to others, school, and the world of work as they wonder, "Who am I?" and imagine, "Who or what can I be?" (Erikson). Through this process of identity formation, early adolescents begin to integrate their beliefs, values, and goals into a sense of self. This identity will serve as the foundation for making life decisions, for judging the value or morality of their actions across the lifespan (Erikson, 1968; Schwartz, 2001; Yeager & Bundick, 2009), and for developing a career identity (Blustein, Devenis, & Kidney, 1989; Blustein, 2006). Marcia (2002) further elaborated on Erikson's theory by presenting adolescent identity development along two dimensions (a) awareness of an identity crisis that needs to be explored or resolved and (b) making a commitment to the identity after a period of exploring choices (crisis and commitment). The resulting four identity statuses are based on the presence or absence of an identity crisis (or exploration) and a commitment to a plan of action.

Adolescents who made a commitment without going through an identity crisis are in *foreclosure*. Marcia (2002) posited that the parents of these adolescents probably made their choices and the adolescents passively accepted the choices. For example, if parents expect their child to be a doctor, the child may accept this decision without considering alternate careers. Adolescents in diffusion neither experienced a crisis nor decided on their goals or values. Continuing the example, although their parents expect them to be a doctor, they do not believe that they have the needed skills. Believing that they cannot meet this expectation, they avoid feelings of failure by avoiding personal and career exploration. These individuals lack focus and direction. Adolescents in moratorium are in the midst of an identity crisis. Preoccupied with finding themselves, they are in the decision-making process. For example, in spite of parental expectations that they will be a doctor, they question whether this role fits their perceptions of self and their place in the world. During this time, they consider alternate careers, but they have not yet made a decision. Finally, individuals who went through an identity crisis and made a commitment attain identity achievement. These individuals have a sense of self and their place in the world of work. Having considered alternate careers, they may decide that a career as a physician is consistent with their sense of self and their role in the workplace. Pursuing their occupation of choice and living by their internalized value system, adolescents in this status achieved the most desirable and mature status (Marcia).

While the family context continues to plays a crucial role in supporting identity development, school now becomes an influential environment in which to negotiate these changes (Erikson, 1968; Roeser, Eccles, & Sameroff, 2000). One of the psychological developmental tasks of adolescents in the U.S. is to attain autonomy and independence as they transition from dependence on their parents to an independent and interdependent form of living (Arnett, 2007). School functions as the primary setting where early adolescents fulfill their needs for trusting and accepting relationships with adults and peers, self-expression, and exploration (Erikson, 1968). It is also a primary context where they will master the cognitive competencies, knowledge, and problem-solving skills essential to participate effectively in society (Bandura, 1994, 2006a, 2006b).

During this time of transition into and establishment in the new social and structural environment of middle school, students assess their academic efficacy and relationships with peers and teachers (Bandura, 2006a). Within this new context, teacher and peers exert a stronger influence on early adolescent's evaluation of self (Bandura, 1994; Barber & Olsen, 2004; Wentzel, Battle, Russell, & Looney, 2010). As early adolescents begin to differentiate from parents, their relationships with their teachers become an important source of emotional and academic support (Collins & Laursen, 2004a, 2004b; Furrer & Skinner, 2003; Reddy, Rhodes, & Mulhall, 2003; Wentzel, 2002). When compared to responses provided the prior year, changes in students' perceived teacher support was the strongest predictor of changes in a range of outcome variables, including school performance, self-esteem, depression, and interpersonal functioning with teachers, peers, deviant peers, and parents during the transition into middle school (Barber & Olsen).

Early adolescents frequently turn to peers to provide support, advice, and acceptance as they search for a coherent identity (Erikson, 1968). Friendships and peer groups provide early adolescents with a reference to test their emerging sense of self (Kroger, 2007) and support from others in the same developmental stage (Erickson; Scholte & van Aken, 2006). Peer groups provide adolescents the opportunity to assume and test various roles and functions they may assume as an adult (Erickson). For early adolescents, peer feedback influences the development and maintenance of their identity, efficacy, and social competence. From this perspective, the imaginary audience is not always imaginary (Bell & Bromnick, 2003). While the quality of peer relationships in Grade 6 was associated with academic achievement in Grade 8 (Veronneau & Dishion, 2011), peer rejection and acceptance were predictive of at-risk behaviors in middle school students (Veronneau & Dishion, 2010). Teachers and peers strongly influence early adolescents' development of their academic and social competencies during the transition to and during middle school (Bandura, 1989, 1994).

Because these multiple biological, psychological, cognitive, and social changes of adolescence occur simultaneously, lack of or developmentally inappropriate opportunities for academic, social, and emotional growth result in greater risk of problems (Eccles, Lord, Roeser, Barber, & Jozefowicz, 1997; Roeser et al., 2000). Research suggests that after the transition to middle school, students reported decreases in self-esteem, sense of belonging, connectedness to school, interpersonal relationships, (Byrnes and Ruby, 2007; Eccles, 2008; Wigfield, Eccles, Mac Iver, Reuman, & Midgley, 1991), perceptions of academic competence (Jacobs, Lanza, Osgood, Eccles, & Wigfield, 2002), motivation (Wigfield, Eccles et al.), and academic performance (Cook, MacCoun, Muschkin, & Vigdor, 2008). Thus, how young people negotiate these developmental changes can have emotional, social, career, academic implications.

Career Decision Making

A crucial aspect of adolescent identity development is the formation of an occupational identity (Blustein, Devenis, & Kidney, 1989; Erikson, 1968). Because of the centrality of work in adult life, career and work are large components of daily life and serve as major sources of personal identity and self-evaluation (Bandura, Barbaranelli, Caprara, & Pastorelli, 2001). As early adolescents begin to answer the question, "Who am I?" they must also ask the question "Who or what can I be?" and "What can I do?" (Erikson). The answers to these questions are linked to early adolescents' perceived competencies and emerging preferences consistent with their developing identity in other domains (Bandura et al.). In fact, congruence between self-concept and career identity is associated with the adequacy of the eventual career decision (Blustein, 1994; Blustein et al.). As such, early adolescents' career development is an important component of their identity development.

Central to the process of career development are learning experiences (Krumboltz, 1979, 2009). Through a complex myriad of learning experiences over the life span, individuals learn about themselves, their interests and preferences, and their place in the world of work (Liben et al., 2001; Weisgram et al., 2010). They acquire the skills, interests, values, beliefs, personal qualities, and problem-solving strategies that guide educational or occupational preferences, decision-making skills, and academic course and career selection (Krumboltz, 1996, 2009).

Learning experiences can be the results of learning activities (e.g., I do well on a math test, and I am rewarded), creating an association between a math task and the outcome of that task (e.g., I can do it and I value the results). They can also occur through observation activities (e.g., I see female crime scene investigators on TV), which expand the available learning experiences (e.g., Women can be crime scene investigators) beyond the immediate environment. Over time, as individuals experience various learning opportunities, they begin to draw unique conclusions about themselves based on their experiences. They construct beliefs about self (e.g., I am good at math) and their place in the world (e.g. I can work in a science lab). Together, these form the basis of beliefs about self and the world.

These generalizations develop into overt and covert "self-talk" that includes subjective evaluation of performance (e.g., "I can do math" after doing well on a test or "I can do that" after watching someone successfully complete a math problem) performance] and of interests, outcomes, and value-congruence (Mitchell & Krumboltz, 1996; Krumboltz, 2009). Worldview generalizations are beliefs about how "life is" (math is unfeminine), how "people are" (e.g., boys are better at math than girls), and how the "world works" (e.g., girls are nurses, boys are doctors). Self-observation and worldview generalizations are the filter by which people evaluate themselves and their relationship to the world, including the world of work. The resultant cognitions, attitudes, and emotions formed through educational and career-related learning experiences can be associated with accurate or inaccurate beliefs about the self and about the world of work (Krumboltz, 1979, 1996, 2009).

Learning experiences also shape the set of strategies or skills used by children and adolescents to cope with, interpret, and adapt to their environment (Krumboltz, 1979, 1996; Mosak & Maniacci, 2008). These task approach skills form the basis foundation of decision-making, including career decision-making. Thus, learning experiences influence the beliefs, values, personality patterns, skills, and work habits, and ultimately the career decision-making process (Mitchell & Krumboltz, 1996; Krumboltz, 2009).

The range of available learning experiences influence children and adolescents' views about self, their knowledge of the world of work, and their strategies for task approach (Bandura, 1994; Krumboltz, 1996, 2009; Schutheiss, Palma, & Manzi, 2005; Weisgram, Bigler, & Liben, 2010). Therefore, their environments will either foster or limit the development of beliefs, values, personality patterns, skills, and work habits used in career decision-making (Mitchell & Krumboltz, 1996). Because the availability of these learning experiences can vary widely, individuals may approach their career decisions based on a limited set of experiences (Krumboltz, 1996, 2009). Furthermore, individuals exposed to the same learning experiences can experience a variety of outcomes from these experiences. For example, equivalent performance may result in praise for some children and ignoring [need different word for ignoring] for others. Based on these learning experiences, children and early adolescents develop a set of skills and interests, negative and positive beliefs about self, congruent and contradictory values, work habits, and personality patterns (Krumboltz, 1996, 2009). Therefore, the availability and quality of learning experiences influences people's ability to engage in career planning and to make informed career decisions.

Children's and adolescents' knowledge about work and occupations gained through learning experiences strongly influences the academic and career choices they make as adolescents and young adults (Porfeli et al., 2008; Schutheiss et al., 2005; Weisgram et al., 2010). There is, however, a prevailing assumption that these career development processes occur almost exclusively during adolescence and early adulthood (Hartung, Porfeli & Vondracek, 2005). Career intervention and much of career development research focuses on this older age group (Hartung, Porfeli & Vondracek, 2008; Porfeli, Hartung & Vondracek, 2008). Hartung et al. (2005) and other researchers suggest that career development begins early in the lifespan. Yet, career practitioners and researchers tend to neglect the career development needs of children and early adolescents (Porfeli et al., 2008).

Developmentally, early adolescents make tentative career choices based on emerging understanding of self and emerging knowledge of the world of work. They use their developing abstract reasoning and analytical skills (Hartung et al., 2008; Porfeli et al., 2008) to process this information. Therefore, the concepts and constructs found in the adolescent and adult literature may not generalize to childhood and early adolescent career development (Palladino Schultheiss, 2008). By conceptualizing career development across the lifespan, career counselors can develop interventions appropriate for each student's or client's' developmental stage. Exposure to a wide range of learning experiences allows consideration for a range of career options, increases perceptions of academic and career competence, and provides a foundation for future life choices, vision of future careers, and development of decision-making (Hartung et al., 2008).

Current models of career decision making recognize that factors such as learning experiences, developmental stages, and person-contextual factors impact both the content and process of making a career choice (Gottfredson, 1981, 1996; Krumboltz & Hamal, as cited in Krumboltz, 1996; Lent, Brown, & Hackett, 1994). In other words, a large number of social, cultural, political, and economic factors outside a person's control (Krumboltz, 1996, 2009) influence the learning experiences that guide career-relevant behaviors and self-assessment of competency, general and specific interests, personal and work values, and the world.

For adolescents, the learning environment created by classroom teachers plays a major role in fostering the career beliefs and decision-making skills needed for optimal career development (Bandura, 2006a). Because early adolescents heavily rely on social comparison, learning experiences such as teacher interpretation of student success and failure, social comparison with peer performance, and peer modeling of cognitive skills significantly influence perceptions and evaluations of academic and career domain-specific efficacy (Bandura, 1997, 2000). Through learning experiences, middle school students construct beliefs about self, develop perceptions of abilities and interests, discover what they value about themselves and others, and ground their sense of self in these values (Bandura, 1989; Eccles, 2008; Eccles et al, 1989).

Because career decision-making proceeds along a developmental trajectory, early socialization narrows or expands academic and career opportunities (Gottfredson, 1981, 1996). Because gender is core to social identity (Reicherzer & Anderson, 2006), gender strongly shapes and may overly restrict career aspirations (Bandura, 1989; Gottfredson & Lapin, 1997). From an early age, socialization and cultural learning experiences strongly influence children's perceptions about self and the world of work (Liben et al., 2001; Trice, 1991; Weisgram et al., 2010). As children observe their environment, they develop a cognitive map that helps them to gain a sense of who they are and where they fit into the world (Mosak & Maniacci, 2008). In this process, children begin to categorize and assign attributes to both self and occupations based on their perceptions of the socially constructed appropriateness of careers (Trice & Rush, 1995 Weisgram et al.). As the cognitive ability of the child grows more complex, their categorization of self and career attributes also increases in complexity. As children develop their sense of where they fit into the world of work, they progressively eliminate from further exploration those occupational fields they believe are incongruent with their developing sense of identity, i.e., *circumscription* (Gottfredson, 1981, 1996).

The process of circumscription parallels cognitive development. By the time children are preschool age, they have moved from magical to intuitive thinking. They begin to classify people in the simplest of ways, big and powerful versus little and weak (Gottfredson, 1981, 1996, 2005). They also begin to identify occupations as adult roles, working at a job is a part of being an adult, and that they, too, will eventually become an adult. As children develop concrete thought (age 6-8), they begin to differentiate and classify based on highly visible attributes, with gender as the most obvious and salient at this age (Bigler & Liben, 1992; Liben et al., 2001; Trice & Rush, 1995; Weisgram et al., 2010). Using dichotomous thought, children observe and classify behaviors and career roles as belonging to one sex but not the other. Furthermore, given the rigid thinking of children at this developmental stage, children view it imperative that people adhere to sex-appropriate behavior (i.e., girls cannot be doctors; girls are nurses). Because of gender role socialization, early adolescents have already eliminated those occupations that are not consistent with their perceptions of appropriate gender roles (Hartung et al., 2005; Porfeli et al., 2008).

As cognitive thought increases in complexity, early adolescents expand their awareness of careers beyond their immediate environment, can now conceptualize career activities they cannot directly observe, and gain an awareness of distinctions in the social class, ability-level, and prestige of occupations (Gottfredson, 1981, 1996, 2005). Cognitively, early adolescents begin to associate occupations with income, education, and standard of living. Moving into the developmental task of identity formation, they become aware of status hierarchies, are sensitive to social evaluation, and conceptualize their place within this social hierarchy. Finally, early adolescents evaluate careers in terms of their perceived academic abilities, ruling out those jobs they view as being beyond their intellectual capabilities. Early adolescents now evaluate careers not only in terms of gender, but also limit their career aspirations to those careers that are within an acceptable social status and academically achievable range of careers. Thus, by the time early adolescents begin to focus on their academic and career choices, they have already narrowed their set of acceptable educational and career options to exclude those they judged as the wrong sex type, too difficult, or lacking in prestige (Gottfredson, 2005).

For early adolescents, classroom interactions provide a reference beyond their family to test sex appropriate behaviors and social acceptability of academic and career-related aspirations (Bandura, 1986; Gottfredson & Lapin, 1997). By middle school, students are aware of broadly held gender role stereotypes, which influence how the students interpret teacher, peer, and self-comparative evaluations of efficacy in math (McKown & Weinstein, 2003). Because stereotypes often are activated from concerns about how one is viewed by others, social comparisons versus self-evaluation can result in the internalization of gender stereotypes, such as girls are inherently inferior to males in math (Good, Aronson & Inzlicht, 2003). Thus, classroom interactions with teachers and peers found in middle school creates a context by which existing gender stereotypes appear to be confirmed and internalized (Good & Aronson, 2008; Good, Dweck, & Aronson, 2007). In turn, this can create a "stereotype climate" that negatively affects individuals from stigmatized groups, such as girls in math classes (Good & Aronson, 2008). Thus, classroom learning experiences influence the process by which early adolescents become aware of, explore, and develop personal, academic, and career-related interests, attitudes, and aptitudes (Bandura, 1994; Krumboltz, 1996, 2009).

Career Interests

Although an elusive construct to define, the development of career interests is a core construct in models of career decision-making and an integral component of career counseling interventions (Hansen, 2005; Jome & Phillips, 2005). The development of career interests is a dynamic process continually shaped through learning experiences and outcomes (Lent, Hackett, & Brown, 1996). Furthermore, learning experiences occurring in childhood and early adolescence are foundational for the development and acquisition of interests (Lent, Brown, & Hackett, 1994). From an early age, people experience a variety of academic and career-related activities. They also observe other people performing various occupational tasks. In addition, within their environment, they receive reinforcement for certain career-related activities over other activities. These in turn become possible career interests. As they engage in these activities, refine their skills, observe modeling behaviors, and receive positive and negative feedback about the quality of their performance, children and early adolescents begin to gain a sense of their potential efficacy (i.e., self-efficacy) for performing the behavior as well as develop expectations about the outcome of engaging in these behaviors (Brown & Bigler, 2005; Ciani et al., 2010; Lent, Brown, & Hackett, 1994). Through these learning experiences, children and early adolescents develop an emerging pattern of likes, dislikes, and disinterests (Lent, 2005) that subsequently help shape the subsequent activities that they will consider for future engagement.

Over time, durable interests in a particular career-related activity form when children and early adolescents (a) believe they are able to perform the task competently and (b) anticipate that performing the activity will produce outcomes they value (Bandura, 1986; Lent et al., 1994; Lent & Brown, 2006). On the other hand, they will likely narrow career interests and prematurely foreclose career paths in domains where they hold low perceptions of their ability to perform the required tasks and/or anticipate negative outcome expectations from performing these activities (Brown & Lent, 1996). Their emerging interests in certain academic and career-related activities help motivate children and early adolescents to continue to engage in those activities associated with the interest area (Lent, 2005). Students who develop positive interests, self-efficacy, and positive outcome expectations for a particular activity are likely to form goals for sustaining or increasing their involvement in the activity. These goals increase the likelihood that they practice the activity, which then can create other learning experiences. These new learning experiences then influence self-efficacy, outcome expectations, and interests.

It is through this cyclic process that interests crystallize over time (Lent & Brown, 1996, 2006). As individuals practice activities associated with their interests, not only do their skills increase, but they also receive additional feedback concerning their efficacy and expected outcomes. Via this feedback loop, these new learning experiences facilitate the revision of their self-efficacy and outcome expectations to accommodate the new information (Lent & Brown, 1996, 2006; Lent et al., 1994). In turn, these revisions influence interests, which further increase the likelihood of practicing and maintaining the behaviors. This dynamic and interactive process of practicing a task and the ensuing revision of self-efficacy and outcome expectations beliefs repeats itself throughout the life span. However, individuals' interests, self-efficacy beliefs, and outcome expectations appear to be most fluid until early adolescence or early adulthood, at which point career interests stabilize (Low & Rounds, 2007; Low, Yoon, Roberts, & Rounds, 2005; Tracey Robbins & Hofsess, 2005).

In a meta-analysis of 107 studies, Low et al. examined the stability of career in eight age categories: early adolescence (ages 11.5–13.9), middle adolescence (ages 14–15.9), late adolescence (ages 16–17.9), college years (ages 18–21.9), emerging adulthood (ages 22–24.9), and three groups of adulthoods (25-30, 30-35, and 35-40). Low et al. found the trajectory of career interests to be relatively stable from early adolescence (age 12) through middle adulthood (Low et al., 2005). In fact, career interests tended to be more stable than personality traits in these age groups, suggesting that interests may have a level of continuity similar to personality traits and abilities. This continuity implies that interests likely exert a similar influence peoples' life-choices as so personality traits and abilities.

Females' interests tended to be more stable than males (Low et al., 2005; Tracey et al., 2005). Tracey et al. found that while females' interests were stable across grades eight through12, males' interests became less stable in grades 10 through 12. Males also demonstrated lower Holland code profile consistency and interest crystallization than females in grades 10 through 12. Interests also tended to develop along stereotypical gender lines, a phenomenon that Low et al. and Low and Rounds attributed to the limited range of career options often available to females. The stability of early adolescents' career interests suggest that career interventions can be effective for students as early as elementary school. Thus, to increase gender parity in STEM interventions designed to expand the scope of available career options must begin at an earlier age than the current focus on adolescents (Low & Rounds, 2007; Low et al.).

Factors Influencing Early Career Interests

While early learning experiences shape the development of early career interests, social, cultural, and economic factors often affect the availability and quality of these learning opportunities (Krumboltz, 1996; Lent, Brown, & Hackett, 1994). Socially constructed variables such as gender, race, and socio-economic status shape the learning opportunities afforded to children as well as the outcome of these experiences (Bandura, 1997; Lent, Hackett, & Brown, 1996). Because a key component of learning and environment involves cultural sex typing (Bandura, 1987), culturally defined gender roles are a major influence in shaping the types of activities selectively reinforced in children and early adolescents (Bandura, 1986; Gottfredson & Lapin, 1997). Through multiple selective sex-typed activities, reinforcement, and role modeling, children learn and internalize gender-appropriate stereotypical academic and career-related behaviors. As a result, the learning experiences of children and early adolescents may unintentionally perpetuate these gender roles.

Culturally defined gender stereotypes influence individuals' perceptions of gender appropriate interests and behaviors. Because of implicit and explicit gender role stereotypes and attitudes held by girls, their parents, teachers and peers, girls are often encouraged to participate in activities that are different from those in which boys are encouraged to participate (Bandura, 1986, 1997; Lent, 2005). Girls may also receive different feedback or reinforcement on their performance in various classroom or group activities (Lent, Hackett, & Brown, 1996). This gender-based access to opportunities, the implicit attitudes held by key socializing agents, and discouragement of stereotypically-male learning activities have consistently been shown to negatively influence women's career-related self-efficacy in traditionally male fields such as math (Hackett & Betz, 1981; Good & Aronson, 2008; McKown & Weinstein, 2003). Gender-based learning experiences of early adolescent girls have likely resulted in a circumscription of interests, particularly the STEM-related activities and fields (Porfeli et al., 2008).

While there is a strong body of research that suggests that gender-based learning experiences often result in a conscription of interests (Hartung et al., 2005, Porfeli et al., 2008), theorists hypothesize that circumscription of occupations can be reversed through interventions designed to broaden their zone of acceptable alternatives (Gottfredson & Lapin, 1997). The limited research examining this premise suggests that interventions can change adolescents' career interests. When career counselors used the result of career assessments for career exploration with middle school students at risk for career underachievement, the students reported increased efficacy in career planning and exploration, expanded the number and range of acceptable careers, and greater congruence between interests and choice (). In a more recent study, Turner and Lapan (2004) found that a brief computer-assisted career guidance intervention resulted in increases interests that were counter to gender stereotypes. Middle school boys reported increased interest in careers associated with Artistic, Social, and Conventional career, while girls reported increased interests in Realistic, Enterprising, and Conventional careers. While few additional studies have examined interventions, these studies provide evidence that career development and exploration interventions can increase the range of acceptable careers in middle school students.

Math Interest

Given the role of interests on career choice, many researchers attempt to explain the current underrepresentation of women and minorities in STEM. They focus on the development of math-related interests, i.e., students' like, dislike, or indifference to the variety of activities, objects, and types of persons associated with math (Lent et al., 1994) as well as the factors that predict the development of interests. Most research focuses on the predictors of interests, such as self-efficacy, as the outcome variable. Research examining math interest as the outcome variable tended to focus on the trajectories of interest through the middle and high schools years. Results of these studies of U.S. students indicate that there is a general decline in math interest over time, with stronger declines observed in females. Similar gender specific developmental trajectories for math interest are found in studies examining U.S. (Eccles et al., 1983, Fredricks &

Eccles, 2002; Watts, Eccles, & Durik, 2006), Australian (Watt, 2004, 2008) and German (Frenzel, Goetz, Pekrun, & Watt, 2010) students. To examine the trajectories of math interest in U. S. students further, I present the results of two studies, Jacob et al. (2002) and Linver, Davis-Kean, & Eccles (2004).

Examining developmental trends in secondary school students' math interest, researchers found significant declines in interest over time, with gender predictive of the slope of the decline. In U.S. students, Jacobs et al. (2002) found an overall decline in math interest between second and 12th grade. The rate of decrease accelerated over time, with the sharpest declines occurring during high school. Overall, competency beliefs accounted for 41% of the change over time in boys and 28% of the decline over time for girls, suggesting that a) self-efficacy is closely associated to math interest and b) there are gender differences in the strength of the influence of self-efficacy on interest. Controlling for math self-efficacy, the linear trend for sixth grade interest reduced by 43%, with a steeper rate of overall decline observed in females. Overall, self-efficacy explained most of the decline in math interest occurring between second and fifth grade, very little of the decline in math interest in middle school, and some of the decline in high school, suggesting that interest may begin to crystallize in early adolescence, insulating interest from further self-efficacy revision in the feedback loop.

Linver, Davis-Kean, & Eccles (2004) found similar results examining U. S. students' math interest trajectories from sixth through 11th grade. Grouping students by gender and high-track (honors and college-prep) or low-track (regular and basic) math courses taken, declines in math interest were observed across all gender and track groups, with high-track boys showing a lower decline in math interest than females in both tracks and low-track boys. Sixth grade interest predicted the slope for all groups except for low-track females, with higher sixth grade math interest slowing the rate of slope decline. Although females' grades were higher or comparable to males, their interest and self-concept, especially for high achieving females, were the same or lower than males. Girls enrolled in the college-honors group reported the greatest decrease in math interest over time than either boys or girls in the low-tracks, even though their grades dropped the least (Linver & Davis Kean, 2005; Linver et al.). Males' grades dropped more than the girls, but their math interest decreased the least. These results suggest that while in general, students lose interest in math over time, college bound females with high performance achievement in math are further narrowing their career interests to exclude math.

These decreases in interests correspond with the decreased overall number of U.S. students entering STEM careers as well as the underrepresentation of women in STEM. Given that expertise in mathematics is a necessary condition for important advances in our society, gender differences in math interest and the consistent decline in math interest during adolescence for both genders are of practical relevance (Nagy et al., 2010). To tap the full potential of talents for the STEM fields, there is a need to attract and hold students' interest in math (Frenzel et al., 2010). To accomplish this task, it is important to understand the factors that influence the development and maintenance of interests. Given the aforementioned factors presented in this review of the literature that influence career interests, Lent, Brown, & Hackett's (1994) Social Cognitive Career Theory (SCCT) provides a theoretical foundation to integrate the social cognitive factors (i.e., self-efficacy and outcome expectations), personal factors such as gender, and contextual learning experiences into a comprehensive model of career interest and choice.

Social Cognitive Career Theory

Social Cognitive Career Theory (Lent et al., 1994) extended Bandura's (1977a, 1977b, 1986, 1989) Social Cognitive Theory to career. While major career development models recognized the effect that people's interactions with their environment has on career behaviors, models tended to conceptualize these person-environment variables as static, trait-oriented attributes (Lent & Hackett, 1994). As such, Lent et al. posited that ascribing global static attributes to people's interactions with their environment likely did not capture the dynamic interactions that occur between developing individuals and their changing contexts. Bandura's (1986) Social Cognitive Theory provided the theoretical grounding for SCCT. SCCT draws on Bandura's conceptualization of the dynamic interactions, or *triadic reciprocality*, occurring in person-environment interaction and the process by which people exercise personal agency. Furthermore, individuals as active agents who influence their environments through their behaviors, receive feedback from their environment, and form cognitions about self and their environment through these interactions. Thus, SCCT focuses on the interactional dynamics of thought to influence the processes used by individuals to (a) develop basic academic and career interests, (b) make and revise educational and vocational plans, and (c) achieve varying levels of varying quality in academic and career pursuits (Lent & Brown, 2006).

Central to SCCT are the social cognitive mechanism of self-efficacy beliefs, outcome expectations, interests, and goals (Lent et al., 1994) relevant to career development. SCCT holds that individuals develop interests in those activities that they view themselves as efficacious and for which they expect positive outcomes when performing the behavior (Bandura, 1986; Lent et al., 1994). In turn, students' primary interests are likely to elicit corresponding goals, which then influence career related interests and choice behavior (Lopez, Lent, Brown, & Gore, 1997). It is through these mechanisms that learning experiences (e.g., prior performance accomplishment, vicarious learning, and modeling behaviors) influence individuals' cognitions and behaviors.

SCCT utilizes three interlocking models of career development: (1) the formation of career interests, (2) selection of academic and career choice options, and (3) performance in educational and occupational pursuits. Because the focus of this study is on the development of math interest, the discussion will center on Lent et al.'s (1994) Model of Interest Development. SCCT holds that self-efficacy and outcome expectations are central to the formation of career interests. Students tend to develop interests in academic subjects and careers when they possess strong self-efficacy and positive outcome expectations. Self-efficacy also influences favorable outcome expectations, producing an indirect effect on interests (see Figure 1).

Emerging interests lead to goals for further exposure to activities, which increases the likelihood of performing and practicing the task behaviors. This, in turn, produces performance attainments, which create revisions of self-efficacy and outcome expectations. This interactive feedback loop of practicing a task and ensuing self-efficacy and outcome expectations revisions repeats itself over the life span. However, once interests stabilize, it tends to take "very compelling experiences to provoke a fundamental reappraisal of career self-efficacy and outcome beliefs" (Lent et al., p.89), such as dramatic changes in life or career circumstances. For mental health, career, and school counselors, these very events may also be the reason the client is seeking professional help, providing a window of opportunity to facilitate the reassessment and potential cultivation of different competencies.

These social cognitive variables do not operate alone in shaping career interests. Rather, other person traits and contextual contexts, such as gender, race, ethnicity, genetic endowment, and socioeconomic status as well as the learning experiences that shape interests influence and function interactively with the social cognitive variables (Lent & Brown, 1996; Lent et al., 1994). Lent et al. posit that person inputs, contextual influences, and learning experiences influence career choice and behaviors through three pathways: a) precursors or sources for the socio-cognitive variables, (b) moderators of the relationships among the social cognitive factors, or (c) direct facilitators or deterrents of behaviors, such as selective reinforcements (Lent et al., 1994, p. 101). Through learning experiences, these contextual variables and person inputs shape self-efficacy and outcome expectations, which in turn influence interests. Thus, SCCT focuses not only on the dynamic and situation-specific aspects of people (i.e., self-efficacy, outcome expectations), but also the interactions of person traits and their environments (Lent & Brown, 2006).

Rather than viewing gender in terms of a physical aspect of the individual, SCCT focuses on the psychological and social effects of gender (Lent, 2005). SCCT holds that because gender is a socially conferred and constructed construct (Mikkola, 2008), the social-cultural environment and the opportunity structures in which career development occurs strongly affect individuals' career development (Lent & Brown, 1996; Lent et al., 1994). For young girls, culturally defined gender roles tend to limit the availability and quality of early learning experiences to gender-appropriate stereotypical academic and career-related behaviors (Krumboltz, 1996; Lent, Brown, & Hackett, 1994). Once internalized, gender stereotypes often unknowingly influence their perceptions of gender appropriate interests and behaviors, further limiting interest shaping learning experiences. Thus, the influence of gender on career interest, choice, and performance operates largely through self-efficacy, outcome expectations, and the differential gendered learning experiences shaping these beliefs (Lent et al., 1994; Turner, Steward, & Lapan, 2004).

SCCT holds that two types of contextual factors: a) background contextual affordances that directly precede learning experiences and b) contextual influences proximal to career choice that influence self-efficacy and outcome expectations. Thus, SCCT accounts for the background contextual affordances, such as the previously described family and social factors that shape learning experiences. Lent et al. posit that these affordances influence self-efficacy and outcome expectations indirectly though learning experiences. Additionally, SCCT identifies and addresses contextual influences proximal to choice behaviors, such as career opportunities and barriers. These proximal factors directly influence choice goals and actions, and moderate the relationships between interests and choice goals, and choice goals and actions. Thus, contextual factors influence interests through multiple pathways.

Math and Social Cognitive Career Theory

To appropriately conceptualize and measure the social cognitive variables that comprise the core of SCCT, these variables must relate to a specific domain of behavior (Betz & Hackett, 2006). In other words, math self-efficacy, math outcome expectations, and math interests do not generalize to other behavioral domains, such as English or writing behaviors. Self-efficacy, outcome expectations, and interests are not trait constructs but are people's cognitive appraisals or judgment of future performance capabilities within distinct realms of functioning (Bandura, 2005). Therefore, some type of delineated behavior domain is required to measure self-efficacy, outcome expectations, and interests (Bandura, 1997, 2005; Lent et al., 1994).

Empirical evidence supports incorporating Bandura's (1986, 1997) assumption for domain specificity of the social cognitive factors into SCCT. Smith and Fouad (1999) examined four social cognitive factors, self-efficacy, outcome expectations, interests, and goals, across four subject domains: math/science, art, social studies, and English. They used parallel measures to test the domain specificity of the social cognitive factors. For example, parallel measures of interests included math interest, art interest, social studies interest, and English interest. They constructed similar parallel measures for self-efficacy, outcome expectations, and goals. A series of factor models were tested for fit to the data (16 total parallel measures) using a confirmatory factor analytical strategy consistent with a multitrait-multimethod (MTMM) design. Analyses ranged from a one-factor model that captured all the variance in the indicators, a four-factor model faceted along the construct or the subject dimensions, or the eight-factor structure, with each indicator loading on the subject as well as the parallel construct.

The results indicated a multidimensional, four construct, four-structure structural equation model provided the best fit of the data. This model is consistent with Bandura's (1986) premise that the social cognitive factors were domain-specific. The four SCCT variables were domain specific and did not generalize across subject domains (Smith & Fouad; 1999). While the SCCT variables did not generalize across domains, Smith and Fouad ran analyzes to test the fit of the model within each subject domain. The structural models for each subject domain indicated that SCCT provided similar predictions of the relationships amongst the social cognitive factors, suggesting that SCCT holds across academic domains (Fouad, Smith, & Zao, 2002; Smith & Fouad). Given the domain specificity of the social cognitive factors, the domain examined was math.

A review of the literature revealed a large body of empirical evidence supporting the use of SCCT's model of career development in the math domain. The annual review of the career literature supports this assertion, noting that SCCT remains one of the preeminent career theories (Chope, 2008; Patton & McIlveen, 2009; Tien, 2007). Analyzing 25 years of self-efficacy research, Gainor (2006) concluded that empirical studies support the use of SCCT when designing, implementing, and evaluating interventions that can assist career choice and development. Betz and Hackett (2006) noted that some researchers appear to disregard the aspects of Bandura's (1977a, 1977b, 1986) Social Cognitive Theory, the theoretical foundation of SCCT. When evaluating the usefulness of study results, the reader should evaluate the study constructs. While researchers using constructs not grounded in SCT still provide useful information on career development, these studies do not provide information on the sources of self-efficacy. Without this information, it is difficult to derive interventions and implications. With these limitations in mind, and given the preponderance of SCCT studies grounded in social cognitive theory, this review of the literature will focus on the results of two studies that examined the suitability of SCCT for middle school students: Fouad and Smith (1996) and Navarro, Flores, and Worthington (2007).

Fouad and Smith (1996) examined the relationships between math and science self-efficacy, outcome expectations, interests, and choice intentions in seventh and eighth grade boys and girls. They used structural equation modeling to test the fit of the model predicting the relationships among the SCCT constructs. The authors included gender and age, but because the study had no measures of learning experiences, they modified the model to include direct paths from gender and age to outcome expectations and to self-efficacy. Path analysis indicated that self-efficacy produced significant direct paths to outcome expectations (.55), interest (.29), and intentions (.13). Outcome expectations directly predicted interest (.18) and intentions (.39), and interest predicted intentions (.28). Age predicted interest (-.11) and gender predicted both interest (.14) and outcome expectations (-.18). The paths in the model fit the relationships posited by Lent et al. (1994). However, the magnitude of the paths differed between girls and boys. Boys reported lower interest but higher outcome expectancies than girls. Thus, SCCT research on math supports the use of SCCT as a measure of the social cognitive factors that are the focus of the present study.

Self-Efficacy

Self-efficacy is at the heart of social cognitive theory (Bandura, 2005; Betz, 2007). Self-efficacy expectations refers to individuals' beliefs concerning their ability to successfully perform a given task or behavior (Bandura, 1986). Self-efficacy beliefs help determine the effort people will expend on an activity, their perseverance when confronting obstacles, and their resilience when facing adverse situations (Bandura, 1977b; Schunk & Pajares, 2002). In social cognitive theory, Bandura did not conceptualize self-efficacy as a singular static, passive, or global trait. Rather, but it is a dynamic and differentiated set of beliefs about self linked to distinct realms of functioning and activities, such as the academic and career tasks associated with math (Lent & Brown, 1997; Lent, Brown, & Gore, 1997).

Social Learning Theory (Bandura, 1986, 1997) posits that students form self-efficacy beliefs by selecting and interpreting information from four primary sources: *mastery experiences* from their own previous performance, *vicarious experiences* of observing other's actions, *social persuasions*, or evaluations, individuals receive from others, and *emotional and physiological states* such as arousal, anxiety, mood, and fatigue (Usher, 2009). While evidence of the four sources of self-efficacy were observed in middle school students in math, mastery experience appear to be the most powerful source of math self-efficacy beliefs (Usher, 2009; Usher & Pajares, 2009). The findings confirmed Bandura's (1997) assertion that the weights students assign to the sources of self-efficacy are not identical across contexts, but are domain specific.

Math Self-Efficacy

Math self-efficacy refers to beliefs about ability to successfully perform a given task or behavior in math (Bandura, 1986). The role of math self-efficacy and STEM-related academic and career behaviors has been highly researched (Chope, 2008; Lent, Lopez, & Bieschke, 1991, 1993; Lent, Lopez, Lopez, & Sheu, 2008; Nagy et al., 2008, 2010; Nauta & Epperson, 2003; Patton & McIlveen, 2009; Tien, 2007). Math self-efficacy is predictive of math achievement (Friedel, Cortina, Turner & Midgley, 2010; Norwich, 1987; Pajares & Urdan, 2006) and of math-related academic and career interest (Byars-Winston & Fouad, 2008).

Math self-efficacy predicts initial interest, choices and subsequent persistence of females pursuing STEM fields (Rottinghaus, Larson, & Borgen, 2003; Usher & Pajares, 2009; Zeldin & Pajares, 2000). Through socialization experiences, women and girls are often not encouraged or, at times, are actively discouraged from engaging in activities that increase and strengthen expectations of personal efficacy, particularly in non-traditional fields (Betz, 2004). As a result, women often report lower levels of self-efficacy in many career-related behaviors, such as the STEM fields (Betz & Hackett, 1981). Because lower levels of self-efficacy often lead to avoidance versus approach behaviors, understanding math self-efficacy beliefs is important when examining career choices of people from groups who tend to underestimate their capabilities or perceive limitations in accessible career options, such as girls in math (Betz, 2004).

Socio-cultural forces affect women's math self-efficacy at an early age (Eccles, 2007). Two key socializers, parents and teachers, have a profound effect in shaping a child's math self-efficacy. Research suggests that teachers and parents have lower expectations for girls than for boys in math (Neuville & Croizet, 2007). Parents who believe boys are better at math than girls are more likely to overestimate their sons' math ability and underestimate their daughters' ability (Bhanot & Jovanovic, 2005). In the classroom, teachers often reinforce broadly held gender stereotypes, particularly during the middle school years (Good et al., 2003). These socially constructed beliefs that girls are not as competent in math as boys shape the child's learning experiences, potentially resulting in girls having lower self-efficacy and interest in math (Plant et al., 2009).

Stereotypical beliefs may also explain differences between girls' self-efficacy beliefs and their actual ability (Thiessen, 2007). Researchers consistently find that as early as middle school, females report lower self-efficacy in their math skills, even when their skills were equal to or better than males (Huguet & Régner, 2007, 2009; Jacobs et al., 2002; Thiessen, 2007). Since performance mastery was found to be the major source of math self-efficacy (Usher, 2009; Usher & Pajares, 2009), these findings suggest that other causal factors may account for boys' higher math self-efficacy and girls' low levels of math self-efficacy. Researchers found that girls did not report the same sense of pride as boys after success in math and identified more with failure than success. After failure, girls were more likely to try to hide their failure to avoid a sense of shame (Frenzel, Pekrun, & Goetz, 2007a, 2007b). Thus, it appeared that gender stereotypes directly influenced girls' perceptions of math self-efficacy beyond the information provided by formal feedback of achievement in terms of grades. Given the role of self-efficacy in career development, the ramifications of this incongruence between performance and girls' early self-efficacy beliefs may resonate throughout women's academic and professional careers (Good et al., 2003).

The incongruence between actual math achievement and perceived math self-efficacy appear to be a major liability for elementary and middle school students (Ramdass & Zimmerman, 2008). Ramdass and Zimmerman designed interventions that increased the extent that self-efficacy aligned with performance in fifth and sixth grade students. Students in the treatment group reported higher congruence between performance and self-efficacy than those in the control group, with an interactional effect by grade and gender. Their research confirms Bandura's (1997) premise that self-efficacy is a dynamic and not a static construct. Students with high levels of self-efficacy set higher goals, use more effective self-regulatory strategies, efficiently monitor their work, demonstrate perseverance with challenging academic tasks, and evaluate performance more accurately than students with low levels of self-efficacy. Examining the dynamics underlying this incongruence in early adolescent girls could help bring congruence to math self-efficacy beliefs and performance. Given the afore-mentioned research suggesting that mastery experience is the strongest source of math self-efficacy in adolescents, these findings suggest that other factors appear to undermine the influence of performance and mastery experience on math self-efficacy in early adolescent girls.

Women's lower levels of math self-efficacy correspond to a lack of interest in math-related careers. A greater proportion of males enroll in higher-level math courses and a greater proportion of females in lower-level courses (Watt, 2006). Both genders had similar prior experience, yet males rated themselves higher in math success, expected success, and were more likely to plan a career in a math-based field than females. Compared to males, females believed math was a more difficult undertaking, perceived themselves as having less talent, and held lower expectations of success in math. Overall, females reported lower levels of math-related self-efficacy, intrinsic value (enjoyment and interest), and utility value (future usefulness), independent of their prior math achievement. These observed gender differences are strong predictors of academic performance, interest, and choices (Bandura, 1997; Eccles, 2007; Lent, Brown, & Hackett, 1994, 1996). Thus, gender differences in math self-efficacy during early adolescents provide a plausible explanation for females opting out of math-related academic and career choices.

