Determining Persistence of Community College Students in Introductory Geology Classes

by

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ABSTRACT

Science, Technology, Engineering & Mathematics (STEM) careers have been touted as critical to the success of our nation and also provide important opportunities for access and equity of underrepresented minorities (URM's). Community colleges serve a diverse population and a large number of undergraduates currently enrolled in college, they are well situated to help address the increasing STEM workforce demands. Geoscience is a discipline that draws great interest, but has very low representation of URM's as majors.

What factors influence a student's decision to major in the geosciences and are community college students different from research universities in what factors influence these decisions? Through a survey-design mixed with classroom observations, structural equation model was employed to predict a student's intent to persist in introductory geology based on student expectancy for success in their geology class, math self-concept, and interest in the content. A measure of classroom pedagogy was also used to determine if instructor played a role in predicting student intent to persist. The targeted population was introductory geology students participating in the Geoscience Affective Research NETwork (GARNET) project, a national sampling of students in enrolled in introductory geology courses.

Results from SEM analysis indicated that interest was the primary predictor in a students intent to persist in the geosciences for both community college and research university students. In addition, self-efficacy appeared to be mediated by interest within these models. Classroom pedagogy impacted how much interest was needed to predict

intent to persist, in which as classrooms became more student centered, less interest was required to predict intent to persist. Lastly, math self-concept did not predict student intent to persist in the geosciences, however, it did share variance with self-efficacy and control of learning beliefs, indicating it may play a moderating effect on student interest and self-efficacy.

Implications of this work are that while community college students and research university students are different in demographics and content preparation, student-centered instruction continues to be the best way to support student's interest in the sciences. Future work includes examining how math self-concept may play a role in longitudinal persistence in the geosciences.

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Introduction

Setting the Stage

In an effort to understand why issues of equity and access to the sciences are important, it helps to consider how the population in the United States is predicted to change and how that will impact future job vacancies in the sciences. By 2050, the current underrepresented population (Hispanic, African-American, Asian and mix of 2 or more races) will comprise nearly half of the population (Day, 1996), as a result, the current majority White population will no longer be the dominant contributors to the job market. If Science, Technology, Engineering and Mathematics (STEM) jobs currently held by the majority are not replaced and filled by individuals in the growing minority groups, the nation faces a possible crisis. If the current shortages in the STEM workforce were filled with representative members of underrepresented groups as currently reflected in the U.S. population, there would be no shortfall in the workforce (May & Chubin, 2003), the challenge for meeting that demand however is our current post-secondary programs are not producing enough STEM majors of any ethnicity to fill the demand (Carnevale, Smith & Strohl, 2010).

In addition to addressing the needs of the nation, STEM careers can provide opportunities of access and equity for underrepresented minorities (URM's). Access is defined as the opportunity for anyone, regardless of ethnicity, sex, socioeconomic status (SES), disability, age or other demographic category to achieve a college education. This is possible due to changing policies from a merit-based access (those who have historically had the ability and the societal opportunities, for example White, Protestant, upper class males in the U. S.) to an equity-based access, in which opportunities are available to help create a level playing field even if those background experiences are not the same, for example, need-based financial support (Clancy & Goastellec, 2007). The importance for providing equitable access is due to the advantages that come for those who are able to obtain a college education. For example, individuals who have a post-secondary education are more likely to have careers where on-the-job training allows for skill development that results in adaptability to changes in technology and job demands (Carnevale, et al., 2010). Current job projections indicate that more than 90% of all STEM jobs will require at least some college within the next decade (Carnevale, et al., 2010).

Some have suggested that a possible source for increasing URM's in STEM overall, as well as within the geosciences, is from the community colleges (e.g., Hagedorn & Purnamasari, 2012; Holdren & Lander, 2012; National Research Council and National Academy of Engineering, 2012; van der Hoeven Kraft, Guertin, Filson, MacDonald & McDaris, 2011a). Community colleges are well situated to potentially provide a greater pool of URM's for STEM, since students from community colleges are generally older (28 vs. 21 yrs. old average age), more diverse (42.7% minorities vs. 37.5% minorities), and have more first generation college students (42% vs. 30%) than their four-year counterparts (National Center for Education Statistics [NCES], 2001; National Science Foundation [NSF], (2009); American Association of Community Colleges [AACC], 2012). In addition, there is evidence that 44% of all students with Science and Engineering (S&E) bachelor's degrees have taken some of their coursework at the community college (Tsapogas, 2004). However, there are tremendous hurdles for students from community colleges to over come in order to become STEM majors. Only 17% of students who receive an associates (2-year) degree go on to complete a 4-year degree (Carnevale, et al., 2010). A recent report on geoscience majors indicated that only 14% of all students with a B.A. or B.S. in the geosciences took a geoscience course at the community college (Wilson, 2013).

Developmental education is a growing role that community colleges fill in preparing students for their academic transfer. Developmental education (also known as remedial, compensatory, preparatory, or basic skills studies) are the courses that students need to take when they enter college that are below the college level coursework, and therefore are not transferrable to four-year institutions (Cohen & Brawer, 2008; Hagedorn & DuBray, 2010). Ninety-eight percent of all community colleges provide some form of developmental education (Parsad & Lewis, 2004).

One of the most problematic developmental courses, especially for STEM majors is math. In one study, more than 76% of all students with a desire for a career in STEM required some form of pre-gatekeeper math class (a class that is needed prior to the college-level course that is part of an actual STEM program), 36% of whom were at the developmental level (Hagedorn & DuBray, 2010). While 75% of students were able to pass their first math course in the trajectory of getting to college-preparedness, it took repeated attempts for some of them to do so (9-17% depending on the course). For these students, the developmental courses *are* gatekeeper courses. If a student enters the community college at the developmental level, it can take four or more semesters of successfully passing each course to get to the math courses that are transferrable to a four-year institution and counted toward a STEM degree (Hagedorn & DuBray, 2010). The difference between students who require a remedial course and those who do not, can be the difference between successfully transferring to a four-year institution and completing within a six-year time frame and taking much longer, if completing at all (Bailey, Jenkins, & Leinbach, 2005). Developmental math courses have been described as, "a firing squad," in response to the attrition that occurs (National Research Council and National Academy of Engineering [NRC & NAE], 2012; p. 32). Math is a major hurdle for students interested in entering STEM.

Literature Review

The following presents the current research on persistence at the college, classroom and individual scale. This literature review helps to set the stage for what gaps remain in the literature about persistence in STEM programs at the college level, particularly, community college students in the geosciences. Geosciences are defined as including geology, physical geography, meteorology, oceanography, and planetary, Earth, and environmental sciences.

Persistence at the College Scale

Tinto (1993) established a model for explaining persistence among students in college in general. Particularly important are issues of academic and social integration. Tinto (1993) describes the importance of both opportunities for students to be engaged academically, with a voice in their learning experience and clear goals for their academic success. This academic engagement is enhanced and augmented by the social interactions. These opportunities for engagement begin in the classroom, and spiral outside from there. As a student has an opportunity to experience a learning community in a classroom, s/he is more likely to engage outside of the classroom with both classmates and the instructor. Tinto argues that this is even more important in institutions that are commuter/non-residential campuses since students are less likely to have interactions outside of the classroom (Tinto, 2006). Evidence shows that students at community colleges are more likely to persist if they engage in learning communities that offer opportunities to develop social networks at the same time as they are academically engaged in their learning environment (Tinto, 1997). In addition, these interactions and feelings of integration are most critical in the first year of college (Tinto, 2006). Most of the current research done on persistence at the college scale has been at four-year colleges, very few have occurred at community colleges (Tinto, 2006). As such, this model may be less appropriate in predicting persistence in STEM for community colleges students, because students at the community college are potentially different based on their preparation level and social capital. Community colleges are more likely to have a higher representation of URM's because of the affordability, the lower admission restrictions and developmental education courses, and the flexibility for working with students who may be working and/or have family obligations (Parsad & Lewis, 2004; Bailey et al., 2005; Horn & Nevill, 2006; Cohen & Brawer, 2008; Provasnik & Planty, 2008). As a result, community colleges should be of interest for recruiting for STEM majors, and has been specifically identified by the President's Council of Advisors on

Science and Technology (PCAST) as one of the possible sources for the 1 million new STEM majors needed to fill the needs of the workforce (Holdren & Lander, 2012).

There are several identified institutional factors that influence persistence in STEM majors, particularly URM's. These factors are common to those identified by Tinto (1993) in his larger persistence model as developing relationships with peers outside of the classroom through school-sponsored organizations and informal study groups (Espinosa, 2011). In addition, opportunities for undergraduate research positively impact persistence, whereas highly selective institutions and those with high ratios of graduate students to undergraduate students negatively predict persistence (Griffith, 2010; Espinosa, 2011).

While students have hurdles to overcome becoming STEM majors at the community college, the geosciences have more challenges than most STEM majors. There are several factors needed for students to choose to become a major: 1) knowledge and interest in the subject area; 2) earning potential (somewhat mediated by socioeconomic status); 3) the skill set required to be successful and an ability to accurately gauge those skills for a given task, and 4) a feeling of a connection to a given community (Tinto, 1997; Montmarquette, Cannings, & Mahseredjian, 2001; Harackiewicz et al., 2008).

Geology is a topic that is generally relegated to middle school curriculum and when taught in high school, is commonly taught as the non-college track Earth Science course (Lewis, 2008). In fact, enrollment in Earth Science in high school was found to be the one science course in high school that negatively predicted persistence in STEM majors in college (Maltese & Tai, 2011). As a result, most students receive very little exposure to the content prior to taking a college-level geology course. Interest researchers may not agree about the semantics of what different degrees of interest are, but they generally do all agree that in order to be interested in a topic, one must have knowledge about it (Krapp, 2002; Hidi & Renninger, 2006). As a result, many students who choose to become geology majors are those who "discover" it in college. Houlton (2010) did research on why students choose to become majors, and she categorized them into three different groups: natives (those who knew about geology prior to taking a course and knew they wanted to become majors), immigrants (those who chose to become majors after exposure to the content) and refugees (those who abandoned/were rejected from other science majors). Most majors are from the middle category, immigrant or introduced[1] (Houlton, 2010; LaDue & Pacheco, 2012). Quantitative data from recent graduates confirms these findings where only 23% of a national sampling of geology majors in 2013 chose to become majors prior to entering college, whereas more than 50% decide to become majors within the first two years of college (Wilson, 2013). Research at Northern Arizona University indicated that students had very little prior knowledge about the topic of geology and what kinds of careers they could have as a geologist (Hoisch & Bowie, 2010). If students lack models for a future pathway, it will be difficult to determine the relevance of the course content at the college level (Husman

[1] Due to the potential confusion of "immigrant" from Houlton's work to immigrant population in the demographics at a community college, I will use the term, "introduced" instead.

et al., 2007). This adds to the importance of the classroom environment above and beyond general persistence research.