Several studies that examined developmental trends in math interest also examined math self-efficacy during the same study. Similar to math interest trajectories, researchers found differences between boys' and girls' math self-efficacy trajectories in U.S. (Eccles et al., 1983, Fredricks & Eccles, 2002; Nagy et al., 2010; Watts, Eccles, &

Durik, 2006), Australian (Nagy et al., 2010; Watt, 2004, 2008), and German (Frenzel, Goetz, Pekrun, & Watt, 2010; Nagy et al., 2010;) students. I present the findings regarding the trajectory of math self-efficacy from the following two studies, Jacob et al. (2002) and Linver, Davis-Kean, & Eccles (2004).

In these two studies, researchers found significant declines in math self-efficacy over time, with gender predictive of the slope of the decline. In U.S. students, Jacobs et al. (2002) found an overall decline in math self-efficacy between second and 12th grade. Initially, second grade girls reported higher math self-efficacy than did boys. Between third and fifth grades, both genders reported similar rates of decline in self-efficacy. By sixth grade, the rate of decline accelerated for girls, with the sharpest rate of decline occurring during high school. Twelfth grade females' math self-efficacy decreased to the same levels as the males. Self-efficacy explained most of the decline in math interest occurring between second and fifth grade, very little of the decline in math interest in middle school, and a portion of the decline in high school. In light of the math interest trajectories previously reported, it would appear that during the period where math interest crystallized, declines in girls' math self-efficacy began to accelerate. These findings support Lent et al.'s (1994) premise that once interests crystallize, students' motivation to practice and engage in math-related activities diminish. Given that mastery/performance is a powerful source of self-efficacy, lack of practice would tend to influence negatively their math self-efficacy revision.

Also examining U. S. students' math self-efficacy trajectories from sixth through 11th grade, Linver et al. (2004) found comparable declines in math self-efficacy across all gender and track groups. Unlike the previously reported slope for math interest, all groups had a similar rate of slope decline, with the exception of high-track boys who maintained higher levels of math self-efficacy throughout middle and high school. There were no significant predictors of boys' slopes. Sixth grade math self-efficacy predicted the slope for high-track girls, with higher self-efficacy associated with a slower decline in the slope. Conversely, low-track girls' slope was negatively associated with self-efficacy, with higher self-efficacy associated with a steeper decline in the slope. Males' grades dropped more than the girls, but their math self-efficacy did not decrease comparatively. These results suggest that females' math achievement does not appear to influence their math self-efficacy in the same way as does males.

Outcome Expectations

In addition to students' belief in their personal capabilities (self-efficacy), their beliefs about the likely effects of engaging in the various actions associated with that type of course or career, i.e., expected outcome of domain-specific behaviors, influence academic and career choice behavior (Bandura, 1986; Lent et al., 1994). Outcome expectations encompass students' perceptions of the expected benefits and costs of performing an academic or career-related behavior (Bandura, 1986, 1989) and answer the question, "If I do this, what will happen?" (Lent & Hackett, 1987, p. 348). Social cognitive theory holds that individuals are more likely to choose the academic or career-related activities in those domains, such as math or English, that they believe offer the most positive outcomes, and they will tend to avoid those behaviors that present negative outcomes (Bandura, 1986, 1989, 1997).

Distinct from behavioral outcomes, which involve the performance of an action; outcome expectations are the person's evaluation of the anticipated outcomes of the behavior *prior* to the behavior occurring (Bandura, 1986, 1997). In other words, based on past learning experiences, individuals develop an expectation of certain outcomes from performing a behavior, versus the action itself, which influence the likelihood that they perform a behavior again. Bandura described three expectancy values of outcome expectations: (a) physical outcomes, including pleasant physical sensations, or pain and physical discomfort; (b) social reactions, such as approval, recognition, monetary reward, and power; or disapproval, feeling shamed, rejection, privilege deprivation, and penalties; and (c) self-evaluations, self-satisfaction, or self-criticisms. The foresight provided by outcome expectations, and the ensuing expectancy values associated with that outcome, exerts an influence on people's behavior (Bandura, 1997).

Thus, for the domain of math, students' outcome expectations form from observing situations involving math and math-related events in their environment as well as outcomes experienced when engaging in prior math-related activities (Bandura, 1997). As students engage in a variety of direct and vicarious math-related learning experiences, they observe consequences of the activity and form an association between the activity and their perception of the value that the math-related outcomes hold for them. Over time, observed consequences of direct and vicarious learning experiences and modeling behaviors, along with the value associated with the outcomes, generalize to encompass similar math-related activities. Now when presented with a similar activity, students use symbolic thinking to imagine possible consequences based on their generalized expectation, as well as the associated value of the outcome. Based on this expectation, they will adjust their behavior accordingly (Bandura, 1977a; Brown & Lent, 1997).

The formation of outcome expectations is complex and unique for each individual. For example, if a young girl sees students laughing at other girls when they give a wrong answer, she may conclude that laughter is the outcome of girls' answering questions wrong. Depending upon her past learning experiences, even if this outcome only occurs in one class, she may generalize this outcome to all girls in all classrooms, which may affect her future behavior. She also bases the effect of an expected outcome on behavior on past learning experiences. If the predominant expected outcome associated with a wrong answer is negative, such as shame after someone laughed at her, then she may avoid answering math questions in the future. Conversely, if she expects a positive outcome based on experiences when she felt a high level of satisfaction from correcting a wrong answer, then she will likely continue to answer math questions in the future. Thus, the learning experiences of the girl shape the generalized expectations and the associated positive and negative value of outcomes (Bandura, 1986, 1997).

Although math self-efficacy beliefs and math outcome expectations are usually positively correlated (Lent & Brown, 2006), it is possible for a student to have high self-efficacy for a task, but low outcome expectations (Bandura, 1997). Thus, an eighth grade girl in algebra could have relatively high efficacy beliefs about her personal capability to master the material, but low outcome expectations about the negative reaction of her classmates if she gets a problem wrong. Low self-efficacy and positive outcome expectations are also possible. High school students may have a positive math outcome expectation that strong mathematics skills are essential for a good SAT score and entry into a four-year university, which in turn, may ensure a comfortable lifestyle. However, poor math self-efficacy about their math abilities would likely keep them from enrolling in advanced math courses, which then limits their ability to successfully take the SAT or be accepted into a four-year university (Pajares 2002).

Recognizing that there is a unique association between self-efficacy and outcome expectations, SCCT extends Bandura's (1986) premise to career-related interests and choice (Lent & Brown, 1996). While self-efficacy influences outcome expectations, outcome expectations may also make a unique contribution to career behavior if there is not a strong link between the outcomes expected and the quality of performance (Lent et al., 1994). When expected outcomes of an action tie into individuals' self-efficacy for the action, SCCT posits that self-efficacy is the stronger determinant of behavior. In other words, SCCT presumes that self-efficacy for math tasks more strongly predict entering a math career than the outcome expectation of the career. Yet, if a woman expects negative outcomes for entering a STEM career, her outcome expectations may predict her not entering that career, even if she has high self-efficacy for math tasks (Fouad & Guillen, 2006). Thus, math outcome expectations can also directly affect math interest, and ensuing career intentions and activities.

SCCT posits that similar sources that influence self-efficacy: i.e., direct reinforcement from engaging in actions and vicarious learning from the consequences of others' actions, also determine outcome expectations. Whereas research has provided empirical evidence that performance accomplishments and mastery experiences are powerful source of self-efficacy (Lopez & Lent, 1992; Usher, 2009; Usher & Pajares, 2009), no similar studies have focused on the sources of outcome expectations.

Math Outcome Expectations

The construct of outcome expectations is a core construct in the SCCT interest and choices models. In their seminal article, Lent, Brown, and Hackett (1994) hypothesized: a) there would be a positive relationship between outcome expectations and interest; b) self-efficacy and outcome expectations would jointly account for more variance in interest than each variable individually. Furthermore, they hypothesizes that c) self-efficacy and outcome expectations would stabilize by late adolescence; d) the variance in the stability of self-efficacy and outcome expectations would account for the variance in the stability of interest; and e) there is a relationship between the changes in self-efficacy and outcome expectations and the changes in interest.

A review of the literature examining math outcome expectations revealed that few studies addressed this core construct of SCCT. However, the available empirical research supports the Lent et al.'s conceptualization of the influence of outcome expectations on interest. Empirical evidence supports the direct influence of outcome expectations on interest. In a meta-analysis reported in their seminal article, Lent et al. (1994) reported that the average weighted correlation between outcome expectations and interest was .52. Other studies found similar results ranging from .40 to .52 (Lent et al., 2001; Lopez, Lent, Brown, & Gore, 1997; Smith & Fouad, 1999). Using path analyzes, several studies supported the joint effect of self-efficacy and outcome expectations on interest (Byers-Winston & Fouad, 2008; Fouad & Smith, 1996; Fouad, Smith, & Zao, 2002; Lent et al., 2001; Nauta & Epperson, 2003). Empirical studies support Lent et al.'s hypothesized relationships between math outcome expectations, math self-efficacy and math interest.

Findings from these studies also suggested that outcome expectations might influence interest with a strength not predicted by the model. In a study designed to test the fit of the SCCT model for middle school students, gender and age were related to math-science outcome expectations and interest but not related to math-science self-efficacy (Fouad & Smith, 1996). Furthermore, math-science self-efficacy influenced math-science interest strongly through the indirect path via math-science outcome expectations rather than the direct path to interest. Their findings suggest the possibility that outcome expectations may influence math interest differently, depending upon the developmental stage of the participants.

Math Gender Stereotypes

Research suggests that the starting in the middle school years, awareness of the gender stereotype that women are intellectually inferior to men in math can result in decreased math achievement and performance (Neuville & Croizet, 2007). Girls' lower math self-efficacy and outcome expectations correspond to a lack of interest to pursue careers in math related fields. These observed gender differences are strong predictors of academic performance and choices (Bandura, 1997; Eccles, 2007; Lent et al., 1994). These findings suggest that early adolescent math learning experiences appear to perpetuate the stereotype that boys are better at math than girls, whereas girls are better than boys at English (Oswald, 2008; Thiessen, 2007; Watt, 2008).

This stereotype appears to be pervasive in U.S. society. Addressing the National Bureau of Economic Research Conference on Diversifying the Science and Engineering workforce, the president of Harvard University, Lawrence Summers (2005), made the following observations:

> I'm going to confine myself to addressing one portion of the problem ... which is the issue of women's representation in tenured positions in science and engineering at top universities and research institutions . . . because it's the only one of these problems that I've made an effort to think in a very serious way about. (para. 1) . . . My best guess, to provoke you, of what's behind all of this is that the largest phenomenon, by far, is the general clash between people's [women's] legitimate family desires and employers' current desire for high power and high intensity; that in the special case of science and engineering, there are issues of intrinsic aptitude, and particularly of the variability of aptitude; and that those considerations are reinforced by what are in fact lesser factors involving socialization and continuing discrimination. (para. 6)

These comments contain explicit and implicit gender stereotypes that likely are similar to those girls and women heard from their parents and teachers (McKown, & Weinstein, 2003; Neuville & Croizet, 2007). Over time, these stereotyped messages can be internalized so that young girls and women believe that the pejorative attributions (i.e., fixed abilities) verbalized by Summers are true, that women inherently are not as capable as men to succeed in the math and science fields (Good et al., 2003).

Middle school girls appear to be negatively affected by this prevailing explicit gender stereotypes that women are less capable than men in higher level math (Good, Aronson, & Harder, 2008). Explicit gender stereotypes often portray the STEM fields as masculine pursuits that are unfeminine, aggressive, and object-oriented versus people-oriented (Eccles, 2007). The present underrepresentation of women in STEM fields tends to lend credibility to the explicit stereotype that careers in STEM are not "normal" for women (Plant et al., 2009). Thus, explicit negative gender stereotypes of math and math-related sciences may reduce interest in STEM careers and discourage middle school girls from taking the math classes needed to pursue a career in these fields (Eccles, 2007; Hargreaves, Homer, & Swinnerton, 2008).

In addition to explicit gender stereotypes about math, research suggests that implicit gender stereotypes contribute to the gender gap in interest, participation, and performance in the STEM fields (Huguet & Régner, 2009; Nosek & Smyth, 2009; Nosek, Smyth, Hansen, et al., 2007). Because implicit processes occur without awareness or control, implicit cognitions that directly contradict explicit, avowed beliefs or values can still exert an influence on behavior (Kiefer & Sekaquaptewa, 2007a). Females endorsing gender equity in math often still show evidence of implicit gender stereotypes regarding math, associating males with math more than associating females with math (Nosek, Banaji, & Greenwald, 2002). Females showed stronger implicit negativity and gender stereotypes toward math than males did (Nosek & Smyth, 2009).

Research suggests that females' implicit associations between gender and math interact with situational cues to influence their math performance, self-efficacy beliefs and interests in math (Kiefer & Sekaquaptewa, 2007a, 2007b) as early as middle school (Good, Dweck, & Rattan, 2008; Huguet & Régner, 2007, 2009). In two studies conducted by Huguet and Régner, (2007, 2009), French middle school students were asked to perform a complex-figure memory task. To activate stereotype cues, researchers told students they would either help develop a geometry test for a textbook or a drawing from memory game for a magazine. The students performed the tasks in either mixed or single gender groups.

Huguet and Régner (2007, 2009) found that French middle school girls' drawings were less accurate than boys' drawings when performing the task under conditions where the girls believed they were helping with a geometry text and more accurate than boys' drawings when the girls believed that they were working on a drawing game. Boys performed equally well under both treatment conditions. In mixed groups, girls' drawings were less accurate under geometry conditions than girls' drawings under drawing game conditions. In same-sex groups, there were no differences between drawing and geometry in either gender, suggesting that classroom context influenced the girls' performance when associating a task with math. In all testing conditions, girls underreported their geometry ability even though their scores were similar to the boys' scores. Given that performance attainment is a powerful source of math self-efficacy (Bandura, 1997; Usher, 2009; Usher & Pajares, 2009), classroom contextual factors appear to decrease the influence of performance attainment on math performance and math self-efficacy in early adolescent girls (Huguet & Régner).

Students' perceptions of teacher and parents' math gender-competency beliefs also can influence math self-efficacy. Kurtz-Costes, Rowley, Harris-Britt, and Woods (2008) found that fourth, sixth, and eighth grade boys' perceptions that their teacher's and parents' held stereotypes favoring boys over girls enhanced their self-efficacy. However, they found mixed results for girls. Fourth, sixth, and eighth grade girls reported positive views of their gender group's performance, but positive gender-group perception of math efficacy did not translate into positive math self-efficacy. While girls' math grades indicated strong performance in math, middle school girls reported lower self-competence than boys. Girls' perceptions of their math ability levels were lower than boys' perceptions, and girls' gender-group competence ratings were not related to their self-perceptions.

Kurtz-Costes et al. (2008) found that fourth grade girls perceptions of parents' and teachers' gender stereotype were related to their assessments of girls' (as a gender) math competence. Sixth grade girls who believed that adults viewed boys as being better than girls in mathematics reported lower levels of math self-efficacy. However, there was no relationship observed in eighth grade girls, suggesting that girls had internalized stereotypical beliefs concerning their math abilities (Kurtz-Costes et al.). Early adolescent girls' perceptions of their parents' and teachers' stereotyped beliefs about girls' math competency influence their math self-efficacy (Good et al., 2003; Huguet & Régner, 2007, 2009; Kurtz-Costes et al., 2008).

The aforementioned association of math performance or math self-efficacy with early adolescent girls' awareness of math gender stereotypes (Neuville & Croizet, 2007) corresponds to their social developmental stage (McKown & Weinstein, 2003). During early adolescence, teacher-student and student-student interactions can nullify or activate broadly held math gender stereotypes, potentially reinforcing explicit and implicit stereotypes in middle school children (Good, Aronson, & Harder, 2008; Huguet & Régner, 2007). In turn, this belief that boys are better in math than girls can influence how early adolescents interpret teacher, peer, and self-comparative evaluations of efficacy in math (McKown & Weinstein, 2003).

Because social comparisons versus self-evaluations shape the development of early adolescents' self-efficacy, teachers' interpretations of students' successes and failures influence self-efficacy (Bandura, 1997, 2000). In early adolescence, students' perceptions of their ability appear to be especially responsive to social comparison information (Ames, 1992). Thus, girls may derive meaning from negative teacher and peer interactions viewed in the context of gender stereotypes, potentially resulting in the internalization of the stereotype that girls are inherently inferior to males in math (Good et al, 2003). Given the predictive power of self-efficacy on the formation of math interest, the classroom learning environment where self-efficacy is formed and gender stereotypes are activated or nullified plays a crucial role in the development of middle school girls' interest and future success in STEM fields (Plant et al., 2009).

Classroom Learning Environment

An important variable in the development of self-efficacy is the environment in which learning occurs (Bandura, 1997). Children develop their cognitive competencies and acquire knowledge and problem-solving skills essential to participate effectively in society (Bandura, 1994) in their family and in school. As children master cognitive skills, they develop a growing sense of their intellectual self-efficacy. However, as noted previously, classroom factors beyond formal instruction also affect the development of self-efficacy (Ciani, et al., 2010). Research on classroom learning environment provides evidence that the social and psychological context in which learning occurs is associated with students' math achievement (Pianta, Belsky, Vandergrift, Houts, & Morrison, 2008), attitudes (Fraser, 1978, 1998; Fraser & Kahle, 2007; LaRocque, 2008; Moos. 1979), emotional well-being (Pianta & Steinberg, 1992; Reddy, Rhodes, & Mulhall, 2003), and math self-efficacy (Dorman, 2001; Fast et al., 2010; Patrick et al., 2007).

The student-teacher relationship appears to be an essential component of the learning environment (Wentzel, 1998), particularly during the transition from elementary to middle school (National Research Council, 2004; Roeser et al., 1998). As adolescents develop identity outside the family, supportive and caring relationships with teachers are particularly important (Ciani et al., 2010; Collins & Laursen, 2004a, 204b; Pianta, Stuhlman, & Hamre, 2002; Wigfield, Lutz, & Wagner, 2005). Midgley, Feldlaufer, & Eccles (1989) found that students' perceptions of support and caring in the student-teacher relationship decreased following the transition from elementary to middle school. These changes in perception of the student-teacher relationship were associated with changes in students' perceptions of math interest (referred to as Valuing) and math outcome expectations (referred to as math Utility Value or Usefulness).

Midgley et al. (1989) also found that the quality of the student-teacher relationship appeared to exert a stronger influence on math interest and math outcome expectations during the first year of middle school than during the last year of elementary school. Low math achieving students perceiving their elementary math teacher as highly supportive, who transitioned to a middle school environment where they perceived their math teacher as less supportive, exhibited sharper declines in math interest and outcome expectations than did average math achieving students experiencing similar changes. Students perceiving their elementary math teachers as low in support, who transitioned to a middle school classroom where they perceived the math teachers as high in support, reported increased levels of math interest (math valuing). These results support the importance of examining the student-teacher relationship as an essential component of the learning environment

Learning Environment Research

A review of the research literature on classroom learning environment revealed that Moos' (1979) classification of learning environment provides the theoretical foundation for these studies of classroom learning environment. Examining junior high and high school classrooms, Moos classified learning environments into three basic dimensions: (a) relationship, (2) personal development; and (3) system maintenance and change. According to Moos (1974, 1976, 1979), r*elationship dimensions* encompasses the nature and intensity of personal relationships, including the extent that students and teachers are involved in their environment, the extent that they help and support one another, and the amount of free and open expression exhibited in the classroom. *Personal Development dimensions* focus on opportunities for personal development and self-enhancement found within the classroom environment. *System Maintenance and System Change dimensions* examines the extent that the environment is orderly, clear in expectations, and is responsive to change (Moos, 1979). Given the aforementioned role of classroom learning experiences on the development of self-efficacy in early adolescent girls (Bandura, 1997; Gottfredson, 1981, 1996; Mitchell & Krumboltz, 1996; Lent, et al., 1994), this study will focus on Moos' relational dimension, specifically teacher-student interactions in the classroom.

In the 34 years since the publication of Moos' (1979) seminal work assessing educational environments, researchers developed several instruments designed to assess the psychosocial classroom learning environment measure various components of these three dimensions (Fraser, 1994, 1998; LaRocque, 2008). While these instruments use Moos' conceptual framework for classifying human environments, and measured the relational dimension, not all instruments specifically measured students' perceptions of the student-teacher relationship. The Learning Environment Inventory (LEI, Fraser, Anderson & Walberg, 1982; Walberg & Anderson, 1968), the My Class Inventory (MCI, Fraser et al., 1982), Classroom Environment Scale (CES, Fisher & Fraser, 1983; Moos, 1979; Moos and Trickett, 1987), and the Individualized Classroom Environment Questionnaire (ICEQ, Fraser, 1981, 1990) measured students' perceptions of the "class as a whole" rather than students' perceptions of the environment in relation to self.

In 1995, Fraser, Giddings, and McRobbie (1995) noted that traditional measures of classroom learning environment potentially created confounds. Rather than view a class as a whole, each student individually constructs the classroom environment based on his or her individual perceptions. For example, boys may view their teachers as more supportive than do girls, yet males and females still could agree when asked for their perceptions about the whole class. To examine students' perceptions of his/her own role within the classroom, instruments such as the What Is Happening in This Classroom? (WIHIC, Fraser, Fisher, & McRobbie, 1996) and the Elementary and Middle School Inventory of Classroom Environments (ICE, Sinclair & Fraser, 2002).

A review of the literature found that these instruments, as well as other scales using variants of these items, have been validated for use in classroom environment research of U.S. middle and high school student in science and math classrooms (Allen & Fraser, 2007; den Brok, Fisher, Rickards, & Bull, 2006; Fraser, 2002; Ogbuehi & Fraser, 2007; Pickett & Fraser, 2009). Furthermore, studies examining the association between learning environment and math self-efficacy used various items from these scales (e.g., Dorman, 2001; Fast et al., 2010; Patrick, Ryan, & Kaplan, 2007). Given the focus of this study, the following discussion of studies will be limited to the variable measuring the student-teacher relationship.

The Student-Teacher Relationship

Learning environment research consistently finds that the perceived quality of the classroom environment in schools to be a significant determinant of student learning (Fraser, 1994, 1998a). In other words, students' learning increases when they perceive the classroom environment positively. A primary aspect of the classroom learning environment is the relationship and the interaction between students and their teacher (Ciani et al., 2010; den Brok, Levy, Brekelmans, & Wubbels, 2005; Pianta, 1999; Van Petegem, Aelterman, Van Keer, & Rosseel, 2008).

Numerous research studies have shown that student perceptions of the classroom environment account for appreciable amounts of variance in learning outcomes, often beyond that attributable to background student characteristics. Researchers find that positive caring teacher-student relationships support social, emotional, and cognitive development in the classroom (Hamre & Pianta, 2005; O'Connor & McCartney, 2007; Pianta & Walsh, 1996), academic motivation (Patrick, Turner, Meyer, & Midgley, 2003; Wentzel & Wigfield, 2007), academic interest (Wentzel, 1998), problem behaviors (Myers & Pianta, 2008), well as influence peer interactions and confidence in their academic abilities (Barber & Olsen, 2004).

The quality of teacher-student interactions was predictive of student achievement, motivation, and behavior in the elementary years (Pianta & Nimetz, 1991) as well as the middle grades (den Brok, Levy, Brekelmans, & Wubbels, 2005; Matsumura, Slater & Crosson, 2008; O'Conner & McCartney, 2007; Wentzel, 1997, 1998; Wentzel &

Wigfield, 2007). In addition, middle school students' perceptions of their teacher's emotional support and caring predicted social goal pursuit, while students' academic and social motivation was associated with the students' perceptions that their teacher communicates high expectations for academic engagement, provision of help, and non-threatening interactions with students (Wentzel, 1997; Wentzel, Battle, Russell & Looney, 2010). Given the developmental challenged faced by middle school students, the student-teacher relationship appears to provide an important emotional and academic support to help students develop and maintain the motivation and engagement needed to successfully navigate the transition the middle school years (Wentzel & Wigfield).

Math Self-Efficacy and the Student-Teacher Relationship

A growing body of research suggests that adolescents' perceptions their learning environments, specifically the student-teacher relationship are associated with self-efficacy. In 2001, researchers studying relationship among perceived learning environment and classroom outcomes first studied the association between classroom environment and self-efficacy. Dorman (2001) found an association between classroom environment and Math Self-Efficacy in 1055 Australian eighth, 10th, and 12th graders from nine schools (27 school year groups). Specifically, Teacher Support, i.e., the students' perception that the teacher helps, befriends, and is interested in them, accounted for 16% of the variance observed in Math Self-Efficacy in eighth, 10th, and 12th grade Australian students. Given this evidence that there is an association between learning environment, including perceptions of support and caring in the student-teacher relationship, and math self-efficacy, Dorman noted the need for further study.

Since Dorman's (2001) study, this researcher found only three studies that examined the relationship between learning environment and math self-efficacy in U.S students. Using 15,362 U.S. tenth grade students from the Educational Longitudinal Study of 2002 (ELS:2002), Fan, Lindt, Arroyo-Giner, and Wolters (2009) examined the relationship between Learning Environment and Math Self-Efficacy. They found that Teacher Support, students' perception that they get along with the teachers and feels encouraged by the teachers, exerted the greatest influence on Math Self-Efficacy for U.S. tenth grade students. Fan et al. also found differences between males' and females' Math and English Self-Efficacy. Consistent with previously referenced studies on gender differences in math self-efficacy, female students reported significantly lower levels of Math Self-Efficacy than males.

Comparing the association between Math Self-Efficacy and Teacher Support or Parent Support, Fan et al. (2009)found that Teacher Support exerted a stronger influence on Math Self-Efficacy than Parent Support in U.S. 10th graders. The standardized coefficient between Teacher Support and Math Self-Efficacy was .39, which was greater than the path between Parent Support and Math Self-Efficacy (.29). These results provide evidence of Bandura's (1997) that as adolescents form an identity apart from their family, supportive and caring relationships with teachers provide an important source of support that influences the development of self-efficacy in adolescent students.

In addition to Fan et al.'s (2009) study, two studies examined the relationship between learning environment and math self-efficacy in fourth, fifth, and sixth grade U.S. student. In a study examining if Math Self-Efficacy mediated the effect of perceived learning environment on Math Performance, Fast et al. (2010) analyzed perceptions of learning environment, Math Self-Efficacy, and Math Performance of 1,163 U.S. fourth, fifth, and sixth graders. Fast et al. found that student perceptions that their teachers take a personal interest in their well-being (Teacher Caring) were associated with higher levels of Math Self-Efficacy. Similarly, Patrick, Ryan, and Kaplan (2007) examined early adolescents' perceptions of classroom learning environment, motivational beliefs, and engagement of participants 602 fifth-grade students. Patrick et al. found that Teacher Emotional Support, students' perceptions that their teacher cares about and will help them, and Teacher Academic Support, i.e., students' perceptions that the teacher cares about their learning, wants to help them learn, and wants them to do their best, were associated with Math Self-Efficacy.

Patrick et al.'s (2007) study also provides evidence that students' perceptions of the student-teacher relationship encompass two distinct factors: teacher emotional support (referred to as Math Classroom Climate in this study) and teacher academic support (referred to as Math Teacher Connection in this study). Patrick et al. found significant path coefficients between Teacher Emotional Support and Math Self-Efficacy (.30). Furthermore, Teacher Academic Support was highly correlated with Teacher Emotional Support (.80), together these constructs were "intertwined" with their sense of self-efficacy (p. 94), yet these two factors were also empirically distinct variables. These finding are consistent with previous studies supporting the distinct nature of these factors was supported by factor analyses (Johnson, Johnson, & Anderson, 1983) and classroom observational studies (Patrick, Anderman, Ryan, Edelin, & Midgley, 2001). Thus, two factors of the student-teacher relationship, Teacher Emotional Support and Teacher

Academic Support, were highly associated with the development of Math Self-Efficacy in fifth grade U.S. students (Patrick et al.).

Based on this limited research examining the relationship between the student-teacher relationship and math self-efficacy in fourth, fifth, sixth, and 10th grade U.S. students, students' perceptions of their math teacher's level of emotional and academic support is an important component of the learning environment. This is particularly relevant given that the role of teacher emotional and academic support is typically not acknowledged as an important trait for math teachers (Pianta, Belsky, Vandergrift, Houts, & Morrison, 2008). Given this emerging research evidence that teacher emotional and academic support in the classroom environment influences self-efficacy, students' perceptions of their Math Classroom Climate and the student's perception of Math Teacher Connection appear to be crucial aspects of the learning environment in the development of math self-efficacy.

In conclusion, studies of psychosocial classroom environment suggested positive links between classroom learning environment and academic self-efficacy (Dorman, 2001; Dorman, Fisher, & Waldrip, 2006; Dorman & Fraser, 2009; Fan, et al., 2009; Fast et al., 2010; LaRocque, 2008; McMahon, Wernsman, & Rose, 2009; Patrick et al., 2007). While there are limited studies examining the influence of learning environment on math self-efficacy in U.S. students, only one study to date examines the relationship between classroom environment and math self-efficacy of U. S. middle school students. Furthermore, no studies have specifically examined classroom learning environment and math outcome expectations in early adolescents. Given the aforementioned research suggesting classroom environment influences self-efficacy as well as gender role socialization (Bandura, 1997), students' perception of support provided by their math teacher (i.e., perceived warmth, respect, and responsiveness to emotional and academic needs) appear to be factors in the learning environment associated with Math Self-Efficacy, Math Outcome Expectations, and Math Interest in early adolescence.

Summary of Chapter 2

In this chapter, I presented a review of the literature, providing the basis for examining the role of math learning environment on early adolescents' math self-efficacy, math outcome expectations, and math interest. This chapter presented a literature review on the population, on the theoretical foundations of the study, and on the constructs Math Interest, Math Self-Efficacy, Math Outcome Expectations, and Math Learning Environment. Chapter 3 provides the methodology of the study.

CHAPTER III

METHODOLOGY

In this chapter, I present the methodology of the study, including the research questions and hypotheses, the research design, the participants, the procedures, the instrumentation, and the data analyses.

Research Questions and Hypotheses

This study examines differences in Math Self-Efficacy, Math Outcome Expectations, Math Learning Environment, and Math Interest for girls and boys in sixth, eighth, and 10th grades. Social Cognitive Career Theory (SCCT; Lent, Brown, & Hackett, 1994) provides the theoretical lens through which to explore the relationship among these constructs, and a modified version of SCCT is the prediction model for the outcome variable of Math Interest. SCCT and the modified model are grounded in Bandura's Social Cognitive Theory (1986; 1997). Moos' (1979) classification of learning environments provides the theoretical basis for the construct of Math Learning Environment. The following research questions guide this study.

Research Question 1

Are there differences in Math Self-Efficacy, Math Outcome Expectations, Math Learning Environment, and Math Interest among boys and girls in Grades 6, 8, and 10 by gender and grade level?

Hypothesis 1. There are differences in Math Self-Efficacy, Math Outcome Expectations, Math Learning Environment, and Math Interest among boys and girls in Grades 6, 8, and 10 by gender and grade level.

Research Question 2

Does Math Learning Environment explain a significant amount of the variance in Math Self-Efficacy for boys and girls in Grades 6, 8, and 10?

Hypothesis 2. Math Learning Environment explains a significant amount of the variance in Math Self-Efficacy for boys and girls in Grades 6, 8, and 10.

Research Question 3

Does Math Learning Environment explain a significant amount of the variance in Math Outcome Expectations for boys and girls in Grades 6, 8, and 10?

Hypothesis 3. Math Learning Environment explains a significant amount of the variance in Math Outcome Expectations for boys and girls in Grades 6, 8, and 10.

Research Question 4

Do Math Self-Efficacy and Math Outcome Expectations explain a significant amount of the variance in Math Interest for boys and girls in Grades 6, 8, and 10?

Hypothesis 4. Math Self-Efficacy and Math Outcome Expectations explain a significant amount of the variance in Math Interest for boys and girls in Grades 6, 8, and 10.

Research Question 5

Do the data fit the modified model of SCCT for girls and boys in grades 6, 8, and 10?

Hypothesis 5. The data fit the modified model of SCCT for girls and boys in grades 6, 8, and 10.

Research Question 6

Is the modified model of SCCT invariant across gender for participants in grades 6, 8, and 10?

Hypothesis 6. Although the data fit the modified model for girls and for boys, the modified SCCT model is non-invariant across gender for girls and boys in grades 6, 8, and 10.

Description of Study Site and Participants

Data for this study were collected from a U.S. Southeastern school district during the 2008-2009 school year. There are approximately 8,700 students in the school district's 11 elementary schools, three middle schools, and two high schools. Four elementary schools, three middle schools, and two high schools participated in the larger study of which this study is a part. The participants in this study came from three middle schools and one high school. All schools have large percentages of both Black/African American and White students, with approximately half of all students eligible to participate in the U.S.D.A. National School Lunch Program (U.S. Department of Agriculture [U.S.D.A.], 2011).

Participant Descriptive Statistics

The number of female participants (58.9%, n = 136) was greater than the number of male participants (41.1%, n = 95). There were approximately equal numbers of White, Non-Hispanic, Anglo, Caucasian, or European (42.9%; n = 99) and Black, African, African-American, or Caribbean (Haitian, Jamaican) (42.0%, n = 97) participants. The rest of the participants were Asian or Asian-American (3.9%; n = 9), Hispanic or Latino (3.5%; n = 8), American-Indian or Eskimo (3.0%, n = 7), and Multiracial or Other Races (4.8%; n = 11).

Over one-third of participants were in sixth grade (36.4%, n = 84), under half were in eighth grade (41.1%; n = 95), and the rest were in 10th grade (22.5%, n = 52). The majority of participants were 11 years old (21.6%, n = 50), 12 years old (13.9%, n = 32), 13 years old (21.2%, n = 49), 14 years old (19.0%, n = 44), or 15 years old (16.9%, n = 39). The remaining participants were 10 years old (0.4%, n = 1), 16 years old (6.5%, n = 15), or 17 years old (0.4%, n = 1). The average participant age was 13.16 years (SD = 1.60). I present the characteristics of all participants in Table 1 through Table 4, by gender in Table 5 through Table 10, and by grade level in Appendix A.

Table 1
Participant Gender

Gender	Frequency	Percent
Female	136	58.9
Male	95	41.1
Total	231	100.0

Table 2
Participant Race or Ethnicity

Race / Ethnicity	Frequency	Percent
Black, African, African-American, or Caribbean (Haitian, Jamaican)	97	42.0
White, Non-Hispanic, Anglo, Caucasian, or European	99	42.9
Asian or Asian-American	9	3.9
Hispanic or Latino	8	3.5
American-Indian or Eskimo	7	3.0
Multiracial or Other Races	11	4.8
Total	231	100.0

Table 3
Participant Grade Level

Grade Level	Frequency	Percent
6th Grade	84	36.4
8th Grade	95	41.1
10th Grade	52	22.5
Total	231	100.0

Table 4
Participant Age

Age in Years	Frequency	Percent
10	1	.4
11	50	21.6
12	32	13.9
13	49	21.2
14	44	19.0
15	39	16.9
16	15	6.5
17	1	.4
Total	231	100.0

Characteristics of Participants by Gender

Female. The majority of female students were Black, African, African-American, or Caribbean (Haitian, Jamaican) (48.5%, n = 66) or White, Non-Hispanic, Anglo, Caucasian, or European (36.0%, n = 49). The remainder of the female students were either Asian or Asian-American (4.4%, n = 6), Hispanic or Latino (2.9%, n = 4), American-Indian or Eskimo (2.9%, n = 4), and Multiracial or Other Races (5.1%, n = 7). Three-fourths of the female students were in sixth grade (38.2%, n = 52) or eighth grade (36.8%, n = 50), while one fourth was in 10th grader (25.0%, n = 34). Over one-fourth of the female students were 11 years old (26.5%, n = 36). Half of the female students were 13 years old (18.4%, n = 25), 14 years old (17.6%, n = 24), or 15 years old (1.2%, n = 28) years old. The remainder of the female students were 10 years old (n = 1, .7%), 12 years old (11.0%, n = 15), or 16 years old (5.1%, n = 7). The average age of female students was 13.08 (SD = 1.65).

Table 5
Race or Ethnicity of Female Students

Race / Ethnicity	Frequency	Percent
Black, African, African-American, or Caribbean (Haitian, Jamaican)	66	48.5
White, Non-Hispanic, Anglo, Caucasian, or European	49	36.0
Asian or Asian-American	6	4.4
Hispanic or Latino	4	2.9
American-Indian or Eskimo	4	2.9
Multiracial or Other Races	7	5.1
Total	136	100.0

Table 6
Grade Level of Female Students

Grade Level	Frequency	Percent
6th Grade	52	38.2
8th Grade	50	36.8
10th Grade	34	25.0
Total	136	100.0

Table 7
Age of Female Students

Age in Years	Frequency	Percent
10	1	.7
11	36	26.5
12	15	11.0
13	25	18.4
14	24	17.6
15	28	20.6
16	7	5.1
Total	136	100.0

Male. The majority of male students were White, Non-Hispanic, Anglo, Caucasian, or European (52.6%, n = 50) or Black, African, African-American, or Caribbean (Haitian, Jamaican) (32.6%, n = 31). The remaining male students were Asian or Asian American (3.2%, n = 3), Hispanic or Latino (4.2%, n = 4), American-Indian or Eskimo (3.2%, n = 3), and Multiracial or Other Races (4.2%, n = 4). About half of male students were in eighth grade (47.4%, n = 45) and one-third of males were in sixth grade (33.7%, n = 32). The remaining male students were in 10th grade (18.9%, n = 18). Almost half of male students were 13 years (25.3%, n = 24) or 14 years old (21.1%, n = 20). One-third of male students were 11 years (14.7%, n = 14) or 12 years old (17.9%, n = 17). The remaining male students were 15 years (11.6%, n = 11), 16 years (8.4%, n = 8), or 17 years old (1.1%, n = 1). The average age of male students was 13.26 (SD=1.52).

Table 8 *Race or Ethnicity of Male Students*

Race/Ethnicity	Frequency	Percent
Black, African, African-American, or Caribbean (Haitian, Jamaican)	31	32.6
White, Non-Hispanic, Anglo, Caucasian, or European	50	52.6
Asian or Asian-American	3	3.2
Hispanic or Latino	4	4.2
American-Indian or Eskimo	3	3.2
Multiracial or Other Races	4	4.2
Total	95	100.0

Table 9 *Grade Level of Male Students*

Grade Level	Frequency	Percent
6th Grade	32	33.7
8th Grade	45	47.4
10th Grade	18	18.9
Total	95	100.0

Table 10 *Age of Male Students*

Age in Years	Frequency	Percent
11	14	14.7
12	17	17.9
13	24	25.3
14	20	21.1
15	11	11.6
16	8	8.4
17	1	1.1
Total	95	100.0

This study includes research questions focusing on participants by gender and grade. I present the cross tabulation of participants by gender and grade level in Table 11. In summary, there were 52 females and 32 males in grade 6, 50 females and 45 males in grade 8, and 34 females and 18 males in grade 10.

Table 11
*Cross Tabulation of Gender and Grade**

	Female	Male	Total
6th Grade	52 (61.9%)	32 (38.1%))	84 (100%)
8th Grade	50 (52.6%)	45 (47.4%)	136 (100%)
10th Grade	34 (65.4%)	18 (34.6%)	95 (100%)
Total	136	95	231

*Percent within Grade

Instrumentation

I obtained approval from the University of Virginia Institutional Review Board (#2011-0067-00) to use survey data collected from the Beliefs, Belonging, and Behavior Project (NSF # 0624724) for this study. The survey consists of several instruments designed to measure Math Self-Efficacy, Math Outcome Expectations, Math Interest, Perception of Barriers, Perceived Mother and Father Support, Perceived Teacher Support, Perceived Peer Support, and Sense of Belonging in Math Class and Math Engagement. All instruments use a Likert-type scale ranging from 1 (strongly disagree) to 5 (strongly agree). The measurement of all scales is the sum of the responses for the scale items. Because the scales have between 8 and 39 items, scale sums are standardized for comparison among scales. I obtained permission from the author, Dr. Marie F. Shoffner, to use the survey data for this study.

Shoffner (2006) developed the Beliefs, Belonging, and Behavior (BBB) Survey for use in a study funded by the National Science Foundation (NSF # 0624724). For each of the scales, Shoffner and her research team conducted an extensive review of the literature (Personal communication). Once she identified instruments previously used to measure the study variables, she selected items from scales that were (a) consistent with the theoretical foundations of the study and (b) reported psychometric properties supporting their use for the intended population. The items used in the scale were revised as needed and then refined through a series of pilot studies. The resultant version of the BBB Survey consisted of 200 items.

Analysis of data collected during the first year of the study indicated that the psychometric properties of the scales supported its use with the study population. All scale reliabilities (internal consistency) were greater than .85. For the second wave of data collection, Shoffner reduced the number of items in the BBB Survey to 133 items, based on item and scale analyses of the first wave of data. In the third and final wave, Shoffner excluded three additional items, with the final instrumentation containing 130 items measuring 8 constructs. For this study, I used the second wave of data and the Math Interest Scale, Math Self-Efficacy Scale, and Math Outcome Expectations Scale.

Math Interest

I measured Math Interest using the Mathematics Interest Scale (MIS; Shoffner, 2006). The MIS is an eight-item instrument (Appendix B) designed to measure the level of math enjoyment and current and future math interest. The psychometric properties of the MIS indicated that this scale was appropriate for use with early adolescent participants (Deacon, Swan, & Clark, 2010; Shoffner & Deacon, 2009, 2010; Shoffner, Deacon, & Rowan-Kenyon, 2010a, 2010b; Shoffner, Rowan-Kenyon, Swan, Steinmetz, & Deacon, 2009a, 2009b). The scale reliability of the MIS ranged from .86 to .90 in studies examining the population intended for this study. Specifically, scale reliability of the MIS for the study population, sixth, eighth, and 10th graders, was .90.

Math Self-Efficacy

I measured Math Self-Efficacy using the Mathematics Self-Efficacy Scale (MSES; Shoffner, 2006). The MSES (see Appendix B) is an eight-item instrument designed to measure perceived level of Math Self-Efficacy, i.e. the participants' belief in their capability to perform math tasks or succeed at math activities at a specified level of competency. The psychometric properties of the MSES indicated that this instrument was appropriate to use with early adolescent participants (Deacon et al., 2010; Shoffner & Deacon, 2009, 2010; Shoffner, Deacon et al., 2010a, 2010b; Shoffner, Rowan-Kenyon et al., 2009a, 2009b). The scale reliabilities of the MSES ranged from .86 to .91. Specifically, scale reliability of the MSES for the study population, sixth, eighth, and 10th graders, was .90.

Math Outcome Expectations

I measured Math outcome expectation using the Mathematics Outcome Expectations Scale (MOES; Shoffner, 2006). The MOES (see Appendix C and Appendix D) is a 39-item instrument designed to measure participants' perceived Math Outcome Expectations, i.e., the participants' expectations of positive results if performing a math-related behavior. The psychometric properties of the MOES indicated that this scale was appropriate for use with early adolescent participants (Deacon et al., 2010; Shoffner & Deacon, 2009, 2010; Shoffner, Deacon et al., 2010a, 2010b; Shoffner, Rowan-Kenyon et al., 2009a, 2009b). The scale reliability of the MOES ranged from .91 to .94. Specifically, scale reliability of the MOES for the study population, sixth, eighth, and 10th graders, was .94.

Math Learning Environment

I derived the scale measuring Math Learning Environment, perceived warmth, respect, and comfort in the student-teacher relationship and perceived level of teacher responsiveness to emotional and academic needs, from items selected from the BBB Survey (See Appendix E). After conducting an extensive review of classroom learning environment, I found research suggesting that there were two distinct components of the students' perceptions of the relationship with their teacher: teacher emotional support and teacher academic support (Johnson, Johnson, & Anderson, 1983; Patrick et al., 2001; Patrick et al., 2007; Pianta, LaParo, & Hamre, 2008). Based on these findings, my initial research design included two measures to measure the two aspects of the student-teacher relationship: Math Classroom Climate (teacher emotional support) and Math Teacher Connection (teacher academic support).

I derived the subscales measuring Math Classroom Climate, perceived level of warmth, respect, and enjoyment in the student-teacher relationship, and Math Teacher Connection, i.e., the participants' perceived level of teacher responsiveness to their emotional and academic needs, from 18 items selected from the BBB Survey (see Appendix E). I selected the items based on Moos (1979) definition of the classroom relational dimension. Conducting an extensive search of classroom psychosocial environment literature, I found an extensive body of research grounded in Moos (1974, 1976, 1979) classification of human psychosocial environments.

Based on Moos' work, researchers developed a number of instruments designed to measure different aspects of the psychosocial classroom environment. Once I identified instruments used to measure the learning environment, I examined the items used by researchers to measure students' perceptions of the teacher-student relationship. I selected items from those scales that were (a) extensively utilized in psychosocial classroom environment research, (b) measured perceptions of the student-teacher relationship; and (c) reported psychometric properties supporting their use for the population examined in this study, sixth, eighth, and 10th graders. The instruments meeting these criteria included Classroom Environment Scale (Moos & Trickett, 1974), Individualized Classroom Environment Questionnaire (Fraser, 1990), Elementary and Middle School Inventory of Classroom Environments (Sinclair & Fraser, 2002), and What Is Happening In this Class Questionnaire (Fraser, Fisher, & McRobbie, 1996). After examining items from these instruments, I selected 18 theoretically based items from the BBB Survey that were comparable to items that measured the perceived quality of interpersonal relationship with the math teacher.

As presented in Chapter 4, subsequent factor analysis indicated that there were strong correlations among the combined items from the two scales and the combined items did not load on two factors as hypothesized. This suggested that the items measured the same construct. Because most measures of the student-teacher relationship use one construct to measure emotional and academic support (Patrick et al., 2007), I constructed a single scale, Math Learning Environment using 13 of the 18 items from the MCCS and MTCS.

I retained the four items Shoffner's (2006) the Sense of Belonging in the Math Classroom and Math Engagement Scale. The remaining 14 items were from Farmer et al.'s (1981) Teacher Support Scale (TSS). After examining the factor loadings of the 18 items, I removed five TSS items with the weakest factor leadings. The psychometric properties of the Math Learning Environment Scale (MLES) indicated that the scale was appropriate for use with early adolescent participants. Specifically, scale reliability of the MLES for the study population, sixth, eighth, and 10th graders was .92. Item total statistics indicate inter-item reliability. Removal of any one item resulted in a Cronbach's alpha ranging from .91 to .93.

Procedures

The Belief, Belonging, and Behavior research team collected the data used for this study during the course of a three-year study funded by the National Science Foundation (Shoffner, 2006). The principle investigator of NSF #0624724, Dr. Marie F. Shoffner, obtained approval to conduct the NSF study from the Institutional Review Board (SBS # 2006-0352-00) of the University of Virginia. Upon IRB approval for the study, the Shoffner contacted and received the support of the superintendent of the school district.

She presented the potential benefits to the school district along with the time commitment needed to conduct the study. Once obtained, members of the researcher team met with the principals of the participating schools. The principals designated a primary contact who was the assistant principal, the school secretary, or a math teacher. Researchers provided each contact person with consent form packets, which included parent, or guardian, informed consent and participant assent forms. The researchers assigned a unique code to students participating in the study to insure anonymity. No names were associated with collected data. The names of the participants associated with the code were stored in a secure location. Once the study is finished, Shoffner will destroy the participant list.

To recruit participants for the larger study, students in fifth, seventh, and ninth grade received consent forms, which students took home to their parents or guardians. Approximately 1,037 consent form packets were distributed (273 fifth graders, 221 seventh graders, 353 ninth graders) and 352 were returned. Researchers collected survey data from 318 students with 300 usable surveys for a response rate of 29%. During the second wave of data collection, students who had participated in the first wave received consent form packets in sixth, eighth and 10th grades. To encourage these students to participate, researchers set up an incentive drawing of a gift card. Of the 318 students who participated in 2007-2008, 187 students also completed surveys in 2008-2009. To refresh the sample, researchers distributed six hundred additional consent packets to students (300 sixth graders, 200 eighth graders, 100 10th graders). This provided 59 usable surveys completed by new participants.

Once researchers collected the consent forms, they scheduled the date for the administration of the study instruments. Researchers administered the surveys in classrooms during non-instructional time during the school day October 2008 to January 2009. Researchers initially collected survey data from 240 participants. They examined surveys for missing items, appropriate grade level, missing data, and obvious response bias. The researchers excluded surveys for which 1) one or more instruments had over 5% missing data; 2) students were not in sixth, eighth, or 10th grades, or 3) responses were obviously invalid were excluded from analysis, yielding 231 usable surveys. This resulted in usable surveys from 231 participants. Participants were 41.6% male and 58.4% female and 36.4% were in Grade 6, 41.1% in Grade 8, and 22.5% in Grade 10. Participants were African-American (41.6%), European-American (42.9%), and other races/ethnicities (15.6%).

Members of the research team administered survey instruments groups of 20 to 30 participants during a non-instructional period. They packaged testing instruments in envelopes labeled with the participant's name and code number. The survey administrator welcomed the participants and gave general directions for data collection. Researchers informed participants that the purpose of the study is "to find out more about their thoughts and feelings about math." The administrator reminded the participants that the team kept their responses confidential. After explaining confidentiality, researchers asked the participants to fill out their demographic sheet and to place completed demographic forms in the envelope. The researchers instructed participants to bubble in their responses to the items on the Beliefs, Belonging, and Behaviors Survey onto the bubble sheet provided.

During data collection, the administrators were available to answer questions from the participants. Administrators were instructed to answer questions and clarify information for the participant (e.g. provide a definition for an unfamiliar word), but to not interact in a manner that could influence a participant's response. Administrators also observed the process, noting any potential confounds (e.g., a participant answering 80 questions in five minutes). When finished, the participants placed their instruments and bubble sheets into the manila envelopes and gave the data packet to the administrator. The administrator inspected the packet to ensure that all testing instruments were in the envelope and sealed it. Researchers placed data packets into a storage file container, locked them in the trunk of the car, and transported data back to the STEM Pipeline Laboratory in Charlottesville, Virginia. All data was stored in a secure location in the laboratory as required.

Data Preparation

Once all of the quantitative data was collected, the demographic data from the "All About Me" form was coded and entered onto the response bubble sheets. Once entered, another member of the research team double-checked all demographic data entries to ensure accuracy of entry. To increase the accuracy of the machine reading of the bubble sheets, members of the research team inspected all data sheets for quality of bubbling prior to scanning the bubble sheets. They examined bubble sheets for erasures, double-bubbled responses, and bubbled not filled in correctly. They filled in incomplete, lightly bubbled, or "sloppily" filled-in bubbles. Bubbles with obvious erasures were re-erased to reduce the likelihood that the reader would inadvertently assign that value to the results.

At times, the participants filled in more than one answer for an item. The Principal Investigator established the following protocol to resolve the presence of double bubbling. In cases where the participant bubbled in 4 (agree) and 5 (strongly agree) or bubbled in 3 (slightly agree) and 4 (agree), the researcher retained the lesser of the two value, 4 and 5 respectively. When the participant answered both 3 (slightly agree) and 5 (strongly agree), the researcher retained 4 as an answer. However, in those cases where the participant bubbled in both 2 (disagree) and 3 (slightly agree), or bubbled in 1 (strongly disagree) and 5 (strongly agree), both bubbles were the kept and the data was considered missing. The rationale for keeping both values was because the opposite directionality of the two responses.

After researchers inspected the bubble sheets, they took the instruments to the university technology center for scanning. Once scanned, the data was sent to the researchers who imported the data into Excel, and from there into SPSS. For all missing data, researchers visually inspected the bubble sheet to verify that the data was missing. When a participant clearly provided a response not read by the machine, one researcher entered the data manually. Another member of the research team double-checked all hand-entered data. After completing this process, the data was ready for analyses.

Analyses

I addressed the quantitative research questions using Pearson's Product Moment, multivariate analysis of variance (MANOVA), multiple linear regression, and path analysis. Data used to answer the research questions were analyzed using IBM SPSS version 19.0. The accepted probability of a Type I error (alpha) was set at .05.

The first research question addressed differences among groups. I answered this question using MANOVA, with gender and grade as independent variables. I used a two by three factorial MANOVA to examine differences by groups.

The second, third, and fourth research questions addressed the explanatory power of combinations of independent variables to explain the dependent variables Math Self-Efficacy, Math Outcome Expectations, and Math Interest. I used correlation and multiple linear regression to examine the explained variance of the dependent variable accounted for by the independent variables.

The fifth and sixth research questions addressed the path coefficients of the data in the modified SCCT model (Lent et al., 1994). I used path analysis to examine relationships within the model. I present the analyses used for each research question in Table 12.

Table 12.
Research Questions and Statistical Analyses

Research Questions	Constructs	Statistical Analysis
RQ 1: Are there differences in Math Self-Efficacy, Math Outcome Expectations, Math Learning Environment, and Math Interest among boys and girls in Grades 6, 8, and 10 by gender and grade level?	MI, MSE, MOE, MLE Gender Grade Level	2 x 3 Factorial MANOVA
RQ 2: Does Math Learning Environment explain a significant amount of the variance in Math Self-Efficacy for boys and girls in Grades 6, 8, and 10?	MSE, MLE	Pearson Product-Moment Correlation
RQ 3: Does Math Learning Environment explain a significant amount of the variance in Math Outcome Expectations of boys and girls in Grades 6, 8, and 10?	MOE, MLE	Pearson Product-Moment Correlation
RQ 4: Do Math Self-Efficacy and Math Outcome Expectations explain a significant amount of the variance in Math Interest of boys and girls in Grades 6, 8, and 10?	MSE, MOE, MI	Multiple Linear Regression
RQ 5: Does the data fit the modified SCCT model for girls and boys in grades 6, 8, and 10?	MSE,MOE, MLE, MI	Path Analysis
RQ6. Is the modified model of SCCT invariant across gender for participants in grades 6, 8, and 10?	MSE,MOE, MLE, MI Gender	Path Analysis

Note. MI = Math Interest, MSE = Math Self-Efficacy, MOE = Math Outcome Expectations, MLE = Math Learning Environment

Summary of Chapter 3

This study examines the role of the math learning environment on early adolescents' math self-efficacy, math outcome expectations, and math interest. Chapter 3 provided the methodology of the study, including the research questions and hypotheses, the research design, the participants, the procedures, the instrumentation, and the data analyses. Chapter 4 presents the results and findings of the analyses described in Chapter 3.

CHAPTER IV

RESULTS

This study examines the role of the math learning environment on early adolescents' math self-efficacy, math outcome expectations, and math interest. Chapter 1 provided the reader with the rationale for the study, the need, purpose, and significance of the study, the research questions, and the definition of terms. Chapter 2 presented a review of the literature on the theoretical foundations of the study, and on Math Interest, Math Self-Efficacy, Math Outcome Expectations, and Math Learning Environment. Chapter 3 provided the methodology for this research.

In this chapter, I present the results and findings of the analyses described in Chapter 3. I provide a description of the data preparation, and item and scale analyses. I then present the results of the analyses used to address the research questions.

Participants

Members of the Belief, Belonging, and Behavior research team collected survey data from 240 participants during year 2 of a larger study funded by the National Science Foundation (NSF #0624724). The research team examined the surveys for missing items (incomplete surveys) and age and grade level of participants. Seven participants were not in the targeted grades and two participants withdrew from the study before completing the survey. Further inspection of the surveys indicated that all surveys had less than 5% missing data. After removing these nine surveys, there were 231 usable student surveys.

Participants were mostly between the ages of 11 and 16 years old, M=13.16 (S.D.=1.60), primarily female, and of diverse race/ethnicity. Complete information about study participants is presented in Chapter 3. Cross-tabulation by gender and grade level was presented in Chapter 3 and is presented again here, in Table 11.

Table 11
Cross Tabulation of Gender and Grade

	Female	Male	Total
6th Grade	52 (61.9%)	32 (38.1%))	84 (100%)
8th Grade	50 (52.6%)	45 (47.4%)	136 (100%)
10th Grade	34 (65.4%)	18 (34.6%)	95 (100%)
Total	136	95	231

*Percent within Grade

Preparation of Scales

Prior to addressing the research questions, I prepared the data for analysis. I reverse coded appropriate items, and then determined descriptive statistics, univariate outliers, and univariate normality. After these analyses, I replaced missing data using multiple imputations. I used IBM SPSS version 19 for all analyses.

Item-Level Analysis

I determined the descriptive statistics (mean, standard deviation, skewness, and kurtosis) for the 73 items included in the five measures of study constructs as presented in Chapter 3 (see Appendix F). All data fell within the expected range (1 to 5). To determine the presence of univariate outliers, I calculated the standardized residual for each item. Examination of standardized Z scores for each item revealed no values greater than 3.29 or less than -3.29, indicating no univariate outliers (Tabachnick & Fidell, 2007). I examined item univariate normality by examining skewness and kurtosis values and through visual inspection of histograms. Inspection of histograms suggested approximate normal distributions. Skewness and kurtosis values for all items were within acceptable limits (< .01) (Tabachnick & Fidell).

Missing Data Imputation

Once I determined that there were no univariate outliers and that all items were normally distributed, I examined the data for missing values. There were 37 items missing, or 0.22% of the data. Twenty-five students had missing survey data. Two student had 5.50% missing data (n=4), one student had 4.1% (n=3), and two students had 2.7% (n=2). The remaining 18 students were missing one item (1.4%). No item was unanswered by more than 10% of the participants. Two students were missing 25% of the items from a scale, one student was missing two items from the Math Interest Scale (25 %), and another student was missing two items from the Math Learning Environment Scale (25%). One student was missing four items (10%) and another student was missing two items (5%) from the Math Outcome Expectations Scale. For the remaining 18 students, there was one item missing from one of the instruments.

The traditional methods for handling missing data are to employ listwise deletion (Peugh & Enders, 2004) or use single imputation techniques such as inserting the mean value of non-missing data (Schlomer, Bauman, & Card, 2010). There is evidence that these strategies produce biased parameter estimates and standard errors (Baraldi & Enders, 2010; Schlomer, Bauman, & Card, 2010). The current study illustrates this potential for bias. While only 0.22% of the data was missing, using listwise deletion would have excluded 10.82% of the data. Consistent with current practice in behavioral science research (Schlomer, Bauman, & Card), I used multiple imputation procedures in the current investigation to address the issue of missing data (Baraldi & Enders, 2010).

I replaced missing data using the module IBM SPSS v. 19 Missing Values Analysis (MVA). MVA uses multiple imputation procedures to analyze the pattern of "missingness" in the data and to replace missing values with plausible estimates (IBM SPSS, 2010). For this data set, I selected the program's fully automatic imputation mode, which analyzes data and chooses the most suitable imputation method. Because there are relationships among all of the items in this data set, I used all 73 items for the imputations. SPSS imputation replaced each missing value with a set of plausible values based on predictive, multivariate distribution among the full data set (Schafer & Olsen, 1998). Based on Little and Rubin's (2003) recommendation, I used SPSS to generate five complete datasets, each with a different set of replacement values. The program averaged the imputed values were averaged for subsequent analyses (see Appendix F).

Item Correlations

I used five scales in this study. Three of them were those used in the Beliefs, Belonging, and Behavior study (NSF # 0624724): Math Interest, Math Self-Efficacy, and Math Outcome Expectations. I derived the Math Learning Environment Scale using items from the study that tapped into conceptions of Classroom Climate and Teacher Connection, as delineated in a literature. Before beginning analyses, I examined the psychometric properties of each of the five scales. Specifically, I examined item-correlations, internal consistency, and item-total statistics.

Math Interest. I measured Math Interest using the Mathematics Interest Scale, which is a revision to the Math and Science Interest Scale (Fouad, Smith, & Enochs, 1997). The MIS is an eight-item instrument (Appendix B) designed to measure levels of math enjoyment and of current and future math interest. All items were correlated with each other, with correlations from .27 to .73 (see Appendix G1) and item total correlations from .52 to .79 (see Appendix H1). Cronbach's alpha for the Math Interest Scale was .90 (Table 13).

Math Self-Efficacy. I measured Math Self-Efficacy using the Mathematics Self-Efficacy Scale (MSES; Shoffner, 2006). The MSES (see Appendix B) is an eight-item instrument designed to measure the participants' belief in their capability to perform math tasks or succeed at math activities at a specified level of competency. All items were correlated with each other, with correlations from .42 to .75 (see Appendix G2) and item total correlations from .59 to .76 (see Appendix H2). Cronbach's alpha for the Math Self-Efficacy Scale was .90 (see Table 13).

Math Outcome Expectations. I measured Math Outcome Expectations using the Mathematics Outcome Expectations Scale (MOES; Shoffner, 2006). The MOES (see Appendix C and Appendix D) is a 39-item instrument designed to measure participants' expectations of positive results for taking advanced math. Math Outcome Expectations has five subscales: Generativity, Physical, Relational, Social Approval, and Self-Satisfaction. I conducted analyses to assess the correlation among scale items, inter-item reliability, factor analysis, and scale reliabilities.

Subscales. All items in the Generativity, Physical, and Self-Satisfaction Subscales were correlated with each other (see Appendix I1, Appendix I2, and Appendix I5) and demonstrated adequate internal consistency (see Appendix J2, Appendix J3, and Appendix J6). One item in the Relational Subscale and two items in the Self-Satisfaction Subscale were not correlated with the remaining items in the respective subscale but increased internal consistency estimates to less than the full subscale's Cronbach's alpha when deleted (see Appendix J3-J4 and Appendix H3-H4). I removed these items from the MOES. Cronbach's alpha for the subscales ranged from .73 to .88 (see Appendix J1).

Math Outcome Expectations. The analysis of the subscales resulted in a reduction in the total number of items in the MOES from 39 to 36 items. For the remaining 36 items in the Math Outcome Expectations Scale, with the exception of the items in the Relational Subscale, items were correlated with each other, with correlations from .16 to .64 (See Appendix I6) and item total correlations from .13 to .75 (see Appendix J7).. Cronbach's alpha for the scale was .94 (see Appendix J1).

Factor analyses of the MOES resulted in a three-factor solution. Correlations among items for Math SCT Outcome Expectations ranged from .14 to .59, Math Generativity Outcomes ranged from .20 to .63, and Math Relational Outcome Expectations ranged from .32 to .48(see Appendix G3 through Appendix G5). Item-total correlations for Math SCT Outcome Expectation s ranged from.44 to .75; Math Generativity Outcome Expectations ranged from .53 to .69, and Math Relational Outcome Expectations ranged from .51 to .55 (see Appendix H3 through Appendix H5). Cronbach's alpha for the three subscales ranged from .76 to .91 (see Table 13).

Math Learning Environment. I measure Math Learning Environment, i.e., perceived warmth, respect, and comfort in the student-teacher relationship and perceived level of teacher responsiveness to emotional and academic needs, from 13 items selected from the BBB Survey (See Appendix E). My initial research design included two subscales to measure these aspects of the student-teacher relationship: Math Classroom Climate (teacher emotional support) and Math Teacher Connection (teacher academic support).

Although I had selected items from two different BBB Survey scales, the MCCS and MTCS did not measure the constructs as designed. Factor analysis indicated that the MCCS and MTCS measured the same construct. Given these results, I examined all of the items from the two scales used to derive the MCCS and MTCS items, Math Teacher Support Scale ([MTSS], Farmer et al., 1981) and Sense of Belonging in the Math Classroom/Math Engagement Scale ([BEMCS], Shoffner, 2006). I used items from the MTSS and BEMCS to derive a new scale, Math Learning Environment.

I examined the wording of the TSS items and selected the 14 TSS items I initially selected for the MCCS and MTCS for potential inclusion in the new scale. To reduce redundant items, I excluded three TSS items because there were items of similar wording already included. When I examined the wording of the BEMCS items, I found that four items in the scale measured student's perceptions of their relationship with their math teacher. Two additional items also measured students perceptions of student-teacher interactions, however, the items were worded in the third person, (e.g., "My math teacher treats some kids better than other kids"). Because these items did not measure how students perceived self, but others, I removed these items from consideration. I retained items B1, B6, B17, and B21 as potential items for the new scale.

I added the items B1, B6, B17, and B21 to the 14 TSS items one at a time. After adding item B1, item total correlations ranged from .427 to .80 (see Appendix K1). Cronbach's alpha with the addition for the scale was .95 (see Table 14). After adding item B6, item total correlations ranged from .43 to .81 (see Appendix K2). Cronbach's alpha for the scale was .95 (see Table 14). After adding item B17, item total correlations ranged from .43 to .81 (see Appendix K3). Cronbach's alpha for the scale was .95 (see

Table 14). When I added item B21, item total correlations ranged from .31 to .81 (see Appendix K4). Cronbach's alpha for the scale was .94 (see Table 15).

Math Learning Environment Scale. To simplify the scale, I removed the five TSS items with the smallest factor loadings, Tchr2, Tchrl 8, Tchr21, Tchr22, and Tchr28. The remaining 13-items comprise a new construct, Math Learning Environment, the participants' perceived level of warmth, respect, and responsiveness to emotional and academic needs in the student-teacher relationship (see Appendix E). All items were correlated with each other, with correlations from .16 to .75 (see Appendix G6). Item-total correlations ranged from .34 to .81 (see Appendix H6). Cronbach's alpha for the scale was .92 (see Table 13).

Table 13
Reliability Statistics for Study Scales

Scale	Cronbach's Alpha	No. of Items
MIS	.90	8
MSES	.90	8
MOES-SCT	.91	20
MOES-G	.89	11
MOES-R	.76	5
MLES	.92	13

Note. MIS = Math Interest Scale, MSES = Math Self-Efficacy Scale, MOES = Math Outcome Expectations Scale, MOES-SCT = Math SCT Outcome Expectations Subscale, MOES-G = Math Generativity Outcome Expectations Subscale, MOES-R = Math Relational Outcome Expectations Subscale, MLES = Math Learning Environment Scale

Table 14 *Reliability Statistic of Preliminary Learning Environment Scale*

	Cronbach's Alpha	No. of Items
MTSS Items	.95	14
Add Item B1	.95	15
Add Item B6	.95	16
Add Item B17	.95	17
Add Item B21	.94	18

Summary. Examination of the Pearson product moment, item-total correlations, and reliability statistics for the Math Interest, Math Self-Efficacy, Math SCT Outcome

Expectations, Math Generativity Outcome Expectations, Math Relational Outcome Expectations, and Math Learning Environment indicated that the items of each scales demonstrated good internal consistency. Specifically, there were statistically significant correlations among the items within each scale. The item-total correlations indicated adequate internal consistency. Cronbach's alpha for the scales ranged from .76 to .94.

Factor Analyses

I conducted factor analysis to examine the factor loading of the scale items and to confirm the validity of the scales. Because much of behavioral science research results in correlation among scales, I used Maximum-Likelihood extraction with Direct Oblimin rotation for all factor analyses (Tabachnick & Fidell, 2007). To determine the number of factors to retain, I evaluated the results against the following criteria: (a) Horn's (1965) parallel analysis; (b) Kaiser's (1958) eigenvalue criterion; (c) total score variance; (d) Cattell's (1966) scree requirement; (e) number and strength of factor loadings; (f) internal consistency of resultant factors; and (h) theoretical considerations and interpretability. I assessed for removal those items with low factor loading (< .40) or low item-total correlation (Garcon, 2011a, 2011b). Once I determined the number of factors to extract and the items to retain, I determined the internal consistency of the identified factors. I present the total variance and factor matrices and scree plots for the study scales in Appendix L through Appendix O.

Math Interest. I conducted factor analysis using Maximum-Likelihood extraction with Direct Oblimin rotation on the eight items in the Math Interest Scale. All items except Int3 and Int4 loaded on Factor 1 (see Appendix M1 and Appendix M1). Correlation between the two extracted factors was .61 (see Appendix M3). Examination of the structure matrix indicated a pattern of cross-loadings for all items in the two factors and correlations between the factors suggest that there is only one factor. Because the MIS is designed as a unidimensional scale, I forced extraction to a single factor (see Appendix L1 and Appendix L3), even though there were two factors with eigenvalues great than 1.00. Extracting a single factor met all the appropriate criteria. All items had acceptable factor loadings (.51 to .88). Items demonstrated good internal consistency.

Math Self-Efficacy. I conducted factor analysis using Maximum-Likelihood extraction with Direct Oblimin rotation on the eight items in the Math Self-Efficacy Scale. Factor analysis extracted one factor (see Appendix L1 and Appendix L4). All items had appreciable factor loadings (.62 to .82). Items demonstrated good internal consistency.

Math Outcome Expectations. I factor analysis to determine the number of factors to retain in each subscale. Once this process was completed, I conducted factor analysis for the full MOES for the remaining items.

Subscales. I conducted separate factor analysis of the items in each MOES subscales using Maximum-Likelihood extraction with Direct Oblimin rotation (see Table E.4). Factor analyses of the Physical Subscale, Relational Subscale, Social Approval Subscale, and Self-Satisfaction Subscale extracted one factor (see Appendix L2 and Appendix L5). All items had acceptable factor loadings (.50 to .79). Because the Generativity Subscale is designed as a unidimensional scale, I forced extraction to a single factor, even though there were two factors with eigenvalues great than 1.00. Extracting a single factor met all the appropriate criteria. All items had acceptable factor loadings (.55 to .74). All subscales demonstrated good internal consistency.

Math Outcome Expectations: Full Scale. I conducted factor analysis of the 36 items in the Math Outcome Expectations Scale using Maximum-Likelihood extraction with Direct Oblimin rotation. Factor analysis indicated that seven eigenvalue were greater than 1. Because the MOES is designed as five subscales, I forced extraction to five factors (see Appendix M1 and Appendix M2). All items loaded on four factors, so I forced extraction to four factors (see Appendix M3 to Appendix M4).

Given the distribution of social cognitive items in the four-factor solution, I extracted three factors (see Appendix L6 and Appendix L7). Extracting three factors met all the appropriate criteria. All items had acceptable factor loadings (.51 to .77). Items demonstrated good internal consistency. The correlation among factors ranged from .13 to .58 (see Appendix L8).

Math Learning Environment. In my initial research design, I used designed two subscales to measure students' perceptions of the emotional (Math Classroom Climate) and academic (Math Teacher Connection) support provided by their math teacher. To determine if the items within each subscale held together, I conducted factor analysis on each subscale. I conducted factor analysis on all items to determine if the two subscales loaded as separate factors. Factor analysis using Maximum-Likelihood extraction with Direct Oblimin rotation on the 17 items in both scales extracted one factor (see Appendix N1). All items had acceptable factor loadings (.43 to .83). The result indicated that the two scales measured the same construct.

As noted previously, I selected 14 items from the TSS and four items from the BEMCS as a preliminary measure of Math Learning Environment. I then conducted factor analysis of the 18 items using Maximum-Likelihood extraction with Direct

Oblimin rotation. Factor analysis extracted two factors. No items loaded on Factor 2, so I forced extraction to a single factor (see Appendix N2). All items had acceptable factor loadings (.31 to .83). I then removed five TSS items with the lowest factor loadings, retaining 13 items in the scale.

Finally, I conducted factor analysis using Maximum-Likelihood extraction with Direct Oblimin rotation on the 13 items in the Math Learning Environment Scale. Factor analysis extracted two factors. No items loaded on Factor 2, so I forced extraction to a single factor (see Appendix L9). Extracting a single factor met all the appropriate criteria. All items had acceptable factor loadings (.33 to .85). Items demonstrated good internal consistency (.34 to .81).

The final scale was consistent with theoretical foundation for the learning environment portion of the study, Moo's classification of environments. While one item had both inadequate factor loading (< 0.4) and item-total correlations indicating that removing the item would improve reliability, I chose to retain this item based on the information that item provided to the study. The psychometric properties of the Math Learning Environment Scale are appropriate for this population.

Scale Correlations. To examining the relationship among the study scales, I computed the Pearson product moment correlations among the scales and subscales. The results indicate that all correlations were statistically significant ($p < .05$). Correlations among the scales ranged from .22 to .61 (see Table.15). Correlations within the Math Outcome Expectations Scale and Subscales ranged from .14 to .96. Descriptive statistics for the standardized sum of each study scale suggest that there is sufficient variability in the individual scores of all scales to detect an effect (see Table 15).

Table 15
Descriptive Statistics and Correlations of Scale Sum Totals of Study Scales

Measure	M	SD	1	2	3	4	5	6
1. MI	275.47	97.37	—					
2. MSE	355.09	91.96	.56	—				
3. MOE-SCT	352.86	64.75	.43	.39	—			
4. MOE-G	370.86	73.07	.39	.48	.74	—		
5. MOE-R	381.14	81.86	.27	.31	**.12**	.30	—	
6. MLE	307.29	80.58	.50	.61	.54	.57	.39	—

Note. Bold correlation was not significant. All other correlations are statistically significant, $p < .05$ (2-tailed). MI = Math Interest, MSE = Math Self-Efficacy, MOE-SCT = Math SCT Outcome Expectations, MOE-G = Math Generativity Outcome Expectations, MOE-R = Math Relational Outcome Expectations, MLE = Math Learning Environment. N = 231.

Scale Properties by Subgroups

I used four scales in this study, Math Interest, Math Self-Efficacy, Math Outcome Expectations (MOE-SCT, MOE-Generativity, and MOE-Relational), and Math Learning Environment. Because this study includes research questions focusing on participants by gender and grade, I examined the reliabilities and correlations among the scales and subscales for each of the six groups (sixth grade boys, sixth grade girls, eighth grade boys, eighth grade girls, 10th grade boys, 10th grade girls). When I examined the reliability estimates by group, Math Relational Outcome Expectations had much lower reliability for sixth grade girls than for the other five groups (see Table 16).

Table 16
Reliability Statistic for MOE-R Subscale (Gender and Grade)

	Cronbach's Alpha
6th Grade Boys	.72
6th Grade Girls	.59
8th Grade Boys	.70
8th Grade Girls	.78
10th Grade Male	.79
10th Grade Female	.83

Results of Analyses by Research Question

In this section, I present the results of the analyses by research question. The study scales for these analyses include the Math Interest Scale (MIS), Math Self-Efficacy Scale (MSES), Math SCT Outcome Expectations Subscale (MOE-SCT), Math Generativity Outcome Expectations Subscale (MOE-G), Math Relational Outcome Expectations Subscale (MOE-R), and Math Learning Environment Scale (MLE). I used IBM SPSS version 19 and AMOS version 19 for all analyses.

Research Question 1

The first research question asks the question: Are there differences in Math Self-Efficacy, Math Outcome Expectations, Math Learning Environment, and Math Interest among boys and girls in Grades 6, 8, and 10 by gender and grade level? To address this question, I examine differences in Math Interest, Math Self-Efficacy, Math Outcome Expectations, and Math Learning Environment by gender, grade, and the interaction among the two through a 2 x 3 MANOVA.

Prior to conducting the analyses to answer the first research question, I examined the six dependent variables of interest in this study (Math Interest, Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, Math Relational Outcome Expectations, and Math Learning Environment) for their compliance with the assumptions underlying multivariate analysis. I examined all variables separately for the six groups used to answer the first research question. Groups for testing the multivariate assumptions were as follows: 6th grade girls, 6th grade boys, 8th grade girls, 8th grade boys, 10th grade girls, and 10th grade boys.

I examined univariate outliers within each group. Using SPSS 19.0, I ran descriptive statistics for the summed totals for the six dependent variables. The statistical program saved standardized scores as new variables for each variable. To detect univariate outliers, I examined the z-scores for each individual score in the six variables (Tabachnick & Fidell, 2007). Examination of the z-scores revealed two potential outliers in the 6th grade girls groups ($Z < 3.29$, $p < .001$). I deleted these two cases, resulting in a total working sample of 229.

The results supported univariate normality for the variables Math Interest, Math SCT Outcome Expectations, and Math Generativity Outcome Expectations. Skewness and kurtosis values were within acceptable limits (< .01) for the six groups (Tabachnick & Fidell, 2007). Visual inspection of the histograms suggested approximately normal distributions and the Shapiro-Wilk test supported normality (all p's > .05/6). I found mixed results for Math Self-Efficacy, Math Learning Environment and Math Relational Outcome Expectations. Visual inspection of the histograms suggested approximately normal distributions. Skewness and kurtosis values for Math Self-Efficacy, Math Learning Environment and Math Relational Outcome Expectations were within the acceptable limits (< .01) for all six groups. However, the Shapiro-Wilk test indicated normality in five of the six groups (all p's > .05/6), but revealed a significant departure from normality for 6th grade females ($p < .05/6$). While the results of the Shapiro-Wilk test indicated a departure from normality, this test is highly sensitive. Balancing these findings along with no observed outliers of this variable for the groups, the assumption of normality was achieved (Konold, 2010).

I conducted Multivariate outlier analyses separately for the six groups on the combined dependent variables. Mahalanobis distance revealed only one multivariate outlier in the 6th grade female group. There were no additional multivariate outliers identified after removing this case. I deleted this case, resulting in a total working sample size of N = 228. Box's test did not support the equality of covariance matrices between groups, multivariate $F = (1.52, 34005) = 1.523, p < .001$.

Multivariate Analysis of Variance

I used a 2 x 3 multivariate analysis of variance (MANOVA) to determine if there were differences between gender and grade level (6th, 8th, and 10th) in participants' reported perceptions of the following dependent variables: Math Interest, Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, Math Relational Outcome Expectations, and Math Learning Environment. Given the uneven number of subjects, I specified Type III sequential adjustments of independent variables for non-orthogonality. I reported the F-statistic derived from Wilk's lambda and the p-value. I calculated effect size using the multivariate η^2 based on Wilk's lambda $(1 - \Lambda)$. I used pairwise comparisons using Hotelling T^2 and univariate tests.

Results from the analysis revealed a statistically significant main effect between males and females across the dependent variables (see Table 17); Wilks's $\Lambda = .92$, $F(6,217) = 3.26$, p = .004. The multivariate η^2 based on Wilk's Λ was .08. In addition, there was a statistically significant main effect for grade level; Wilks's $\Lambda = .89$, $F(12, 434) = 2.20$, p = .01. The multivariate η^2 based on Wilk's Λ was .11. Finally, there was a statistically significant interaction between gender and grade; Wilks's $\Lambda = .88$, $F(12, 434) = 2.34$, p = .006. The multivariate η^2 based on Wilk's Λ was .12.

Table 17
Multivariate Tests by Gender and Grade

	λ Value	*F*	*df*	*Error df*	*p*	η^2
Gender	.92	3.26[a]	6	217	.004	.08
Grade	.89	2.20[a]	12	434	.011	.11
Gender * Grade	.88	2.34[a]	12	434	.01	.12

Gender. When compared to boys, girls had higher levels of Math Generativity Outcome Expectations, $F(1, 222) = 8.06, p = .005$, Math Relational Outcome Expectations, $F(1, 222) = 14.16, p < .001$ and Math Learning Environment, $F(1, 222) = 5.47, p = .02$ (see Table 18). Table 19 contains the means and standard deviations of the dependent variables by gender.

Table 18
Tests of Between-Subjects Effects (Gender)

Source	Dependent Variable	*df*	*Error df*	*MS*	*F*	*p*
Gender	MI	1	222	26.09	0.47	.49
	MSE	1	222	97.52	1.94	.17
	MOE-SCT	1	222	67.10	0.94	.33
	MOE-G	1	222	1503.91	8.06	.01
	MOE-R	1	222	214.79	14.16	.000
	MLE	1	222	609.23	5.47	.02

Note. MI = Math Interest, MSE = Math Self-Efficacy, MOE-SCT = Math SCT Outcome Expectations, MOE-G = Math Generativity Outcome Expectations, MOE-R = Math Relational Outcome Expectations, MLE = Math Learning Environment

Table 19
Descriptive Statistics (Gender)

Dependent Variable	Female (n=133)		Male (n=95)		Total (n=228)	
	M	SD	M	SD	M	SD
MI	22.73	7.83	21.03	7.54	22.02	7.74
MSE	29.36	7.21	27.30	7.23	28.50	7.27
MOE-SCT	34.66	8.55	33.03	8.98	33.98	8.75
MOE-G	76.85	11.98	71.30	16.16	74.53	14.11
MOE-R	20.00	3.56	17.87	4.25	19.11	3.99
MLE	46.17	10.63	41.45	11.41	44.20	11.18

Grade. Examination of the tests of between-subject effects indicated that there was a significant difference in Math Learning Environment by grade (see Table 20). Post hoc analyses for the main effect of grade consisted of conducting pairwise comparisons using Tukey HSD test (see Table 21). Significant differences in Math Learning Environment were found between 6th grade and 8th grade students, p = .01. Table 22 contains the means and standard deviations of the dependent variables by grade.

Table 20
Tests of Between-Subjects Effects (Grade)

Source	Dependent Variable	*df*	*Error df*	*MS*	*F*	*P*
Grade	MI	2	222	129.48	2.33	0.10
	MSE	2	222	84.35	1.68	0.19
	MOE-SCT	2	222	174.49	2.44	0.09
	MOE-G	2	222	155.99	0.84	0.44
	MOE-R	2	222	0.84	0.06	0.95
	MLE	2	222	596.58	5.35	0.01

Table 21
Tukey HSD Post Hoc Pairwise Comparisons (Grade)

Dependent Variable	(I)Grade	(J) Grade	*MD (I-J)*	*SE*	*p.*	*95% CI*
Math LE	Grade 6	Grade 8	5.94*	1.60	.001	[2.18, 9.70]
		Grade 10	2.52	1.88	.37	[-1.91, 6.95]
	Grade 8	Grade 6	-5.94*	1.60	.001	[-9.70, -2.17]
		Grade 10	-3.42	1.82	.15	[-7.71, 0.88]
	Grade 10	Grade 6	-2.52	1.88	.37	[-6.95, 1.91]
		Grade 8	3.42	1.82	.15	[-.88, 7.71]

Note. * The mean difference is significant at the .05 level.

Table 22
Descriptive Statistics (Grade)

Dependent Variable	6th Grade (n=81)		8th Grade (n=95)		10th Grade (n=52)		Total (n=228)	
	M	SD	M	SD	M	SD	M	SD
MI	23.74	7.27	20.80	7.70	21.60	8.19	22.02	7.74
MSE	29.92	6.67	28.10	7.69	27.04	7.13	28.50	7.27
MOE-SCT	35.87	9.07	32.35	8.56	34.01	8.12	33.98	8.75
MOE-G	76.66	14.83	73.85	14.00	72.46	12.94	74.53	14.11
MOE-R	19.08	3.54	19.01	4.30	19.35	4.15	19.11	3.99
MLE	47.25	11.75	41.31	11.03	44.73	9.22	44.20	11.18

Gender and Grade. Examination of the omnibus tests of between-subject effects indicated that there were significant difference in Math Interest, Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Learning Environment Math Learning Environment by gender and grade (see Table 23). I conducted post hoc analyses to determine the significant pairs.

Table 23
Tests of Between-Subjects Effects (Gender and Grade)

Source	Dependent Variable	*df*	*Error df*	*MS*	*F*	*p*
Grade	MI	2	222	381.28	6.87	0.00
	MSE	2	222	157.84	3.14	0.05
	MOE-SCT	2	222	413.20	5.77	0.00
	MOE-G	2	222	711.84	3.82	0.02
	MOE-R	2	222	1.27	0.08	0.92
	MLE	2	222	521.38	4.68	0.01

I used Hotelling T^2 and univariate tests to conduct post hoc analyses of the interaction by gender and grade level. Seven of the 15 pairs were statistically significant (see Table 24). Since multivariate tests are omnibus tests, a significant finding does not reveal the significant variables contributing to the effect. I examined the univariate tests for all statistically significant pairs (see Appendix P1). The plots of the interaction effects observed by grade and gender are presented in Appendix Q.