The research clearly identifies that creating a community is critical for student persistence in college in general, STEM fields, and geosciences specifically. However, most of this research has been done at the four-year college level. What has not been clearly identified is the role of community at community colleges, particularly for STEM and geoscience majors.

Measuring Persistence at the Classroom Scale

Most of the research of persistence in academic classrooms and college in general is done at four-year institutions, however an important common theme across different studies is the role of the classroom. There are many factors over which teachers and institutions have very little control, such as students' background experiences and cultural values. The environment created within the classroom is an example of a predictor of general academic persistence.

Barnett (2011) applied Tinto's model of persistence at college to a community college classroom setting in an effort to determine what the role of the classroom and instructor played in a student's decision to remain in college. She argued that the role of the classroom was the most critical for persistence of community college persistence since most students are non-residential and working at least part time, they do not have the opportunity to engage in social interactions outside of the classroom. In addition, she argued that URM students are less likely to fit the same integration model proposed by Tinto (1993), and that they would need to feel validated before they could feel integrated

(Barnett, 2011). As a result, she measured student feelings of validation and student feelings of integration in the classroom. She administered a survey to students in English 101 classes, which was a requirement for all programs in the general education transfer pathway. The survey asked questions around categories of 1) students known and feeling valued, 2) caring instruction, 3) appreciation for diversity, and 4) mentoring and a modified pre-existing survey on feelings of integration. She found that academic integration was mediated by student feelings of validation in the classroom (the strongest predictor was caring instruction), which then predicted persistence as measured by intending to enroll the following semester (Barnett, 2011). The key idea here is that the classroom experience that a faculty creates for students does play a role in predicting persistence.

Another way that the classroom experience has been measured is from an external observer than from student self-report. The external observer has the opportunity to see interactions on a more global scale than the individual student's perspective. One measure that captures this classroom environment, through instructor pedagogy, specifically designed for the STEM college classroom is from the Reformed Teaching Observation Protocol (RTOP) instrument. The RTOP is designed to quantify the classroom pedagogy at the college level through a series of measures that capture how reformed a classroom is based on student and teacher interactions as well as from the environment that the teacher creates for his/her students (Sawada et al., 2002). It was originally designed to measure the instructional practices in college science courses tied to the Arizona Collaborative for the Excellence in the Preparation of Teachers (ACEPT) program (Sawada et al., 2002). However, due to the wide range of capabilities of the RTOP, it has been used in many different science classrooms (e.g., Ebert-May et al., 2011 for Biology; Falconer, Wycoff, Joshua, & Sawada, 2001 for Physics; Roehrig & Garrow, 2007 for Chemistry; Budd et al., 2010 for Geology) for purposes ranging from measuring fidelity of professional growth programs (Ebert-May et al., 2011) to characterizing classroom learning environments from teacher-centered to student-centered based on the learning environment creating by the teacher and the level of interactions between the teacher and the student and between the students (Budd, van der Hoeven Kraft, McConnell & Vislova, 2013). The RTOP instrument specifically looks for instructor-student interactions, student-student interactions, and the classroom environment created for students by the instructor. These factors are the key aspects that Tinto argues are so critical for creating the learning communities within the classrooms as the first step toward integrating students onto campus (Tinto, 2006).

By measuring the classroom pedagogy through the specific factors identified in the RTOP, it is possible to determine how instructors may shape the development of interest and student persistence. Prior research indicates that instructors can help to develop student's value of science and expectancy for careers in STEM through interventions where students make connections between what they are learning in the class and their own personal interests (Hulleman & Harackiewicz, 2009). The environment that the teacher creates for students is particularly important in helping to sustain interest for females through middle school and high school (Maltese & Tai, 2010).

The sense of community that is created in the geosciences is something that is commonly cited as one of the largest reasons for becoming and persisting as a major for both majority and minority populations (Levine, Gonzalez, Cole, Fuhrman, & Carlson Le Floch, 2007; LaDue & Pacheco, 2012) and extends beyond the individual classroom community. This sense of community is similar to those factors described by Tinto (1997). Specific factors beyond the classroom community that help encourage (or discourage) students to persist as geoscience majors include the outdoor experiences and associated culture as well as an appreciation for Earth, which are unique to the field sciences such as the geosciences (Levine et al., 2007; LaDue & Pacheco, 2012). With this strength in recruiting majors, also lies geosciences greatest weakness. The geosciences are NOT just outdoor activities. Some students who are less inclined to camp outdoors or hike in the wilderness may find aspects of geosciences very interesting, but because the culture of geosciences focuses on the outdoors it can deter some students from choosing to pursue it as a major (Levine et al., 2012). In fact, a disconnect or discomfort with the outdoors can be a deterrent and a detriment to learning for those who have more of an urban-based identity (Orion & Hofstein, 1994; Gruenewald, 2003), who may be a larger representation of students attending suburban and urban community colleges. By supporting students to generate a connection to the content through curriculum that imbues a connection to a place of meaning has been strongly advocated in the geoscience community (e.g., Semken & Butler-Freeman, 2008), and may be a way to support developing community for students who don't readily identify with the outdoors.

What remains to be examined are what the characteristics of community college classrooms that help to lead to persistence in the geosciences. We know general aspects that encourage or discourage students to persist at the college level in general due to classroom experiences and within different STEM environments. The geosciences have experiences in and out of the classroom, although the introductory level general limits the opportunities for some of the field-based experiences that have been found to encourage students to become majors. In addition, the challenges of providing meaningful outdoor experiences for community college students have been relatively unexplored (Wilson, 2012).

Measuring Persistence at the Individual Scale

While the classroom experience is critical for many students in choosing to persist, there are also individual factors that motivate an individual to choose to persist. The motivation theories of Expectancy x Value, interest, and self-concept have all been identified as powerful individual predictors for student persistence at the college level and in STEM particularly.

Expectancy-Value Theory. The Expectancy x Value (E x V) theory in motivation is a powerfully predictive model of student persistence in education in general (Eccles & Wigfield, 2002). Expectancy is a measure of one's belief that they are capable of being successful in a given task or domain and is informed based on previous feedback of performance and how it is internalized. Value is a measure of a combination of utility, attainment, intrinsic/interest, and perceived cost. Utility value is how useful a given topic or task is for an individual, attainment value is how important the topic or task is, interest is how much the topic or task is enjoyable and perceived cost is a gauge of how much time and effort one is willing to put forth (Schunk, Pintrich, & Meece, 2008). Both components are critical for determine motivating behaviors such as persistence, choice and performance (Eccles, 1983; Eccles & Wigfield, 2002). Eccles (1983) first described this theory in an effort to explain the lack of presence of women in the sciences. The critical essence of E x V theory is that women may perform just as well as men in math and sciences, but they do not choose to enter those domains as majors or professions. E x V explains this phenomenon by ascribing the differences in both expectancy and value for these topics because if either function of the theory is low, than the motivation to persist declines and disappears altogether if either of the two functions becomes zero (Eccles, 1983; Nagengast et al., 2011). In order to better understand student motivation to learn, why students persist in the light of failure, and how to influence it, the E x V theory becomes more relevant, this is particularly salient for URM's in the sciences (Eccles, 1994; Wigfield & Eccles, 2000).

Wigfield & Eccles (2000) found that expectancy for success declines as students get older, either due to better gauging and understanding of feedback and students are engaged more in social comparison with peers or because the school environment changes in a way that makes evaluation more important and competition between peers more likely thus lowering their achievement beliefs. Either way, as a result, utility value generally declines over time/age. As such, not all measure of value may be as helpful for measuring students at the college level.

Pintrich, Smith, Garcia and McKeachie (1991; 1993) developed an instrument, the Motivated Strategies for Learning Questionnaire (MSLQ) that measures constructs for expectancy and value and has demonstrated strong predictive validity for student performance and persistence across both four and two year colleges (Pintrich, Smith, Garcia & McKeachie, 1991; Duncan & McKeachie, 2005).

Sullins, Hernandez, Fuller, and Tashiro (1995) applied an expectancy-value framework with students in a college-level biology course in an effort to determine who was more likely to persist in science courses (as measured by continued enrollment in courses). They found that students who ranked high in both expectancy and value were more likely to enroll in another science course than those who ranked either expectancy, value or both low.

The MSLQ has been applied in many different college science classrooms (for example, McKeachie, Lin & Strayer, 2002 in Biology; Zusho, Pintrich, & Coppola, 2003 in chemistry; Zusho, Karabenick, Rhee Bonney, and Sims, 2007 in psychology and chemistry; Salamonson, Everett, Koch, Wilson & Davidson, 2009 with medical students) and has predicted persistence, use of self-regulatory strategies for students, and performance.

An example of the application of the MSLQ as it pertains to persistence within the framework of E x V theory, was in a high school biology course, where it was used to determine measures of student motivation as a predictor of persistence in science, measured as a self-report of effort engaged in a given task (DeBacker & Nelson, 1999).

The authors found a difference in male versus female effort reports, but both reports of effort were impacted by value and expectancy for success.

Recent work from the NSF-funded project, “Geoscience Affective Research NETwork” (GARNET) has collected data on the interests, expectancies for success, and classroom experiences in introductory geology classes primarily from administration of the MSLQ (McConnell et al., 2009). Over 3,000 students have responded to survey questions about their introductory geology courses over the past 4 years. From these data, we are beginning to learn more about this introductory geology student population. However, as is common in motivation research (e.g., Vanderstoep, Pintrich, & Fagerlin, 1996; van der Veen & Peetsma, 2009) student motivations generally decline through the course of the semester. What is intriguing is that this decline appears to be buffered by the classroom environment (van der Hoeven Kraft, Stempien, Matheney, & McConnell, 2011b), incoming interest and outgoing expectancy for success (Hilpert, van der Hoeven Kraft, Husman, Jones & McConnell, 2013). In addition, we see differences with URM’s in these introductory geology classroom with regards to motivation and use of self-regulatory strategies that may have implications for teaching practices at the community colleges who serve a greater percentage of URM’s (van der Hoeven Kraft et al., 2010a; 2010b).

Recent analysis of the GARNET data indicates that the subscales of self-efficacy and control of learning are the most reliable measures from the original MSLQ that measure expectancy (Hilpert, Stempien, van der Hoeven Kraft, & Husman, 2013). The difference between expectancy and self-efficacy is that self-efficacy helps to inform expectancy. Expectancy is a more future-oriented motivation, and thus predictive of future actions. Prior experiences help to inform current expectancies in addition to social environment and cultural background. How prior experiences are interpreted can influence memories and perceptions of a future task, which then inform the expectancy and value for persisting in a given task (Schunk, Pintrich, & Meece, 2008).

Interest as a Measure of Value. Value for the expectancy x value theory has multiple constructs (Eccles & Wigfield, 2002). In science classrooms, interest has been demonstrated to be a strong predictor of persistence, more so than performance. Although a correlation exists between interest and achievement, which is stronger in the sciences than in the humanities, performance alone neither guarantees increased interest nor does it predict future actions, e.g., continuing on as a major (Shiefele, Krapp & Winteler, 1992; Harackiewicz, Durik, Barron, Linnenbrink-Garcia, & Tauer, 2008). Interest is a blend of both affective and cognitive components that drives motivation and involves some form of an interaction between the individual and the environment (Hidi, Renninger, & Krapp, 2004; Renninger & Hidi, 2011). In addition, interest is content-specific, which means there must be interest in something specific in order for interest to develop.

What may be most beneficial for developing interest, and with it a growing level of expertise, is what happens at the classroom level through the way the content is addressed, the community that is created within the classroom, if learning is well-supported, and with opportunities for students to be partners in their collective learning experience (Alexander, 1997; Häussler & Hoffman, 2000; Hulleman & Harackiewicz, 2009; Rotgans & Schmidt, 2011).

At the college level, Harackiewicz and her colleagues (2000 & 2008) examined persistence with students in psychology classrooms as measured by continuing to take another course in psychology and also continuing on as majors. They found that the culture created in the classroom can foster the development of interest. A well-developed interest in the subject can lead to registering for another course (Harackiewicz, Barron, Tauer, Carter & Elliot, 2000) and even continue on as a major (Harackiewicz et al., 2008). While the classroom environment can strongly influence student's interest, the measure of interest is at the individual student level.

Interest has been measured in many different ways, but a number of studies specific to the sciences and persistence examine interest as levels of interest. For example, Palmer (2009) asked students to rate their interest in different parts of an inquiry science lesson from very boring to very interesting. Swarat, Ortony and Revelle (2012) had students rate different topics in biology on a Likert scale from 1-6 on different topics and lessons for what they found was interesting. Post, Stewart & Smith (1991) measured interest by a basic measure of not interested to very interested (4 options) for different STEM and non-STEM careers, and found that interest better predicted Black women persisting than did measures of self-efficacy.

Within the geosciences, in the GARNET project, we have found that a high number (31%) of students enter introductory geology courses with at least some prior interest in the sciences (Gilbert et al., 2012). Preliminary analyses indicate that this prior interest is one of the greatest predictors for measures of persistence as determined by student self-report of taking another geology course (Hilpert et al., 2013). With these different studies in STEM and in geology specifically, it is possible that interest is a better measure of value than value from the MSLQ.

Math Self-Concept. Self-concept is generally considered to be a more global construct as an individual gauge of expectancy for success based on both cognitive and affective experiences, whereas self-efficacy is a more task-specific construct that is based on a cognitive evaluation of prior performances (Bong & Clark, 1999; Bong & Skaalvik, 2003). For example, there is some evidence that math self-efficacy and anxiety both impact an individuals math self-concept (Parajes & Miller, 1994). Math self-efficacy is gauged much more toward the confidence to solve specific math problems and performance in task-specific math problems, and less about the overall confidence toward math courses in general (Parajes & Miller, 1994). Math self-concept is based on social comparison of others, and as a result, is more predictive measure of affective measures like value rather than performance-based measures (Bong & Clark, 1999).

Math self-concept may be particularly salient for URM's, due to the role of social comparison. African-American students who have a strong race centrality and possess racial stereotypes about academic prowess, are more likely to have lowered academic self-concept (Okeke, Howard, Kurtz-Costes, & Rowley, 2009). In addition, research has shown, that when controlling for academic ability, URM students attending a four-year college were just as likely to declare a STEM major as white males were, however they did not persist in equal numbers (Riegle-Crumb & King, 2010). So even if URM's have high self-efficacy for their academic experience, if they are particularly cognizant of social comparison, self-concept may be a more reliable predictor of persistence at the college level.

For students at the community college, the choice to persist in college, and STEM courses particularly, may have more to do with the global construct of math self-concept rather than the more task specific math self-efficacy due to the social comparison and the population that is more likely to attend a two-year college (Marsh, 1986; Grandy, 1998). This is based on the ongoing development of identity and the high degree of students attending community college who require developmental math courses (Arnett & Tanner, 2006; Hagedorn & DuBray, 2010). Due to these challenges, self-concept may extend beyond just URM's at the community college population, to the population at large.

Math courses are important predictors in choosing to pursue STEM degrees. Math is critical for STEM degrees, and persistence in STEM is somewhat dictated by a students ability to persist in math. Maltese & Tai (2011) followed students from high school to college completion to determine what factors influence persistence in STEM. While ultimately, the greatest predictor of STEM degrees was the number of science courses taken in high school, they did find that confidence in math at the 10^{th} grade was an important predictor in persistence in STEM degrees. In addition, Eccles (1994) found that it wasn't math self-efficacy that predicted women choosing to pursue STEM degrees, rather it was their valuing of math (and science). Astin and Astin (1992) found that math and academic competency measures were the greatest predictors in students choosing to pursue STEM degrees. Mau (2003) found that the greatest predictor of URM's in persistence for STEM degrees were math self-efficacy and academic proficiency (as measured by standardized instruments of reading and math).

For URM's who had high SAT math scores (over 550), math and science performance were still likely to play a role in predicting persistence in STEM degrees (Grandy, 1998). Because there are factors beyond just the cognitive gauging of prior performances that may be influencing students perceptions of math ability, math self-concept may be more appropriate of a measure than math self-efficacy for predicting persistence in STEM programs.

In order to best capture the full experience of students in introductory geology classrooms at the community college, it is important to measure both the classroom level and the individual factors (such as expectancy, interest and math self-concept) that may influence persistence in geology courses. Particularly important is the math self-concept in distinguishing between university and community college populations of geology students. Grandy (1998) found that students who attended two-year colleges had an impact on persistence in STEM degrees for males who already had higher math achievement. Since many of the two-year college population lack a strong math background (Hagedorn & DuBray, 2010), this makes math self-concept all the more critical for this particular population in predicting persistence.

When considering the skill set required for geoscience majors rather than an introductory geoscience course, there is generally a disconnect. Most introductory geology courses do not have pre-requisite math courses and most students who enroll in introductory geology courses are enrolled for the purposes of fulfilling a general science requirement (Gilbert et al., 2012). However, the requirement for most geoscience majors is calculus at a minimum. After enrolling in an introductory geoscience course, many students will choose to not persist when confronted with the math requirements relative to their own capability perceptions. Even those who became majors described the math curriculum as one of their greatest challenges (LaDue & Pacheco, 2013). So while they may be interested, it may not be enough of an internalized interest to overcome the work required to become a major, or it may be that the math requirements preclude some students who lack a strong self-concept in math. As such, I would predict that math self-concept would play a larger role in predicting persistence in the geosciences at the community colleges than it would at the university.

In order to for students to better understand geosciences and potentially persist as majors, the critical aspect is to have students return to take another course. The more content to which they are exposed, the broader of a perspective and understanding of what is involved in geosciences, the more they may be able to visualize a future career and thus choose to persist as a major (Montmarquette et al., 2001).

The question is, how do these different factors influence a student's decision to enroll in another geology course and potentially begin on a pathway as a geology major? Ultimately, I believe it is influenced by both classroom level factors and the individual factors students bring to the classroom. As identified by this literature review, there are large gaps in what we know about factors that affect student persistence in geoscience classrooms at the community college.

Hypothesis & Research Questions

When considering persistence in the geosciences at the community college, it is important to consider the factors of efficacy and interest in the content area as a measure of expectancy x value. Expectancy x value has shown to predict motivation to persist in other disciplines and grade levels. In addition, I predicted that the classroom may play a role, for some students in these classrooms. Lastly, I hypothesized that math self-concept will play a role for students in the community college setting as compared to those at four-year institutions since math self-concept is more influenced by past experiences of success and/or failure (Marsh, 1986). I hypothesized that these factors helped to predict student intent to persist in the introductory geoscience courses. As such, the research questions for this proposal were:

1) Was there a demographic difference between students attending introductory geology at four-year colleges (specifically research 1 institutions, R1) versus those attending community colleges (CC)?
2) Did students attending R1 universities differ significantly from students at a community college in their expectancy, interest, and math self-concept?
3) Was there a significantly positive relationship between expectancy, interest and decision to continue in another geology class?
4) Was there a differential impact of classroom environment on efficacy, interest, as it pertained to persistence?
5) Did math self-concept contribute to the overall measure of geology expectancy for either R1 or CC students?

6) How did the role of math self-concept impact the predictive validity of a student's intent to persist in R1 Universities as compared to those attending a community college?