Table 24

Pairwise Comparison Multivariate Tests: Wilk's Lambda (λ)

Pairwise Comparison	*λ Value*	*F*	*df*	*Error df*	*Sig.*
M6xF6	0.76	4.00	6	74	0.002
M6xM8	0.90	1.35	6	70	0.25
M6xF8	0.87	1.95	6	75	0.08
M6xM10	0.85	1.31	6	43	0.27
M6xF10	0.86	1.59	6	59	0.17
F6xM8	0.77	4.43	6	87	0.001
F6xF8	0.79	4.04	6	92	0.001
F6xM10	0.81	2.37	6	60	0.04
F6xF10	0.80	3.27	6	76	0.01
M8xF8	0.88	1.95	6	88	0.08
M8xM10	0.73	3.42	6	56	0.01
M8xF10	0.73	3.42	6	56	0.01
M8xF10	0.89	1.54	6	72	0.18
F8xM10	0.78	2.82	6	61	0.02
F8xF10	0.89	1.57	6	77	0.17
M10xF10	0.78	2.18	6	45	0.06

When compared to 6th grade and 8th grade males, sixth grade females had higher levels of Math Interest (M_{6F} = 25.84; M_{6M} = 20.51; M_{8M} = 19.91), Math Self-Efficacy (M_{6F} = 31.19; M_{6M} = 27.99; M_{8M} = 26.27), Math SCT Outcome Expectations (M_{6F} = 38.50; M_{6M} = 31.84; M_{8M} = 32.92), Math Generativity Outcome Expectations- (M_{6F} = 81.60; M_{6M} = 69.10; M_{8M} = 72.98), Math Relational Outcome Expectations (M_{6F} = 19.95; M_{6M} = 17.73; M_{8M} = 17.82), and Math Learning Environment (M_{6F} = 50.90; M_{6M} = 41.66; M_{8M} = 39.31).

Sixth grade females had higher levels of Math Interest (M_{6F} = 25.84; M_{8F} = 21.60; M_{10F} = 19.91), Math SCT Outcome Expectations (M_{6F} = 38.50; M_{8F} = 31.84; M_{10F} = 33.28), Math Generativity Outcome Expectations (M_{6F} = 81.60; M_{8F} = 74.64; M_{10F} = 73.23), and Math Learning Environment (M_{6F} = 50.90; M_{8F} = 43.12; M_{10F} = 43.82) compared to 8th grade and 10th grade females and greater Math Self-Efficacy (M_{6F} = 31.19; M_{10F} = 26.18) than 10th grade girls.

Sixth grade females also had higher levels of Math Outcome Expectation-Generativity (M_{6F} = 81.60; M_{10M} = 71.00) than 10th grade males. However, when compared to 10th grade males, eighth grade males had lower levels of Math Interest (M_{8M} = 19.91; M_{10M} = 24.78) and Math Learning Environment (M_{8M} = 39.31; M_{10M} = 46.44). There were statistically significant differences across the dependent variables between 8th grade females and 10th grade males; Wilks's $\Lambda = .78$, $F(6, 61) = 2.82$, p = .02. However, the univariate tests were not significant for any of the dependent variables.

While there were no statistically significant differences across the dependent variables for seven pairs of gender-grade comparisons (see Appendix A.10), there were statistically significant differences observed in the univariate tests for Math Interest, Math Self-Efficacy and Math Relational Outcome Expectations among these groups (see Appendix P2). Tenth grade males had higher levels of Math Interest (M_{10M} = 24.78; M_{6M} = 20.51; M_{10F} = 19.91) than 6th grade males and 10th grade females. Eight grade females had higher levels of Math Self-Efficacy (M_{8F} = 29.74; M_{8M} = 26.27; M_{10F} = 26.18) than 8th grade males and 10th grade females. Sixth grade males (M_{6M} = 17.73) and 8th grade males (M_{8M} = 17.82) each had lower levels of Math Relational Outcome Expectations (M_{8F} = 20.08; M_{10F} = 19.94) than both 8th grade and 10th grade females. There were no significant differences observed across the dependent variables for 6th grade males when compared to 8th grade males (see Appendix P3). Appendix P4 contains the means and standard deviations for the dependent variables by gender and grade.

Summary of Results

There were several statistically significant results from the Multivariate Analyses of Variance. There was an interaction observed by grade and gender, with most effects observed in sixth grade girls. When compared to sixth and eighth grade boys, sixth grade girls had higher levels of Math Interest, Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, Math Relational Outcome Expectations, and Math Learning Environment.

Sixth grade girls also had higher levels of Math Interest, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Learning Environment than eighth and 10th grade girls and higher Math Self-Efficacy scores than 10th grade girls. Compared to 10th grade males, sixth grade girls had higher levels of Math Generativity Outcome Expectations and Math Learning Environment. Inconsistent with the main effect for grade, 10th grade males had higher Math Interest and Math Learning Environment scores compared 8th grade males. No differences were observed in eighth and 10th grade females when compared to sixth grade males.

There were also statistically significant main effects observed for gender and for grade: Girls' had higher levels of Math Learning Environment, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations than did boys. Sixth graders had higher Math Learning Environment scores compared to eighth graders. There were no statistically significant differences between sixth and tenth graders or eighth sixth and tenth graders.

In one of the 15 groups, there was a statistically significant difference in the multivariate tests when sixth grade males were compared to eighth grade males, but no differences were detected using univariate tests. This phenomenon occurs when the cumulative effect of the individual variables yields a significant result (Manly, 2004). Conversely, in seven of the 15 groups, the multivariate tests were not significant, but the univariate tests were significant. Because more than one dependent variable is examined in MANOVA, the presence of non-significant variables can mask the presence of significant variables. Following the recommendation of Tabachnick and Fidell (2007), I provided the results of the significant univariate tests.

Univariate tests were significant for Math Interest, Math Self-Efficacy, and Math Relational Outcome Expectations. Tenth grade males reported greater Math Interest than 6th grade males and 10th grade females. Eighth grade females had higher levels of Math Self-Efficacy than 8th grade males and 10th grade females, as well as higher Math Relational Outcome Expectations than sixth and eighth grade males. Tenth grade females also had higher levels of Math Relational Outcome Expectations than sixth and eighth grade males.

Research Question 2

The second research question asks the question: Does Math Learning Environment explain a significant amount of the variance in Math Self-Efficacy for boys and girls in Grades 6, 8, and 10? Because Math Learning Environment is now measured with one scale instead of two subscales, the answer to this question can now be addressed through a simple correlation, as presented in Table 15. A Pearson-moment correlation coefficient was computed to determine the relationship between Math Learning Environment and Math Self-Efficacy. There was a positive correlation between Math Learning Environment and Math Self-Efficacy ($r = .62, p < .001$) (Table 25). Math

Learning Environment accounted for 37% of the variance observed in Math Self-Efficacy.

Table 25

Correlation of MLE and MSE

Model	MLE	MSE
MLE	—	
MSE	.62	—

* $p \leq .05$ (2-tailed).

Summary

My hypothesis for the second research question was supported. Math Learning Environment explained a significant amount of the variance (37%) in Math Self-Efficacy.

Research Question 3

The third research question asks the question: Does Math Learning Environment explain a significant amount of the variance in Math Outcome Expectations for boys and girls in Grades 6, 8, and 10? Based on the results of factor analysis and reliability and item-total statistics, I expanded the scope of the question to include the three sub-scales of Math Outcome Expectations: Math SCT Outcome Expectations (MOE-SCT), Math Generativity Outcome Expectations (MOE-G), and Math Relational Outcome Expectations (MOE-R). Because Math Learning Environment is now measured with one scale instead of two subscales, the answer to this question can now be addressed through a simple correlation, as presented in Table 15. A Pearson-moment correlation coefficients were computed to determine the relationship between Math Learning Environment and 1) Math SCT Outcome Expectations as the criterion variable; 2) Math Generativity Outcome Expectations as the criterion variable; and 3) Math Relational Outcome Expectations.

Math SCT Outcome Expectations

A Pearson-moment correlation coefficient was computed to determine the relationship between Math Learning Environment and Math SCT Outcome Expectations. There was a positive correlation between Math Learning Environment and MOE-SCT ($r = .54, p < .001$) (Table 26). Math Learning Environment explained 29% of the variance observed in Math SCT Outcome Expectations.

Math Generativity Outcome Expectations

A Pearson-moment correlation coefficient was computed to determine the relationship between Math Learning Environment and Math Generativity Outcome Expectations. There was a positive correlation between Math Learning Environment and MOE-G ($r = .57, p < .001$) (Table 26). Math Learning Environment accounted for 33% of the variance observed in Math Generativity Outcome Expectations.

Math Relational Outcome Expectations

A Pearson-moment correlation coefficient was computed to determine the relationship between Math Learning Environment and Math Relational Outcome Expectations. There was a positive correlation between Math Learning Environment and MOE-R ($r = .39, p < .001$) (Table 27). Math Learning Environment accounted for 15% of the variance observed in Math Relational Outcome Expectations.

Table 26
Correlation of MLE and MOE-SCT, MOE-G, and MOE-R

	MOE-SCT	MOE-G	MOE-R
MLE	.54	.57	.39

Note. All correlations are statistically significant, $p < .05$ (2-tailed).

Summary

My hypothesis for the second research question was supported. Math Learning Environment explained the variance in the three sub-scales of Math Outcome Expectations: Math SCT Outcome Expectations (28%), Math Generativity Outcome Expectations (30%), and Math Relational Outcome Expectations (15%).

Research Question 4

The fourth research question asks the question: Do Math Self-Efficacy and Math Outcome Expectations explain a significant amount of the variance in Math Interest for girls and boys in grades 6, 8, and 10? Based on the item and scale analyses of the Outcome Expectations Scale, I found that Math Outcome Expectations consisted of three clear factors. Therefore, I revised this Research Question to the following: Do Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations explain a significant amount of the variance in Math Outcome Expectations for boys and girls in Grades 6, 8, and 10? To answer Research Question 4, I conducted hierarchical linear regression analyses. Hierarchical regression analysis allows me to examine the effects of the independent variables on Math Interest after controlling for the three components of Math Outcome Expectations (Pedhazur, 1997). I used Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations as independent variables and Math Interest as the dependent variable.

Analyses Results

The results of multiple linear regression indicated that the overall contribution of the four independent variables ($r = .62$, $F(4, 223) = 33.84$; $p < .001$) accounted for 39%

of the variance observed in Math Interest (see Table 27). The coefficients for Math Self-Efficacy (B = .48; β = .45) and MOE-SCT (B = .25; β = .28) of the regression equation were statistically significant, $p < .001$ (see Table 28). The coefficients for MOE-G (B = -.04; β = -.07, p = .44) and MOE-R (B =.21; β = .11, p = .06) were not statistically significant, suggesting that they did not explain of Math Interests in the model. The raw score (unstandardized) regression equation of Math Interest (Y'_{MI}) regressed on Math Self-Efficacy, MOE-SCT, MOE-G, and MOE-R (X_4) is:

$$Y'_{MI} = -1.54 + .48\ (MSE) + .25\ (MOE\text{-}SCT) - .04\ (MOE\text{-}G) + .22\ (MOE\text{-}R)$$

The standardized regression equation of Math Interest (Z'_{MI}) regressed on Math Self-Efficacy (Z_1), MOE-SCT (Z_2), MOE-G (Z_3), and MOE-R (Z_4) is:

$$Z'_{MI} = .45\ (Z_{MES}) + .28\ (Z_{MOE\text{-}SCT}) - .07\ (Z_{MOE\text{-}G}) + .11\ (Z_{MOE\text{-}R})$$

Table 27
Summary for Combined Independent Variables Regressed on Math Interest

Model	*R*	R^2	*Adj.* R^2	*SE Est.*	ΔR^2	ΔF	df1	df2	Sig. ΔF
1	.62[a]	.38	.37	6.16	.39	33.84	4	223	.000

a. Independent Variables: (Constant), MSE, MOE-SCT, MOE-G, MOE-R

Table 28
Coefficients of Regression Equation for Combined Independent Variables

Model		*B*	*SE B*	β	*t*	*p*	VIF
1	(Constant)	-1.54	2.62		-.59	.56	
	Self-Efficacy	.48	.07	.45	7.28	.00	1.37
	MOE-SCT	.25	.07	.28	3.57	.00	2.26
	MOE-G	-.04	.05	-.07	-.77	.44	2.58
	MOE-R	.21	.11	.11	1.90	.06	1.18

a. Dependent Variable: Math Interest

Hierarchical Linear Regression

Together, Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations accounted for 39% of the variance observed in Math Interest. When there are correlations among the independent variables, the portion of increment of variance attributed to each independent variable depends on the entry order into the regression analysis (Pedhazur, 1997). Hierarchical, or incremental, partitioning of variance allowed me to examine the effect of a variable(s) on the dependent variable after controlling for another variable(s). To examine the effects of Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations on Math Interest, I conducted hierarchical linear regression. Conducting a series of linear regression analyses, I sequentially entered the independent variables to determine the impact that each independent variable has on Math Interest. Because the theoretical foundation of the study, Social Cognitive Career Theory (SCCT, Lent, Brown, & Hackett, 1994), posits that Math Self-Efficacy is the strongest predictor or Math Interests, I entered Math Self-Efficacy as the lone independent variable in Block 1. Because Lent et al. (1994) grounded SCCT in Bandura's (1977a, 1977b, 1986) Social Cognitive Theory (SCT), I entered the measure consistent with the expectations of outcomes posited by SCT, Math SCT Outcome Expectations, into Block 2.

The measures of Math Generativity Outcome Expectations and Math Relational Outcome Expectations are components of outcome expectations beyond those identified by Bandura (Shoffner, Newsome, & Barrio, 2004). Therefore, there has not been any published research on these constructs. However, there was a stronger relationship between Math Interest and Math Generativity Outcome Expectations ($r = .39$) than between Math Interest and Math Relational Outcome Expectations ($r = .26$). Furthermore, there was a strong correlation between Math SCT Outcome Expectations and Math Generativity Outcome Expectations ($r = .74$) and no correlation between Math

SCT Outcome Expectations and Math Relational Outcome Expectations (r = .12). Given these relationships, I entered Math Generativity Outcome Expectations into Block 3 and Math Relational Outcome Expectations into Block 4.

Hierarchical linear regression analysis (see Table 29) indicated that Math Self-Efficacy accounted for a large proportion of Math Interest ($R^2 = .32$; $F(1, 226) = 105.44$; $p < .001$). Math SCT Outcome Expectations accounted for an additional 5% of the variance in Math Interest ($\Delta R^2 = .05$, $\Delta F(1, 225) = 17.52$; $p < .001$) after controlling for Math Self-Efficacy. The addition of Math Generativity Outcome Expectations did not yield a significant ΔR^2 ($\Delta R^2 = .01$, $\Delta F(1, 224) = 3.12$; $p = .78$) after controlling for the variables in Block 2. The addition of Math Relational Outcome Expectations did not yield a significant ΔR^2 ($\Delta R^2 = .00$, $\Delta F(1, 223) = .59$; $p = .44$) after controlling for the variables in Block 3...

Table 29

Model[b] Summary for Incremental R^2 Regressed on Math Interest (Model 1)

Model	R	R^2	ΔR^2	ΔF	$df1$	$df2$	$p\ \Delta F$
1	.56[a]	.32	.32	105.44	1	226	.000
2	.61[b]	.37	.05	17.52	1	225	.000
3	.61[c]	.38	.01	3.12	1	224	.78
4	.62[d]	.38	.00	.59	1	223	.44

a. Independent Variables: (Constant), Self-Efficacy
b. Independent Variables: (Constant), Self-Efficacy, MOE-SCT
c. Independent Variables: (Constant), Self-Efficacy, MOE-SCT, MOE-G
d. Independent Variables: (Constant), Self-Efficacy, MOE-SCT, MOE-G, MOE-R

I conducted a second linear regression exchanging the entry order of Math Generativity Outcome Expectations and Math Relational Outcome Expectations. As outlined previously, I entered Math Self-Efficacy in Block 1 and Math SCT Outcome Expectations into Block 2. I entered Math Relational Outcome Expectations into Block 3 and Math Generativity Outcome Expectations into Block 4. I present the results of the second hierarchical regression on Table 30.

Math Self-Efficacy accounted for 32% of the variance observed in Math Interest. Math SCT Outcome Expectations accounted for an additional 5% of the variance in Math Interest after controlling for Math Self-Efficacy. Math Relational Outcome Expectations did not yield a significant ΔR^2 ($\Delta R^2 = .00$, $\Delta F(1, 224) = .09$; $p = .76$) after controlling for the Math Self-Efficacy and Math SCT Outcome Expectations. Math Generativity Outcome Expectations also did not yield a significant ΔR^2 ($\Delta R^2 = .01$, $\Delta F(1, 223) = 3.62$; $p = .06$) after controlling for the variables in Block 3.

Table 30

Model[b] Summary for Incremental R^2 Regressed on Math Interest (Model 2)

Model	*R*	R^2	ΔR^2	ΔF	*df1*	*df2*	*p* ΔF
1	.56[a]	.32	.32	105.44	1	226	.000
2	.61[b]	.37	.05	17.52	1	225	.000
3	.61[c]	.38	.00	.09	1	224	.76
4	.62[d]	.38	.01	3.62	1	223	.06

a. Independent Variables: (Constant), Self-Efficacy
b. Independent Variables: (Constant), Self-Efficacy, MOE-SCT
c. Independent Variables: (Constant), Self-Efficacy, MOE-SCT, MOE-R
d. Independent Variables: (Constant), Self-Efficacy, MOE-SCT, MOE-R, MOE-G

These results were consistent with both the theoretical foundation of the study, Social Cognitive Career Theory (SCCT, Lent, Brown, & Hackett, 1994) and strong empirical support from previous work (Navarro, Flores, & Worthington, 2007; Rottinghaus, Larson, & Borgen, 2003; Usher & Pajares, 2009) that Math Self-Efficacy is the strongest predictor of Math Interests. However, both theory and consistent research findings suggest there is a strong relationship between expectations about the results of engaging in an activity or task and interest in that task. In this study, there were strong correlations between Math Interest and Math SCT Outcome Expectations (r = .43), Math Generativity Outcome Expectations (r = .39), and Math Relational Outcome Expectations (r = .26). Given the correlations among the independent variables, the portion of incremental variance attributed to each independent variable depended on the order of entry into the regression analysis (Pedhazur, 1997). Because Math Self-Efficacy explained all but 5% of the observed variance in Math Interest, I could not examine the effect of the three subscales of Math Outcome Expectations on Math Interest.

Math Outcome Expectations Subscales. I used hierarchical regression, or incremental partitioning of variance, to examine the unique effects of each of the variables Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations on Math Interest, after controlling for the other Math Outcome Expectation variables. Using theory, past empirical support, and results from previous analyses, I knew that Math SCT Outcome Expectations explained a portion of the variance observed in Math Interest. Entering this construct first, I could then examine the effect of Math Generativity Outcome Expectations and Math Relational Outcome Expectations on Math Interest after controlling for Math SCT Outcome Expectations. I entered Math SCT Outcome Expectations, into Block 1.

As noted previously, there has not been any published research on the measures of Math Generativity Outcome Expectations and Math Relational Outcome Expectations However, Math Relational Outcome Expectations had a weaker relationship with Math Interest, Math SCT Outcome Expectations and Math Generativity Outcome Expectations (r = .14, .12, and .27 respectively). Math Relational Outcome Expectations also has some shared variance with Math Interest beyond that of the other two other components of

Outcome Expectations in this study. Results from previously presented factor analyses indicate that the second factor of a three-factor extraction (containing only the Relational items) explained 7.83% percent of total variance of the Math Outcome Expectations Scale (see Appendix L1). Given these relationships, I added Math Generativity Outcome Expectations into Block 2. I present the results of this analysis on Table 35.

Math SCT Outcome Expectations accounted for 18% of the variance in Math Interest ($\Delta R^2 = .18, \Delta F(1, 226) = 49.92; p < .001$). Math Generativity Outcome Expectations accounted for an additional 1% of the variance in Math Interest after controlling for by Math SCT Outcome Expectations ($\Delta R^2 = .01, \Delta F(1, 225) = 3.91;\ p = .049$). Math Relational Outcome Expectations accounted for an additional 4% of the variance in Math Interest after controlling for Math SCT Outcome Expectations and Math Generativity Outcome Expectations ($\Delta R^2 = .04, \Delta F(1, 224) = 10.19;\ p = .002$). I present the results in Table 31.

Table 31
Math Outcome Expectations Regressed on Math Interest (Model 1)

Model	R	R^2	ΔR^2	ΔF	$df1$	$df2$	$p\ \Delta F$
1	.43[a]	.18	.18	49.92	1	226	.000
2	.44[b]	.19	.01	3.91	1	225	.049
3	.48[c]	.23	.04	10.19	1	224	.002

a. Independent Variables: (Constant), OE-SCT
b. Independent Variables: (Constant), OE-SCT, OE-G
c. Independent Variables: (Constant), OE-SCT, OE-G, OE-R

To examine further the Math Outcome Expectations proposed by Shoffner (2004), I conducted a second hierarchical linear regression, exchanging the entry order of Math Generativity Outcome Expectations and Math Relational Outcome Expectations (see Table 32). Math SCT Outcome Expectations accounted for 18% of the variance in Math Interest ($\Delta R^2 = .18, \Delta F(1, 226) = 49.92; p < .001$). Math Relational Outcome

Expectations accounted for an additional 5% of the variance in Math Interest after controlling for Math SCT Outcome Expectations ($\Delta R^2 = .05$, $\Delta F(1, 225) = 13.46$; $p < .001$). In Block 3, Math Generativity Outcome Expectations not yield a significant ΔR^2 after controlling for Math SCT Outcome Expectations and Math Relational Outcome Expectations ($\Delta R^2 = .00$, $\Delta F(1, 224) = .81$; $p = .37$).

Table 32

Math Outcome Expectations Regressed on Math Interest (Model 2)

Model	R	R^2	ΔR^2	ΔF	$df1$	$df2$	$p.\ \Delta F$
1	.43[a]	0.18	0.18	49.92	1	226	.000
2	.48[b]	0.23	0.05	13.46	1	225	.000
3	.48[c]	0.23	0.00	0.81	1	224	.368

a. Independent Variables: (Constant), MOE-SCT,
b. Independent Variables: (Constant), MOE-SCT, MOE-G,
c. Independent Variables: (Constant), MOE-SCT, MOE-G, MOE-R

In the first hierarchical linear analysis in which I entered Math Generativity Outcome Expectations before Math Relational Outcome Expectations, all three components of Math Outcome Expectations explained a significant amount of the variance in Math Interest. However, when I entered Math Relational Outcome Expectations before Math Generativity Outcome Expectations, Math Generativity Outcome Expectations no longer explained a significant amount of the variance observed in Math Interests. To examine the unique explanatory powers of Math Generativity Outcome Expectations and Math Relational Outcome Expectations, I conducted a third hierarchical linear regression. Because Math Relational Outcome Expectations had the weakest correlation to Math Interest (see Table 15), I entered it first. I need entered Math Generativity Outcome Expectations, followed by Math SCT Outcome Expectations.

Math Relational Outcome Expectations accounted for 7% of the variance in Math Interest ($\Delta R^2 = .07$, $\Delta F(1, 226) = 17.06$; $p < .001$). Math Generativity Outcome

Expectations accounted for an additional 11% of the variance in Math Interest beyond Math Relational Outcome Expectations ($\Delta R^2 = .11$, $\Delta F(1, 225) = 29.56$; $p < .001$). Math SCT Outcome Expectations added an additional 5% of the variance in Math Interest after entering both Math Relational Outcome Expectations and Math Generativity Outcome Expectations ($\Delta R^2 = .05$, $\Delta F(1, 224) = 15.06$; $p < .001$). I present the results of the analyses in Table 33.

Table 33

Math Outcome Expectations Regressed on Math Interest (Model 3)

Model	*R*	R^2	Adj. R^2	*SE Est.*	ΔR^2	ΔF	*df1*	*df2*	$p\ \Delta F$
1	.27[a]	0.07	0.07	7.48	0.07	17.06	1	226	.000
2	.42[b]	0.18	0.17	7.05	0.11	29.56	1	225	.000
3	.48[c]	0.23	0.22	6.84	0.05	15.06	1	224	.000

a. Independent Variables: (Constant), MOE-R,
b. Independent Variables: (Constant), MOE-R, MOE-G,
c. Independent Variables: (Constant), MOE-R, MOE-G, MOE-SCT

Summary

Results partially supported my hypotheses for the fourth research question. Two independent variables, Math Self-Efficacy and Math SCT Outcome Expectations, explained a statistically significant amount of the variance in Math Interest. The remaining two independent variables, Math Generativity Outcome Expectations and Math Relational Outcome Expectations, did not explain a statistically significant amount of the variance in Math Interest. Math Self-Efficacy explained 32% of the variance observed in Math Interest, while Math SCT Outcome Expectations explained an additional 5% beyond that explained by Math Self-Efficacy. Math Generativity Outcome Expectations and Math Relational Outcome Expectations did not contribute additional explanatory power to the model beyond Math Self-Efficacy and Math SCT Outcome Expectations.

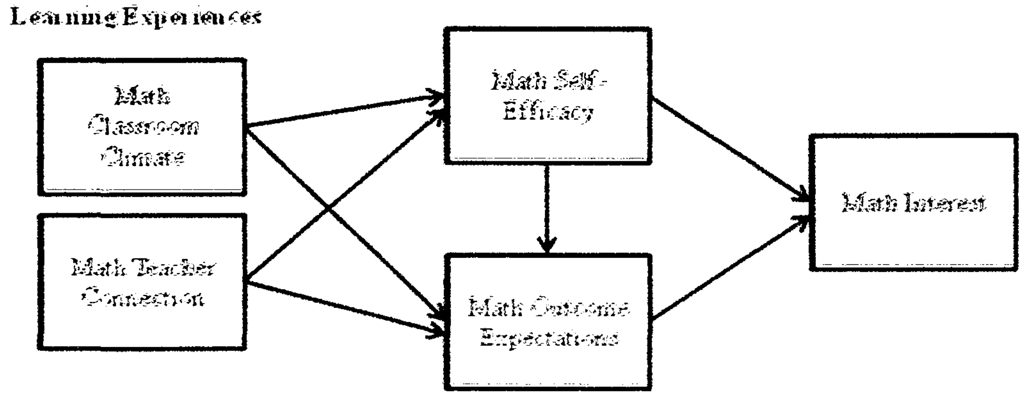
When I enter the Outcome Expectation subscales into the hierarchical regression Math SCT Outcome Expectations explained 18% of the variance in Math Interest. Math Generativity Outcome Expectations explained an additional 1% of the variance in Math Interest beyond Math SCT Outcome Expectations. Math Relational Outcome Expectations explained an additional 4% of the variance in Math Interest beyond Math SCT Outcome Expectations and Math Generativity Outcome Expectations.

When I reversed the order of forced inclusion of Math Generativity Outcome Expectations and Math Relational Outcome Expectations, Math Relational Outcome Expectations explained an additional 5% of the variance in Math Interest, Math Generativity Outcome Expectations did not explain the variance observed in Math Interest after controlling for the other two factors of Math Outcome Expectations. When I based the order of forced inclusion by entering variables from weakest to strongest correlation to Math Interest, Math Relational Outcome Expectations explained 7% of the variance in Math Interest. Math Generativity Outcome Expectations explained an additional 11% of the variance in Math Interest. Math SCT Outcome Expectations explained an additional 5% of the variance in Math Interest beyond Math Relational Outcome Expectations and Math Generativity Outcome Expectations.

Research Question 5

The fifth research question asks the question: Do the data fit the modified SCCT model (see Figure 1) for girls and boys in grades 6, 8, and 10? To answer the question, I used linear regression to calculate the path coefficients in the modified SCCT model.

Figure 1
Modified Social Cognitive Career Theory Model



(Adapted from Lent, Brown, & Hackett, 1994)

Revised Model

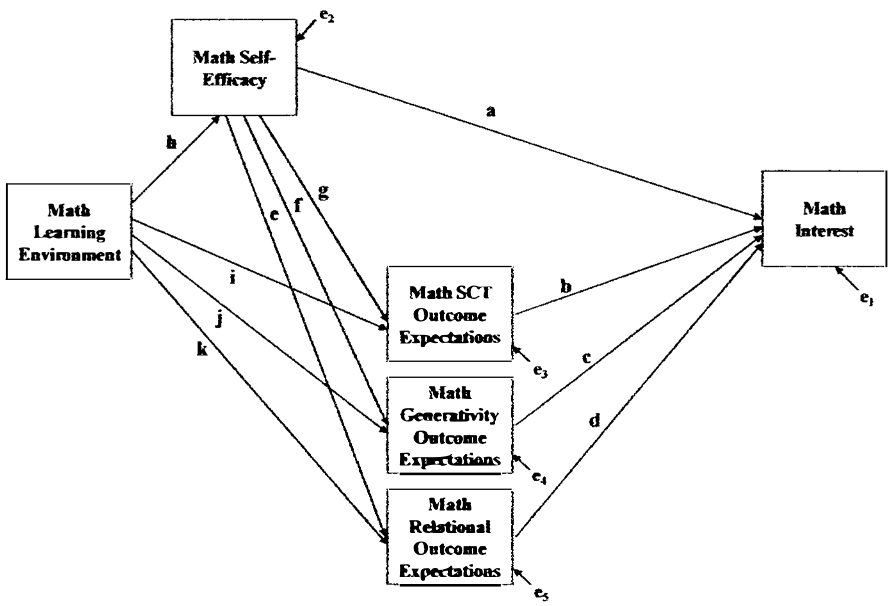
I adapted the model of Social Cognitive Career Theory (SCCT; Lent, Brown, Hackett, 1994) with the hypothesized relationships among study constructs. As noted previously, I hypothesized that the items selected to measure the student-teacher relationship would take the form of two separate and distinct scales of Math Classroom Climate and Math Teacher Connection. Factor analysis indicated that the identified items constituted only one factor, a unidimensional construct of Math Learning Environment. In keeping with Bandura's theory (1986), Lent et al. hypothesized Outcome Expectations as a unidimensional construct in the SCCT model. Factor analysis of the Outcome Expectations items indicated that they loaded on three factors. These factors were Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations. Based on these results, I revised the model.

In this model, I now have three subscales for the measure of Math Outcome Expectations: Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations. I hypothesized that each of these constructs would directly influence Math Interest. I added the following paths to Math Interest: path (b) from Math SCT Outcome Expectations, path (c) from Math Generativity Outcome Expectations, and path (d) from Math Relational Outcome Expectations.

In the SCCT model, Math Self-Efficacy directly influences Math Outcome Expectation. I hypothesized that Math Self-Efficacy would directly influence Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations. I added the following paths from Math Self-Efficacy: path (e) to Math SCT Outcome Expectations, path (f) to Math Generativity Outcome Expectations, and path (g) to Math Relational Outcome Expectations.

In the SCCT model, Math Learning Environment has a direct effect on Math Self-Efficacy and Math Outcome Expectations. I hypothesized that Math Learning Environment would directly influence Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations. I added path (h) from Math Learning Environment to Math Self-Efficacy, path (i) to Math SCT Outcome Expectations, path (j) to Math Generativity Outcome Expectations, and path (k) to Math Relational Outcome Expectations.

Figure 2
Revised Modified Social Cognitive Career Theory Model



Path Analysis

To conduct path analysis, I ran a linear regression analysis for each endogenous variable. I identified the following endogenous variables in the model: Math Interest, Math Self-Efficacy (MSE), Math SCT Outcome Expectations (MOE-SCT), Math Generativity Outcome Expectations (MOE-G), and Math Relational Outcome Expectations (MOE-R). I used the standardized coefficients of the regression analyzes for the path coefficients in the model. To determine the path coefficients of the model, I ran five linear regression analyses with the endogenous variable as the dependent variable, and the variables that had a direct effect on the dependent variable as the independent variable(s) as follows:

1) Math Interest = a (MSE) + b (MOE-SCT) + c (MOE-G) + d (MOE-R)

2) Math Self-Efficacy = h (MLE)

3) Math SCT Outcome Expectations = i (MLE) + e (MSE)

4) Math Generativity Outcome Expectations = j (MLE) + f (MSE)

5) Math Relational Outcome Expectations = k (MLE) + g (MSE)

Path Analysis Calculations

I conducted multiple linear regression using Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations as independent variables and Math Interest as the dependent variable (see Table 34). The results indicated the following regression equation: Math Interest = .45 (MSE) + .28 (MOE-SCT) - .07 (MOE-G) + .11 (MOE-R). The statistically significant path coefficients were .45 (a) and .28 (b). The path coefficients for (c) and (d) were not statistically significant (-.07 and.11).

I conducted linear regression using Math Learning Environment as the independent variable and Math Self-Efficacy as the dependent variable (see Table 34). The results indicated the following regression equation: Math Self-Efficacy = .62(MLE). The path coefficient for (h) was statistically significant at.62.

I conducted multiple linear regression using Math Learning Environment and Math Self-Efficacy as the independent variables and Math SCT Outcome Expectations as the dependent variable (see Table 34). The results indicated the following regression equation: Math SCT Outcome Expectations = .48(MLE) + .10(MSE). The path coefficient for (i) was not statistically significant at .48. The path coefficient for (e) was not statistically significant at.10.

I conducted multiple linear regression using Math Learning Environment and Math Self-Efficacy as the independent variables and Math Generativity Outcome

Expectations as the dependent variable (see Table 34). The results indicated the following regression equation: Math Generativity Outcome Expectations = .45(MLE) + .21(MSE). The statistically significant path coefficients were.45 (j) and .21 (f).

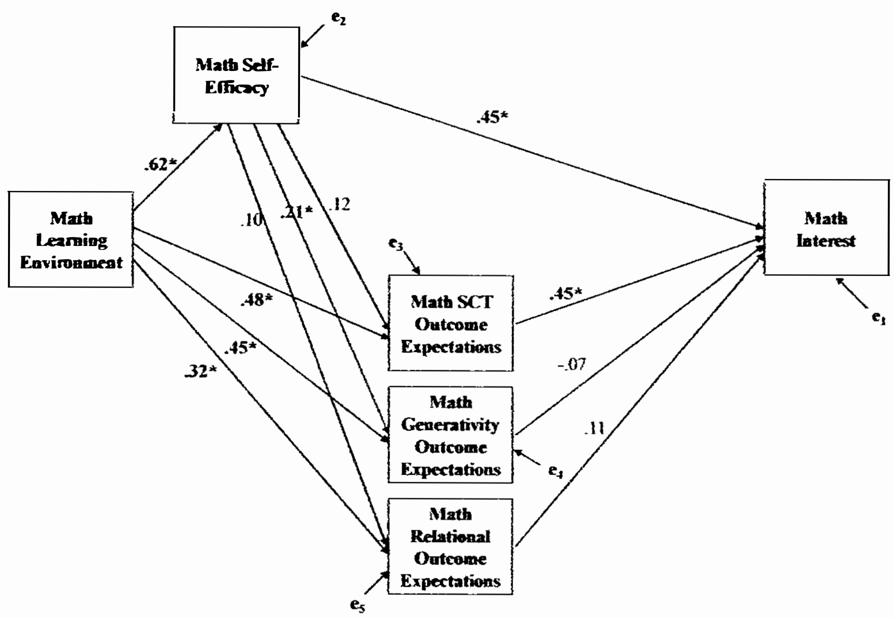
I conducted multiple linear regression using Math Learning Environment and Math Self-Efficacy as the independent variables and Math Relational Outcome Expectations as the dependent variable (see Table 34). The results indicated the following regression equation: Math Relational Outcome Expectations = .32(MLE) + .12(MSE). The statistically significant path coefficient was .32 (k). The remaining path coefficient was not significant at .12 (g).

Table 34
Coefficients of Regression Equation for Full Model

	Dependent Variable		β	t	p
1	MI	(Constant)		-.59	.56
		MSE	.45	7.28	.000
		MOE-SCT	.28	3.57	.000
		MOE-G	-.07	-.77	.44
		MOE-R	.11	1.90	.06
1	MSE	(Constant)		6.92	.000
		MLE	.66	11.83	.000
1	MOE-SCT	(Constant)		6.42	.000
		MSE	.10	1.34	.18
		MLE	.48	6.75	.00
1	MOE-G	(Constant)		11.29	.000
		MSE	.21	3.02	.003
		MLE	.45	6.52	.000
1	MOE-R	(Constant)		11.21	.000
		MSE	.12	1.53	.13
		MLE	.32	4.05	.000

I present the full model, with all path coefficients entered, in Figure 3. I used the above regression equations to determine the path coefficients of the model.

Figure 3
Revised Modified Social Cognitive Career Theory Model Path Coefficients.



Calculation of Total Effects

Once I entered all path coefficients into the model, I calculated the total effect for those independent variables that had an indirect effect on Math Interest. I used the path coefficient to obtain the direct effect of MSE on MI and of MLE on MI. The following are the path coefficients used for my calculations of total effect: a = .45*; b = .28*; c = -.07; d = .11; e = .10; f = .21*; g = .12; h = .62*; i = .48*; j = .45*; k = .32*

To determine the total effects of the mediator variables, Math Self-Efficacy and Math Learning Environment, on Math Interest, I first conducted a correlation analysis. I present the results in Table 35.

Table 35
Correlations of Scale Sum Totals of Study Scales

Measure	1	2	3	4	5	6
1. MI	—					
2. MSE	.56	—				
3. MOE-SCT	.43	.39	—			
4. MOE-G	.39	.48	.74	—		
5. MOE-R	.27	.31	**.12**	.30	—	
6. MLE	.50	.62	.54	.57	.39	—

Note. Bold correlation was not significant. All other correlations are statistically significant, $p < .05$.

Math Self-Efficacy. Math Self-Efficacy had a direct effect on Math Interest. This path contributed a statistically significant portion ($r = .45$; $t = 7.28$, $p < .001$) of the total correlation between Math Self-Efficacy and Math Interest ($r = .56$). The indirect effect Math Self-Efficacy on Math Interest through Math SCT Outcome Expectations ($r = (.10)(.28) = .03$), Math Generativity Outcome Expectations ($r = (.21)(-.07) = -.01$), and Math Relational Outcome Expectations ($r = (.12)(.11) =.01$) was .03. The total effect of Math Self-Efficacy on Math Interest was .48, the sum of the direct and indirect effects. In the analysis, .08 of the effect was unaccounted for in the modified SCCT model.

The results of the path analyses did not find an indirect effect of Math Self-Efficacy on Math Interest mediated through the three forms of Math Outcome Expectations examined in this study, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations. These findings are not consistent with the theoretical foundation of the study, SCCT, or empirical evidence from previous research. However, these three aspects of outcome expectations are not discrete constructs, but subscales of Math Outcome Expectations. To test if Math Self-Efficacy has an indirect effect on Math Interest through Math

Outcome Expectations, I examined the SCCT model using a unidimensional measure for Math Outcome Expectations.

Math Outcome Expectations. I ran a multiple linear regression, with Math Interest as the dependent variable and Math Self-Efficacy and Math Outcome Expectations as the dependent variables (see Table 36). I ran a second multiple linear regression, with Math Outcome Expectations as the dependent variable and Math Self-Efficacy and Math Learning Environment as the dependent variables. Math Self-Efficacy had a direct effect on Math Outcome Expectations, ($\beta = .19$; $t = 2.87$, $p = .004$). Math Outcome Expectations had a direct effect on Math Interest ($\beta = .23$; $t = 3.68$, $p < .001$). The indirect effect Math Self-Efficacy on Math Interest through Math Outcome Expectations (r = [.19][.23]) was .04. The total effect of Math Self-Efficacy on Math Interest was .49, the sum of the direct and indirect effects.

Table 36
Coefficients of Regression Equation for Full Model (MOE Single Construct)

	Dependent Variable		β	t	p
1	MI	(Constant)		-.63	.53
		MSE	.45	7.25	.000
		MOE	.23	3.68	.000
1	MSE	(Constant)		6.92	.000
		MLE	.66	11.83	.000
1	MOE	(Constant)		12.50	.000
		MSE	.19	2.87	.004
		MLE	.52	7.99	.000

Math Learning Environment. Math Learning Environment had an indirect effect on Math Interest. The indirect effect Math Learning Environment on Math Interest through Math Self-Efficacy (r = (.62)(.44) =.28), Math SCT Outcome Expectations (r = (.48)(.28) =.13), Math Generativity Outcome Expectations (r = (.45)(-.07) = -.03), and

Math Relational Outcome Expectations (r = (.32)(.11) =.04) contributed .42 of the total correlation between Math Learning Environment and Math Interest (r =.50). In the analysis, .08 of the effect was unaccounted for in the modified SCCT model.

There is empirical evidence from previous research suggesting that the learning environment influences math interest. To test this premise, I added a direct path from Math Learning Environment to Math Interest and recalculated the effects as delineated below. To determine if Math Learning Environment had a direct effect on Math Interest in the modified SCCT model, I ran a multiple linear regression, with Math Interest as the dependent variable and Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations and Math Learning Environment (see Table 37). I did not need to re-run the regression equations for the endogenous variables, Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations, as the addition of a direct effect path from Math Learning Environment to Math Interest does not change these path coefficients.

The results of the multiple linear regression found that there was not a statistically significant direct path from Math Learning Environment to Math Interest, (r = .05, t = 1.66, p = .10). The indirect effect Math Learning Environment on Math Interest through Math Self-Efficacy (r = (.62)(.40) = .25), Math SCT Outcome Expectations (r = (.48)(.25) = .12), Math Generativity Outcome Expectations (r = (.45)(-.08) = -.04), and Math Relational Outcome Expectations (r = (.32)(.12) =.04) contributed .37 of the total correlation between Math Learning Environment and Math Interest (r =.50). The total effect of Math Learning Environment on Math Interest was .42. In the analysis, .08 of the effect was unaccounted for in the modified SCCT model.

Table 37
Coefficients of Regression Equation for Math Interest (Adding MLE)

Model	β	t	p
1 (Constant)		-.50	.61
MSE	.40	5.83	.000
MOE-SCT	.25	3.05	.003
MOE-G	-.08	-.34	.40
MOE-R	.12	1.43	.16
MLE	.05	1.66	.10

Model Adequacy

I ran multiple linear regression analyses to determine the adequacy of the modified SCCT model. In other words, did the direct effect paths hypothesized in the modified SCCT explain statistically significant portions of the variance observed in the five endogenous variables, Math Interest, Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations? For each endogenous or dependent variable, I determined the amount of observed variance explained by the model's posited independent variables. I examined the Analysis of Variance *F* statistic to determine significance.

In the modified SCCT model, Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations accounted for 38% of the variance observed in Math Interest (see Table 38). Using Cohen's (1988) suggested guidelines, this equates to a large effect size ($R^2 = .38$). The corresponding F-statistic was significant, $F(4, 223) = 33.84$, $p < .001$, indicating that the independent variables in the modified SCCT model, Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational

Outcome Expectations, explained a statistically significant amount of variance observed in Math Interest.

In the modified SCCT model, Math Learning Environment accounted for 38% of the variance observed in Math Self-Efficacy (see Table 38). Using Cohen's (1988) suggested guidelines, this equates to a large effect size ($R^2 = .38$). The corresponding F-statistic was significant, $F(1, 226) = 139.54$, $p < .001$, indicating that the independent variable in the modified SCCT model, Math Learning Environment, explained a statistically significant proportion of variance observed in Math Self-Efficacy.

In the modified SCCT model, Math Self-Efficacy and Math Learning Environment accounted for 29% of variance observed in Math SCT Outcome Expectations (see Table 38). Using Cohen's (1988) suggested guidelines, this equates to a large effect size ($R^2 = .29$). The corresponding F-statistic was significant, $F(2, 225) = 47.33$, $p < .001$, indicating that the independent variables in the modified SCCT model, Math Self-Efficacy and Math Learning Environment, explained a statistically significant proportion of variance observed in Math SCT Outcome Expectations.

In the modified SCCT model, Math Self-Efficacy and Math Learning Environment accounted for 35% of the variance observed in Math Generativity Outcome Expectations (see Table 38). Using Cohen's (1988) suggested guidelines, this equates to a large effect size ($R^2 = .35$). The corresponding F-statistic was significant, $F(2, 225) = 51.67$, $p < .001$, indicating that the independent variables in the modified SCCT model, Math Self-Efficacy and Math Learning Environment, explained a statistically significant proportion of the variance observed in Math Generativity Outcome Expectations.

In the modified SCCT model, Math Self-Efficacy and Math Learning Environment accounted for 16% of the variance observed in Math Relational Outcome Expectations (see Table 38). Using Cohen's (1988) suggested guidelines, this equates to a medium effect size ($R^2 = .16$). The corresponding F-statistic was significant, $F(2, 225) = 21.34$, $p < .001$, indicating that the independent variables in the modified SCCT model, Math Self-Efficacy and Math Learning Environment, explained a statistically significant proportion of variance observed in Math Relational Outcome Expectations .

Table 38
Model Summary for All SCCT Model Endogenous Variables

Independent Variable	*R*	R^2	R^2	*F*	*df 1*	*df 2*	*p*
MI	.62	.38	.37	33.84	.4	223	.000
MSE	.61	.38	.38	139.54	1	226	.000
MOE-SCT	.54	.29	.29	47.33	2	225	.000
MOE-G	.60	.35	.34	61.57	2	225	.000
MOE-R	.40	.16	.15	21.34	2	225	.000

Summary

The results generally supported my hypothesis for the fifth research question. Path analyses indicated that the data fits the SCCT model. Significant path coefficients indicated that Math Learning Environment exerted a direct effect on Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations. Results indicated that Math Self-Efficacy and Math SCT Outcome Expectations exerted a significant direct effect on Math Interest. There were no significant direct effects of Math Generativity Outcome Expectations and Math Relational Outcome Expectations on Math Interest. Math Self-Efficacy had a significant direct effect on Math Generativity Outcome Expectations, but Math Self-Efficacy did not have a significant direct effect on Math SCT Outcome Expectations and Math Relational Outcome Expectations.

Math Self-Efficacy did not exert an indirect effect on Math Interest through the factors of Math Outcome Expectations. While there was a statistically significant path from Math Self-Efficacy to Math Generativity Outcome Expectations, the path from Math Generativity Outcome Expectations to Math Interest was not statistically significant. Similarly, while the path from Math SCT Outcome Expectations to Math Interest was statistically significant, the path from Math Self-Efficacy to Math SCT Outcome Expectations was not statistically significant. However, when examining Math Outcome Expectations as a single construct, there were statistically significant paths from Math Self-Efficacy to Math Outcome Expectations and from Math Outcome Expectations to Math Interest. Math Self-Efficacy exerted an indirect effect on Math Interest through Math Outcome Expectations.

The results of the multiple linear regression analyses supported the adequacy of the modified SCCT model. The direct paths from the hypothesized independent variables in the modified SCCT model explained statistically significant portions of the variance observed in the endogenous variables: Math Interest, Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations. Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations explained a statistically significant portion of the variance observed in Math Interests. Math Learning Environment accounted for a statistically significant portion of the variance observed in Math Self-Efficacy. Math Learning Environment and Math Self-

Efficacy, accounted for a statistically significant portion of the variance observed in Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations ($R^2 = .16$), a medium effect size.

Research Question 6

The sixth research question asks the question: Is the modified model of SCCT invariant across gender for participants in Grades 6, 8, and 10? To answer the question, I used linear regression to calculate the path coefficients in the modified SCCT model.

Path Analysis by Gender

To conduct path analysis, I split the SPSS file by gender and compared these groups during all analyses. I ran a linear regression analysis for each endogenous variable. I identified the following endogenous variables in the model: Math Interest, Math Self-Efficacy (MSE), Math SCT Outcome Expectations (MOE-SCT), Math Generativity Outcome Expectations (MOE-G), and Math Relational Outcome Expectations (MOE-R). I used the standardized coefficients of the regression analyzes for the path coefficients in the model. To determine the path coefficients of the model, I ran five linear regression analyses with the endogenous variable as the dependent variable, and the variables that had a direct effect on the dependent variable as the independent variable(s) as follows:

1) Math Interest = a (MSE) + b (MOE-SCT) + c (MOE-G) + d (MOE-R)

2) Math Self-Efficacy = h (MLE)

3) Math SCT Outcome Expectations = i (MLE) + e (MSE)

4) Math Generativity Outcome Expectations = j (MLE) + f (MSE)

5) Math Relational Outcome Expectations = k (MLE) + g (MSE)

Path Analysis Calculations for Males

I conducted multiple linear regression using Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations as independent variables and Math Interest as the dependent variable (see Table 39). The results indicated the following regression equation: Math Interest = .34 (MSE) + .34 (MOE-SCT) + .07 (MOE-G) + .02 (MOE-R). The statistically significant path coefficients were .34 (a) and .34 (b). The path coefficients for (c) and (d) were not statistically significant.

I conducted linear regression using Math Learning Environment (MLE) as the independent variable and Math Self-Efficacy as the dependent variable (see Table 39). The results indicated the following regression equation: Math Self-Efficacy = .61 (MLE). The path coefficient was .61 (h).

I conducted linear regression using Math Learning Environment and Math Self-Efficacy as the independent variables and Math SCT Outcome Expectations as the dependent variable (see Table 39). The results indicated the following regression equation: Math SCT Outcome Expectations = .51 (MLE) + .19 (MSE). The path coefficient (i) was statistically significant at .51. The path coefficient for (e) was not statistically significant.

I conducted linear regression using Math Learning Environment and Math Self-Efficacy as the independent variables and Math Generativity Outcome Expectations as the dependent variable (see Table 39). The results indicated the following regression equation: Math Generativity Outcome Expectations = .50 (MLE) + .24 (MSE). The statistically significant path coefficients were .50 (j) and .24 (f).

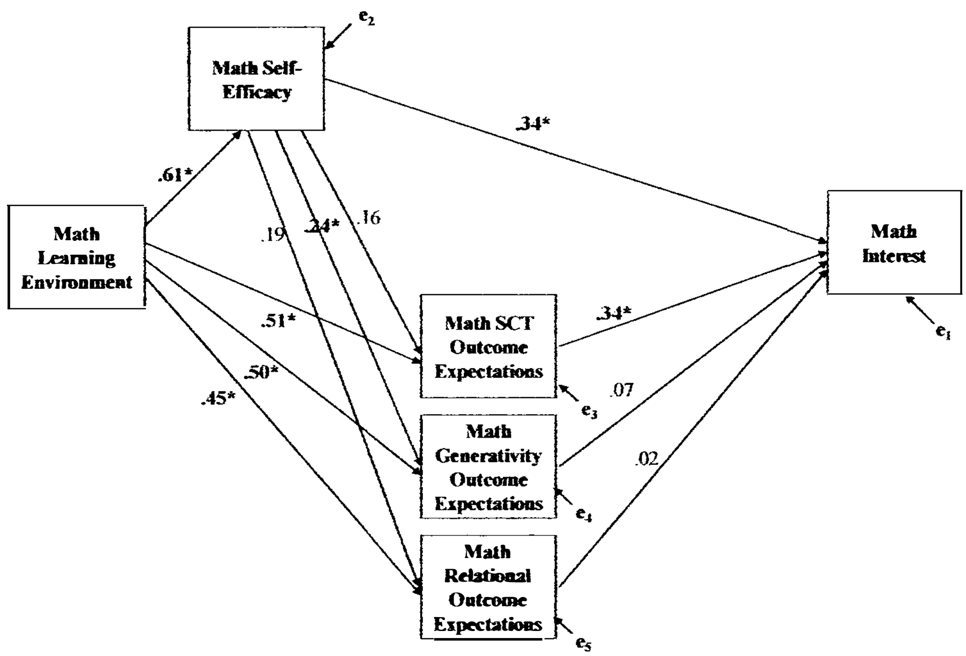
I conducted linear regression using Math Learning Environment and Math Self-Efficacy as the independent variables and Math Relational Outcome Expectations as the dependent variable (see Table 39). The results indicated the following regression equation: Math Relational Outcome Expectations = .45 (MLE) + .16 (MSE). The path coefficient for (k) was statistically significant at .45. The remaining path coefficient was not significant.

Table 39
Coefficients of Regression Equation for Males

	Dependent Variable		β	t	p
1	MI	(Constant)		-.29	.78
		MSE	.34	3.40	.001
		MOE-SCT	.34	2.80	.01
		MOE-G	.07	.56	.58
		MOE-R	.02	.21	.84
1	MSE	(Constant)		5.06	.000
		MLE	.61	7.39	.000
1	MOE-SCT	(Constant)		3.28	.001
		MSE	.19	1.89	.06
		MLE	.51	5.02	.000
1	MOE-G	(Constant)		5.16	.000
		MSE	.24	2.42	.02
		MLE	.50	5.18	.000
1	MOE-R	(Constant)		5.35	.000
		MSE	.16	1.47	.15
		MLE	.45	4.14	.000

I present the full model for males, with all path coefficients entered, in Figure 4. I used the above regression equations to determine the path coefficients of the model.

Figure 4
Revised Modified SCCT Model Path Coefficients: Males



Path Analysis Calculations for Females

I conducted multiple linear regression using Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations as independent variables and Math Interest as the dependent variable (see Table 40). The results indicated the following regression equation: Math Interest = .51 (MSE) + .33 (MOE-SCT) + -.19 (MOE-G) + .16 (MOE-R). The statistically significant path coefficients for a, b, and d were .51, .33, and .16 respectively. The path coefficient for (c) was not statistically significant.

I conducted linear regression using Math Learning Environment as the independent variable and Math Self-Efficacy as the dependent variable (see Table 40).

The results indicated the following regression equation: Math Self-Efficacy = .61 (MLE). The path coefficient for (h) was statistically significant at .61.

I conducted linear regression using Math Learning Environment and Math Self-Efficacy as the independent variables and Math SCT Outcome Expectations as the dependent variable (see Table 40). The results indicated the following regression equation: Math SCT Outcome Expectations = .45 (MLE) + .03 (MSE). The path coefficient for (i) was statistically significant at .45. The path coefficient for (e) was not statistically significant.

I conducted linear regression using Math Learning Environment and Math Self-Efficacy as the independent variables and Math Generativity Outcome Expectations as the dependent variable (see Table 40). The results indicated the following regression equation: Math Generativity Outcome Expectations = .35 (MLE) + .19 (MSE). The path coefficients for (j) and (f) were statistically significant at .35 and .19 respectively.

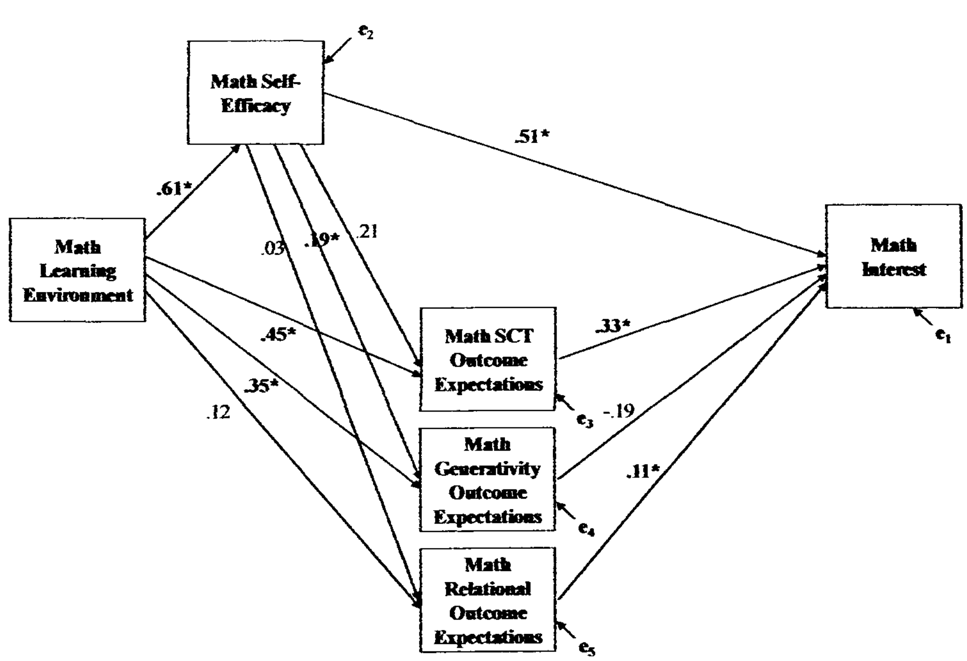
I conducted linear regression using Math Learning Environment and Math Self-Efficacy as the independent variables and Math Relational Outcome Expectations as the dependent variable (see Table 40). The results indicated the following regression equation: Math Relational Outcome Expectations = .12 (MLE) + .10 (MSE). The path coefficients for (k) and (g) were not statistically significant.

I present the full model for females, with all path coefficients entered, in Figure 5. I used the regression equations to determine the path coefficients of the model:

Table 40
Coefficients of Regression Equation for Females

	Dependent Variable		β	t	p
1	MI	(Constant)		-.34	.74
		MSE	.51	6.60	.000
		MOE-SCT	.33	2.97	.004
		MOE-G	-.19	-1.70	.09
		MOE-R	.16	2.22	.03
1	MSE	(Constant)		4.62	.000
		MLE	.61	8.792	.000
1	MOE-SCT	(Constant)		5.37	.000
		MSE	.03	.28	.78
		MLE	.45	4.55	.000
1	MOE-G	(Constant)		11.20	.000
		MSE	.19	2.01	.046
		MLE	.35	3.62	.000
1	MOE-R	(Constant)		11.41	.000
		MSE	.10	.89	.38
		MLE	.12	1.09	.28

Figure 5
Revised Modified SCCT Model Path Coefficients: Females



Calculation of Total Effects for Males

Once I entered all path coefficients into the model, I calculated the total effect for those independent variables that had an indirect effect on Math Interest. I used the path coefficient to obtain the direct effect of MSE on MI and of MLE on MI. The following are the path coefficients used for my calculations of total effect: a = .34*; b = .34*; c = .07; d = .02; e = .19; f = .24*; g = .16; h = .61*; i = .51*; j = .50*; k = .48* (* $p < .05$). To determine the total effects of the mediator variables, Math Self-Efficacy and Math Learning Environment, on Math Interest, I conducted a correlation analysis. I present the results in Table 41.

Table 41
Correlation of Study Scale for Males

	MI	MSE	MOE-SCT	MOE-G	MOE-R	MLE
MI	—					
MSE	.56	—				
MOE-SCT	.57	.50	—			
MOE-G	.51	.54	.73	—		
MOE-R	.31	.53	.34	.42	—	
MLE	.48	.61	.62	.64	.55	—

Note. All correlations are significant, $p < .05$ (2-tailed).

Math Self-Efficacy: Math Self-Efficacy had a direct effect on Math Interest for males. This path contributed a statistically significant (r = .34; t = 3.40, p = .001) portion of the total correlation between Math Self-Efficacy and Math Interest (r = .56) for males. The indirect effect Math Self-Efficacy on Math Interest through Math SCT Outcome Expectations (r = (.19)(.34) = .06), Math Generativity Outcome Expectations (r = (.24)(.07) = .02), and Math Relational Outcome Expectations (r = (.16)(.02) =.003) was .08. The total effect of Math Self-Efficacy on Math Interest was .41, the sum of the direct and indirect effects (.34 + .06 + .01+ .003). In the analysis, .15 of the effect is unaccounted for in the modified SCCT model.

Math Learning Environment. Math Learning Environment had an indirect effect on Math Interest for males. The indirect effect Math Learning Environment on Math Interest through Math Self-Efficacy ($r = (.61)(.34) = .21$), Math SCT Outcome Expectations ($r = (.51)(.34) = .17$), Math Generativity Outcome Expectations ($r = (.50)(.07) = .04$), and Math Relational Outcome Expectations ($r = (.45)(.02) = .01$) contributed .43 (.21 + .17 + .04 + .01) of the total correlation between Math Learning Environment and Math Interest ($r = .48$). In the analysis, .05 of the effect is unaccounted for in the modified SCCT model.

There is empirical evidence from previous research suggesting that the learning environment influences math interest. To test this premise, I added a direct path from Math Learning Environment to Math Interest for males and recalculated the effects as delineated below (see Table 42). To determine if Math Learning Environment had a direct effect on Math Interest in the modified SCCT model, I ran a multiple linear regression, with Math Interest as the dependent variable and Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations and Math Learning Environment. I did not need to re-run the regression equations for the endogenous variables, Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations, as the addition of a direct effect path from Math Learning Environment to Math Interest does not change these path coefficients.

The results of the multiple linear regression (see Table 42) found that there was not a statistically significant direct path from Math Learning Environment to Math Interest, (r = .02, t = .16, p = .87) for males. The indirect effect Math Learning Environment on Math Interest through Math Self-Efficacy (r = (.61)(.34) =.21), Math SCT Outcome Expectations (r = (.51)(.33) =.17), Math Generativity Outcome Expectations (r = (.50)(.07) = .04), and Math Relational Outcome Expectations (r = (.45)(.01) =.01) contributed .37 of the total correlation between Math Learning Environment and Math Interest (r =.50). The total effect of Math Self-Efficacy on Math Interest was .42, the sum of the direct and indirect effects (.02 + .21 + .17 + .04+ .01 = .45). In the analysis, .03 of the effect is unaccounted for in the modified SCCT model.

Table 42
Coefficients of Regression Equation for Math Interest Adding MLE (Males)

Model		β	t	p
1	(Constant)		-.27	.79
	MSE	.34	3.17	.00
	MOE-SCT	.33	2.65	.01
	MOE-G	.07	.51	.61
	MOE-R	.01	.14	.89
	MLE	.02	.16	.87

Calculation of Total Effects for Females

Once I entered all path coefficients into the model, I calculated the total effect for those independent variables that had an indirect effect on Math Interest. I used the path coefficient to obtain the direct effect of MSE on MI and of MLE on MI. The following are the path coefficients used for my calculations of total effect: a = .51*; b = .33*; c = -.19*; d = .16*; e = .03; f = .19*; g = .10; h = .61*; i = .45*; j = .35*; k = .12 (* $p < .05$). To determine the total effects of the mediator variables, Math Self-Efficacy and Math

Learning Environment, on Math Interest for females, I first conducted a correlation analysis. I present the results in Table 43

Table 43
Correlation of Study Scale for Females

	MI	MSE	MOE-SCT	MOE-G	MOE-R	MLE
MI	—					
MSE	.56	—				
MOE-SCT	.32	.30	—			
MOE-G	.28	.41	.75	—		
MOE-R	.20	**.17**	**-.12**	**.09**	—	
MLE	.49	.61	.46	.47	.18	—

Note. Bold correlations are not significant. All other correlations are significant, $p < .05$ (2-tailed).

Math Self-Efficacy: Math Self-Efficacy had a direct effect on Math Interest for females. This path contributed a statistically significant (r = .51; t = 6.60, $p < .000$) portion of the total correlation between Math Self-Efficacy and Math Interest (r = .56) for females. The indirect effect Math Self-Efficacy on Math Interest through Math SCT Outcome Expectations (r = (.03)(.33) = .01), Math Generativity Outcome Expectations (r = (.19)(-.19) = -.04), and Math Relational Outcome Expectations (r = (.10)(.16) =.02) was -.01. The total effect of Math Self-Efficacy on Math Interest was .50, the sum of the direct and indirect effects (.51 + .01 - .04 + .02). In the analysis, .06 of the effect is unaccounted for in the modified SCCT model.

Math Learning Environment. Math Learning Environment had an indirect effect on Math Interest for females. The indirect effect Math Learning Environment on Math Interest through Math Self-Efficacy (r = (.61)(.51) =.31), Math SCT Outcome Expectations (r = (.45)(.33) =.15), Math Generativity Outcome Expectations (r = (.35)(-

.19) = -.07), and Math Relational Outcome Expectations (r = (.12)(.16) =.02) contributed .41 (.31 + .15 - .07 + .02) of the total correlation between Math Learning Environment and Math Interest (r =.49) for females. In the analysis, .08 of the effect is unaccounted for in the modified SCCT model.

There is empirical evidence from previous research suggesting that the learning environment influences math interest. To test this premise, I added a direct path from Math Learning Environment to Math Interest for males and recalculated the effects as delineated below (see Table 44). To determine if Math Learning Environment had a direct effect on Math Interest in the modified SCCT model, I ran a multiple linear regression, with Math Interest as the dependent variable and Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations and Math Learning Environment. I did not need to re-run the regression equations for the endogenous variables, Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations, as the addition of a direct effect path from Math Learning Environment to Math Interest does not change these path coefficients.

The results of the multiple linear regression (see Table 44) found that there was not a statistically significant direct path from Math Learning Environment to Math Interest, (r = .17, t = 1.78, *p* = .08) for females. The indirect effect Math Learning Environment on Math Interest through Math Self-Efficacy (r = (.61)(.43) =.26), Math SCT Outcome Expectations (r = (.45)(.27) =.12), Math Generativity Outcome Expectations (r = (.35)(-.20) = -.07), and Math Relational Outcome Expectations (r = (.12)(.14) =.02) contributed .33 of the total correlation between Math Learning

Environment and Math Interest (r =.49). The total effect of Math Self-Efficacy on Math Interest was .42, the sum of the direct and indirect effects (.17 + .26 + .12 - .07+ .02 = .45). In the analysis, -.01 of the effect is unaccounted for in the modified SCCT model.

Table 44
Coefficients of Regression Equation for Math Interest Adding MLE (Females)

Model	β	t	p
1 (Constant)		-.27	.79
MSE	.34	3.17	.00
MOE-SCT	.33	2.65	.01
MOE-G	.07	.51	.61
MOE-R	.01	.14	.89
MLE	.02	.16	.87

Model Adequacy for Males

I ran multiple linear regression analyses to determine the adequacy of the modified SCCT model for males. In other words, did the direct effect paths hypothesized in the modified SCCT explain statistically significant portions of the variance observed in the five endogenous variables, Math Interest, Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations? For each endogenous or dependent variable, I determined the amount of observed variance explained by the model's posited independent variables. I examined the Analysis of Variance *F* statistic to determine significance.

In the modified SCCT model, Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations accounted for 42% of the variance observed in Math Interest (see Table 45). Using Cohen's (1988) suggested guidelines, this equates to a large effect size (R^2 = .42). The corresponding F-statistic is significant, $F(4, 90) = 16.28, p < .001$, indicating that the independent variables in the modified SCCT model, Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations, explained a statistically significant amount of variance observed in Math Interest for males.

In the modified SCCT model, Math Learning Environment accounted for 37% of the variance observed in Math Self-Efficacy (see Table 45). Using Cohen's (1988) suggested guidelines, this equates to a large effect size ($R^2 = .37$). The corresponding F-statistic is significant, $F(1, 93) = 54.65, p < .001$, indicating that the independent variable in the modified SCCT model, Math Learning Environment, explained a statistically significant proportion of variance observed in Math Self-Efficacy for males.

In the modified SCCT model, Math Self-Efficacy and Math Learning Environment accounted for 41% of variance observed in Math SCT Outcome Expectations (see Table 44). Using Cohen's (1988) suggested guidelines, this equates to a large effect size ($R^2 = .41$). The corresponding F-statistic is significant, $F(2, 92) = 32.01, p < .001$, indicating that the independent variables in the modified SCCT model, Math Self-Efficacy and Math Learning Environment, explained a statistically significant proportion of variance observed in Math SCT Outcome Expectations for males.

In the modified SCCT model, Math Self-Efficacy and Math Learning Environment accounted for 45% of the variance observed in Math Generativity Outcome Expectations (see Table 45). Using Cohen's (1988) suggested guidelines, this equates to a large effect size ($R^2 = .45$). The corresponding F-statistic is significant, $F(2, 92) = 38.06, p < .001$, indicating that the independent variables in the modified SCCT model, Math Self-Efficacy and Math Learning Environment, explained a statistically significant proportion of the variance observed in Math Generativity Outcome Expectations for males.

In the modified SCCT model, Math Self-Efficacy and Math Learning Environment accounted for 32% of the variance observed in Math Relational Outcome Expectations (see Table 45). Using Cohen's (1988) suggested guidelines, this equates to a medium effect size ($R^2 = .32$). The corresponding F-statistic is significant, $F(2, 92) = 21.24, p < .001$, indicating that the independent variables in the modified SCCT model, Math Self-Efficacy and Math Learning Environment, explained a statistically significant proportion of variance observed in Math Relational Outcome Expectations for males.

Table 45
Model Summary for Endogenous Variables (Males)

Independent Variable	R	R^2	R^2	F	df 1	df 2	p
MI	.65	.42	.37	16.28	4	90	.000
MSE	.61	.37	.38	54.65	1	93	.000
MOE-SCT	.64	.41	.29	32.01	2	92	.000
MOE-G	.67	.45	.34	38.06	2	92	.000
MOE-R	.56	.32	.15	21.24	2	92	.000

The results of the multiple linear regression analyses supported the adequacy of the modified SCCT model for boys. The independent variables, Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations explained a statistically significant amount of the variance observed in Math Interest. Math Learning Environment explained a statistically significant amount of the variance observed in Math Self-Efficacy. Math Learning Environment and Math Self-Efficacy explained a statistically significant amount of the variance observed in Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations.

Model Adequacy for Females

I ran multiple linear regression analyses to determine the adequacy of the modified SCCT model for females. In other words, did the direct effect paths hypothesized in the modified SCCT explain statistically significant portions of the variance observed in the five endogenous variables, Math Interest, Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations? For each endogenous or dependent variable, I determined the amount of observed variance explained by the model's posited independent variables. I examined the Analysis of Variance *F* statistic to determine significance.

In the modified SCCT model, Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations accounted for 37% of the variance observed in Math Interest (see Table 46). Using Cohen's (1988) suggested guidelines, this equates to a large effect size ($R^2 = .37$). The corresponding F-statistic is significant, $F(4, 128) = 18.76, p < .001$, indicating that the independent variables in the modified SCCT model, Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations, explained a statistically significant amount of variance observed in Math Interest for females.

In the modified SCCT model, Math Learning Environment accounted for 37% of the variance observed in Math Self-Efficacy (see Table 46). Using Cohen's (1988) suggested guidelines, this equates to a large effect size ($R^2 = .37$). The corresponding F-statistic is significant, $F(1, 131) = 77.31$, $p < .001$, indicating that the independent variable in the modified SCCT model, Math Learning Environment, explained a statistically significant proportion of variance observed in Math Self-Efficacy for females.

In the modified SCCT model, Math Self-Efficacy and Math Learning Environment accounted for 21% of variance observed in Math SCT Outcome Expectations (see Table 46). Using Cohen's (1988) suggested guidelines, this equates to a medium effect size ($R^2 = .21$). The corresponding F-statistic is significant, $F(2, 130) = 17.74$, $p < .001$, indicating that the independent variables in the modified SCCT model, Math Self-Efficacy and Math Learning Environment, explained a statistically significant proportion of variance observed in Math SCT Outcome Expectations for females.

In the modified SCCT model, Math Self-Efficacy and Math Learning Environment accounted for 24% of the variance observed in Math Generativity Outcome Expectations (see Table 46). Using Cohen's (1988) suggested guidelines, this equates to a medium effect size ($R^2 = .24$). The corresponding F-statistic is significant, $F(2, 130) = 20.67$, $p < .001$, indicating that the independent variables in the modified SCCT model, Math Self-Efficacy and Math Learning Environment, explained a statistically significant proportion of the variance observed in Math Generativity Outcome Expectations for females.

In the modified SCCT model, Math Self-Efficacy and Math Learning Environment accounted for 04% of the variance observed in Math Relational Outcome Expectations (see Table 46). Using Cohen's (1988) suggested guidelines, this equates to a weak effect size (R^2 = .04). The corresponding F-statistic is not significant, $F(2, 130)$ = 2.50, p = .09, indicating that the independent variables in the modified SCCT model, Math Self-Efficacy and Math Learning Environment, did not explain a statistically significant proportion of variance observed in Math Relational Outcome Expectations for females.

Table 46
Model Summary for Endogenous Variables (Females)

Independent Variable	R	R^2	R^2	F	$df\,1$	$df\,2$	p
MI	.61	.37	.37	18.76	4	128	.000
MSE	.61	.37	.38	77.31	1	131	.000
MOE-SCT	.47	.21	.29	17.74	2	130	.000
MOE-G	.49	.24	.34	20.67	2	130	.000
MOE-R	.19	.04	.15	2.50	2	130	.000

The results of the multiple linear regression analyses partially supported the adequacy of the modified SCCT model for girls. The independent variables, Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations explained a statistically significant amount of the variance observed in Math Interest. Math Learning Environment explained a statistically significant amount of the variance observed in Math Self-Efficacy. Math Learning Environment and Math Self-Efficacy explained a statistically significant amount of the variance observed in Math SCT Outcome Expectations and Math Generativity Outcome Expectations. However, Math Learning Environment and Math Self-Efficacy did not explain a statistically significant amount of the variance observed in Math Relational Outcome Expectations.

Model Fit Indices

I used AMOS version 19 to determine model fit the boys, girls, and multiple group comparisons. I accounted for the covariance among the unobserved variables of math outcome expectations. The primary fit indices used to evaluate model fit were the comparative fit index (CFI), the normed fit index (NFI), and the root mean square error of approximation (RMSEA). Based on Hu and Bentler's (1999) recommended indices, I used CFI and NFI values near .95, and RMSEA values close to .06 indicators of a good model fit. The fit indices (CFI, TLI, and RMSEA) for the modified SCCT model provided evidence that the modified SCCT model fit the data for boys (CFI = 1.00, NFI = 1.00, RMSEA=.00). The fit indices (CFI, TLI, and RMSEA) for the modified SCCT model also provided evidence that the modified SCCT model fit the data adequately for girls (CFI = 0.99, NFI = 0.99, RMSEA=.08). I present the goodness-of-fit indices in Table 47.

Table 47
Goodness-of-Fit Indices for Modified SCCT Model (Males and Females)

Fit indices	χ^2 (df)	RMSEA	Low 90	High 90	NFI	CFI
Females	3.28 (2); p=.19	.07	.00	.20	.99	.99
Males	.06 (2); p=.77	.00	.00	.14	1.00	1.00

I conducted multiple group comparisons using AMOS to examine if the modified SCCT model fit the data across gender. I found the goodness-of-fit statistics for a fully unconstrained model and a fully constrained model. I then compared the fit indices to determine if there was a worsening of fit. The resultant $\Delta\chi^2$ indicated that there was a statistically significant worsening of fit when comparing chi square of the unconstrained and constrained models. This worsening of fit indicated non-invariance of the path coefficients (Byrne, 2010) by gender (Table 48).

Table 48
Constrained Goodness-of-Fit Indices for Modified SCCT Model (Males and Females)

Fit indices	χ^2 (df)	RMSEA	Low 90	High 90	NFI	CFI
No Constraints	3.79(4); p=.44	.00	.00	.10	.99	.99
Measure Constraints	35.50 (17); p=.01	.08	.06	.11	.94	.95
Difference	31.71 (13); p=.003	-.08	-.06	-.01	.05	.04

Having found evidence of non-invariance when holding all path coefficients equal across groups, I tested for the invariance of the path coefficients of individual paths. I sequentially placed equality constraints on individual paths on the fully unconstrained model and calculated the $\chi^2$and CFI goodness-of-fit indices. I calculated the changes in $\chi^2$and CFI goodness-of-fit indices between the partially constrained and fully unconstrained models. Significant χ^2 differences (Byrne) or CFI differences greater than .01 (Cheung & Rensvold, cited in Byrne) indicated invariance of the newly constrained path coefficient across gender. For path coefficient parameters found to be invariant across gender, I cumulatively maintained the equality constraint of these parameters throughout the remaining invariance-testing process (Byrne). I present the results of the tests of path coefficient invariance across gender in Table 49.

First, I examined the paths associated with Math Self-Efficacy. I placed equality constraints on the path coefficients of Math Self-Efficacy on Math SCT Outcome Expectations (path e), Math Generativity Outcome Expectations (path f), and Math Relational Outcome Expectations (path g). The resultant $\Delta\chi^2$ (p = .58) and ΔCFI (.00) indicated invariance across gender for paths e, f, and g of the modified SCCT model. I placed an equality constraint on the path coefficient of Math Self-Efficacy on Math Interest (path a). The resultant $\Delta\chi^2$ (p = .37) and ΔCFI (.00) indicated invariance across gender for path a of the modified SCCT model. I placed an equality constraint on the path coefficient of Math Learning Environment on Math Self-Efficacy (path h). The resultant $\Delta\chi^2$ (p = .49) and ΔCFI (.00) indicated invariance across gender for path h of the modified SCCT model. These results indicated that paths associated with Math Self-efficacy were invariant across gender.

Next, I examined the paths from Math Learning Environment to Math Outcome Expectations MOE-SCT, MOE-G, and MOE-R). I placed an equality constraint on the path coefficient of Math Learning Environment on Math SCT Outcome Expectations (path i). The resultant $\Delta\chi^2$ (p = .39) and ΔCFI (.00) indicated invariance across gender for path j of the modified SCCT model. I placed an equality constraint on the path coefficient of Math Learning Environment on Math Generativity Outcome Expectations (path j). The resultant $\Delta\chi^2$ (p = .07) and ΔCFI (.011) indicated potential non-invariance across gender for path j of the modified SCCT model. Given these mixed results, I removed the constraint from path j. I placed an equality constraint on the path coefficient of Math Learning Environment on Math Relational Outcome Expectations (path k). The resultant $\Delta\chi^2$ (p = .01) and ΔCFI (.022) indicated non-invariance across gender for path k of the modified SCCT model. I removed the constraint from path k.

Finally, I examined the paths from Math Outcome Expectations MOE-SCT, MOE-G, and MOE-R) to Math Interest (paths b, c, and d, respectively). I placed an equality constraint on the path coefficient of Math SCT Outcome Expectations to Math

Interest (path b). The resultant $\Delta\chi^2$ (p = .50) and ΔCFI (.00) indicated invariance across gender for path b of the modified SCCT model. I placed an equality constraint on the path coefficient of Math Generativity Outcome Expectations to Math Interest (path c). The resultant $\Delta\chi^2$ (p = .32) and ΔCFI (.002) indicated invariance across gender for path c of the modified SCCT model. I placed an equality constraint on the path coefficient of Math Relational Outcome Expectations to Math Interest (path d). The resultant $\Delta\chi^2$ (p = .27) and ΔCFI (.006) indicated invariance across gender for path d of the modified SCCT model.

Table 49
Goodness-of-Fit Statistics for Invariance of Path Coefficients across Gender

	Model	Path	χ^2 (df)	$\Delta\chi^2$ (Δdf)	p	CFI	ΔCFI
1	No Constraints		3.79 (4)			1.00	1.00
2	SE→OE's	e, f, g	5.76 (7)	1.97 (3)	.58	1.00	.00
3	SE→MI	a	8.04 (8)	4.25 (4)	.37	1.00	.00
4	LE→SE	h	8.21 (9)	4.42 (5)	.49	1.00	.00
5	LE→OE-SCT	i	10.08 (10)	6.29 (6)	.39	1.00	.00
5	LE→OE-G	j	16.68 (11)	12.89 (7)	.07	.989	.011
6	LE→OE-R	k	22.92 (11)	12.89 (7)	.01	.978	.022
7	OE-SCT→MI	b	10.17 (11)	6.39 (7)	.50	1.00	.00
8	OE-G→MI	c	13.10 (12)	9.31 (8)	.32	.998	.002
9	OE-R→MI	d	14.94 (13)	11.15 (9)	.27	.994	.006
10	Full Constraints		35.50 (17)	31.71 (13)	.003	.965	.035

These results indicated that the path coefficient k varied by gender. When compared across gender, Math Learning Environment explained differing amounts of the variance observed in Math Relational Outcome Expectations (β_{Boys} = .45, t = 4.14, p < .001; β_{Girls} = .12, t = 1.09, p = .28) for boys than girls. Differences in the goodness-of-fit indices of invariance across gender of path j (Math Learning Environment on Math Generativity Outcome Expectations) provided mixed results. According to Byrne (2010), when divergent findings occur, the decision as to which goodness-of-fit statistic to accept is at the discretion of the researcher. Given that the statistical stringency of the $\Delta\chi^2$ tends to indicate invariance to a greater extent than ΔCFI (Byrne) Cheung and Rensvold's (, I chose to follow Cheung & Rensvold's (2002) recommendation and use ΔCFI (.011) as the test for invariance. The path coefficient j (Math Learning Environment on Math Generativity Outcome Expectations) was non-invariant across gender.

I conducted a Potthoff analysis to examine the differences in path coefficients for the regression equation MI = (a)(MSE). The independent variables were Math Self-Efficacy, Gender (Male = 0; Female = 1), and MSE*Gender (see Table 50). The results indicated that the difference was not statistically significant ($\Delta F(2, 224) = .18$, $p = .84$).

Table 50
Model Summary of Regression on Math Interest

	R	R^2	*SE Est.*	ΔR^2	ΔF	*df1*	*df2*	ΔF
1	.56[a]	.32	6.41	.32	105.44	1	226	.000
2	.57[b]	.33	6.43	.001	.18	2	224	.84

a. Predictors (Constant) Math Self-Efficacy
b. Predictors (Constant) Math Self-Efficacy, Gender, MSE*Gender

Summary

The results supported my hypothesis for the sixth research question. The data fit the modified SCCT model differently for boys and girls. The results of the multigroup comparisons found non-invariance by gender. The result of testing the invariance of each path found differences in the direct effect of Math Learning Environment on Math Relational Outcome Expectations across gender. Math Learning Environment had a statistically significant direct effect on Math Relational Outcome Expectations for boys, but not for girls. Examining differences across gender for the direct effect of Math Learning Environment on Math Generativity Outcome Expectations produced mixed results. While this path coefficient was statistically significant for both males and females, constraining the path resulted in a worsening on fit (ΔCFI) compared to the unconstrained model.

There were other potential differences between girls and boys in magnitude and statistical significance for path coefficients in the modified model of SCCT. Although the value of the path coefficient for the direct effect of Math Self-Efficacy was larger in females (.51) than males (.34), the difference was not statistically significant ($\Delta F(2, 224) = .18, p = .84$). Math Relational Outcome Expectations had a statistically significant direct effect on Math Interest for girls, but not for boys. Changes in goodness-of-fit statistics when constraining this path coefficient indicated invariance across gender.

For both boys and girls, Math Learning Environment had a statistically significant direct effect on Math Self-Efficacy, Math SCT Outcome Expectations, and Math Generativity Outcome Expectations. Math Self-Efficacy exerted a statistically significant direct effect on Math Generativity Outcome Expectations, but did not exert a statistically significant direct effect on Math SCT Outcome Expectations or Math Relational Outcome Expectations. There were no statistically significant path coefficients for the direct effect of Math Generativity Outcome Expectations on Math Interest for males or females. Finally, Math SCT Outcome Expectations had a statistically significant direct effect on Math Interest for both boys or girls.

The results of the multiple linear regression analyses supported the adequacy of the modified SCCT model for boys, according to the goodness-of-fit indices (χ^2 (2) = .06,

p = .77; RMSEA = .00; NFI = 1.00; CFI = 1.00). The direct paths from the hypothesized independent variables in the modified SCCT model explained statistically significant portions of the variance observed in the endogenous variables: Math Interest, Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations. Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations explained a statistically significant portion of the variance observed in Math Interests. Math Learning Environment accounted for a statistically significant portion of the variance observed in Math Self-Efficacy. Math Learning Environment and Math Self-Efficacy accounted for a statistically significant portion of the variance observed in Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations. In the modified SCCT model, the R^2 values for the Math Interest, Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations equated to a large effect size for boys.

While the goodness-of-fit indices for the path model suggest adequacy of the modified SCCT model for girls (χ^2 (2) = 3.18, p = .119; RMSEA = .07; NFI = .99; CFI = .99), the multiple linear regression analyses provided mixed results. The direct paths from the hypothesized independent variables in the modified SCCT model explained statistically significant portions of the variance observed in four of the five endogenous variables: Math Interest, Math Self-Efficacy, Math SCT Outcome Expectations, and Math Generativity Outcome Expectations. Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome

Expectations explained a statistically significant portion of the variance observed in Math Interests. Math Learning Environment accounted for a statistically significant portion of the variance observed in Math Self-Efficacy. The R^2 values for the variance in Math Interest and Math Self-Efficacy explained by the model equated to a large effect size for girls. The R^2 values for the variance in Math SCT Outcome Expectations and Math Generativity Outcome Expectations explained by the model equated to a medium effect size for girls. Math Learning Environment and Math Self-Efficacy did not account for a statistically significant portion of the variance observed in Math Relational Outcome Expectations.