Because the GARNET project was already implemented in introductory geology classrooms around the country, I was well situated to pose this question to a readily available population across the country. The GARNET project is a continuing NSF-funded program to assess what the level of motivation and self-regulation are with introductory geology students both entering and leaving the classroom (McConnell & van der Hoeven Kraft, 2011). MSLQ, RTOP, and demographic data (Appendix A) have been collected from 3 different R1 institutions and 7 different community colleges (in addition to other institution types) since 2008.) Persistence was be measured as Harackiewicz et al. (2000) and Sullins et al., 1995 both measured persistence, by intention to enroll in another course of the same topic.

Methods

Participants

Two sets of data for this project were used: the larger GARNET data set of students from 2008-2013, and a smaller subset of data that included the math self-concept items from Spring 2013. All data were collected in introductory physical geology classrooms. The spring 2013 data were collected at the following research institutions: University of Colorado at Boulder, North Carolina State University, and University of North Dakota, and the following community colleges: Mesa Community College (AZ), Scottsdale Community College (AZ), North Hennepin Community College (MN), and Los Angeles Valley College (CA). Additional data from the larger dataset included data from Highline Community College (WA) and Community College of Rhode Island, in addition to the previous institutions listed. All of these institutions were participants in the GARNET project. In previous semesters, we have had almost 50:50 representation of men and women (48.75 and 51.25, respectively), 57.86% of participants were 18-21 years old, the largest percent of older students were represented at the community college (20% of the student population was greater than 25 years old), and most of the participants were Caucasian (79.94%), with a highest percent of non-Caucasian participants at the community college and public four-year institutions (approximately 30% of both populations had identified some race/ethnicity other than non-Hispanic white).

Measures

The measures for this research included the following valid and reliable instruments: the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich, Smith, Garcia & McKeachie, 1993), specifically the self-efficacy and control of learning beliefs sub-scales; the Self Description Questionnaire III (SDQ III; Marsh, 1984), specifically the math self-concept subscale; the Reformed Teaching Observation Protocol (RTOP; Sawada et al., 2002) to measure the classroom environment, and an additional survey (from the GARNET project) to determine outgoing interest, intent to persist as measured by intending to take another geology course, as well as general demographic information such as ethnicity, sex, age, and prior course work in STEM at both high school and college level. Table 1 presents a breakdown of the instruments and the time frame of data used as they related to the research questions and the methods for analyzing them.

Table 4.1

Detailed breakdown of methods and instruments applied to the research questions

Research Question	Instrument	Data Gathered	Analysis	Dataset
Was there a demographic difference between students attending introductory geology at four-year colleges (specifically research 1 institutions [R1]) versus those attending community colleges (CC)?	GARNET demographic Survey (Appendix A)	Age, Sex (Gender on the survey), and Race/Ethnicity	Chi-squared	Spring 2013 (CC_S and $R1_S$)
Did students attending R1 differ significantly from students at a CC in their expectancy, interest, and math self-concept?	MSLQ (Appendix B), GARNET survey, & SDQIII (Appendix C)	Self-efficacy, control of learning beliefs (Geology expectancy), interest & math self-concept	Chi-squared and t-test	Spring 2013 and compared to 2008-2013 dataset
Was there a significantly positive relationship between expectancy, interest and decision to continue in another geology class?	MSLQ & GARNET survey	Geology expectancy, interest & reported decision to enroll in another geology course	Structural Equation Modeling (SEM)	2008-2013 (CC_F and $R1_F$)
Was there a differential impact of classroom environment on efficacy, interest, as it pertained to persistence?	MSLQ, GARNET survey, RTOP (Appendix D)	Geology expectancy, interest, and classroom experience	SEM	2008-2013 (CC_F and $R1_F$)
Did math self-concept contribute to the overall measure of geology expectancy for either R1 or CC students?	MSLQ, GARNET survey, SDQ III	Geology expectancy, interest, math self-concept, and classroom experience	SEM	Spring 2013 (CC_S and $R1_S$)
How did the role of math self-concept impact the predictive validity of a student's intent to persist in R1 Universities as	MSLQ, GARNET survey, SDQ III	Geology expectancy, interest, math self-concept, and classroom	SEM	Spring 2013 (CC_S and $R1_S$)

compared to those attending a community college?	experience

Geology Expectancy. The MSLQ subscale items of self-efficacy and control of learning beliefs have been determined to be excellent predictors of the overall measure of geology course expectancy (Hilpert et al., 2012). The MSLQ has been applied in introductory science courses at the community college, and found to be valid and reliable measures (Duncan & McKeachie, 2005; Gilbert et al., 2012). Statements such as, “If I try hard enough, then I will understand the course material,” are measured on a 7-point Likert scale. The items for this instrument are in Appendix B.

Value. Interest as a measure of value has a rich and well-developed literature base (for a full review, see Renninger & Hidi, 2011). While there are disagreements about how to measure interest and what are the key factors that determine a triggered interest (external) from an internal, developed interest (Hidi & Renninger, 2006; Krapp, 2002), it is almost universally agreed that interest in a topic requires one to know something about the topic. By asking a general question about a students’ interest in the discipline after the course is completed will help to gauge a global measure of interest. Interest will be measured in response to the question, “in general, how interested in science are you?” on a 4-point Likert scale. This measure of interest is similar to that measured by Post et al. (1991), Palmer (2009), and Swarat et al. (2012). The item for this instrument are available in Appendix A.

Math Self-Concept. Math self-concept is closely linked to actual math performance (Marsh, 1986) and can be measured from the SDQ III (Marsh, 1984). The SDQ III was specifically designed for university-aged students, so while the community college may have a greater age range, the general target population has been addressed within the validity research of this instrument. Items from this instrument are in Appendix C.

Classroom Environment. The RTOP measures interactions that occur in the classroom to determine the degree to which the classroom is reformed from teacher to student-centered (Lawson et al., 2002, Sawada et al., 2002). This instrument has content validity (Piburn et al., 2000) and when observers are trained, the instrument has high reliability (Sawada et al., 2002). Recently, the RTOP was used to characterize introductory geology classrooms. This research was with some of the same classrooms as used in this research project (Budd et al., 2013). Since community college students spend most of their time on campus in the classroom, the environment the instructor creates through his/her pedagogical approach is an important factor in determining how well engaged and integrated students may become in the geosciences (Barnett, 2010; Center for Community College Student Engagement, 2010). The rubric used for scoring these classrooms as developed by Budd et al. (2013) is in Appendix D.

Intent to persist. Intent to persist was measured based on student report of choosing to take another geology course at the conclusion of their current geology course. This is part of the survey from the GARNET project is presented in Appendix A.

Procedure

In order to test this model, I used a survey-design mixed with classroom observation. Most of these questions were already implemented in the GARNET design, the SDQ III added 10 questions (Appendix C) that were implemented into the existing

GARNET survey structure for the Spring of 2013. Institutional Review Board exemption status was granted by Arizona State University prior to the collection of the Spring 2013 data, and had previously been approved at Maricopa Community College District for the data collected prior to that date (Appendix E).

All analyses were quantitative, which means that I should be able to make generalizations to a broader population of students in introductory geology courses at these types of institutions with statistically significant findings. Because GARNET has the largest collection of student motivation data, at this time, it represents our closest approximation of the true population of students in introductory geology classrooms in the U.S.

Characterizing the data. The dataset collected in the spring of 2013 was a sample of the larger dataset gathered as part of the GARNET project. GARNET has collected data every fall and spring semester since Fall 2008. Spring 2013 was the first semester to collect math self-concept. In order to leverage the full dataset when math self-concept was not a part of the analysis, I did a comparison between the full dataset and the spring 2013 subset to assure that the spring 2013 population was representative of the larger population dataset. This larger dataset represents over 4000 students in more than 130 different geology sections across the country (Stempien et al., 2013). Because this represents the largest sampling of introductory geology students in any research context, much less with motivation and interest data, this larger dataset currently represents the best representation of the introductory geology population as a whole in the U.S.

I did chi-squared tests for the ordinal items of interest and intent for the comparison between the spring sample and the GARNET population. For the continuous items of self-efficacy and control of learning beliefs, I ran a t-test. In an effort to prevent an increase in type-1 error, I combined self-efficacy and control of learning beliefs into the one variable of expectancy, as advocated by Hilpert et al., 2013. However, since this sample is much smaller than the population dataset, it is inappropriate to run a t-test with such large difference in population values (Boos, 2003; McKinnon, 2009), so I ran a bootstrap of the full dataset to create 1,000 trial runs of the appropriate population size randomly selected from the entire GARNET dataset for the R1 and the CC populations each and ran a one-item t-test. I also compared effect sizes for all analyses, because analyses with large sample sizes can result in statistically significant findings, even when they are not meaningful, so effect sizes can better reveal an appropriate comparison across populations (Cohen, 1969).

The MSLQ items have been tested for reliability with this population previously (Gilbert et al., 2012), but the math self-concept items had not. As a result, these items were analyzed for reliability with the introductory geology students using Cronbach's alpha, which tests the internal consistency of items in a survey instrument (Cronbach, 1951).

Since individuals were nested within institutions, I tested the variance within the student samples as compared to between classrooms with each institutional type ($R1_S$ and CC_S) to determine if multi-level modeling would be a more appropriate approach to the analysis. In multilevel modeling, instructors would be on one level and students would be on a different level to account for the non-randomness that situates students in individual classrooms. Testing for the variance within the classroom as compared to between the classrooms determines where the greater source of variance lies. If the variance was greater within each classroom than between each classroom, multilevel modeling would not add much benefit (Hox & Maas, 2001).

I used a listwise deletion approach to missing data when characterizing the population and doing the descriptive statistics, which is to say, I removed students from the pre-analysis who had not completed a post-analysis for the CC_S and $R1_S$ samples. In order to assure that I was not making assumptions about this missing population relative to previous GARNET analyses, I calculated the response rate for students who completed the pre but not the post, and compared these results to those of the GARNET project data as a whole. Lastly, I analyzed the basic characteristics of the sample data to determine if the responses were normally distributed.