Summary of Chapter 4

In this chapter, I presented the results and findings of the analyses described in Chapter 3. I provided a description of the data preparation, and item and scale analyses. I presented the results of the analyses used to address the research questions. In Chapter 5, I present the results of the analyses by research question, an overall discussion of important findings, the implications of these findings for researchers, theorists, counselors, and counselor educators, and the limitations of the study.

CHAPTER 5

DISCUSSION

This study examined the role of the math learning environment on early adolescents' math self-efficacy, math outcome expectations, and math interest. Chapter 1 provided the reader with the rationale for the study, the need, purpose, and significance of the study, the research questions, and the definition of terms. Chapter 2 presented a review of the literature on the theoretical foundations of the study, and on Math Interest, Math Self-Efficacy, Math Outcome Expectations, and Math Learning Environment. Chapter 3 provided the methodology for this research. Chapter 4 presented the results and findings of the analyses. In this chapter, I present the results of the analyses by research question, an overall discussion of important findings, and the implications of these findings for researchers, theorists, counselors, and counselor educators. I also include the limitations of the study.

Discussion of Results

In this section, I provide a discussion of results for each research question. In my discussion, I will relate the results in the context of prior research studies, indicating ways my study supports previous findings, ways it contradicts previous findings, and areas in which more research is needed.

Bivariate Correlations

There were positive correlations among all study variables. There were strong relationships ($r = .50$ to $.62$) among Math Interest, Math Self-Efficacy, and Math

Learning Environment, as well as between these variables and each of the three subscales, Math Outcome SCT Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations (r = .27 to .57). Among the Math Outcome Expectation Subscales, the relationships between Math Outcome SCT Expectations and Shoffner's (2006) subscales were strong for Math Generativity Outcome Expectations Subscale (r = .74) and uncorrelated for Math Relational Outcome Expectations (.r = .12). There was a moderate relationship between Shoffner's Math Generativity Outcome Expectations and Math Relational Outcome Expectations (r = .30). The positive relationships among all scales and subscales found in this study are consistent with Lent et al.'s (1994) posited relationships among variables in their SCCT model. While there were strong correlations among variables, subsequent analyses determined there was no multicolinearity among these variables.

Research Question 1

The first research question asks, "Are there differences in Math Self-Efficacy, Math Outcome SCT Expectations, Math Generativity Outcome Expectations, Math Relational Outcome Expectations, Math Learning Environment, and Math Interest among boys and girls in Grades 6, 8, and 10 by gender and grade level?" The results of the Multivariate Analysis of Variance (MANOVA) indicated differences in Math Self-Efficacy, Math Outcome SCT Expectations, Math Generativity Outcome Expectations, Math Relational Outcome Expectations, Math Learning Environment, and Math Interest among boys and girls in Grades 6, 8, and 10 by gender and grade level.

Overall, there were significant differences between sixth grade girls and the other grade-gender groups. Sixth grade girls had higher math interest, greater confidence in their math competency, expected more positive outcomes from taking advanced math courses (MOE-SCT and MOE-G), and perceived higher levels of math teacher support than did sixth and eighth grade boys. Sixth grade girls also had higher interest in math, anticipated more positive outcomes from taking advanced math courses (MOE-SCT and MOE-G), and perceived higher levels of academic and emotional support from their math teacher than eighth or 10th grade girls, and higher confidence in their math competency than 10th grade girls. Finally, sixth grade girls had higher expectations that taking advanced math would help them make a difference for others than 10th grade boys.

When I examined differences in perceived teacher support (MLE) by gender and grade, the more positive the participants perceived their learning environment, the higher their levels of math self-efficacy, math interest, and math outcome expectations. Students who perceived higher levels of support from their math teacher also had stronger math competency beliefs (self-efficacy), enjoyed math (interest), and expected positive results from taking higher-level math classes (outcome expectations), such as being better prepared for college, having their parents proud of them, or feeling better about self. These results are consistent with prior findings that students' perception of support from their math teacher positively influences the factors that research has shown predict Math Interest: Math Self-Efficacy (Ciani, Ferguson, Bergin, & Hilpert, 2010; Navarro et al., 2007; Wentzel, Battle, Russell, & Looney, 2010) and Math Outcome Expectations (Navarro et al.).

When I examined the differences between the genders, sixth grade girls in the first semester of middle school had higher math interest, greater confidence in their math competency, anticipated more positive outcomes from taking advanced math courses

(MOE-SCT, MOE-G, and MOE-R), and perceived higher levels of academic and emotional support from their math teacher than did sixth grade boys. However, there were no differences in math interest, math self-efficacy, math outcome expectations (MOE-SCT, MOE-G, and MOE-R), and perceived levels of math teacher support between eighth grade boys and girls or between 10th grade boys and girls. This is consistent with the decreases in math interest and math self-efficacy over time observed by other researchers (Fredricks & Eccles, 2002; Jacobs et al., 2002; Linver, Davis-Kean, & Eccles, 2004; Nagy et al., 2010; Watts, Eccles, & Durik, 2006).

When I examined difference between genders, sixth grade girls' levels of confidence in their math ability and interest in math were higher when compared to sixth grade boys, but in eighth and 10th graders, there were no differences between eighth and 10th grade boys' and girls' levels of math self-efficacy or math interest. However, the present study is a cross-sectional study. Further research is needed to examine these results longitudinally. By examining the trajectory of girls' interest, researchers can help find those critical junctions to monitor and intervene to lessen the gender differences in math interest and self-efficacy.

When I examined differences by grade within gender, sixth grade girls had higher perceptions of teacher support, more math interest, and greater expectations that taking advanced math would produce positive outcomes (MOE-SCT and MOE-G), compared to eighth and 10th grade girls. Sixth grade girls also had lower math self-efficacy than 10th grade girls. However, these results were not observed in males. There were no differences in sixth grade boys' perceptions of teacher support, confidence in their math competency, expected outcomes from taking advanced math classes, and math interest compared to eighth and 10th grade boys.

Apart from the sixth grade girls, there were multivariate differences between eighth and 10th grade boys. Tenth grade boys had higher math interest and more positive perceptions of the academic and emotional support provided by their math teacher than eighth grade boys. This increased level of math interest is consistent with Tracey et al.'s (2005) findings. Tenth grade boys are approaching graduation. These 10th grade boys perceived a more supportive math learning environment, which in turn influences their higher math interests. Further research is needed to further explore this positive association between perceptions of academic and emotional support from their math teacher and students' math interest.

There were fewer 10th grade boys' than in the other five grade-gender groups. The few differences observed between 10th grade boys and the other groups could be explained in part by the small sample size in 10th grade boys. Because there were medium to large effect sizes found for the model adequacy in this study, the number of 10th grade boys is within Cohen's (1988) observation that 30 participants per cell provided sufficient power (80%) to detect an effect (Maxwell, 2004). Research is needed to further examine the influence of the Math Learning Environment on 10th grade boys' Math Self-Efficacy and Outcome Expectations.

There were no multivariate differences between any other grade-gender groups. Although inconclusive, there were univariate differences between groups in this study. The univariate results found that eighth grade girls had higher expectations that taking advanced math would positively influence their relationships with family and friends when compared to sixth grade boys, and higher math self-efficacy than both eighth grade boys and 10th grade girls. Tenth grade girls also had higher relational outcome expectations when compared to sixth and eighth grade boys. Tenth grade males had higher levels of math interest than 10th grade females. Given the potential for Type I error and the inconclusiveness of univariate results, I provided this information as possible areas for future research (Manly, 2004; Tabachnick & Fidell, 2007).

There was a statistically significant gender effect observed in two constructs that did not demonstrate an interactional effect by grade and gender, Math Generativity Outcome Expectations and Math Relational Outcome Expectations. The girls had higher expectations that taking advanced math would allow them to make a difference for others (MOE-G, Generativity) and enhance their relationships with family and friends (MOE-R, Relational) than did the boys. These results suggest there is a relationship between girls' outcome expectations for taking higher-level math and their perceptions of academic and emotional support from their math teacher (MLE). Girls who perceived higher levels of academic and emotional support from their math teacher had higher expectations that taking advanced math courses would not affect their relationships (OE-R). Similarly, girls who perceived support from their math teacher had higher expectations that taking advanced math courses would result in a chance for them to make a difference in the world (OE-G). These two forms of outcome expectations have never been, to my knowledge, included in instruments designed to measure math outcome expectations.

Overall, the results of this study found positive relationships between students' perceptions of academic and emotional support from their math teacher and the social cognitive constructs. However, this study cannot unpack the qualities of the teacher relationship that shape participants' perceptions of their math learning environment. Because the results of this study do not provide an explanation of the perceptions reported by participants, future research should include qualitative approaches to elicit more detailed, rich data about participants' perceptions of the classroom context and its connection to math interest, self-efficacy, and math outcome expectations.

Also, given the positive associations observed between students' perceptions of their math teacher's support (MLE) and anticipated outcomes if taking advanced math, these results suggest research is needed to further examine the effect that students' perceptions of math teacher academic and emotional support has on their expectations of positive results from taking higher-level math classes. The results also highlight the need to examine outcome expectations beyond those defined by Bandura (1986) to include Shoffner et al.'s (2004) generativity and relational outcome expectations. This is consistent with research findings that females endorse altruistic values more than males (Vida & Eccles, 2003), which negatively predicts females' math interest (Weisgram & Bigler, 2006; Weisgram, Bigler, & Liben, 2010) and selection of math and science majors (Vida & Eccles).

Research Question 2

The second research question asks, "Does Math Learning Environment explain a significant amount of the variance in Math Self-Efficacy for boys and girls in Grades 6, 8, and 10?" Students' perception of the academic and emotional support provided by their teacher explained 37% of the variance in their perception of their competence in math, which was a statistically significant amount. This result suggested that students' perceptions of academic and emotional support from their teacher explained a significant portion of the variance in math self-efficacy observed in middle school students. This finding suggests that the academic and emotional support provided by the teacher positively influences the math self-efficacy beliefs of middle school students. Given the observed positive relationships between math self-efficacy and perceptions of teacher support in the MANOVA results by gender, this association appears particularly beneficial for females. In other words, if girls perceive academic and emotional support from their math teacher, they are more likely to develop or maintain higher levels of math self-efficacy.

This result supports Lent et al.'s (1994) premise that learning experiences of individuals influence the development of math self-efficacy for performing a math-related activity or action. The positive correlation between perceptions of their math teacher's academic and emotional support (learning environment) and math self-efficacy is also consistent with prior research results (Ciani, Ferguson et al., 2010; Dorman, 2001; Dorman & Fraser, 2009; Fan et al., 2009; Fast et al., 2010; Patrick et al., 2007). These studies examined the influence of students' perception of teacher support on math self-efficacy. In the present study, the items I used from Farmer et al.'s (1981) Teacher Support Scale to measure students' perceptions of their math teacher's academic and emotional support. These items were similar to Patrick et al.'s eight-item Academic and Personal Support scales, Fast et al.'s three-item Teacher Caring scale, and Dorman and Fraser's eight-item Teacher Support scales, such as "My teacher really cares about me" and "My teacher liked to help me learn." However, there was a stronger correlation between the math learning environment and math self-efficacy found in this study (r = .61) than found in these learning environment studies, with correlations ranging from .27

to .44. Prior meta-analyses found that math self-efficacy predicted math interest in the SCCT model, with effect sizes of .52 (Lent et al., 1994; Rottinghaus et al., 2003). Therefore, in the present study, students' perceptions of teacher support strongly explained one of the strongest predictors of math interest, math self-efficacy.

Research Question 3

The third research question asks, "Does Math Learning Environment explain a significant amount of the variance in Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations for boys and girls in Grades 6, 8, and 10?" The results of the multiple linear regression analysis found that students' perceptions of their math teacher's support (Math Learning Environment) explained physical (e.g., "I will be prepared for more difficult courses"), social-approval (e.g., "My teachers will be glad that I did it"), and self-satisfaction (e.g., "I will feel better about myself") math outcome expectations (28%).

Students' perceptions of teacher support also explained Generativity Outcome Expectations (30%), and Relational Outcome Expectations (16%). These results support Lent et al.'s (1994) premise that learning experiences influence the formation of anticipated results regarding specific activities. Students who felt their teacher treated them with respect and encouraged them to learn (i.e., had higher scores on Math Learning Environment) also expected taking advanced math courses would better prepare them to go to college, increase their ability to do many different types of careers, allow them to contribute to society, and positively influence their relationships with friends and family.

The results of this study support the use of three aspects of outcome expectations versus a unidimensional construct. While individuals develop expectations of certain outcomes from performing a behavior, it is the individuals' evaluation of the value, or importance, of the outcome expectation that influences the likelihood they would perform that behavior (Bandura, 1986, 1997). Bandura identified three separate expectancy values, or forms, of outcome expectations: physical (e.g., better grades, able to support my family), social-approval (e.g., from family and teachers), and self-satisfaction (e.g., feel more competent and happier with themselves in their jobs). Shoffner et al. (2004) found two additional forms of outcome expectations: students' expectation that taking advanced math would allow them to help make the world a better place (generativity) and would affect the amount of time spent with family, friends, and social events (relational). In this study, Math Learning Environment significantly explained the variance in Math SCT Outcome Expectations (28%), Math Generativity Outcome Expectations (30%), and Math Relational Outcome Expectations (16%). Presently, however, many instruments designed to measure outcome expectations do not fully measure Bandura's forms of outcome expectations (Fouad & Guillen, 2006).

In studies examining outcome expectations in middle school students, researchers often used Fouad, Smith and Enoch's (1997) Math-Science Outcome Expectancies scale, or an adapted form of it, for their study. These studies provide strong empirical evidence supporting Lent et al.'s (1994) hypothesized relationships between math outcome expectations, math self-efficacy and math interest (Fouad & Guillen, 2006). These studies support the joint effect of self-efficacy and outcome expectations on interest (Byers-Winston & Fouad, 2008; Fouad & Smith, 1996; Fouad, Smith, & Zao, 2002; Lent et al., 2001; Nauta & Epperson, 2003). I examined the scales used to measure outcome expectations in several studies of middle school students (Alliman-Brissett & Turner, 2010; Cupani, Richaud de Minzi, Pérez, & Pautassi, 2010; Fouad et al., 1997; Fouad & Smith, 1996; Fouad et al.; Navarro et al., 2007; Smith & Fouad, 1999; Turner et al., 2004). The scales did not specifically measure Bandura's forms of outcome expectations (Fouad & Guillen, 2006) nor did they contain items related to making a difference in one's community or curtailing time spent with family and friends. One item on the Math-Science Outcome Expectancies Scale referenced an outcome involving friends (Fouad et al.; Fouad & Smith): "If I get good grades in math and science, my friends will approve of me". However, this item measures a social-approval and not a relational outcome expectation. No items addressed the expectation of making a difference beyond personal gain. Future research is needed to further explore outcome expectations using explicit measures of Bandura's forms as well as Shoffner et al.'s (2004) Generativity and Relational Outcome Expectations.

Research Question 4

The fourth research question asks, "Do Math Self-Efficacy and Math Outcome Expectations explain a significant amount of the variance in Math Interest of boys and girls in Grades 6, 8, and 10?" The results of the multiple linear regression analyses found that Math Self-Efficacy and expectations of physical (e.g., prepared for more difficult courses, more likely to reach future goals), social-approval (especially from parents and teachers), or self-satisfaction results from taking advanced math courses explained sixth, eighth, and 10th grade participants' Math Interest. These results are consistent with prior research (Byars-Winston & Fouad, 2008; Fouad & Smith, 1996; Fouad, Smith, & Zao, 2002; Lent et al., 2001; Nauta & Epperson, 2003; Navarro et al., 2007; Smith & Fouad,1999) suggesting the combined role of self-efficacy and outcome expectations in explaining interests. Students who were confident in their math ability and anticipated that taking math will result in positive outcomes will likely be interested in pursuing math-related academics and careers.

While students' math self-efficacy strongly influenced their math interest, students' outcome expectations (MOE-SCT) also influenced math interest beyond self-efficacy. This result is consistent with the theoretical premise of the study, SCCT (Lent et al., 1994). Students' belief that they were good in math strongly explained their interest in math; however, math outcome expectations also had an independent influence on their math interest.

While outcome expectations play a unique role in the development of math interest (Lent et al., 1994) and subsequent choices and behaviors (Bandura, 1977a, 1977b, 1986, 1997), outcome expectations are not widely studied in social cognitive research (Fouad & Guillen, 2006). The results of this study highlight the importance of examining outcome expectations in social cognitive research. Furthermore, while outcome expectations consistent with Social Cognitive Theory explained a significant portion of math interest, many outcome expectation scales do not explicitly measure Bandura's forms of outcome expectations (Fouad & Guillen).

There is strong theoretical and empirical support that math outcome expectations influenced math interest. Outcome expectations are strong predictors of math interest in the SCCT model. Lent et al.'s (1994) meta-analyses found effect sizes of .53 for math for outcome expectations. Given that students' perceptions of teacher support within the their learning environment explained math outcome expectations, these results suggest that the students' perceptions of the academic and emotional support provided by the teacher can positively influence students' anticipated outcome from taking advanced math courses. Students need to take advanced math courses to enter the STEM fields. Interventions that increase students' expectations of a positive outcome if taking advanced math courses can influence the likelihood that they will enroll in these courses. These results suggest the need for further research examining the role played by students' perception of the academic and emotional support provided by their math teacher on students' expectation of a positive outcome from taking these advanced math courses.

The current study also provides evidence of the importance of examining the forms of outcome expectations proposed by Shoffner et al. (2004). The results of the hierarchical analyses examining the explanatory power of expectations of outcomes consistent with Bandura's posited three forms, and Shoffner et al'.s relational and generativity outcome expectations, support the need to examine an expanded conceptualization and operationalization of math outcome expectations. Students' expectations of tangible benefits (e.g., I will get better grades, I will be better prepared to go to college), social-approval (e.g., My parents will be proud of me), and self-satisfaction (e.g., I will know more, I will feel better about myself) math outcomes explained the largest portion of students' interest in math. However, students' anticipation that taking advanced math will help them contribute to society and positively affect their relationships with family and friends provided additional explanation for students' interest in math. Given these results, research is needed to further examine the role that students' expectations of giving to others (making a difference) and maintaining their relationships with family and friends have on math interest in middle and high school students.

Research Question 5

The fifth research question asks, "Do the data fit the modified SCCT model for girls and boys in grades 6, 8, and 10?" The result of path analyses for this study generally supported the use of the modified SCCT model (Figure 2) to explain math interest in sixth, eighth, and 10th grade boys and girls. Consistent with previous research findings using the SCCT model, math self-efficacy and the physical, social-approval, and self-satisfaction forms of outcome expectations predicted math interests (Byars-Winston & Fouad, 2008; Ciani, Ferguson et al., 2010; Fouad & Smith, 1996; Fouad, Smith, & Zao, 2002; Lent et al., 2001; Nauta & Epperson, 2003; Navarro et al., 2007; Smith & Fouad, 1999). Students' expectations that taking advanced math courses would allow them to make a contribution to society or positively influence their relationships did not influence students' interest in math.

The results contradicted SCCT research findings (Lent et al., 2001; Lent et al., 2003; Lent, Sheu et al., 2008) that self-efficacy directly influences outcome expectations for two aspects of outcome expectations examined in this study. Math self-efficacy did not significantly influence students' expected outcomes that explicitly measured Bandura's (1986, 1997) physical, social-approval, and self-satisfaction forms of outcome expectations. As noted previously, many scales used in SCCT studies do not explicitly measure Bandura's forms of outcome expectations (Fouad & Guillen, 2006; Fouad et al., 1997). Furthermore, this is the first study to include Shoffner et al.'s (2004) generativity and relational outcome expectations. These results found that students' belief that they were good at math influenced their expectation that taking advanced math courses would allow them to contribute to society, but self-efficacy did not influence the expected outcome of taking advanced math on their relationships and social activities. When examining Math Outcome Expectations as a single construct, however, math self-efficacy directly influenced students' overall expectations of the outcome of taking advanced math classes and indirectly influenced students' math interest as mediated through math outcome expectations. This suggests the importance of examining both the individual and combined aspects of math outcome expectations.

These results supported Lent et al.'s hypothesis that individuals' learning experiences influence self-efficacy and outcome expectations. This study examined an essential aspect of the learning environment, students' perceptions of support provided by their teacher (den Brok et al., 2005; Pianta, 1999; Van Petegem et al., 2008). Students' perceptions of their teacher's levels of support predicted math self-efficacy and the physical, social-approval, self-satisfaction, generativity, and relational forms of math outcome expectations. Students' perception of teacher support did not directly influence math interest.

Students' perception of the academic and emotional support provided by their teacher and math self-efficacy accounted for a statistically significant portion of the variance observed in the three aspects of outcome expectations in the model (MOE-SCT, MOE-G, and MOE-R). The associated R-square values in the model indicated large effect sizes, with the exception of Math Relational Outcome Expectations, which demonstrated a medium effect size. Students' perceptions of teacher support have a significant direct effect on math self-efficacy and students' anticipated outcomes from taking advanced math courses. These results are consistent with Lent et al.'s (1994) hypotheses that learning experiences exert a direct influence on math self-efficacy and outcome expectations.

Finally, while students' perceptions of math self-efficacy influenced students' expectation that taking advanced math would help them contribute to their communities, students' math self-efficacy did not influence their expectations that there would be tangible benefit, approval from others, or self-improvement by taking advanced math classes. This finding was not consistent with the theoretical and empirical findings that self-efficacy is a precursor of outcome expectations (Lent & Brown, 2006; Lent et al., 1994; Lent et al., 2010; Lent, Sheu, et al., 2008). Further research is needed to examine the forms of outcome expectations that researchers examine when conducting studies of middle school students.

Research Question 6

The sixth research question asks, "Is the modified model of SCCT invariant across gender for participants in Grades 6, 8, and 10?" The result of testing the invariance of each path found differences in the direct effect of Math Learning Environment on Math Generativity Outcome Expectations and Math Relational Outcome Expectations across gender. The results suggest that boys' perceptions of the academic and emotional support provided by their math teacher exerted a stronger influence on their expectations of positive relational and generativity outcome expectations when compared to girls. This result highlights the aforementioned importance of examining a broad range of outcome expectations, including those suggested by Shoffner et al. (2004).

The result of path analyses provided mixed results for the adequacy of the modified SCCT model for girls. The model explained girls' math interest, math self-efficacy, and one measure of outcome expectations (MOE-SCT). There was a large effect size for math interest and math self-efficacy and a medium effect size for the SCT and generativity-based forms of outcome expectations. However, the model did not support hypothesized direct effects of students' perceptions of teacher support and math self-efficacy on relational outcome expectations. The model demonstrated a good fit for boys. All direct paths from the independent variables to the endogenous variables in the modified SCCT model explained the variance observed in the five endogenous variables: Math Interest, Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations.

Although the data fit the modified models for girls and for boys, there is a difference in path coefficients between girls and boys. While there were differences in the magnitude of the path coefficients between boys and girls, the difference was not significant. Further research is needed to explore potential gender differences in the effect that math self-efficacy has on girls' and boys' math interest.

For females, their expectations that taking advanced math would positively influence their relationships with family and friends had a statistically significant direct effect on their math interest, an effect that was not observed in boys or the full data set. This finding suggests that for girls, the lower the level of anticipation that math would have a negative effect on their relationships, the higher the level of Math Interest. This finding suggests that there are potential differences in the influence of math outcome expectations that are gender-specific. Further research is needed to explore the influence relational outcome expectations have on Math Interest, particularly in females.

Surprisingly, while girls' expectations that taking advanced math would positively influence their relationships with family and friends directly influenced math interest, girls' perceptions of teacher support did not directly influence this relational outcome expectation. After examining wording of the items on the MOE-R, the anticipated effect of taking advanced math classes on relationships measured were potentially external to the classroom environment for girls. Therefore, further research could focus on how supportive relationships with their math teacher could enhance relationship-based outcome expectations.

Summary of the Discussion

These results suggest that a primary aspect of the learning environment, the relationship between students and their teacher (Ciani, Ferguson, et al. 2010; den Brok, Levy, Brekelmans, & Wubbels, 2005; Pianta, 1999; Van Petegem, Aelterman, Van Keer, & Rosseel, 2008), strongly influences students' beliefs that they are competent in math and their expectation of a positive outcome from taking advanced math courses. This finding is particularly relevant given that providing emotional and academic support to students typically is not considered an important trait for math teachers (Pianta et al., 2008). Yet students who perceive their teacher as caring and supportive are more likely to believe that they are competent in math. They will also anticipate that taking advanced math classes will help them to have a better life, please their parents and teachers, feel better about themselves, contribute to society, and enhance their relationships and social life. In turn, these students will then be more likely to enjoy math and plan to use math in their future careers. Thus, the academic and emotional support provided by the math teacher strongly influences their students' interest in and choice of math-related academics and careers.

This study also supports the use of the SCCT model to explain the influence that students' perceptions of the academic and emotional support provided by their teacher have on math interests of boys and girls in Grades 6, 8, and 10. The relationships among math learning environment, specifically students' perceptions of the academic and emotional support provided by their math teacher, and the other SCCT variables were as predicted by the modified SCCT model. Presently, few studies use SCCT with this age group (Cupani et al., 2010). Given that math interest is a factor in subsequent choice, goals, performance, and persistence in math-related academic and career activities, SCCT can provide a model to conceptualize the development of interests in early adolescents.

Of particular interest was the non-invariance observed across gender in the SCCT model used in this study. While not statistically significant, further research is needed to explore if the indirect effect of students' perceptions of their teachers' academic and emotional support on math interest is stronger for girls than for boys. The results also found that girls' expectation that taking advanced math would enhance their relationships positively influenced their interest in math. Yet this relation-based factor was not observed in the full model. This finding highlights the importance of both expanding the scope of outcome expectations to include relational outcome expectations as well as the importance of examining the relationships among the SCCT variables by gender.

Finally, the MANOVA results found an interaction effect between gender and grade level. With the exception of differences between tenth and eighth grade boys, all other significant differences were observed between 6th grade girls and the other gender-grade groups. Overall, sixth grade girls had the high levels of math interest, confidence in their math competence, expected positive outcomes from taking advanced math and perception of a supportive math learning environment compared to the sixth and eighth grade boys and other gender grade levels. However, when compared to the sixth grade girls, the eighth and 10th grade girls had lower levels of math interest, expected fewer positive outcomes from taking advanced math, perceived a less supportive math learning environment, and had less math self-efficacy (10th grade only). Rather, eighth and 10th grade girls had the same levels of all SCCT constructs as the sixth and eighth grade boys. This is consistent with research findings that girls' self-efficacy and interests decrease during the middle school years.

Limitations

There are several limitations to this study. First, the study participants were limited to those individuals who returned consent forms. It is possible that students who volunteered to participate in the study were motivated, successful, or interested in math. As such, this sample may not accurately represent the student population at the district's middle and high schools. Furthermore, the participants were situated in only one school district, which may not be representative of other school districts in rural or larger urban areas or different regions of the country. Therefore, generalizability of the findings is limited. It is hoped that the detailed demographic information will help researchers and educators to apply the results of this study accurately.

The use of cross-sectional data is another limitation of this study. The results reflected participants' perceptions of Math Interest, Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, Math Relational

Outcome Expectations, and Math Learning Environment within their distinct grade cohort. As a result, no inferences can be made of the trajectory of the constructs from sixth through 10th grade. However, the study provides valuable information regarding boys' and girls' perceptions of Math Interest, Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, Math Relational Outcome Expectations, and Math Learning Environment at three different points in their career development.

A third limitation of the study concerns the time of year participants took the survey. Researchers administered the survey instruments to two thirds of the students (n=154, 67%) in December 2008, one fourth of the participants (n=61, 27%) took the survey in October 2008 and 7% (n=15) filled it out in January 2009. While the survey was administered within a three month timespan, this period spanned participants' winter break, with the majority of participants taking the survey just prior to break. This variability in the administration of the survey presents the possibility that different administration conditions existed for participants taking the survey in December than participants taking the survey in October or January. The activities of the holiday season can disrupt school schedules, and participants could lose focus when anticipating the upcoming break and holiday season. To address this potential, the researchers monitored the participants for overt signs of distractibility and recorded any anomalies observed during the administration of the survey.

The length of the instruments presents the potential that test fatigue affected the participant's responses, particularly during the later items. All students filled out a 133-item survey. For this study, I used 65 items between Item 1 and Item 88. While this lessens the likelihood that test fatigue influenced participants' responses, items appearing early in the survey could better reflect participants' perceptions of the constructs than those answered towards the end of the survey. To address this potential confound, researchers observed the participants for overt signs of test fatigue. They noted any behaviors suggesting that participants were losing focus. Researchers also examined all bubbled response sheets for evidence of data bias, such as changes in response patterns. Finally, the reliabilities of all Beliefs, Belonging, and Behavior scales were greater than .85. This suggested that participants provided the same level of response for scales completed later in the survey as those scales completed earlier.

The scales used in this study demonstrated acceptable to high internal consistency for the full data. When I examined the reliabilities of the six scales by grade and gender, I observed differences in the Math Relational Outcome Expectations. The reliability of the MOE-R was lower for sixth grade girls than the other gender-grade groups. Could you more clearly explain why this is a limitation? It sounds more like just a fact of the study.

Despite these limitations, this study provides important information about the association of girls' and boys' perception of Math Learning Environment with Math Interest, Math Self-Efficacy, Math SCT Outcome Expectations, Math Generativity Outcome Expectations, and Math Relational Outcome Expectations. Given that Math Self-Efficacy and the three aspects of Math Outcome Expectations explained Math Interest, the knowledge gained about the explanatory power of the learning environment on math self-efficacy and math outcome expectations give researchers, counselors, and educators valuable information about early factors that may help explain decreases in girls' and women's Math Self-Efficacy and Math Interests. This study also provides information about the predictive power of Math Outcome Expectations in girls' Math Interest. Thus, this examination of classroom and social cognitive factors associated with Math Interest adds to the research literature on women's career development, providing career, school, and mental health counselors with information about early factors that may keep women from equitably participating in math-related academic and career fields.

Implications for Researchers

Based on the findings, this study has several implications for future research. First, further research is needed to examine the role that the learning environment has on the development of students' math self-efficacy and math outcome expectations. This study found that the perceived academic and emotional support provided by the teacher positively influenced these social cognitive factors. However, this study cannot fully explain the qualities of the teacher relationship that shape participants' perceptions of their math learning environment. Qualitative approaches could be used to examine those qualities of the student-teacher relationship that were particularly meaningful to participants in facilitating the development of their math interest, self-efficacy, and math outcome expectations. Given that women's math self-efficacy appears to be more strongly influenced by relational episodes than mastery experiences (Zeldin & Pajares, 2000; Zeldin et al., 2008), it is important to hear the voices of the students in order to better understand the role that relational support has on the math self-efficacy, math outcome expectations, and math interests (Zeldin et al.).

SCCT holds that students' learning experiences are instrumental in the development of math self-efficacy and indirectly influence students' interest in pursuing math-related courses and subsequent careers in STEM fields. While learning experiences are crucial for both understanding the initial development of self-efficacy and designing the interventions to increase self-efficacy, learning experiences are not typically operationalized for research (Betz, 2007). A strength of this study is the operationalization of a relational dimension of students' classroom learning experiences. The relationship of students' perceptions of the support provided by their math teacher on math self-efficacy and math outcome expectations found in this study are consistent with the strong empirical evidence (Fouad & Smith, 1996; Navarro, Flores, & Worthington, 2007; Rottinghaus, Larson, & Borgen, 2003; Usher & Pajares, 2009) supporting the posited relationship among the SCCT constructs. Further research is needed to operationalize other learning experiences using the SCCT model.

Using the SCCT model in educational and career counseling research can provide a bridge between two large bodies of research that are relevant to the development of interest in STEM: learning environment research and career development research. Researchers could conduct further research on the use of learning environment measures with the modified SCCT model. Presently, learning environment research is beginning to focus on the influence of perceived classroom environment (teacher support) on math achievement mediated through math self-efficacy (Fan et al., 2009; Fast et al., 2010). Yet for middle school girls, their math self-efficacy and math interest decrease in spite of their math achievement levels (Dalton et al., 2007; Halpern et al., 2007a; Halpern et al., 2007b; Kenney-Benson et al., 2006; Rampey et al., 2009). Further research using the modified SCCT model in learning environment research would allow researchers to investigate the influence of math self-efficacy on math interest. Math interest is a factor in subsequent academic and career choice, goals, performance, and persistence in math-related behaviors. Using the modified SCCT model would allow researchers exploring learning environment to examine math outcome expectancies and math interest, both important components of motivation and choice behaviors.

The results of this study were consistent with SCCT theory, which posits that math outcome expectations play an important role in the development and continued growth of math interest (Fouad & Guillen, 2006; Lent et al., 1994). This study utilized Shoffner's (2006) Math Outcome Expectation Scale. This scale provided explicit measures of Bandura's (1986; 1977b) three forms (physical, social-approval, self-satisfaction) of math outcome expectations as well as Shoffner et al.'s (2004) two additional forms (generativity, relational). The psychometric properties of the scale suggest that it is an appropriate measure of sixth, eighth, and 10th grade participants' outcome expectations. As noted previously, most instruments used to measure math outcome expectations in SCCT research do not explicitly measure Bandura's forms, nor do they measure other forms such as those posited by Shoffner et al. The present research finding that girls' relational outcome expectations influence their math interest highlights the importance of measuring outcomes that are relevant to the population being studied. Further research is needed to find and test specific forms of outcome expectations beyond what is presently measured.

Implications for Practitioners

The results of this study suggest the importance of viewing the math learning environment as an early factor that influences math self-efficacy, math outcome expectations, and math interest in early adolescent students. Specifically, these findings suggest that students' perceptions of academic and emotional support from their math teachers positively influence sixth, eighth, 10th graders' math self-efficacy, outcome expectations, and interest in math. The current study provides evidence that school counselors, teachers, and counselor educators can use to understand the factors that influence early STEM career development and to develop interventions to help girls and women gain greater access to predominately male STEM fields. This, in turn, will promote gender equity, broaden career options for a large portion of our citizens, and improve the effectiveness of interventions to assist girls and women with their career development and decision-making (Betz & Hackett, 1997; Coogan & Chen, 2007; Lent & Brown, 2006).

School Counselors

An important role of the school counselor is to address the career development needs of all students, helping to "ensure equitable academic, career, post-secondary access and personal/social opportunities for all students through the use of data to help close achievement gaps and opportunity gaps" (American School Counselor Association [ASCA], 2010, A.3.b). By conceptualizing career development in terms of SCCT, school counselors can develop research-based interventions that can facilitate the development of math-related academic and career interest (Betz, 2007). Specifically, learning experiences are crucial for both understanding the initial development of self-efficacy and designing the interventions to increase self-efficacy, as well as positive math outcome expectations. These, in turn, increase interest, which can help reduce the achievement and opportunity gaps for girls and students from other historically underrepresented populations in STEM fields.

As noted previously, learning experiences are crucial for understanding the development of, and designing interventions to increase, self-efficacy. While math self-efficacy is the strongest predictor of math interests, there is also a strong relationship between expectations about the results of engaging in an activity or task and interest in that task. The development of interest influences students' academic and career choices. Given that the students' perceptions of the academic and emotional support provided by their math teacher strongly influence students' levels of these precursors to math interest, school counselors can work with teachers and school administrators to increase the level of support provided by teachers in the math classroom. By helping math teachers establish supportive interpersonal relationships with their students, school counselors may facilitate the enhancement of students' math efficacy and math outcome expectations, which in turn increases students' interest in pursuing math-related academics and careers. School counselors are uniquely positioned to assist teachers in enhancing the quality of the student-teacher relationship (Wigfield et al., 2005).

In addition to working with teachers, school counselors can provide new learning experiences to students in the form of guidance lessons. Given the potential importance of verbal persuasion and vicarious learning on females' math self-efficacy (Zeldin & Pajares, 2000; Zeldin et al., 2008), school counselors can directly influence the development of students' math self-efficacy and interest. For example, the use of role models is particularly useful in generating new associative learning experiences (Krumboltz, 2009). In selecting potential role models, it is important that the students can identify in some way with the person. To help students explore the role of family and career, the role model should be a woman who has successfully blended these roles. If the role model functions more as a mentor, the school counselor should help ensure that the student can build a quality relationship with the role model. This is important as the levels of support and quality of relationships of role models, particularly teachers, contribute to the development of school-prompted math interest (Ciani, Ferguson, Bergin & Hilpert, 2010).

Teachers

The results of this study found positive relationships between sixth, eighth , and 10th grade students' perceptions of teacher support and math self-efficacy, outcome expectations, and math interest. However, prior research suggests that students' perceptions of support and caring in the student-teacher relationship often decrease during the transition from elementary to middle school (Barber & Olsen, 2004; Cook et al., 2008; Jacobs et al., 2002; Midgley, Feldlaufer, & Eccles, 1989; Wigfield, Lutz, & Wagner, 2005). Therefore, students are feeling less support from their teacher during a time in their lives when caring and supportive student-teacher relationships have been shown to positively influence students' academic motivation, academic effort, positive social behavior, and well-being (Furrer & Skinner, 2003; Reddy, Rhodes, & Mulhall, 2003; Wentzel, 2002; Wentzel, Battle, Russell, & Looney, 2010) as well as the career development process (Ciani, Ferguson, et al., 2010).

Math teachers who provide a supportive and positive classroom learning environment can decrease mathematics implicit associations and increase mathematics self-concept (Nosek, Smyth, Sriram et al., 2009). This, in turn, ultimately maintains or increases math interest and eventual interest in and choice of STEM options. Perceived lack of teacher support can result in students feeling that they do not "fit in" (Good, Dweck, & Rattan, 2008). The degree that students feel they are part of the mathematics learning environment is crucial to students' developing sense of fit, especially for girls (Good, Aronson, & Harder, 2008; Good, Dweck, & Rattan, 2008; Good et al., 2008). This lack of fit can reinforce nascent stereotypes and implicit associations about females and STEM (Good, Dweck, & Aronson, 2007), which in turn may contribute to existing stereotypes and lower math self-efficacy. Students who believe that their teachers and classroom peers support their mathematics work and see them as capable will have higher levels of mathematics self-efficacy than those who do not.

Career Counselors

For women to receive optimal career counseling, counselors must be aware of early factors that influence career interest and choice when assisting women with career planning and decision-making (Betz & Hackett, 2006; Borman & Guido-DiBrito, 1986; Coogan & Chen, 2007; Weisgram, Bigler, & Liben, 2010). The results of this study suggest that one early factor is clients' perception of the academic and emotional support provided by their math teachers, particularly during their middle school years. These early experiences in the math learning environment, in turn, have been shown to affect students' career development in the long term, particularly for women (Zeldin & Pajares, 2000). Females in STEM careers cited verbal persuasion and support from math teachers as critically influential to the development of their math self-efficacy, whereas men cited mastery experiences as a major source of their math self-efficacy (Zeldin & Pajares, 2000; Zeldin, Britner & Pajares, 2008). In fact, the women participating in the Zeldin and Pajares study noted that they relied heavily on these verbal persuasions to help them persist when they encountered barriers as women in a male-dominated field. Therefore, career counselors should pay close attention for these forms of learning experiences that have shaped their female clients' beliefs about self and their place in the world of work, particularly in math-related academic and career options.

The results of this study also highlight the value of conceptualizing career development using the SCCT model. Consistent with Bandura's Social Cognitive Theory, past learning experiences, such as those observed in the present study, influenced their clients' career aspirations and beliefs, particularly concerning STEM careers. As such, the counselor would explore the role that these past learning experiences played in their clients' present level of math self-efficacy, outcome expectations, and math interest. The results of this study suggest that when providing career counseling for a female client, the career counselor should explore how significant student-teacher relationships shaped their clients' career aspirations and beliefs, particularly concerning STEM careers.

For example, given the prevailing gender stereotype that boys are better than girls in math, middle school girls could interpret a perceived lack of teacher support as evidence that they are not "good" at math (Fast et al., 2010). This is critical given the research suggesting gender role socialization influences achievement-related perceptions and beliefs, which then influences women's decisions to enroll in or avoid certain educational programs. By exploring the clients' perceived support provided by their math teachers, the counselor can help the client to not only verbalize the encounters, but to explore the clients' interpretation of these experiences in regard to math self-efficacy.

In addition, the results of this study suggest that it is important for counselors to explore the client's perceptions of outcomes from pursuing math-based fields. The results of this study found that expected outcomes dealing with relational aspects of math-related fields positively influenced girls' math interest. Middle school girls' expectation that taking advanced math would result in "My friends won't want to be with me anymore," "I will have less time to be with friends," or "I will need to participate in fewer social activities" negatively influenced math interest. This in turn could reinforce the stereotype that math-based careers do not fit well into future family role plans. The counselor may need to help the client explore these beliefs and challenge them through new learning experiences.

Other aspects of the client's outcome expectations also may result in the female client excluding the STEM fields. Because of gender socialization, female clients likely want to pursue careers that will allow them to help others (Eccles, 2007; Weisgram & Bigler, 2006; Weisgram, Bigler, & Liben, 2010). For example, consistent with the items used in this study, the client may not expect that taking advanced math will allow her to "be able to contribute more to society" or "be able to help people more." This, in turn, will affect their educational choices. Yet a client's decision to reject careers in STEM fields because it is not a "people" field may be based on inaccurate information. The counselor can facilitate new learning by providing the client with more complete information about the full ranges of opportunities in the STEM fields.

The early factors identified by this study provide counselors are ones that can respond to interventions [WHAT]for promoting new career learning experience opportunities. These include traditional counseling techniques such as exploration of meaning of early childhood messages, cognitive restructuring, countering irrational beliefs internalized though their perception of teacher support, and narrative analysis. Based on the results of this study, one underlying goal is to help female students identify and challenge beliefs internalized through their perceived support from their teacher, expand their interests to include non-traditional gender roles, and increase their understanding of their values, particularly the value they place on helping others and having time to spend with family and friends. In turn, this can help women expand their potential learning activities to include math-based activities.