Characterizing the population. I compared the responses from the demographic survey (Appendix A) with a chi-squared analysis comparing participants from the $R1_S$ to the CC_S samples in the nominal and ordinal values of age, sex (gender on the survey), race/ethnicity, previous science and math courses, reason for choosing the course, and choice in majors. I also compared the responses of expectancy and math self-concept at the different institution types using a paired t-test. Because these scores were based on items with more than 5 stem options (7 for expectancy and 8 for math self-concept), it was appropriate to use these as continuous variables (Rhemtulla, Brosseau-Liard, & Savalei, 2012). However, because interest and intent have only 4 stem options (e.g., very likely, somewhat likely, somewhat unlikely, very unlikely), I treated them as ordinal variables and as a result applied a chi-squared test when comparing these scores.

In order to determine if the variables of self-efficacy, control of learning beliefs, interest, and math self-concept were appropriate measures for predicting intent to persist, I initially tested the variables in a bivariate regression. Bivariate regression examines the linear relationship between two variables in which they are normalized to represent a range of 0-1: no relationship to a perfect correlation, respectively. There are three major assumptions with this analysis: 1) there is no measurement error in any of the individual scales, 2) values are independent from each other and represent a random sample from the population, and 3) variances are normally distributed across values (Cohen, Cohen, West & Aiken, 2003). For variables that are ordinal, the Spearman rho correlation is more appropriate than the Pearson product-moment correlation (Green & Salkind, 2008).

SPSS software, version 21.0 (IBM, 2012) was used for all of the descriptive statistics and general characterizations of the data (e.g., t-tests, chi-squared tests, bivariate correlations, and bootstrapping).

Using Structural Equation Modeling. Multiple regression is a common method to analyze the relationship between multiple variables like those in this project. Multiple regression allows researchers to determine the correlation between a given outcome variable (dependent variable) and multiple independent variables (Cohen et al., 2003). However, one of the assumptions in standard multiple regression is that there is no measurement error, which in social science research is almost never the case. Another limitation of multiple regression is that there are a limited number of relationships that can be specified between variables (Cohen et al., 2003). Structural Equation Modeling (SEM) is more powerful than a standard multiple regression analysis because it allows you to account for 1) measurement error which results in a more reliable measure of regression and 2) multiple variables and the relations between those variables (Hoyle, 2012).

Structural Equation Modeling is a statistical approach to assessing a hypothesis through a series of regression equations such that the relationships can be modeled pictorially (Byrne, 2012). SEM is used to test a series of constructs through a theoretically-proposed model using both continuous and discrete variables that allow researchers to make predictions (Tabachnick & Fidell, 2001).

SEM analysis contains two unique models: 1) a measurement model, which tests the relationship the data have to each other through a factor analysis; and 2) a structural model that allows researchers to make theory-driven claims about the directional relationship of the data (Kline, 2012), these directional claims are what allow for predictions. So the measurement model tests if relationships exist between the proposed constructs in the model and the structural model allows researchers to test if the proposed directionality maps onto those constructs. Figure 4.1 introduces basic terminology associated with the measurement model and figure 4.2 introduces the basic terminology associated with the structural model.

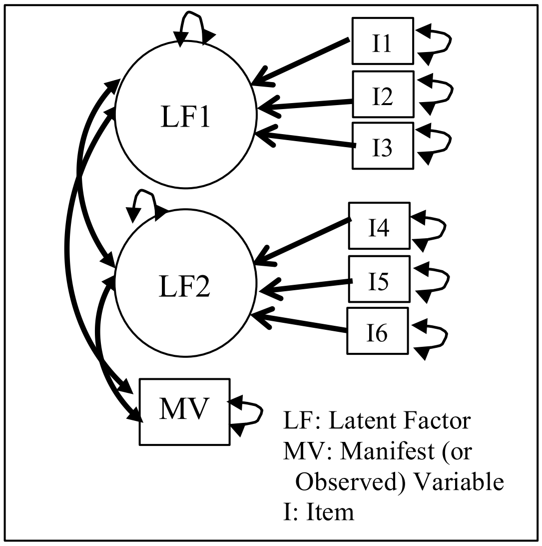

Figure 4.1. Illustration of the basic structure of a measurement model for SEM.

The latent factors are larger constructs (e.g., self-efficacy) that are informed by a series of survey items (or other variables, such as test scores). Manifest (or observed) variables are similar to latent construct, but they are represented by only one survey item or by a directly observed measure. The arrows in the model that circle back onto a variable or factor represent the measurement error for the individual items, or individual variance that exists for a given factor. The single headed arrow from the individual items to the constructs represent the factor loadings, which is the amount that each individual item contributes to a given construct. The double-headed curved arrows between the factors represents the shared variance, or correlation, between the different factors. A manifest variable can be used in measurement models, but they are items that either have only one item to represent a given construct or are a directly observed phenomena. The weakness of a manifest is due to the lack of accounting for measurement error. However, because manifest variables can have a shared variance with other factors it is important to keep them at the factor level (Byrne, 2012; Hoyle, 2012).

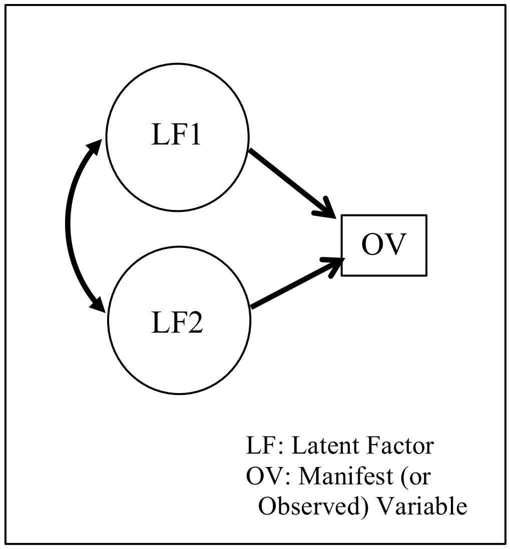

Figure 4.2. Illustration of the basic structure of a structural model for SEM.

In figure 4.2, the structural model has the same elements as the measurement model, but there is now a directional path, which minimizes some of the correlations. As a result, the structural model is nested within the measurement model. Nesting measures a goodness-of-fit for the structural model. The goodness-of-fit does not assess the directionality of the arrow, because that is theory-based rather than quantitatively assessed (Byrne, 2012; Hoyle, 2012).

The proposed measurement and structural models for this research are presented in Figure 4.3 and 4.4. The predictive variable in the structural model is intent to persist. The latent variables are the Math Self-Concept (MSC), Self-Efficacy (SE), Control of Learning Beliefs (CLB). Interest is a manifest variable and Classroom Pedagogy (RTOP) is measured at the instructor level and is an observed variable, so will be treated differently.

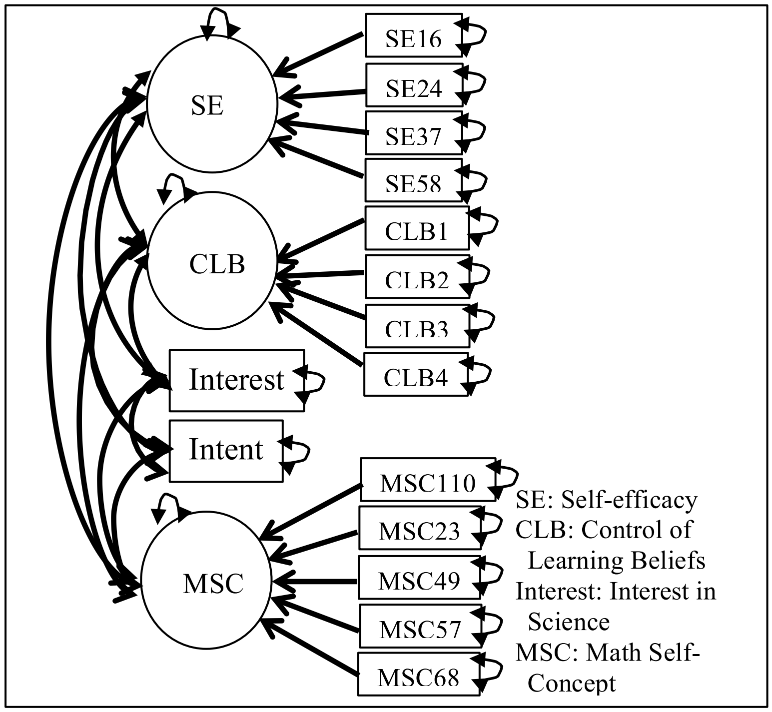

Figure 4.3. Proposed measurement model for this research project

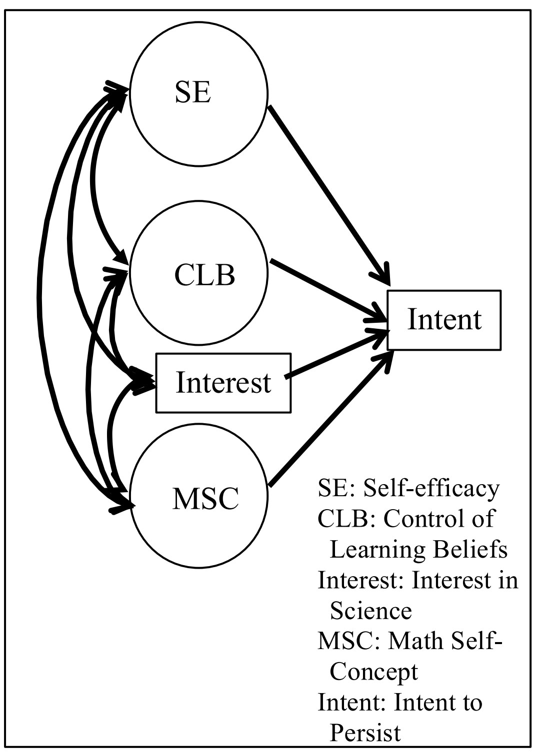

Figure 4.4. Proposed structural model for this research project

The method for establishing a SEM with a solid foundation is based in many decisions. Some of these decisions are with the data itself prior to analysis, how to best analyze the data based on those initial decisions, what type of measurement model to use, choosing when to modify the measurement model, and what the a priori structural model should be. Figure 4.5 is a flow chart representing the decisions made for this research. Some of these decisions were based on the software, all SEM analyses were done using MPlus version 7.0 (Muthén & Muthén, 1998-2012).

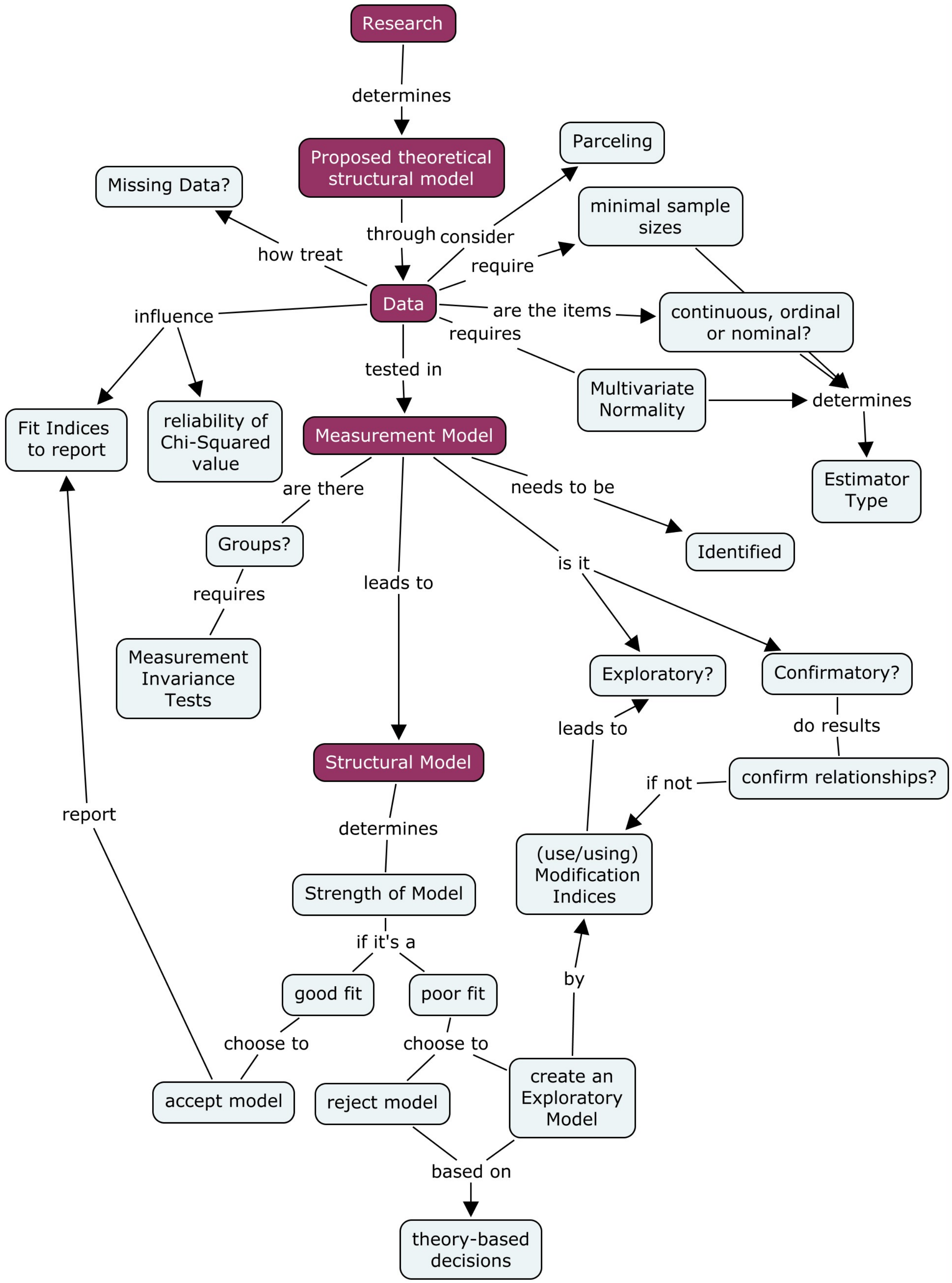

Figure 4.5. A decision map for SEM analysis

Data assumptions and decisions. Prior to any measurement or structural analysis of the data, it is important for the researcher to be aware of the general characteristics of the data. Measurement decisions are influenced by the normality or non-normality of the data, the type of data collected, whether it be continuous variables, ordinal, or nominal data, and how to best arrange the data for the structural model in order to make the most parsimonious possible model.

Standard SEM analyses assume all data are multivariate normal. Data that are heavily skewed by a shift in means and/or kurtotic by a shift in variance relationships can impact the shape of the normal curve, which then impacts the accurate fit and interpretation of the data (DeCarlo, 1997; Byrne, 2012). When data are not normally distributed, there are ways to address this in MPlus software, however, it is important to be aware of the degree of normality or non-normality of your data prior to analysis (Yuan & Chan, 2005). In addition, ordinal or nominal data are generally not normally distributed, and as such will influence the decisions made for the type of analysis. For this project, I did an analysis of the normality of the data prior to any SEM analysis. In addition, both the interest and intent variables were ordinal, and as a result, informed some of my chosen methods to employ in MPlus.

SEM generally requires large sample sizes, 100 at a minimum, and many analyses rely on more than 1,000, particularly as models become more complex (Tabachnick & Fidell, 2001). When sample sizes are below 100, the models can become underpowered and difficult to determine if the models are appropriate. The tests to determine if a model is appropriate can become skewed and less reliable with smaller sample sizes (Bentler, 1990). The data collected from the Spring 2013 CC sample (CC_S) were lower than predicted, and thus impacted the choice of estimator.

Data characteristics are important to know, because they influence the researchers decisions with which estimator method to use. An estimation method informs how the model is analyzed, based on how the data are treated. Which estimation method is chosen can influence the quality of the model parameter estimates, their associated standard error estimates, and the overall model fit statistics (Lei & Wu, 2012). An estimator essentially determines how well the variance-covariance matrix fits to the model of how it should ideally fit through an iterative process. The most common estimator is the Maximum Likelihood estimator (ML), with the assumption that the data are multivariate normally distributed and continuous data. If data are non-normal and/or categorical (fewer than 5 categories; Rhemtulla et al., 2012), than the ML estimator is not robust and can lead to inflated model fit likelihood and deflated standard error estimates (Lei & Wu, 2012). More recently, estimators are available that adjust the ML estimator for non-normal data known as an adjusted version of the Satorra-Bentler statistic (Lei & Wu, 2012). For categorical data, the weighted least squares (WLS) takes a different approach to estimating the model fit so that it relaxes the asymptotic assumption of the data distribution, and as such can be much more robust to model fit, but relies on large (>1,000) sample sizes (Lei & Wu, 2012). In general, ordinal data represent a larger spectrum of a construct, but are represented by a smaller range (Byrne, 2012). For example, interest in science is represented by an infinite range of possible responses from strongly agree to strongly disagree, but in this research it was only represented by four options. The WLS estimator accounts for this theoretically larger range by calculating thresholds and using those thresholds in the place of means in a continuous item (Rhemtulla et al., 2012). More recent modifications have allowed for using a smaller sample size with a modified version of the WLS, known as the Diagonally Weighted Least Squares (DWLS) where it is computationally less intense (Lei & Wu, 2012). Depending on which data I was using determined my estimator. When just analyzing data from continuous variables, I used the MLR (ML estimator in MPlus available for non-normally distributed continuous data). When analyzing the variables, both continuous and ordinal (interest and intent), I used the DWLS estimator in MPlus, WLSMV (Muthén & Muthén, 1998-2012).

Another concern is when data are missing in a larger data set. There are several options for missing data, the most common approach in the social sciences has been listwise deletion (Graham & Coffman, 2012). For example, students who did not complete the semester (and/or the post-survey) were not included in an analysis because we did not have their post-data. The problem with listwise deletion, particularly with SEM, is that this method removes information that is not missing at random. Because, for example, the reasons a student did not complete the course or the survey are probably due to specific reasons. This non-randomness of removal potentially impacts the overall score means, the strength of relationships between variables, and may result in estimation bias and a loss of statistical power (Graham & Coffman, 2012). However, where there are small sample sizes, listwise deletion may be the best option since other variables rely on a large data set to draw inferences about the missing data (Little, 2013). Multiple imputation (MI) is another approach to handling missing data, where it pulls from the data that does exist to estimate a plausible value. However, it is still based on the idea that the data are missing at random, rather than not-at-random (Graham & Coffman, 2012). In addition, it requires a large dataset from which to pull other possible variables (Little, 2013), if large percentages of a small data set are missing, it may rely too heavily on the data that are present, in addition MI can be problematic for ordinal variables (Graham & Coffman, 2012). Lastly, Full-Information Maximum Likelihood (FIML) is the most robust way of treating missing data in which there are multiple steps to impute the missing data pulling from the full dataset (Graham & Coffman, 2012). When dealing with missing data in this project, most of the analysis was based only on post-results, so there was no need for handling missing data as the subjects of focus were those students completing the course, and there were no missing data from the Spring 2013 (CC_S and $R1_S$) post-survey responses. However, in cases within the larger 2008-2013 GARNET dataset (CC_F and $R1_F$) where there were missing data, I employed the MPlus default for handling missing data, which is a form of FIML for the SEM measurement and structural analyses.

When creating a theoretical model for SEM analysis, there are decisions that need to be made about how individual items measure larger latent constructs. A researcher can accept the default created by the original designers of survey items. Alternatively, parceling is an option if there are similar items that may co-vary. Parceling is the process of bundling individual items and taking their average score as a manifest or observed variable that informs a larger latent construct. The benefit of parceling is that it maximizes the reliability, or the common-to-unique factor variance, increases the tendency toward multivariate normality, and creates a more parsimonious model (Little, Cunningham, Shahar & Widaman, 2002). The disadvantage is that it can increase the possibility of Type-I error by capitalizing on chance (Marsh et al., 2013). However, when the larger latent construct is of interest rather than individual items, and when parceling is considered carefully with theoretical considerations, it can greatly strengthen the overall model fit (Little et al., 2002; Little, Rhemtulla, Gibson & Schoemann, 2013). I chose to parcel the self-efficacy (from eight items to four) and math self-concept items (from ten items to five).