Conclusion

Given the growing importance of math in expanding academic and career options and the persistent underrepresentation of women in science, technology, engineering, and mathematic fields, the knowledge gained by investigating classroom factors associated with Math Interest will help gender-sensitive educators and counselors understand the early factors associated with girls' and women's decreased participation in math and math-intensive educational programs. This in turn can help career, school, and mental health counselors develop research-based interventions to assist girls and women with their career development and decision-making, facilitating more equitable participation of girls and women in STEM. This research will thus help counselors, counselor educators, educators, and researchers promote gender equity, broaden career options for a large portion of our citizens, and thus advance social justice.

Summary of the Study

This study examined the role of the math learning environment on early adolescents' math self-efficacy, math outcome expectations, and math interest. Chapter 1 provided the reader with the rationale for the study, the need, purpose, and significance of the study, the research questions, and the definition of terms. Chapter 2 presented a review of the literature on the theoretical foundations of the study, and on Math Interest, Math Self-Efficacy, Math Outcome Expectations, and Math Learning Environment. Chapter 3 provided the methodology for this research. Chapter 4 presented the results and findings of the analyses. Chapter 5 presented the results of the analyses by research question, an overall discussion of important findings, the implications of these findings for researchers, theorists, counselors, and counselor educators, and the limitations of the study.

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Appendix A

Additional Descriptive Statistics

Sixth Grade. There were more female sixth grade students (61.9%, n = 52) than male students (38.1%, n = 32). The majority of sixth grade students were Black, African, African-American, or Caribbean (Haitian, Jamaican) (42.9%, n = 36) or White, Non-Hispanic, Anglo, Caucasian, or European (41.7%, n = 35). Additionally, sixth graders were Asian or Asian American (1.2%, n = 1), Hispanic or Latino (3.6%, n = 3), American-Indian or Eskimo (4.8%, n = 4), and Multiracial or Other Races (6.0%, n = 5). Over half of the sixth students were 11 years old (59.5%, n = 50), over a third were 12 years old (38.1%, n = 32), and two students were either 10 (1.2%) or 13 (1.2%) years old. The average age for sixth grade students was 11.39 (SD = .54).

Table A1
Gender of Sixth Grade Students

Gender	Frequency	Percent
Female	52	61.9
Male	32	38.1
Total	84	100.0

Table A2
Race or Ethnicity of Sixth Grade Students

Race / Ethnicity	Frequency	Percent
Black, African, African-American, or Caribbean (Haitian, Jamaican)	36	42.9
White, Non-Hispanic, Anglo, Caucasian, or European	35	41.7
Asian or Asian-American	1	1.2
Hispanic or Latino	3	3.6
American-Indian or Eskimo	4	4.8
Multiracial or Other Races	5	6.0
Total	84	100.0

Table A3
Age of Sixth Grade Students

Age in Years	Frequency	Percent
10	1	1.2
11	50	59.5
12	32	38.1
13	1	1.2
Total	84	100.0

Eighth Grade. There were more female eighth grade students (52.6%, n = 50) than male students (47.4%, n = 45). Over half of the eighth grade participants were White, Non-Hispanic, Anglo, Caucasian, or European (51.6%, n = 49), while over one third were Black, African, African-American, or Caribbean (Haitian, Jamaican) (35.8%, n = 34). The other eighth grade student were Asian or Asian-American (2.1%, n = 2), Hispanic or Latino (1.1%, n = 1), American-Indian or Eskimo (3.2%, n = 3), and Multiracial or Other Races (6.3% n = 6). Most of the eighth grade students were 13 years old (50.5%, n = 48) or 14 years old (45.3%, n = 43). The rest of the eighth grade students were 15 years old (4.2%, n = 4). The average age of eight grade students was 13.54 (SD = .58).

Table A4
Gender of Eighth Grade Students

Gender	Frequency	Percent
Female	50	52.6
Male	45	47.4
Total	95	100.0

Table A5
Race or Ethnicity of Eighth Grade Students

Race / Ethnicity	Frequency	Percent
Black, African, African-American, or Caribbean (Haitian, Jamaican)	34	35.8
White, Non-Hispanic, Anglo, Caucasian, or European	49	51.6
Asian or Asian-American	2	2.1
Hispanic or Latino	1	1.1
American-Indian or Eskimo	3	3.2
Multiracial or Other Races	6	6.3
Total	95	100.0

Table A6
Age of Eighth Grade Students

Age in Years	Frequency	Percent
13	48	50.5
14	43	45.3
15	4	4.2
Total	95	100.0

Tenth Grade. There were approximately twice as many tenth grade females (65.4%, n = 34) as tenth grade males (34.6%, n = 18). Over half of 10th grade students were Black, African, African-American, or Caribbean (Haitian, Jamaican) (51.9%, n = 27), while over one-fourth were White, Non-Hispanic, Anglo, Caucasian, or European (28.8%, n = 15). The other tenth graders were Asian or Asian-American (11.5%, n = 6) and Hispanic or Latino (7.7%, n = 4). Over two-thirds of the students were 15 years old (67.3%. n = 35), over one-fourth were 16 years old (28.8%, n = 15), one student was 14 years old (1.9%) and another student was 17 years old (1.9%). The average age of tenth grade students was 15.31 (SD = .54).

Table A7

Gender of 10th Grade Students

Gender	Frequency	Percent
Female	34	65.4
Male	18	34.6
Total	52	100.0

Table A8

Race or Ethnicity of 10th Grade Students

Race / Ethnicity	Frequency	Percent
Black, African, African-American, or Caribbean (Haitian, Jamaican)	27	51.9
White, Non-Hispanic, Anglo, Caucasian, or European	15	28.8
Asian or Asian-American	6	11.5
Hispanic or Latino	4	7.7
Total	52	100.0

Table A9

Age of 10th Grade Students

Age in Years	Frequency	Percent
14	1	1.9
15	35	67.3
16	15	28.8
17	1	1.9
Total	52	100.0

APPENDIX B

Math Interest Scale and Math Self-Efficacy Scale

Math Interest Scale (8 Items)
I plan to enter a career which uses math. (Int3)
I plan to use math in my future career. (Int4)
I have a lot of interest in solving math problems (Int5)
I have a lot of interest in reading articles or books about math (Int6)
I have a lot of interest in working on a project using math (Int7)
I have a lot of interest in solving complicated math problems (Int8)
I enjoy solving math problems (Int9)
I enjoy math classes (Int10)

Math Self-Efficacy Scale (8 Items)
I am good at math (SE1)
I think I will do well in math this year (SE2)
I have been doing well in math this year (SE3)
When taking a math test I've studied for, I do well (SE4)
If I ranked all the students in my math class, I would be at the top (one of the best). (SE5)
Compared to most of my other school subjects, I am very good at math (SE6)
I have confidence that I will do well in math (SE9)
I have the ability to earn an A or B in math this year (SE10)

APPENDIX C

Math Outcome Expectations Scale and Subscales

Math Outcome Expectations Scale (39 Items)
I will earn more money (OE1-P1)
I will feel superior to others (OE2-SS1)
I will be able to support my family (OE3-P2)
I will score higher on college admissions tests (OE4-P3)
I will feel more challenged (OE6-SS2)
I would be able to make the world a better place (OE7-G1)
I will be able to discover something important (OE8-G2)
I will know more (OE9-SS3)
I will have less time to be with friends (OE10-R1)
I would get rewards from my family (OE11-SA1)
I will be able to help my school be a better school (OE12-G3)
I will have worse relationships with friends (OE13-R2)
I will be prepared for more difficult courses (OE14-P5)
I will be better prepared to go to college (OE15-P6)
My parents will be pleased (OE16-SA2)
I will be able to invent things (OE21-G4)
I would be able to take care of older generations (OE23-G5)
I would be happier with myself in my job (OE26-SS6)
I will feel better about myself (OE28-SS7)
I won't have time to go places with my family (OE30-R5)
I will need to participate in fewer social activities (OE34-R7)
I will have a better life after college (OE36-P10)
My friends won't want to be with me anymore (OE38-R9)
I will be able to get better grades (OE39-P12)
I would be able to give back to my community (OE40-G6)
My parents would be even prouder of me (OE41-SA7)
I will feel more competent (OE42-SS8)
I will be able to do more hands-on type of activities (OE43-SS9)
I will not be in classes with my friends (OE44-R10)
I will be more likely to reach my future goals (OE45-P13)
I will have a better job (OE46-P14)
I would be able to contribute more to society (OE47-G7)
I will be able to do many different types of careers (OE48-P15)
My teachers will be glad that I did it (OE49-SA8)
I will be able to think better (OE50-SS10)
I would be able to help people more (OE51-G8)
My classmates will look up to me (OE52-SA9)
I would be able to make improvements in medicine (OE53-G9)
I will be able to create more things (OE54-G10)

Generativity Outcome Expectations: (10 Items)
I would be able to make the world a better place (OE7-G1)
I will be able to discover something important (OE8-G2)
I will be able to help my school be a better school (OE12-G3)
I will be able to invent things (OE21-G4)
I would be able to take care of older generations (OE23-G5)
I would be able to give back to my community (OE40-G6)
I would be able to contribute more to society (OE47-G7)
I would be able to help people more (OE51-G8)
I would be able to make improvements in medicine (OE53-G9)
I will be able to create more things (OE54-G10)

Physical Outcome Expectations: (10 Items)
I will earn more money (OE1-P1)
I will be able to support my family (OE3-P2)
I will score higher on college admissions tests (OE4-P3)
I will be prepared for more difficult courses (OE14-P5)
I will be better prepared to go to college (OE15-P6)
I will have a better life after college (OE36-P10)
I will be able to get better grades (OE39-P12)
I will be more likely to reach my future goals (OE45-P13)
I will have a better job (OE46-P14)
I will be able to do many different types of careers (OE48-P15)

Relational Outcome Expectations: (6 Items)
I will have less time to be with friends (OE10-R1)
I will have worse relationships with friends (OE13-R2)
I won't have time to go places with my family (OE30-R5)
I will need to participate in fewer social activities (OE34-R7)
My friends won't want to be with me anymore (OE38-R9)
I will not be in classes with my friends (OE44-R10)

Self Satisfaction Outcome Expectations: (8 Items)
I will feel superior to others (OE2-SS1)
I will feel more challenged (OE6-SS2)
I will know more (OE9-SS3)
I would be happier with myself in my job (OE26-SS6)
I will feel better about myself (OE28-SS7)
I will feel more competent (OE42-SS8)
I will be able to do more hands-on type of activities (OE43-SS9)
I will be able to think better (OE50-SS10)

Social Approval Outcome Expectations: (5 Items)
I would get rewards from my family (OE11-SA1)
My parents will be pleased (OE16-SA2)
My parents would be even prouder of me (OE41-SA7)
My teachers will be glad that I did it (OE49-SA8)
My classmates will look up to me (OE52-SA9)

APPENDIX D

Study Subscales of Math Outcome Expectations Scale (Shoffner, 2006)

Math SCT Outcome Expectations: (20 Items)
I will earn more money (OE1-P1)
I will be able to support my family (OE3-P2)
I will score higher on college admissions tests (OE4-P3)
I will be prepared for more difficult courses (OE14-P5)
I will be better prepared to go to college (OE15-P6)
I will have a better life after college (OE36-P10)
I will be able to get better grades (OE39-P12)
I will be more likely to reach my future goals (OE45-P13)
I will have a better job (OE46-P14)
I will be able to do many different types of careers (OE48-P15)
I will know more (OE9-SS3)
I would be happier with myself in my job (OE26-SS6)
I will feel better about myself (OE28-SS7)
I will feel more competent (OE42-SS8)
I will be able to do more hands-on type of activities (OE43-SS9)
I would get rewards from my family (OE11-SA1)
My parents will be pleased (OE16-SA2)
My parents would be even prouder of me (OE41-SA7)
My teachers will be glad that I did it (OE49-SA8)
I will be able to invent things (OE21-G4)

Math Generativity Outcome Expectations: (11 Items)
I would be able to make the world a better place (OE7-G1)
I will be able to discover something important (OE8-G2)
I will be able to help my school be a better school (OE12-G3)
I would be able to take care of older generations (OE23-G5)
I would be able to give back to my community (OE40-G6)
I would be able to contribute more to society (OE47-G7)
I would be able to help people more (OE51-G8)
I would be able to make improvements in medicine (OE53-G9)
I will be able to create more things (OE54-G10)
I will be able to think better (OE50-SS10)
My classmates will look up to me (OE52-SA9)

Math Relational Outcome Expectations: (5 Items)
I will have less time to be with friends (OE10-R1)
I will have worse relationships with friends (OE13-R2)
I won't have time to go places with my family (OE30-R5)
I will need to participate in fewer social activities (OE34-R7)
My friends won't want to be with me anymore (OE38-R9)

APPENDIX E

Math Learning Environment Scale

Math Learning Environment (13 Items)
When I am in math class, I feel like I really belong in the class (Belng1)
In my math class, I am treated with the same respect as other students (Belng6)
The math teacher encourages us to say what we think (Belng17)
People in my math class are interested in what I have to say (Belng21)
My teacher makes me feel I'm a good person (Tchr5)
My teacher likes me as a person (Tchr10)
My teacher enjoys having me in his or her class (Tchr23)
My teacher will listen if I want to talk about a problem (Tchr27)
My teacher tells me I can succeed in school (Tchr11)
My teacher thinks I am a hard worker (Tchr12)
My teacher sees me as a person with many abilities (Tchr14)
My teacher helps me understand my strengths (Tchr20)
My teacher encourages me to learn (Tchr24)

Classroom Climate (10 Items)
When I am in math class, I feel like I really belong in the class (Belng1)
In my math class, I am treated with the same respect as other students (Belng6)
The math teacher encourages us to say what we think (Belng17)
People in my math class are interested in what I have to say (Belng21)
My teacher makes me feel I'm a good person (Tchr5)
My teacher likes me as a person (Tchr10)
My teacher wants me to do well in math class (Tchr22)
My teacher enjoys having me in his or her class (Tchr23)
My teacher will listen if I want to talk about a problem (Tchr27)
My teacher is easy to talk to about school things (Tchr28)

Teacher Connection (8 Items)
My teacher tells me I can succeed in school (Tchr11)
My teacher thinks I am a hard worker (Tchr12)
My teacher sees me as a person with many abilities (Tchr14)
My teacher pushes me to succeed in math (Tchr18)
My teacher helps me understand my strengths (Tchr20)
My teacher helps me understand ways I need to get better (Tchr21)
My teacher encourages me to learn (Tchr24)
My teacher is quick to help me when I need it (Tchr2)

Appendix F

Item Descriptive Statistics Pre- and Post-Imputation

Table F1

Item Descriptive Statistics for Math Interest Scale

	Pre-Imputation			Post-Imputation		
Item	N	M	SD	N	M	SD
Int3	231	3.06	1.26	231	3.06	1.26
Int4	231	3.21	1.26	231	3.21	1.26
Int5	230	2.80	1.32	231	2.81	1.32
Int6	231	1.91	1.01	231	1.91	1.01
Int7	230	2.46	1.23	231	2.45	1.23
Int8	230	2.60	1.38	231	2.60	1.38
Int9	231	2.89	1.37	231	2.89	1.37
Int10	231	3.11	1.35	231	3.11	1.35

Table F2

Item Descriptive Statistics for Math Self-Efficacy Scale

	Pre-Imputation			Post-Imputation		
Item	N	M	SD	N	M	SD
SE1	230	3.60	1.22	231	3.59	1.22
SE2	231	3.74	1.16	231	3.74	1.16
SE3	231	3.71	1.15	231	3.71	1.15
SE4	231	3.54	1.30	231	3.54	1.30
SE5	231	2.99	1.29	231	2.99	1.29
SE6	229	3.01	1.25	231	3.00	1.25
SE9	230	3.71	1.16	231	3.70	1.16
SE10	231	4.13	1.06	231	4.13	1.06

Table F3

Item Descriptive Statistics for Math Outcome Expectations Scale

	Pre-Imputation			Post-Imputation		
Item	N	M	SD	N	M	SD
OE1	230	3.64	1.12	231	3.63	1.13
OE2	228	2.99	1.18	231	2.99	1.18
OE3	230	3.83	1.16	231	3.82	1.16
OE4	231	4.04	0.99	231	4.04	0.99
OE6	231	3.70	1.09	231	3.70	1.09
OE7	231	2.93	1.22	231	2.93	1.22
OE8	231	3.16	1.20	231	3.16	1.20
OE9	231	3.99	1.08	231	3.99	1.08
OE10	229	3.28	1.28	231	3.28	1.27
OE11	231	3.23	1.17	231	3.23	1.17
OE12	231	2.91	1.16	231	2.91	1.16
OE13	230	4.08	1.06	231	4.08	1.06
OE14	231	3.87	0.99	231	3.87	0.99
OE15	231	4.06	0.99	231	4.06	0.99
OE16	231	4.15	1.04	231	4.15	1.04
OE21	231	2.75	1.14	231	2.75	1.14
OE23	231	3.00	1.17	231	3.00	1.17
OE26	231	3.54	1.16	231	3.54	1.16
OE28	231	3.69	1.14	231	3.69	1.14
OE30	230	3.90	1.13	231	3.90	1.13
OE34	231	3.64	1.17	231	3.64	1.17
OE36	230	3.76	1.14	231	3.76	1.14
OE38	231	4.16	1.09	231	4.16	1.09
OE39	230	3.81	1.10	231	3.80	1.11
OE40	231	3.14	1.14	231	3.14	1.14
OE41	230	3.92	1.10	231	3.92	1.09
OE42	231	3.48	1.06	231	3.48	1.06
OE43	230	3.15	1.14	231	3.15	1.14
OE44	229	3.42	1.14	231	3.41	1.14
OE45	231	3.71	1.16	231	3.71	1.16
OE46	231	3.84	1.18	231	3.84	1.18
OE47	230	3.14	1.08	231	3.14	1.08
OE48	231	3.70	1.14	231	3.70	1.14
OE49	230	3.78	1.12	231	3.78	1.11
OE50	231	3.55	1.06	231	3.55	1.06
OE51	229	3.35	1.20	231	3.35	1.19
OE52	229	2.87	1.23	231	2.87	1.22
OE53	230	2.96	1.19	231	2.96	1.19
OE54	231	3.03	1.11	231	3.03	1.11

Table F4
Item Descriptive Statistics for Math Learning Environment Scale

	Pre-Imputation			Post-Imputation		
Item	N	M	SD	N	M	SD
LE1	231	3.50	1.19	231	3.50	1.19
LE2	230	3.50	1.17	231	3.50	1.17
LE3	230	3.46	1.17	231	3.45	1.17
LE4	231	3.22	1.16	231	3.22	1.16
LE5	231	3.68	1.12	231	3.68	1.12
LE6	231	3.30	1.21	231	3.30	1.21
LE7	231	3.78	1.25	231	3.78	1.25
LE8	230	3.10	1.24	231	3.10	1.24
LE9	231	2.74	1.17	231	2.74	1.16
LE10	231	3.41	1.22	231	3.41	1.22
LE11	231	3.51	1.16	231	3.51	1.16
LE12	231	3.52	1.18	231	3.52	1.18
LE13	231	3.52	1.23	231	3.52	1.23

Appendix G

Scale Items Correlation of Study Scales

Table G1

Item Correlations on Math Interest Scale

	Int3	Int4	Int5	Int6	Int7	Int8	Int9	Int10
Int3	—							
Int4	.73	—						
Int5	.43	.47	—					
Int6	.27	.32	.44	—				
Int7	.41	.47	.63	.57	—			
Int8	.35	.45	.73	.41	.66	—		
Int9	.39	.48	.80	.40	.61	.71	—	
Int10	.39	.47	.63	.45	.60	.55	.68	—

Note. All correlations are significant at the 0.05 level (2-tailed).

Table G2

Item Correlations on Math Self-Efficacy Scale

	SE1	SE2	SE3	SE4	SE5	SE6	SE9	SE10
SE1	—							
SE2	.60	—						
SE3	.60	.75	—					
SE4	.48	.43	.46	—				
SE5	.42	.44	.52	.48	—			
SE6	.58	.56	.53	.43	.53	—		
SE9	.57	.65	.68	.50	.52	.57	—	
SE10	.52	.58	.54	.49	.49	.44	.60	—

Note. All correlations are significant at the 0.05 level (2-tailed).

Table G3

Item Correlations on Math SCT Outcomes Subscale

	P1	P2	P3	P5	P6	P10	P12	P13	P14	P15	SA1	SA2	SA7	SA8	SS3	SS6	SS7	SS8	SS9	G4
P1	—																			
P2	.46	—																		
P3	.36	.34	—																	
P5	.27	.29	.31	—																
P6	.32	.45	.49	.51	—															
P10	.28	.41	.31	.40	.43	—														
P12	.26	.28	.43	.37	.36	.49	—													
P13	.32	.39	.39	.48	.49	.49	.50	—												
P14	.33	.46	.33	.43	.48	.53	.44	.61	—											
P15	.32	.31	.40	.37	.42	.38	.44	.55	.59	—										
SA1	.23	.38	.26	.29	.33	.45	.42	.36	.38	.27	—									
SA2	.26	.26	.38	.34	.54	.37	.48	.47	.49	.35	.40	—								
SA7	.09	.27	.19	.18	.32	.40	.46	.46	.48	.38	.30	.46	—							
SA8	.25	.34	.35	.33	.42	.36	.47	.47	.40	.55	.33	.33	.41	—						
SS3	.25	.37	.43	.42	.51	.56	.53	.40	.43	.39	.32	.39	.30	.41	—					
SS6	.23	.43	.28	.52	.57	.56	.41	.62	.60	.40	.46	.40	.41	.44	.45	—				
SS7	.23	.40	.29	.39	.48	.43	.46	.58	.51	.42	.44	.47	.52	.44	.40	.62	—			
SS8	.20	.31	.25	.21	.27	.27	.34	.42	.37	.44	.21	.22	.43	.44	.29	.36	.41	—		
SS9	.22	.33	.19	.37	.31	.37	.24	.48	.49	.43	.19	.25	.37	.34	.32	.56	.41	.38	—	
G4	.13	.26	**.06**	.24	.20	.33	.24	.25	.30	.20	.28	.23	.28	.20	.34	.39	.27	.20	.45	—

Note. Bold correlation is not significant. All other correlations are significant at the 0.05 level (2-tailed).

Table G4
Item Correlations on Math Relational Outcomes Subscale

	G1	G2	G3	G5	G6	G7	G8	G9	G10	SS9	SA10
G1	—										
G2	.63	—									
G3	.45	.50	—								
G5	.42	.43	.38	—							
G6	.40	.34	.54	.48	—						
G7	.43	.41	.46	.42	.53	—					
G8	.46	.45	.40	.41	.46	.52	—				
G9	.49	.39	.32	.26	.21	.38	.37	—			
G10	.48	.44	.32	.39	.44	.44	.46	.44	—		
SA9	.43	.43	.40	.38	.34	.38	.51	.35	.44	—	
SS10	.48	.39	.32	.38	.41	.42	.55	.45	.46	.53	—

Note. All correlations are significant at the 0.05 level (2-tailed).

Table G5
Item Correlations on Math Relational Outcomes Subscale

	R1	R2	R5	R7	R9
R1	—				
R2	.35	—			
R5	.47	.33	—		
R7	.38	.37	.41	—	
R9	.32	.48	.33	.32	—

Note. All correlations are significant at the 0.05 level (2-tailed).

Table G6. *Correlations of Items on Math Learning Environment Scale*

	T5	T10	T11	T12	T14	T20	T23	T24	T27	B1	B6	B17	B21
T5	—												
T10	.66	—											
T11	.62	.61	—										
T12	.64	.71	.67	—									
T14	.65	.69	.72	.75	—								
T20	.70	.65	.66	.65	.62	—							
T23	.62	.69	.66	.62	.67	.66	—						
T24	.68	.57	.66	.57	.67	.63	.65	—					
T27	.65	.68	.56	.61	.66	.65	.67	.62	—				
B1	.37	.34	.25	.37	.38	.36	.33	.36	.35	—			
B6	.43	.45	.30	.34	.38	.32	.42	.40	.47	.35	—		
B17	.43	.36	.40	.42	.43	.45	.39	.41	.40	.32	.26	—	
B21	.24	.29	.23	.24	.33	.28	.21	.27	.28	.27	.16	.25	—

Note. All correlations are significant at the 0.05 level (2-tailed).

Appendix H

Reliability and Item-Total Statistics for Study Scales

Table H1
Reliability and Item Total Statistics for Math Interest Scale

	Corrected Item-Total Correlation	Cronbach's α if Item is Deleted
Int3	0.54	0.90
Int4	0.63	0.89
Int5	0.79	0.87
Int6	0.52	0.90
Int7	0.74	0.88
Int8	0.73	0.88
Int9	0.78	0.87
Int10	0.71	0.88

Table H2.
Reliability and Item Total Statistics for Math Self-Efficacy Scale

	Corrected Item-Total Correlation	Cronbach's Alpha if Item is Deleted
SE1	0.70	0.89
SE2	0.74	0.88
SE3	0.76	0.88
SE4	0.59	0.90
SE5	0.62	0.89
SE6	0.67	0.89
SE9	0.76	0.88
SE10	0.67	0.89

Table H3

Reliability and Item Total Statistics for SCT Outcomes

	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
P1	0.44	0.93
P2	0.56	0.93
P3	0.53	0.93
P5	0.60	0.93
P6	0.68	0.93
P10	0.67	0.93
P12	0.65	0.93
P13	0.75	0.93
P14	0.75	0.93
P15	0.65	0.93
SA1	0.53	0.93
SA2	0.57	0.93
SA7	0.56	0.93
SA8	0.60	0.93
SS3	0.63	0.93
SS6	0.74	0.93
SS7	0.70	0.93
SS8	0.51	0.93
SS9	0.55	0.93
G5	0.59	0.93

Table H4

Reliability and Item Total Statistics for Generativity Outcomes

	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
G1	0.69	0.88
G2	0.66	0.88
G3	0.59	0.89
G5	0.62	0.88
G6	0.57	0.89
G7	0.64	0.88
G8	0.67	0.88
G9	0.53	0.89
G10	0.66	0.88
SA9	0.59	0.89
SS10	0.62	0.88

Table H5

Reliability and Item Total Statistics for Relational-Outcomes

	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
R1	0.53	0.72
R2	0.54	0.71
R5	0.55	0.71
R7	0.52	0.72
R9	0.51	0.72

Table H6

Reliability and Item Total Statistics for Math Learning Environment Scale

	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Tchr5	0.78	0.91
Tchr10	0.78	0.91
Tchr11	0.73	0.92
Tchr12	0.76	0.91
Tchr14	0.81	0.91
Tchr20	0.77	0.91
Tchr23	0.76	0.91
Tchr24	0.75	0.91
Tchr27	0.76	0.91
BE1	0.45	0.93
BE6	0.48	0.92
BE17	0.51	0.92
BE21	0.34	0.93

Appendix I

Correlation Tables for MOES Subscales

Table I1

Item Correlations on Generativity Subscale

	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10
G1	—									
G2	.64	—								
G3	.46	.50	—							
G4	.50	.52	.37	—						
G5	.41	.42	.37	.28	—					
G6	.40	.33	.53	.34	.50	—				
G7	.45	.42	.48	.45	.40	.52	—			
G8	.48	.47	.42	.44	.40	.45	.54	—		
G9	.48	.39	.31	.387	.28	.23	.37	.36	—	
G10	.49	.46	.346	.61	.38	.43	.46	.48	.43	—

All correlations are significant at the 0.05 level (2-tailed).

Table I2

Item Correlations on Physical Subscale

	P1	P2	P3	P5	P6	P10	P12	P13	P14	P15
P1	—									
P2	.61	—								
P3	.57	.63	—							
P5	.46	.47	.53	—						
P6	.41	.55	.51	.52	—					
P10	.46	.51	.52	.40	.46	—				
P12	.41	.47	.51	.41	.44	.55	—			
P13	.44	.37	.43	.47	.36	.53	.37	—		
P14	.33	.47	.41	.30	.42	.46	.31	.36	—	
P15	.34	.35	.34	.29	.30	.35	.30	.39	.48	—

All correlations are significant at the 0.05 level (2-tailed).

Table I3
Item Correlations on Relational Subscale

	R1	R2	R5	R7	R9	R10
R1	—				.	.
R2	.35	—		.		
R5	.49	.35	—			
R7	.38	39	.42	—		.
R9	32	.50	.35	.34	—	
R10	21	.16	**.10**	16	.30	—

Note. Bold correlation is not significant.
All other correlations are significant at the 0.05 level (2-tailed).

Table I4
Item Correlations on Social Approval Subscale

	SA1	SA2	SA7	SA8	SA9
SA1	—				
SA2	.39	—			
SA7	.31	.47	—		
SA8	.33	.34	.43	—	
SA9	.33	.21	.30	.43	—

All correlations are significant at the 0.05 level (2-tailed).

Table I5
Item Correlations on Self-Satisfaction Subscale

	SS1	SS2	SS3	SS6	SS7	SS8	SS9	SS10
SS1	—							
SS2	**.08**	—						
SS3	.27	.36	—					
SS6	.19	.19	.47	—				
SS7	.18	.23	.42	.63	—			
SS8	.20	.16	.31	.37	.42	—		
SS9	.21	.18	.34	.57	.44	.39	—	
SS10	**.11**	.33	.53	.44	.44	.42	.45	—

Note. Bold correlation is not significant.
All other correlations are significant at the 0.05 level (2-tailed).

Table I6

Item Correlations on Outcome Expectations Scale

	P1	P2	P3	G1	G2	SS3	R1	SA1	G3	R2	P5	P6	SA2	G4	G5	SS6	SS7	R5	R7	P10	R9	P12	G6
P1	1.0																						
P2	0.5	1.0																					
P3	0.4	0.3	1.0																				
G1	0.2	0.4	0.2	1.0																			
G2	0.2	0.4	**0.1**	0.6	1.0																		
SS3	0.3	0.4	0.4	0.4	0.4	1.0																	
R1	**-0.1**	**0.0**	**0.1**	**0.1**	**0.0**	0.1	1.0																
SA1	0.2	0.4	0.3	0.4	0.3	0.3	**0.0**	1.0															
G3	0.2	0.3	0.2	0.4	0.5	0.3	**0.0**	0.4	1.0														
R2	0.1	0.1	0.2	**0.1**	**0.1**	0.2	0.3	0.2	**0.1**	1.0													
P5	**0.3**	0.3	0.3	0.3	0.3	0.4	**0.1**	0.3	0.4	0.2	1.0												
P6	0.3	0.4	0.5	0.3	0.3	0.5	**0.0**	0.3	0.2	0.2	0.5	1.0											
SA2	0.3	0.3	0.4	0.2	0.3	0.4	**0.1**	0.4	0.3	0.2	0.3	0.5	1.0										
G4	0.1	0.3	**0.1**	0.5	0.5	0.3	**-0.1**	0.3	0.4	**0.0**	0.2	0.2	0.2	1.0									
G5	0.4	0.4	0.2	0.4	0.4	0.3	**0.0**	0.4	0.4	**0.1**	0.5	0.4	0.3	0.3	1.0								
SS6	0.2	0.4	0.3	0.4	0.4	0.4	**0.1**	0.5	0.4	0.2	0.5	0.6	0.4	0.4	0.6	1.0							
SS7	0.2	0.4	0.3	0.3	0.4	0.4	**0.1**	0.4	0.4	0.2	0.4	0.5	0.5	0.3	0.5	0.6	1.0						
R5	**0.0**	0.1	0.2	0.1	0.1	0.1	0.5	**0.1**	**0.0**	0.3	0.2	0.2	**0.1**	**0.0**	0.1	0.2	0.2	1.0					
R7	**0.0**	**0.0**	0.2	**-0.1**	**-0.1**	**0.1**	0.4	**0.1**	**0.0**	0.4	**0.1**	**0.1**	0.2	**0.0**	**-0.1**	**0.1**	**0.1**	0.4	1.0				
P10	0.3	0.4	0.3	0.4	0.4	0.6	**0.1**	0.4	0.3	0.1	0.4	0.4	0.4	0.3	0.5	0.6	0.4	0.0	**0.0**	1.0			
R9	**0.1**	0.3	0.2	0.2	**0.0**	0.3	0.3	0.3	0.1	0.5	0.2	0.3	0.2	**0.0**	0.2	0.3	0.3	0.3	0.3	0.2	1.0		
P12	0.3	0.3	0.4	0.3	0.2	0.5	0.2	0.4	0.4	0.2	0.4	0.4	0.5	0.2	0.4	0.4	0.5	**0.1**	0.1	0.5	0.2	1.0	
G6	0.2	0.4	0.2	0.4	0.3	0.3	**0.0**	0.4	0.5	**0.1**	0.3	0.3	0.3	0.3	0.5	0.4	0.5	**0.1**	**0.0**	0.4	0.1	0.5	1.0
SA7	**0.1**	0.3	0.2	0.3	0.2	0.3	**0.0**	0.3	0.3	0.2	0.2	0.3	0.5	0.3	0.3	0.4	0.5	**0.1**	0.1	0.4	0.2	0.5	0.4
SS8	0.2	0.3	0.3	0.2	0.2	0.3	**0.0**	0.2	0.3	0.2	0.2	0.3	0.2	0.2	0.3	0.4	0.4	**0.1**	0.2	0.3	0.2	0.3	0.4
SS9	0.2	0.3	0.2	0.4	0.4	0.3	**0.0**	0.2	0.4	0.2	0.4	0.3	0.2	0.4	0.4	0.6	0.4	**0.1**	**0.0**	0.4	**0.1**	0.2	0.3
P13	0.3	0.4	0.4	0.3	0.3	0.4	0.2	0.4	0.3	0.3	0.5	0.5	0.5	0.3	0.4	0.6	0.6	0.2	0.2	0.5	0.3	0.5	0.4

Note. Bold correlations are not significant. All other correlations are significant at the 0.05 level (2-tailed).

Table I6 (Continued)

Item Correlations on Outcome Expectations Scale

	P1	P2	P3	G1	G2	SS3	R1	SA1	G3	R2	P5	P6	SA2	G4	G5	SS6	SS7	R5	R7	P10	R9	P12	G6
P14	0.3	0.5	0.3	0.4	0.3	0.4	**0.1**	0.4	0.4	0.3	0.4	0.5	0.5	0.3	0.6	0.6	0.5	0.2	**0.1**	0.5	0.3	0.4	0.4
G7	**0.1**	0.3	0.2	0.4	0.4	0.3	**0.0**	0.3	0.5	0.1	0.3	0.2	0.2	0.4	0.4	0.5	0.4	0.1	**0.0**	0.4	0.2	0.4	0.5
P15	0.3	0.3	0.4	0.3	0.3	0.4	**0.1**	0.3	0.3	0.2	0.4	0.4	0.3	0.2	0.4	0.4	0.4	0.2	**0.1**	0.4	0.2	0.4	0.4
SA8	0.2	0.3	0.3	0.3	0.3	0.4	**0.1**	0.3	0.3	0.1	0.3	0.4	0.3	0.2	0.4	0.4	0.4	0.2	**0.1**	0.4	0.3	0.5	0.4
SS10	0.3	0.3	0.3	0.5	0.4	0.5	**0.1**	0.4	0.3	0.2	0.4	0.4	0.3	0.4	0.4	0.4	0.4	0.1	**0.0**	0.6	0.2	0.5	0.4
G8	0.1	0.3	0.1	0.5	0.5	0.3	**0.0**	0.3	0.4	**0.1**	0.3	0.3	0.3	0.4	0.4	0.5	0.4	**0.1**	**0.0**	0.4	**0.1**	0.3	0.5
SA9	0.1	0.3	0.2	0.4	0.4	0.3	**-0.1**	0.3	0.4	**0.0**	0.3	0.3	0.2	0.4	0.4	0.4	0.4	**0.1**	**-0.1**	0.3	**0.1**	0.3	0.3
G9	0.2	0.2	0.1	0.5	0.4	0.3	**0.1**	0.2	0.3	**0.1**	0.4	0.2	0.1	0.4	0.3	0.4	0.3	0.2	**0.0**	0.3	0.2	**0.1**	0.2
G10	0.3	0.4	0.2	0.5	0.4	0.3	**0.0**	0.4	0.3	**0.1**	0.3	0.3	0.2	0.6	0.4	0.5	0.5	**0.1**	**0.0**	0.3	**0.1**	0.3	0.4

Note. Bold correlations are not significant. All other correlations are significant at the 0.05 level (2-tailed).

Table I6 (Continued)

Item Correlations on Outcome Expectations Scale

	SA7	SS8	SS9	P13	P14	G7	P15	SA8	SS10	G8	SA9	G9	G10
SA7	1.0												
SS8	0.4	1.0											
SS9	0.4	0.4	1.0										
P13	0.5	0.4	0.5	1.0									
P14	0.5	0.4	0.5	0.6	1.0								
G7	0.3	0.4	0.5	0.4	0.4	1.0							
P15	0.4	0.4	0.4	0.5	0.6	0.4	1.0						
SA8	0.4	0.4	0.3	0.5	0.4	0.4	0.5	1.0					
SS10	0.4	0.4	0.5	0.5	0.4	0.4	0.5	0.5	1.0				
G8	0.4	0.4	0.5	0.4	0.4	0.5	0.5	0.4	0.5	1.0			
SA9	0.3	0.3	0.5	0.4	0.4	0.4	0.4	0.4	0.5	0.5	1.0		
G9	0.2	0.2	0.4	0.3	0.2	0.4	0.3	0.3	0.4	0.4	0.3	1.0	
SA7	0.4	0.3	0.5	0.4	0.4	0.4	0.4	0.3	0.5	0.5	0.4	0.4	1.00

All correlations are significant at the 0.05 level (2-tailed).

Appendix J

Item-Total Correlations for MOES Subscales and 36-Item Scale

Table J1.
Reliability Statistic for Math Outcome Expectations Subscale

Subscale	Cronbach's Alpha	No. of Items
Generativity	.88	10
Physical	.88	10
Relational	.76	5
Social Approval	.73	5
Self-Satisfaction	.83	6
36-Item MOES	.94	36

Table J2
Reliability and Item Total Statistics for Generativity Subscale

	Corrected Item-Total Correlation	Cronbach's Alpha if Item is Deleted
G1	0.69	0.87
G2	0.67	0.87
G3	0.60	0.87
G4	0.62	0.87
G5	0.54	0.88
G6	0.58	0.87
G7	0.65	0.87
G8	0.64	0.87
G9	0.50	0.88
G10	0.65	0.87

Table J3
Reliability and Item Total Statistics for Physical Subscale

	Corrected Item-Total Correlation	Cronbach's Alpha if Item is Deleted
P1	0.49	0.88
P2	0.55	0.88
P3	0.58	0.88
P5	0.59	0.88
P6	0.67	0.87
P10	0.63	0.87
P12	0.60	0.87
P13	0.71	0.87
P14	0.71	0.87
P15	0.64	0.87

Table J4

Reliability and Item Total Statistics for Relational Subscale

	Item-Total Correlation	Cronbach's Alpha*		Item-Total Correlation	Cronbach's Alpha*
R1	0.53	0.69	R1	.53	.72
R2	0.52	0.69	R2	.54	.71
R5	0.51	0.69	R5	.55	.71
R7	0.50	0.69	R7	.52	.72
R9	0.54	0.68	R9	.51	.74
R10	0.26	0.76			

*Cronbach's Alpha if Deleted

Table J5

Reliability and Item Total Statistics for Social Approval Subscale

	Corrected Item-Total Correlation	Cronbach's Alpha if Item is Deleted
SA1	0.47	0.69
SA2	0.49	0.69
SA7	0.52	0.67
SA8	0.54	0.67
SA9	0.44	0.71

Table J6

Reliability and Item Total Statistics for Self-Satisfaction Subscale

	Item-Total Correlation	Cronbach's Alpha*		Item-Total Correlation	Cronbach's Alpha*
SS1	0.26	0.82	SS3	0.55	0.81
SS2	0.32	0.80	SS6	0.68	0.78
SS3	0.60	0.76	SS7	0.64	0.79
SS6	0.64	0.75	SS8	0.50	0.82
SS7	0.62	0.76	SS9	0.59	0.80
SS8	0.49	0.78	SS10	0.61	0.80
SS9	0.57	0.77	SS3	0.55	0.81
SS10	0.60	0.76			

*Cronbach's Alpha if Deleted

Table J6

Reliability and Item Total Statistics for Math Outcome Expectations-Scale

	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
P1	0.38	0.94
P2	0.55	0.94
P3	0.46	0.94
P5	0.58	0.94
P6	0.62	0.94
P10	0.65	0.94
P12	0.62	0.94
P13	0.71	0.94
P14	0.71	0.94
P15	0.65	0.94
G1	0.60	0.94
G2	0.57	0.94
G3	0.56	0.94
G4	0.49	0.94
G5	0.60	0.94
G6	0.59	0.94
G7	0.62	0.94
G8	0.63	0.94
G9	0.46	0.94
G10	0.62	0.94
R1	0.16	0.94
R2	0.31	0.94
R5	0.28	0.94
R7	0.13	0.94
R9	0.37	0.94
SA1	0.56	0.94
SA2	0.52	0.94
SA7	0.56	0.94
SA8	0.62	0.94
SA9	0.52	0.94
SS3	0.62	0.94
SS6	0.75	0.94
SS7	0.69	0.94
SS8	0.52	0.94
SS9	0.61	0.94
SS10	0.67	0.94

Appendix K

Reliability and Item Total Statistics for Preliminary Learning Environment Scale

Table K1

Reliabilities and Item Total Statistics Adding BE1

	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Tchr2	0.71	0.95
Tchr5	0.79	0.95
Tchr10	0.77	0.95
Tchr11	0.78	0.95
Tchr12	0.76	0.95
Tchr14	0.81	0.95
Tchr18	0.66	0.95
Tchr20	0.80	0.95
Tchr21	0.73	0.95
Tchr22	0.69	0.95
Tchr23	0.79	0.95
Tchr24	0.80	0.95
Tchr27	0.76	0.95
Tchr28	0.69	0.95
BE1	0.42	0.95

Table K2

Reliabilities and Item Total Statistics Adding BE6

	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Tchr2	0.71	0.95
Tchr5	0.79	0.94
Tchr10	0.78	0.94
Tchr11	0.77	0.94
Tchr12	0.76	0.94
Tchr14	0.81	0.94
Tchr18	0.66	0.95
Tchr20	0.79	0.94
Tchr21	0.72	0.95
Tchr22	0.69	0.95
Tchr23	0.79	0.94
Tchr24	0.79	0.94
Tchr27	0.77	0.94
Tchr28	0.69	0.95
BE1	0.43	0.95
BE6	0.48	0.95

Table K3

Reliability and Item total statistics Adding BE17

	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Tchr2	0.70	0.95
Tchr5	0.79	0.94
Tchr10	0.77	0.94
Tchr11	0.76	0.94
Tchr12	0.76	0.94
Tchr14	0.81	0.94
Tchr18	0.66	0.95
Tchr20	0.80	0.94
Tchr21	0.73	0.94
Tchr22	0.68	0.95
Tchr23	0.78	0.94
Tchr24	0.79	0.94
Tchr27	0.77	0.94
Tchr28	0.69	0.95
BE1	0.44	0.95
BE6	0.48	0.95
BE17	0.52	0.95

Table K4

Reliabilities and Item Total Statistic Adding B21

	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Tchr2	0.70	0.94
Tchr5	0.79	0.94
Tchr10	0.77	0.94
Tchr11	0.76	0.94
Tchr12	0.76	0.94
Tchr14	0.81	0.94
Tchr18	0.66	0.94
Tchr20	0.80	0.94
Tchr21	0.73	0.94
Tchr22	0.68	0.94
Tchr23	0.78	0.94
Tchr24	0.79	0.94
Tchr27	0.77	0.94
Tchr28	0.69	0.94
BE1	0.44	0.95
BE6	0.48	0.95
BE17	0.53	0.94
BE21	0.31	0.95

Appendix L

Total Variance Explained and Factor Matrices for Study Scales

Table L1
Total Variance Explained for Math Interest Scale

Scale	Factor	Eigenvalue	% of Variance	Cumulative %
MIS	1	4.68	58.54	58.54
	2	1.05	13.14	71.68
MSES	1	4.76	59.48	59.48
MOES	1	12.73	35.35	35.35
	2	2.73	7.59	42.93
	3	1.99	5.52	48.45
	4	1.45	4.03	52.49
	5	1.20	3.32	55.81
	6	1.11	3.08	58.89
	7	1.05	2.91	61.80
MLES	1	7.07	54.41	54.41
	2	1.02	7.88	62.29

Note. MIS = Math Interest Scale, MSES = Math Self-Efficacy Scale, MOES = Math Outcome Expectations Scale, MLE = Math Learning Environment Scale
Extraction Method: Maximum Likelihood

Table L2
Total Variance Explained of Math Outcome Expectations Subscales

Scale	Factor	Eigenvalue	% of Variance	Cumulative %
GEN	1	4.90	49.00	49.00
	2	1.01	10.05	59.05
PHY	1	4.95	49.46	49.46
REL	1	2.66	44.39	44.39
SA	1	2.42	48.47	48.47
SS	1	3.46	43.30	43.30

Note. GE = Generativity Subscale, PHY = Physical Subscale, REL = Relational Subscale, SA = Social Approval Subscale, SS = Self-Satisfaction Subscale

Table L3

Factor Matrix[a] for Math Interest Scale

	Factor
	1
Int5	0.88
Int9	0.87
Int8	0.81
Int7	0.76
Int10	0.75
Int4	0.59
Int6	0.54
Int3	0.51

Extraction Method: Maximum Likelihood.
a. 1 factor extracted. 4 iterations required.