Measurement model decisions. Once the data have been analyzed and established into a measurement model, the next steps in decision making include how to assure that your model is appropriately identified, how to handle comparison of models across groups, and whether to employ a confirmatory or exploratory factor analysis with the data.

The identification of a given model is based on the number of correlations within the model as compared to the number of parameters, or the number of factor loadings and number of factor correlations. The number of correlations minus the number of parameters represents the degrees of freedom. In order to generate a meaningful measurement model, it must be a minimum of a just-identified model, where the number of parameters is equal to the number of correlations, and the degrees of freedom are zero. In other words, the number of variances and co-variances are equal to the things in the model a researcher would like to estimate. Much more meaningful comparisons occur when models are over-identified, or there are leftover degrees of freedom. Models are not possible when they are under-identified. In addition, you must have more than two latent constructs predicting one outcome in the final structural model in order to be more than just-identified (Byrne, 2012; Hoyle, 2012).

When comparing different groups, one of the most critical parts of the measurement model analysis is to establish multiple group invariance or equivalency in response to the items across these groups. Groups are defined by the researcher, and ones that represent different populations that may be expected to respond to survey items differently, such as individuals from different countries, different age groups of students, or students attending different types of institutions. Because these groups are independent of one another, I need to establish that the data are not invariant across the groups (Byrne, 2012). Jöreskog (1971) was the first to describe this process, by which he argued that if groups are invariant, they can be pooled for analysis. By examining the variances and co-variances across the groups, a researcher can determine if participants in different groups are responding to questions in a similar manner. This would indicate that both groups are interpreting the questions in the same way, thus making the items invariant to the groups. The traditional way to measure invariance is to test at three levels of increasing restriction to the model across the groups where configural tests the parameters across groups, which are then followed by a weak invariance, testing the measurement equivalence and the strong invariance, testing the structural equivalence. In this research, I was particularly interested if I could compare how R1 students responded to the survey items as compared to CC students. As a result, an invariance test was required. The challenge for this project was that by combining manifest and latent variables due to the properties of the data, the traditional measures of group invariance were not available to be tested (Byrne, 2012). As a result, my test for invariance was less conservative than the more traditional configural test with follow-ups. I chose to employ a test that compared groups invariance through an omnibus goodness-of-fit test, which essentially equates to the configural test, but does not allow for follow-up tests (Byrne, 2008). However, measurement and structural equivalence were tested across the latent variables (SE, CLB, & MSC).

The last decision prior to doing the factor analysis of a measurement model is determining if it will be a Confirmatory Factor Analysis (CFA) or an Exploratory Factor Analysis (EFA). Both factor analyses measure the variance and covariances between different measures or indicators. In a CFA, these variances are restricted to a parsimonious, theoretically-driven idea of what should and should not correlate. Whereas an EFA is a data-driven decision making process, which allows the researcher to free up all the variables and create a more parsimonious model based on the data itself (Brown & Moore, 2012). In SEM analysis, the CFA-EFA process can be somewhat fluid, where starting with a CFA of pre-defined theoretical constructs can change into an EFA by looking at the modification indices in the output from the analysis. At the measurement level, choosing a CFA or EFA is largely based on the goals of the researcher. If I were testing the individual items and whether they mapped onto a given construct, an EFA would be the logical process. The modification indices are what would be the source of information from which choices can be made about better fitting models based on variables that share variance with multiple latent constructs and/or other items (Byrne, 2012). I chose not to employ an EFA approach for my measurement models since the self-efficacy, control of learning beliefs, and math self-concept subscales are already well supported within the literature, so I used a CFA in which I examined the relationships between the constructs. In fact, using modification indices at the measurement model as an EFA could lead to a bad model that would be based on data rather than prior work (Byrne, 2012).

Structural model decisions. The last step in SEM analysis is the actual structural analysis. In this portion of modeling, a model is generated that predicts an outcome, which is directionally based. The analysis measures the loading on the predicted outcome by the different predicted measures based on the CFA/EFA measurement model. The final decisions for the structural model are how to best compare the best-fitting models, which are based on fit indices.

In SEM, the most traditionally reported fit index is the chi-squared, goodness-of-fit test. A chi-squared test determines how well your more parsimonious model fits relative to a completely unrestrained model with all parameters varying with one another (Bentler, 1990). Chi-squared tests are highly subject to poor measurement fit when the models have large sample sizes or are not multivariate normally distributed. As a result, most models in the social sciences will be underestimated applying a chi-squared test because they tend to either violate the multivariate normality assumption or contain large sample sizes (Yu, 2002; West, Taylor & Wu, 2012). As a result, different fit indices (both goodness and badness of fit) have emerged. There are absolute fit indices, such as

Standardized Root Mean square Residual (SRMR), which measures the parameters relative to the error variances relative to a weight matrix, and has been standardized to a 0-1 value, in which the closer to 0 the better (a badness of fit). It is sensitive to N, but does not penalize someone for a more complex model or greater number of parameters (West et al., 2012). For non-normally distributed data, particularly with ordinal data, the WRMR has the most consistent power with acceptable type I error across all sample sizes (Yu, 2002). An example of comparative fit is the Comparative Fit Index (CFI), which is robust to non-normality and small sample sizes, but it may be overly conservative with an N less than 200 (Bentler, 1990). It is generally encouraged that researchers report the chi-squared and several selected model fit indices to illustrate the overall fit of a model. Table 4.2 represents the indices I used for this project and the generally accepted cut-off values. It should be noted however, that rigorous cut-off values are less appropriate when data are non-normally distributed (Yuan & Chan, 2005), so any criteria for cut-offs with a non-normally distributed and small data sets must be measured with caution.

Table 4.2

Fit indices reported in this research with cut-off values and affordances and constraints of each.

Fit Index	Cutoff	Type of Fit	Reason for including
Chi-Square	< 0.05	Goodness	Standard practice to report, unreliable with smaller sample sizes[a]
RMSEA	< 0.06	Badness	Standard practice to report, tends to over reject with smaller sample sizes[a,b]
CFI	> 0.95-.96	Goodness	Least sensitive to N and robust to non-normality[a, b, c]
WRMR	< 0.95-1.0	Badness	Appropriate with ordinal data (low type-I error for non-normally distributed data)[b]
SRMR	< 0.08	Badness	Appropriate for continuous data, sensitive to N, but not to model complexity[a]

[a] West et al., 2012, [b] Yu, 2002 [c] Bentler, 1990

Ultimately, the fit indices are what are used to make decisions about how well a structural model fits the data. If a model does not fit the data, the researcher can decide to stop and end the research, or decide to do a post-hoc analysis using modification indices, similar to that mentioned in the measurement model of a CFA analysis moving into a an EFA. The same caution serves the researcher here, such that decisions that are still theoretically sound rather than simply relying on the data to inform these decisions. While I did not employ an EFA during the measurement model phase, I did choose to employ post-hoc analyses of structural models which resulted in some EFA based on the reality of the actual data rather than the idealized theoretically proposed model. However, all decisions were checked to assure they still met with the original intent of the proposed model.

Finally, when different estimators are used, the traditionally reported chi-squared tests may not be as reliable of a comparison. In this project, with the use of ordinal variables, interest and intent to persist, a different estimator was used. As a result, the chi-squared test comparison required a "difftest" result, in which a hypothesis test of nested models was used to obtain a reliable chi-squared value (Muthén & Muthén, 1998-2012). When comparing the two groups (R1 and CC), I tested the chi-squared tests as a modification of the standard test Δchi-squared = [chi-squared$_1$ –chi-squared$_2$], Δdf = [df$_1$-df$_2$]. Traditionally, in SEM, degrees of freedom are determined by the number of parameters in the model, however, in this case, since both models had the same number of parameters, it was not possible to obtain a traditional measure of Δdf. As a result, I modified the Δdf test to be = [n_1-n_2] (a more traditional measure of degrees of freedom in regression analysis; Cohen et al., 2003). Cutoff criterion for this test were $p > 0.05$ for ΔX^2 and < 0.01 for ΔCFI (Cheung & Rensvold, 2002), because I was testing the hypothesis that there was not a significant difference between these populations. When testing for invariance across the continuous variables only (SE, CLB, & MSC), the estimator used was MLR in MPlus, which is treated for non-normally distributed data. As a result, X^2 for each MLR model is reported, but are not reliable to be used for goodness-of-fit comparisons.

Using Structural Equation Modeling to Compare and Contrast Populations. In order to determine if there was a significantly positive relationship between geology expectancy, interest and students intent to persist in another geology class, I conducted a SEM analysis for both the $R1_F$ and CC_F population. When analyzing a model with a second order model, like expectancy as represented by sub-latent constructs of CLB & SE, a minimum of three constructs must be used in order to assure that the model is not just identified (Byrne, 2012). As a result, in this initial analysis, I treated CLB and SE as their own latent constructs rather than as a second order expectancy construct. Further analyses determined if expectancy was an appropriate assumption for these SEM models.

Ideally, the most appropriate analysis for determining the role of instructor in student's intent to persist should be multi-level modeling (MLV) in which instructor RTOP score is on one level and the student data are on a different level (Byrne, 2012). Some argue that a minimum of 100 instructors would be required to do a MLV analysis (Hox & Maas, 2001), but others have argued that stability and reliability can still be obtained with numbers closer to 50 (Cheung & Au, 2005). Even at 50, there were not enough instructor RTOP scores for any institution from the entire GARNET population to be able to do this analysis. As a result, I treated the different RTOP groups as ordinal variables as student-centered, transitional, and traditional (high to low) as defined by Budd et al., 2013. In order to test this variable, I separated students from different classrooms into different models comparing the high RTOP category with the medium RTOP category for the community college population and all RTOP categories for the R1 population. I only created two categories for the community college population because there was only one classroom that fit the low category. I ran each of the tests as an omnibus test similar to how I tested for invariance across groups. If these populations were different, they would fail the invariance test.

Lastly, I examined the role that math self-concept played in these models. Initially, I ran a CFA model with the continuous items only (SE, CLB, and MSC) to determine if a 2nd order factor of overall geology expectancy was a more appropriate fit for the data in either population. Based on these findings, I ran a final structural model using SE, CLB, MSC, and Interest in predicting intent to persist (Intent) for both populations (figure 4.4).