Table L4

Factor Matrix[a] for Math Self-Efficacy Scale

	Factor
	1
SE3	0.82
SE2	0.80
SE9	0.81
SE1	0.74
SE10	0.71
SE6	0.71
SE5	0.65
SE4	0.62

Extraction Method: Principal Axis Factoring.
a. 1 factor extracted. 4 iterations required.

Table L5

Factor Matrices[a] for Math Outcome Expectations Subscales

	Factor		Factor		Factor		Factor		Factor
Item	1	Item	1	Item	1	Item	1	Item	1
G1	0.74	P13	0.77	R5	.65	SA7	0.66	SS6	0.79
G2	0.72	P14	0.77	R2	.64	SA8	0.65	SS7	0.74
G10	0.69	P6	0.71	R1	.62	SA2	0.60	SS9	0.66
G7	0.68	P15	0.69	R7	.61	SA1	0.55	SS10	0.65
G8	0.68	P10	0.68	R9	.60	SA9	0.52	SS3	0.61
G5	0.67	P12	0.65					SS8	0.54
G3	0.64	P5	0.64					SS6	0.79
G6	0.62	P3	0.60						
G5	0.57	P2	0.57						
G9	0.55	P1	0.50						

Extraction Method: Maximum Likelihood.

Table L6

Pattern Matrix[a] of Math Outcome Expectation Scale

	Factor		
	1	2	3
P6	**0.74**	0.04	-0.05
P12	**0.71**	0.01	-0.02
P3	**0.71**	0.05	-0.22
P13	**0.70**	0.11	0.07
SA2	**0.69**	0.05	-0.13
P14	**0.67**	0.04	0.13
SS7	**0.58**	0.08	0.19
P10	**0.58**	-0.08	0.22
P15	**0.56**	0.08	0.16
SS3	**0.55**	0.06	0.14
SS6	**0.52**	0.06	0.34
P5	**0.52**	0.04	0.15
P1	**0.51**	-0.10	-0.04
SA7	**0.50**	0.00	0.15
SA8	**0.46**	0.11	0.21
P2	**0.45**	0.01	0.18
G5	**0.39**	-0.01	0.32
SA1	**0.39**	0.04	0.24
SS8	**0.38**	0.11	0.18
R1	-0.10	**0.66**	0.01
R5	-0.03	**0.66**	0.08
R7	0.03	**0.63**	-0.15
R2	0.10	**0.59**	0.00
R9	0.17	**0.56**	0.01
G1	-0.03	0.05	**0.75**
G5	-0.06	-0.07	**0.71**
G2	0.02	-0.04	**0.70**
G9	-0.15	0.17	**0.66**
G10	0.13	0.02	**0.62**
G8	0.20	-0.03	**0.59**
SA9	0.10	-0.07	**0.57**
G7	0.20	0.01	**0.55**
SS9	0.23	-0.02	**0.53**
G3	0.20	-0.05	**0.50**
SS10	0.33	0.06	**0.44**
G6	0.31	-0.02	**0.39**

Note. Extraction Method: Maximum Likelihood.
Boldface indicates highest loadings

Table L7

Structure Matrix[a] of Math Outcome Expectation Scale

	Factor		
	1	2	3
P13	**0.77**	0.30	0.49
P14	**0.76**	0.23	0.53
SS6	**0.73**	0.24	0.64
P6	**0.72**	0.22	0.38
SS7	**0.71**	0.25	0.54
P12	**0.70**	0.19	0.39
P10	**0.68**	0.10	0.54
P15	**0.67**	0.24	0.49
SS3	**0.64**	0.22	0.47
SA2	**0.63**	0.21	0.27
P5	**0.61**	0.19	0.45
SA8	**0.61**	0.26	0.48
P3	**0.59**	0.20	0.19
SA7	**0.59**	0.15	0.44
G5	**0.57**	0.13	0.54
P2	**0.55**	0.15	0.44
SA1	**0.54**	0.17	0.47
SS8	**0.51**	0.23	0.41
P1	**0.46**	0.03	0.24
R5	0.19	**0.66**	0.15
R1	0.08	**0.64**	0.04
R2	0.25	**0.62**	0.14
R7	0.10	**0.61**	-0.06
R9	0.32	**0.60**	0.18
G1	0.41	0.13	**0.74**
G2	0.42	0.06	**0.71**
G8	0.53	0.09	**0.70**
G10	0.49	0.13	**0.69**
G5	0.34	0.00	**0.67**
G7	0.51	0.13	**0.66**
SS9	0.53	0.10	**0.66**
SS10	0.59	0.20	**0.63**
SA9	0.41	0.03	**0.62**
G3	0.47	0.07	**0.60**
G9	0.27	0.21	**0.60**
G6	0.53	0.11	**0.56**

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization

Table L8

Correlation of Factors of Math Outcome Expectations Scale

Factor	1	2	3
1	1.000		
2	.259	1.000	
3	.576	.126	1.000

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization

Table L9

Factor Matrix[a] for Math Learning Environment Scale

	Factor
	1
LE3 (TS14)	0.85
LE11 (TS10)	0.82
LE2 (TS12)	0.81
LE10 (TS5)	0.81
LE12 (TS23)	0.81
LE4 (TS20)	0.80
LE1 (TS11)	0.79
LE13 (TS27)	0.79
LE5 (TS24)	0.78
LE8 (BE17)	0.51
LE7 (BE6)	0.49
LE6 (BE1)	0.44
LE9 (BE21)	0.33

Extraction Method: Maximum Likelihood.
a. 1 factor extracted. 3 iterations required.

Appendix M

Pattern and Structural Matrices for Math Interest and Math Outcome Expectation Scales

Table M1.

Pattern Matrix[a] for Math Interest Scale

	Factor	
	1	2
Int9	.917	
Int5	.913	
Int8	.853	
Int7	.700	
Int10	.698	
Int6	.497	
Int3		.845
Int4		.838

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization.
a. Rotation converged in 3 iterations.

Table M2

Structure Matrix[a] Math Interest Scale

	Factor	
	1	2
Int5	.884	.510
Int9	.879	.497
Int8	.818	.463
Int7	.749	.507
Int10	.743	.500
Int6	.527	.353
Int4	.574	.876
Int3	.487	.828

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization.

Table M3

Correlation of Factors

Factor	1	2
1	1.000	
2	.610	1.000

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization.

Table M4

Pattern Matrix[a] for Generativity Sub-Scale

	Factor	
	1	2
G2	.804	.073
G1	.769	.000
G5	.717	.031
G9	.626	.089
G10	.617	-.120
G8	.535	-.201
G7	.442	-.325
G3	.388	-.355
G6	-.050	-.960
G5	.304	-.366

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization.
a. Rotation converged in 8 iterations.

Table C7

Structure Matrix for Generativity Sub-Scale

	Factor	
	1	2
G1	.769	-.446
G2	.762	-.393
G5	.699	-.385
G10	.686	-.478
G8	.651	-.511
G7	.630	-.581
G3	.593	-.579
G9	.574	-.273
G6	.506	-.931
G5	.516	-.542

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization.

Table C8

Correlation of Factors of Generativity Sub-Scale

Factor	1	2
1	1.000	-.580
2	-.580	1.000

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization.

Table M4

Pattern Matrix[a] of Math Outcome Expectation Scale

	Factor				
	1	2	3	4	5
SA7	0.66	0.05	0.00	-0.07	0.00
G6	0.59	-0.22	-0.02	0.06	0.13
SS8	0.58	0.02	0.11	-0.02	-0.07
P12	0.57	0.08	0.02	-0.24	0.43
SA8	0.49	-0.09	0.12	-0.13	0.09
G8	0.47	-0.39	-0.04	0.01	-0.09
G7	0.46	-0.35	0.01	0.01	-0.06
P15	0.45	-0.02	0.09	-0.28	-0.05
SS10	0.41	-0.34	0.07	-0.07	0.17
SS7	0.40	-0.06	0.09	-0.36	-0.08
G1	-0.04	-0.81	0.06	-0.05	0.14
G2	-0.04	-0.70	-0.03	-0.15	0.03
G5	0.12	-0.60	-0.08	-0.01	-0.05
G9	-0.03	-0.60	0.17	0.00	-0.09
G10	0.22	-0.46	0.02	-0.14	-0.19
SA9	0.34	-0.41	-0.07	0.02	-0.07
G3	0.28	-0.40	-0.04	-0.08	0.04
R1	0.00	-0.05	0.67	0.15	0.11
R5	-0.07	-0.10	0.66	-0.02	-0.03
R7	0.10	0.17	0.63	0.08	-0.02
R2	-0.01	-0.01	0.60	-0.11	-0.09
R9	0.01	-0.04	0.57	-0.13	0.03
P6	-0.05	-0.01	0.06	-0.80	-0.04
P3	0.05	0.13	0.07	-0.61	0.16
P5	0.00	-0.15	0.05	-0.58	-0.05
P1	-0.03	-0.01	-0.08	-0.53	0.00
SS6	0.20	-0.23	0.07	-0.51	-0.19
P14	0.33	-0.04	0.06	-0.50	-0.13
SS3	0.02	-0.25	0.08	-0.50	0.31
P2	-0.02	-0.22	0.03	-0.50	-0.02
P13	0.43	0.09	0.12	-0.48	-0.15
SA2	0.25	0.13	0.07	-0.47	0.09
P10	0.17	-0.25	-0.06	-0.45	0.20
G5	0.20	-0.27	0.00	-0.30	-0.01
SA1	0.15	-0.26	0.06	-0.27	0.18
SS9	0.33	-0.31	-0.03	-0.19	-0.33

Extraction Method: Maximum Likelihood. Rotation Method: Oblimin with Kaiser Normalization.

Table M5

Structure Matrix of Math Outcome Expectation Scale

	Factor				
	1	2	3	4	5
SA7	0.68	-0.31	0.16	-0.44	0.02
P12	0.68	-0.28	0.21	-0.59	0.46
SS7	0.66	-0.43	0.26	-0.63	-0.04
G6	0.66	-0.47	0.11	-0.38	0.11
G8	0.65	-0.62	0.09	-0.41	-0.12
P15	0.65	-0.38	0.25	-0.57	-0.02
SS10	0.63	-0.56	0.21	-0.49	0.15
SA8	0.63	-0.38	0.27	-0.49	0.10
G7	0.63	-0.58	0.13	-0.40	-0.09
SS8	0.61	-0.29	0.23	-0.37	-0.06
SS9	0.58	-0.57	0.10	-0.47	-0.34
G1	0.40	-0.80	0.14	-0.39	0.09
G2	0.38	-0.74	0.06	-0.41	-0.01
G5	0.40	-0.66	0.00	-0.31	-0.09
G10	0.53	-0.64	0.13	-0.45	-0.20
G9	0.30	-0.60	0.21	-0.27	-0.13
SA9	0.52	-0.56	0.03	-0.33	-0.11
G3	0.51	-0.56	0.07	-0.40	0.01
R5	0.13	-0.14	0.66	-0.18	-0.01
R1	0.08	-0.03	0.64	-0.04	0.11
R2	0.18	-0.10	0.62	-0.24	-0.06
R7	0.10	0.11	0.61	-0.05	0.00
R9	0.23	-0.15	0.61	-0.30	0.06
P6	0.43	-0.33	0.24	-0.79	0.04
SS6	0.62	-0.56	0.25	-0.72	-0.16
P14	0.65	-0.42	0.25	-0.71	-0.08
P13	0.69	-0.35	0.32	-0.71	-0.09
SS3	0.45	-0.45	0.24	-0.66	0.35
P10	0.54	-0.50	0.11	-0.66	0.22
P5	0.42	-0.40	0.20	-0.65	0.00
P3	0.35	-0.14	0.22	-0.62	0.23
SA2	0.48	-0.19	0.23	-0.59	0.15
P2	0.38	-0.42	0.16	-0.58	0.01
G5	0.51	-0.49	0.14	-0.53	0.00
P1	0.27	-0.22	0.04	-0.50	0.05
SA1	0.45	-0.44	0.18	-0.50	0.19

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization.

Table M6

Pattern Matrix[a] of Math Outcome Expectation Scale

	Factor			
	1	2	3	4
SA7	0.69	0.08	-0.01	0.06
SS8	0.63	0.04	0.10	-0.02
G6	0.53	-0.19	-0.03	0.03
G8	0.53	-0.37	-0.04	-0.04
P15	0.50	0.00	0.08	0.25
SA8	0.49	-0.04	0.11	0.16
G7	0.48	-0.35	0.01	-0.02
P13	0.47	0.07	0.12	0.40
SS7	0.44	-0.06	0.08	0.32
SS9	0.44	-0.33	-0.03	0.05
SS10	0.40	-0.28	0.06	0.15
SA9	0.39	-0.39	-0.07	-0.05
G1	-0.05	-0.75	0.06	0.14
G2	-0.04	-0.69	-0.03	0.19
G5	0.14	-0.60	-0.07	0.01
G9	0.02	-0.59	0.17	-0.03
G10	0.28	-0.47	0.02	0.08
G3	0.26	-0.39	-0.04	0.12
R1	-0.05	-0.05	0.67	-0.09
R5	-0.06	-0.11	0.66	0.01
R7	0.09	0.16	0.63	-0.09
R2	0.02	-0.02	0.59	0.07
R9	0.02	-0.03	0.56	0.14
P6	0.01	0.00	0.06	0.75
P3	0.01	0.16	0.06	0.67
SS3	-0.04	-0.19	0.08	0.61
P5	0.02	-0.17	0.06	0.55
P1	-0.04	-0.01	-0.09	0.54
P10	0.13	-0.20	-0.07	0.54
SA2	0.23	0.15	0.06	0.50
P2	0.00	-0.20	0.02	0.50
P14	0.38	-0.04	0.05	0.44
P12	0.40	0.11	0.02	0.42
SS6	0.27	-0.25	0.07	0.41
SA1	0.10	-0.23	0.05	0.37
G5	0.20	-0.26	0.00	0.32

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization.
a. Rotation converged in 13 iterations.

Table M7

Structure Matrix[a] of Math Outcome Expectation Scale

	Factor			
	1	2	3	4
P13	0.71	-0.33	0.31	0.68
SA7	0.68	-0.28	0.15	0.44
SS7	0.68	-0.40	0.26	0.63
G8	0.67	-0.61	0.09	0.41
P15	0.67	-0.35	0.25	0.57
SA8	0.64	-0.35	0.26	0.50
G7	0.64	-0.57	0.13	0.40
SS10	0.63	-0.53	0.20	0.51
G6	0.63	-0.45	0.11	0.41
SS8	0.62	-0.26	0.23	0.37
SS9	0.62	-0.56	0.10	0.43
G1	0.41	-0.78	0.13	0.42
G2	0.40	-0.74	0.05	0.42
G5	0.42	-0.67	0.00	0.30
G10	0.55	-0.63	0.13	0.43
G9	0.33	-0.60	0.21	0.26
G3	0.51	-0.56	0.07	0.41
SA9	0.54	-0.55	0.03	0.32
R5	0.14	-0.13	0.66	0.18
R1	0.06	-0.03	0.64	0.06
R7	0.10	0.11	0.62	0.06
R2	0.20	-0.09	0.62	0.23
R9	0.24	-0.13	0.61	0.30
P6	0.47	-0.29	0.24	0.77
P14	0.67	-0.39	0.24	0.69
SS6	0.65	-0.54	0.25	0.69
SS3	0.44	-0.42	0.23	0.69
P10	0.54	-0.47	0.11	0.68
P5	0.44	-0.39	0.20	0.64
P3	0.35	-0.11	0.22	0.63
P12	0.61	-0.25	0.20	0.63
SA2	0.47	-0.16	0.22	0.60
P2	0.40	-0.40	0.16	0.58
G5	0.52	-0.48	0.13	0.54
SA1	0.44	-0.42	0.18	0.52
P1	0.27	-0.20	0.04	0.50

Extraction Method: Maximum Likelihood.

Rotation Method: Oblimin with Kaiser Normalization. Extraction Method: Maximum Likelihood.

Rotation Method: Oblimin with Kaiser Normalization.

Table M8

Correlation of Factors of Math Outcome Expectations Scale

Factor	1	2	3	4	5
1	1.000				
2	-.49	1.000			
3	.21	-.08	1.000		
4	-.58	.42	-.24	1.000	
5	.002	.07	.03	-.10	1.000

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Nonnalization

Table M9

Correlation of Factors of Math Outcome Expectations Scale

Factor	1	2	3	4
1	1			
2	-.48	1		
3	.22	-.06	1	
4	.60	-.39	.24	1

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization

Appendix N

Factor Matrices for Preliminary Math Learning Environment Scale

Table N1

Factor Matrix[a] for Combined MCC Scale and MTC Scale Items

	Factor
	1
TC4	.833
TC6	.818
CC5	.811
CC8	.809
TC8	.807
TC2	.799
CC6	.798
TC3	.790
CC9	.785
TC7	.737
TC1	.728
CC10	.721
CC7	.702
TC5	.683
CC3	.524
CC2	.481
CC1	.434

Extraction Method: Maximum Likelihood.

Table N2

Factor Matrix[a] for Preliminary Learning Environment Scale

	Factor
	1
Tchr14	.834
Tchr20	.818
Tchr5	.811
Tchr23	.808
Tchr24	.807
Tchr11	.799
Tchr10	.799
Tchr12	.790
Tchr27	.786
Tchr21	.737
Tchr2	.727
Tchr28	.721
Tchr22	.701
Tchr18	.682
BE17	.525
BE6	.482
BE1	.436
BE21	.313

Extraction Method: Maximum Likelihood.

Appendix O

Scree Plots for Study Scales

Figure O1

Scree Plot for Math Interest Scale

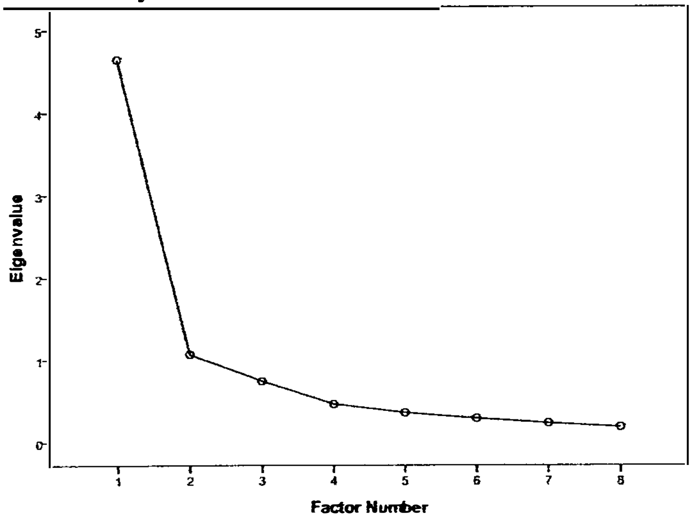


Figure O2

Scree Plot for Math Self-Efficacy Scale

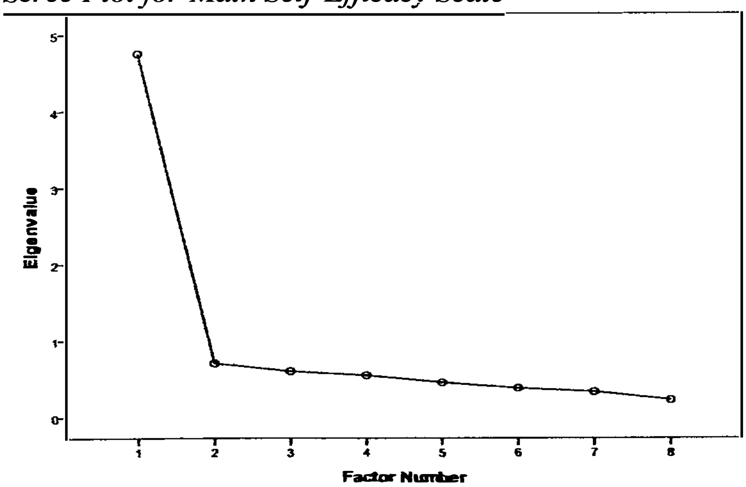


Figure O3.
Scree Plot for Math Outcome Expectation Scale

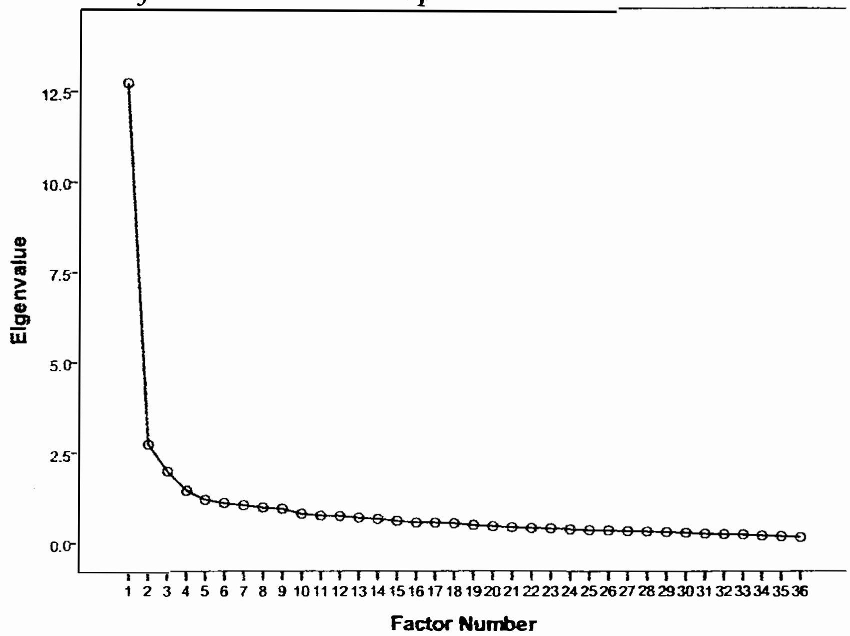
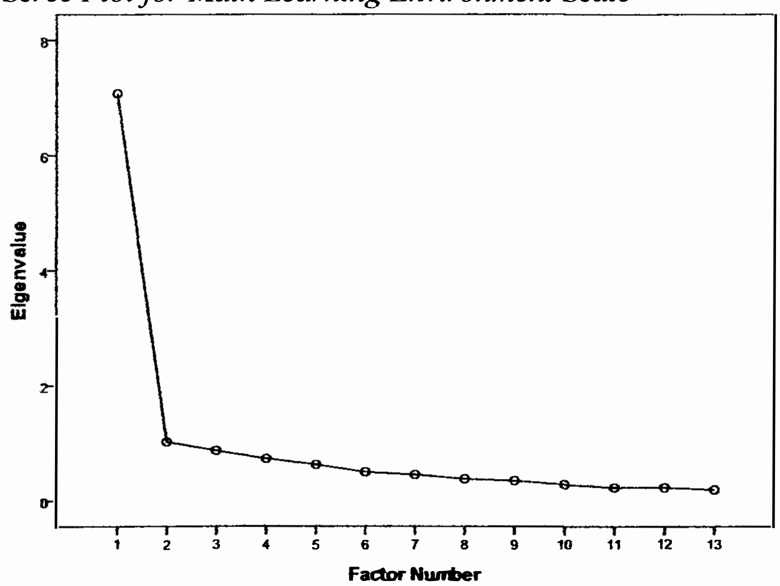


Figure O4
Scree Plot for Math Learning Environment Scale



Appendix P

Supplemental Tests of Between Subject Effects and Descriptive Statistics

Table P1
Tests of Between Subject Effects (Multivariate Significant)

		df1	*df 2*	*F*	*p*
F6xM6	MI	1	79	11.85	.001
	MSE	1	79	4.66	.03
	MOE-SCT	1	79	11.85	.001
	MOE-G	1	79	16.41	.000
	MOE-R	1	79	8.34	.005
	MLE	1	79	13.92	.000
F6xM8	MI	1	92	15.63	.000
	MSE	1	92	11.10	.001
	MOE-SCT	1	92	9.24	.003
	MOE-G	1	92	9.02	.003
	MOE-R	1	92	7.23	.01
	MLE	1	92	24.71	.000
F6xF8	MI	1	97	8.24	.005
	MSE	1	97	1.07	.30
	MOE-SCT	1	97	15.38	.000
	MOE-G	1	97	8.33	.005
	MOE-R	1	97	0.03	.86
	MLE	1	97	14.00	.000
F6xM10	MI	1	65	0.29	.59
	MSE	1	65	1.84	.18
	MOE-SCT	1	65	1.52	.22
	MOE-G	1	65	8.00	.01
	MOE-R	1	65	3.08	.08
	MLE	1	65	2.43	.12
F6xF10	MI	1	81	13.17	.000
	MSE	1	81	11.03	.001
	MOE-SCT	1	81	8.52	.005
	MOE-G	1	81	11.54	.001
	MOE-R	1	81	0.00	.99
	MLE	1	81	9.83	.002
M8xM10	MI	1	61	5.08	.03
	MSE	1	61	1.28	.26
	MOE-SCT	1	61	0.89	.35
	MOE-G	1	61	0.19	.67
	MOE-R	1	61	0.10	.75
	MLE	1	61	5.18	.03
F8xM10	MI	1	66	2.18	.14
	MSE	1	66	0.29	.60
	MOE-SCT	1	66	2.19	.14
	MOE-G	1	66	0.92	.34
	MOE-R	1	66	2.76	.10
	MLE	1	66	1.52	.22

Table P2

Tests of Between Subject Effects (Not Multivariate Significant)

		df1	*df2*	*F*	*p*
M6xF8	MI	1	80	0.43	0.51
	MSE	1	80	1.22	0.27
	MOE-SCT	1	80	0.00	1.00
	MOE-G	1	80	3.17	0.08
	MOE-R	1	80	7.38	0.01
	MLE	1	80	0.38	0.54
M6xM10	MI	1	48	4.08	0.05
	MSE	1	48	0.12	0.73
	MOE-SCT	1	48	1.82	0.18
	MOE-G	1	48	0.15	0.70
	MOE-R	1	48	0.16	0.69
	MLE	1	48	2.36	0.13
M6xF10	MI	1	64	0.11	0.74
	MSE	1	64	1.18	0.28
	MOE-SCT	1	64	0.61	0.44
	MOE-G	1	64	1.64	0.21
	MOE-R	1	64	5.60	0.02
	MLE	1	64	0.75	0.39
M8xF8	MI	1	93	1.14	0.29
	MSE	1	93	5.02	0.03
	MOE-SCT	1	93	0.38	0.54
	MOE-G	1	93	0.33	0.57
	MOE-R	1	93	6.95	0.01
	MLE	1	93	2.89	0.09
M8xF10	MI	1	77	0.00	1.00
	MSE	1	77	0.00	0.96
	MOE-SCT	1	77	0.04	0.85
	MOE-G	1	77	0.01	0.93
	MOE-R	1	77	4.89	0.03
	MLE	1	77	3.38	0.07
F8xF10	MI	1	82	0.95	0.33
	MSE	1	82	4.92	0.03
	MOE-SCT	1	82	0.71	0.40
	MOE-G	1	82	0.32	0.58
	MOE-R	1	82	0.03	0.87
	MLE	1	82	0.11	0.74
M10xF10	MI	1	50	4.44	0.04
	MSE	1	50	1.45	0.24
	MOE-SCT	1	50	0.79	0.38
	MOE-G	1	50	0.35	0.56
	MOE-R	1	50	2.06	0.16
	MLE	1	50	0.95	0.33

Table P3

Tests of Between Subject Effects (Not Multivariate Significant)

		df1	*df2*	*F*	*p*
M6xM8	MI	1	75	0.13	0.72
	MSE	1	75	1.05	0.31
	MOE-SCT	1	75	0.29	0.59
	MOE-G	1	75	1.11	0.30
	MOE-R	1	75	0.01	0.93
	MLE	1	75	0.77	0.38

Table P4

Descriptive Statistics (Grade x Gender)

	Females (n = 133)						Males (n = 133)					
	6^{th} Grade (n=49)		8^{th} Grade (n=50)		10^{th} Grade (n=34)		6^{th} Grade (n=32)		8^{th} Grade (n=45)		10^{th} Grade (n=18)	
	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
MI	25.84	6.93	21.60	7.75	19.91	7.86	20.51	6.65	19.91	7.62	24.78	8.04
MSE	31.19	6.56	29.74	7.35	26.18	7.04	27.99	6.46	26.27	7.73	28.67	7.23
MOE-SCT	38.50	8.73	31.84	8.16	33.28	6.84	31.84	8.17	32.92	9.05	35.39	10.20
MOE-G	81.60	11.83	74.64	12.18	73.23	9.79	69.10	15.92	72.98	15.88	71.00	17.69
MOE-R	19.95	3.11	20.08	3.85	19.94	3.81	17.73	3.77	17.82	4.50	18.22	4.65
MLE	50.90	10.72	43.12	9.96	43.82	9.16	41.66	11.18	39.31	11.90	46.44	9.34

Appendix Q

MANOVA Interaction by Gender and Grade

Figure Q1Math Interest by Gender and Grade

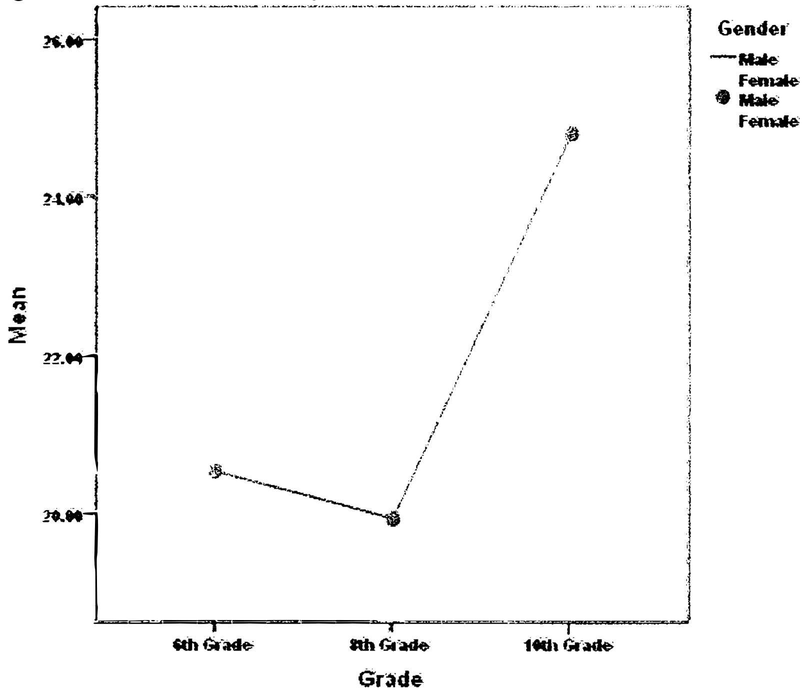


Figure Q2
Math Interest by Gender and Grade

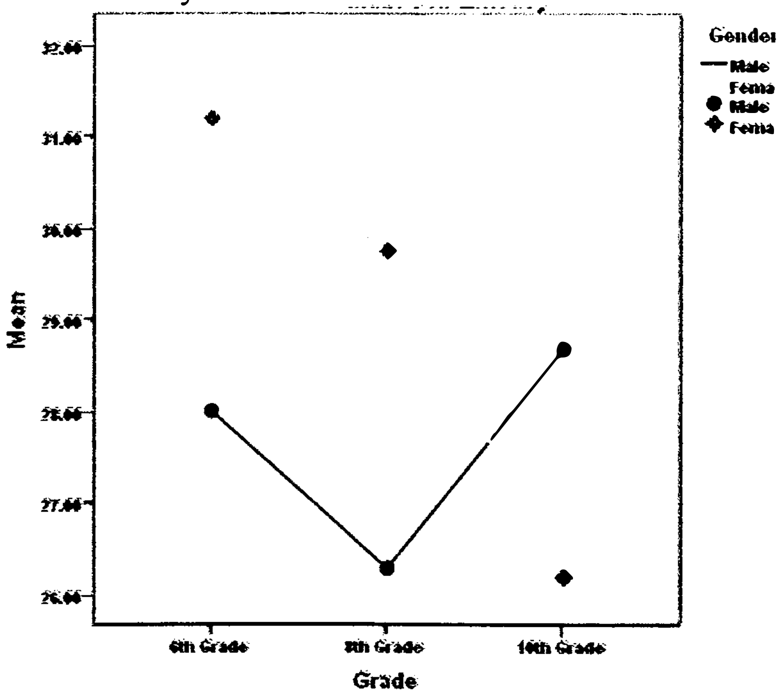


Figure Q3
Math Learning Environment by Gender and Grade

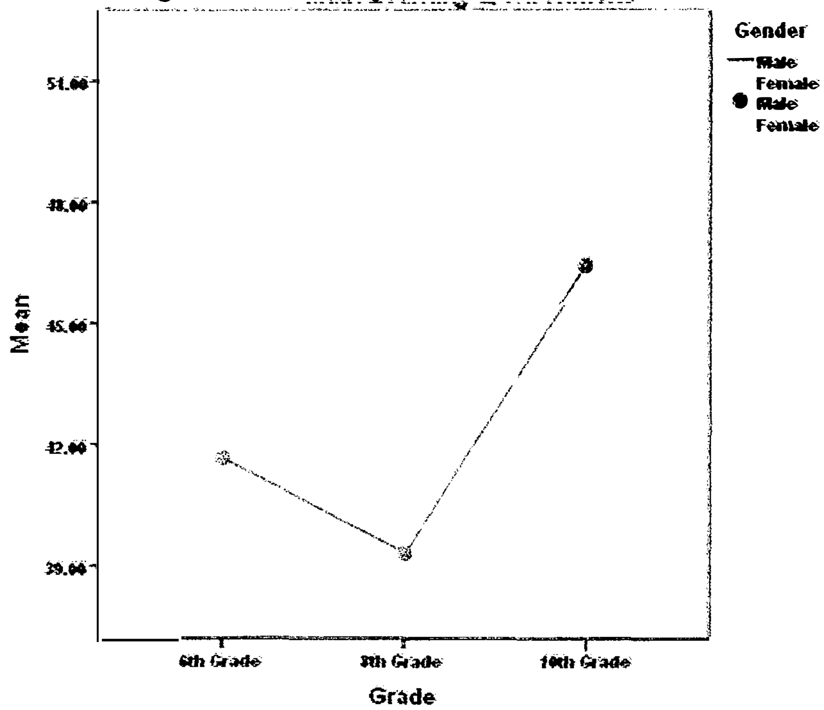


Figure Q4
Math SCT Outcome Expectations by Gender and Grade

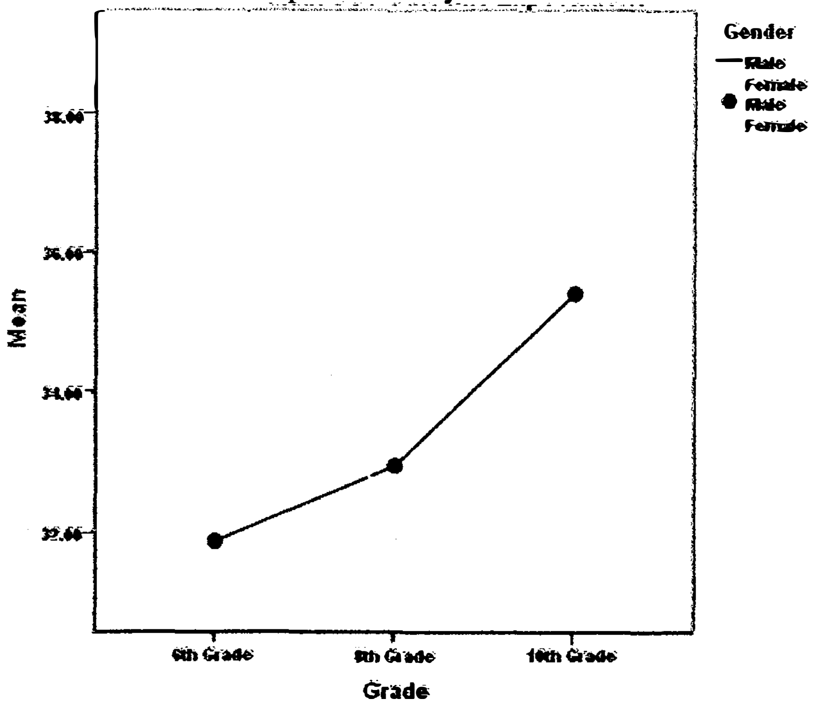


Figure Q5
Math Generativity Outcome Expectations by Gender and Grade

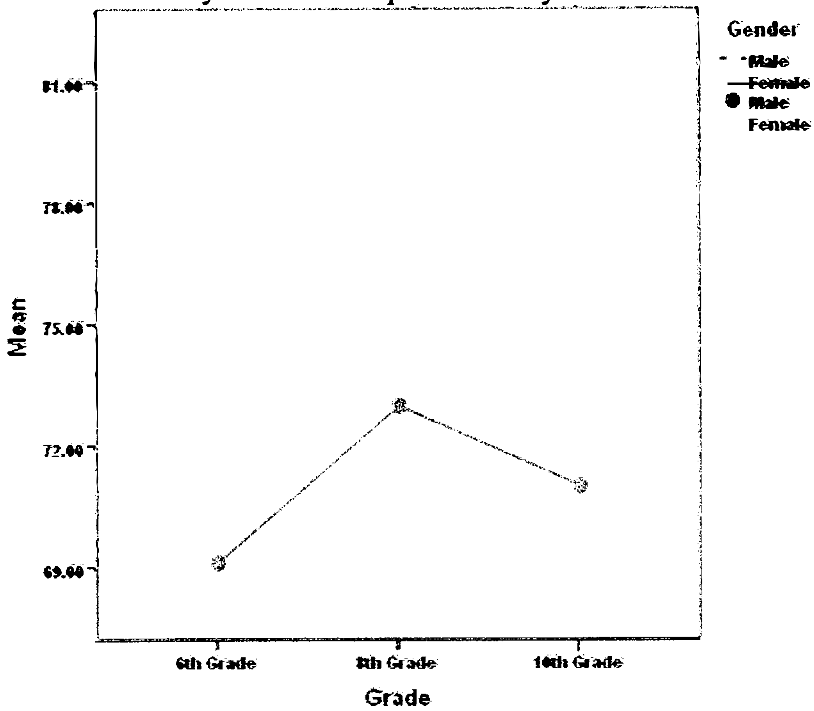


Figure Q6
Math Relational Outcome Expectations by Gender and Grade