After all models were analyzed, I then tested for mediation and moderation. Baron and Kenny (1986) proposed a method to test for mediation and moderation of an outcome illustrated in figure 4.6 and 4.7. In mediation, if a variable, such as interest were removed from the model, and another variable, such as self-efficacy were to predict intent to persist, the original variable (e.g., interest) may serve as a mediator. A further test for this mediation is if those same variables were significantly related in a basic regression. So if self-efficacy were to predict intent to persist when interest was removed, but only co-varied with interest when interest was in the model, then it would be likely that interest served as a mediator.

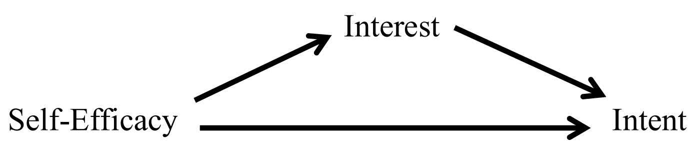

Figure 4.6. Adapted model of mediation from Baron & Kenny (1986)

In contrast, moderation influences a model in a much more subtle way. Figure 4.7 illustrates how moderation might influence variables within this model.

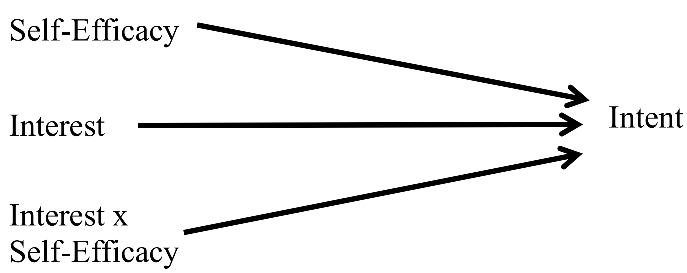

Figure 4.7. Adapted model of moderation from Baron & Kenny (1986)

In this case, if both variables self-efficacy and interest predicted intent to persist, but there was an interaction that influenced the strength or even the direction of the predictor, it may indicate a moderating relationship. Put another way, a moderating variable can impact the strength of an association either through dampening or enhancing an effect (Little, 2013).

Results

Characterizing the data

In order to compare the $R1_S$ and CC_S sample responses, chi-squared tests compared the interest and intent to persist variables. Results are reported in table 5.1.

Table 5.1

Results from Chi-squared tests comparing $R1_S$ and CC_S to the $R1_F$ and CC_F.

Variable	Institution	X^2	*df*	*p*	Cramér's V
Interest	R1	54.11	4	< 0.001	0.15
	CC	8.33	4	0.08	0.13
Intent	R1	24.53	4	< 0.001	0.10
	CC	3.61	4	0.46	0.08

Note: $R1_S$ and CC_S represent the Spring 2013 GARNET dataset, $R1_F$ and CC_F represent the full GARNET population

Table 5.1 illustrates that while there are statistically significantly differences between $R1_F$ and $R1_S$, they are not meaningful differences based on the Cramér's V effect size. Effect sizes less than 0.30 are considered to be small and less than 0.10 are inconsequential (Cohen, 1969). The sample sizes of the full GARNET data set for these analyses were 2,339 and 454 for the $R1_F$ and CC_F populations, respectively. After bootstrapping the larger population to calculate a t-value and standard deviation for an equivalent size population, t-test comparisons revealed minor differences in $R1_F$ and $R1_S$ and no difference between CC_F and CC_S. Results reported in table 5.2 illustrate that while there were statistically significant differences between $R1_F$ and $R1_S$, the differences were small as the effect size from Cohen's d illustrates.

Table 5.2.

Results from t-test comparing $R1_S$ and CC_S with bootstrapped population of $R1_F$ and CC_F.

Institution	Sample set	*N*	*M*	*sd*	*t*	*df*	*p*	*d*
R1	Bootstrap	167	60.91	13.21	3.24	165	0.001	-0.24
	Spring 13	166	63.96	12.13				
CC	Bootstrap	79	63.38	13.22	-0.27	77	0.79	-0.02
	Spring 13	78	63.09	15.06				

Note: $R1_S$ and CC_S represent the Spring 2013 GARNET sample, $R1_F$ and CC_F represent the full GARNET population

Item reliability tests determined if the math self-concept items could be appropriately used with this population. These resulted in highly reliable Cronbach alpha values ($\alpha = 0.941$; $\alpha_{R1S} = 0.946$; $\alpha_{CCS} = 0.930$) which were better than or the same reliability as the initially reported results of $\alpha = 0.93$ (Marsh, 1984).

Analysis of variance components of the CC_S and $R1_S$ demonstrated that between 83.3% and 97.1% of the variability in the expectancy scores was attributable to within student variability, as opposed to between institution/classrooms, and that between 93.1% and 95.1% of the variability in the math self-concept scores was attributable to within student variability, as opposed to between instructors. In addition, analysis of variance components demonstrated that between 98.6% and 99.4% of the variability in the interest scores was attributable to within student variability, as opposed to between instructor and that between 90.9% and 94.4% of the variability in intent to persist was attributable to within student variability, as opposed to between instructor/institution. All of this suggests that multilevel modeling would not provide much benefit. In addition, as reported in Budd et al., 2013, many of these introductory geology classrooms are similar in what is happening in these classrooms.

In examining the missing data for the CC_S and $R1_S$ sample, the range of students who completed both pre and post tests were 43%-100%. Other than the lowest completion percent (27), this range was well within the general range of responses within the entire GARNET data set for 2012-2013 collection year (29-94%, average 71% response rate). One classroom's data were thrown out from the CC_S dataset due to the large number of missing post-responses (73%) and the procedure for reminding faculty to administer the post-survey was not followed. As such it seemed to represent an outlier of extreme missing data and would likely not be representative of the larger data set, and could even possibly skew the results. In addition, all of the items analyzed for the SEM analyses were from post-semester responses only, as a result, this cross-sectional dataset prevented the need to handle a large degree of missing data. In SEM analysis, there were between 2 and 3 missing data patterns for the $R1_F$ population and between 1 and 2 missing data patterns for the CC_F population.

In examining the descriptive statistics for characterizing the general scores from student responses to the categories of expectancy, math self-concept, interest and intent to persist, there was a small to moderate negative skew to a number of the items. Table 5.3 provides a characterization of the data. The non-normality of these data were not extreme (Rhemtulla et al., 2012), but were considered when analyzing the data.

Table 5.3.

Descriptive statistics of the four major subscales used for this research at each institution.

Subscale item	Institution type	Mean	s.d.	Skewness	Kurtosis
Interest	R1	3.08	0.962	-0.625	-0.783
	CC	2.99	0.845	-0.903	0.647

Intent	R1	2.46	1.094	0.150	-1.282
	CC	2.37	0.982	0.200	-0.932
Expectancy	R1	63.96	12.13	-0.298	-0.475
	CC	62.92	15.00	-0.627	-0.255
Math Self-concept	R1	50.24	18.38	-0.200	-0.694
	CC	45.08	19.07	-0.101	-1.042

Note: These data are from the CC_S and $R1_S$ sample

In comparing the samples of $R1_S$ to CC_S for measurement invariance when using SEM, I conducted an omnibus test comparing chi-squared values and CFI values. Table 5.4 reports the values between these two samples.

Table 5.4

Measurement invariance omnibus test all variables.

Population	*N*	$X^{2\,a}$	*df*	CFI
R1	166	28.19	4	0.94
CC	78	25.34	4	0.94

Note: These tests are based on CFA that included self-efficacy, control of learning beliefs, math self-concept, interest and intent to persist variables
[a] X^2 is a report of the difftest result from MPlus software due to use of categorical and continuous variables.

Chi-squared difference test (X^2_{R1}- X^2_{CC}, N_{R1}-N_{CC}) revealed that $\Delta X^2 = 2.85$, ΔN (substituting for df) = 88, $p = 1.0$. The ΔCFI values = -0.006, which is within the accepted cutoff of 0.01 (Cheung & Rensvold, 2002). These results allowed me to make comparisons across institutional populations in a meaningful and consistent way.

In testing the continuous variables only, for a full invariance test, I tested for configural, weak and strong invariance. The results are reported in table 5.5. The test for invariance holds across all levels, so the sample of $R1_S$ and CC_S responses can be compared across groups. While the nested p value for the strong invariance test is less than the 0.05 cutoff, because it is still within the CFI < 0.01, which is a more reliable measure for small sample sizes, I found this to be an acceptable measure of invariance.

Table 5.5

Measurement invariance tests for continuous items

Test	X^2	df	nested p	CFI	ΔCFI
Configural	200.78	124		0.96	
Weak	214.34	134	0.19	0.96	0.002
Strong	233.15	144	0.04	0.95	0.005

Note: Each test is nested within the previous.

Characterizing the population

In order to characterize and compare $R1_S$ sample to the CC_S sample, a series of chi-squared analyses tested demographic differences. The first test comparing the proportion of sex represented in the sample (gender on the survey) revealed that there was no significant difference between the two groups (Pearson $X^2_{sex}(1, N = 245) = 1.76$, $p = 0.18$, $\Phi = 0.09$). There were 88 men and 79 women in the $R1_S$ data set and 34 and 44 men and women, respectively, in the CC_S dataset. In comparing the proportion of different ages, races, and choice of major, there were significant differences between these two samples (Pearson $X^2_{age}(3, N = 245) = 29.55$, $p < 0.001$, Cramérs V = 0.35; Pearson $X^2_{race\text{-}all}(8, N = 245) = 44.04$, $p < 0.001$; Pearson $X^2_{race\text{-}condensed}(1, N = 245) = 30.49$, $p < 0.001$, $\Phi = 0.35$; Pearson $X^2_{major}(3, N = 245) = 18.54$, $p < 0.001$, Cramérs V = 0.28). Results from these comparisons are visually presented as comparisons in figures 5.1-5.3.

Students attending CC were older than those at a R1. The proportion of students over the age of 22 in a CC classroom was 0.33 relative to 0.11 for a R1 student. The probability of a student over the age of 22 attending a CC as 3.0 times as likely than at a R1.

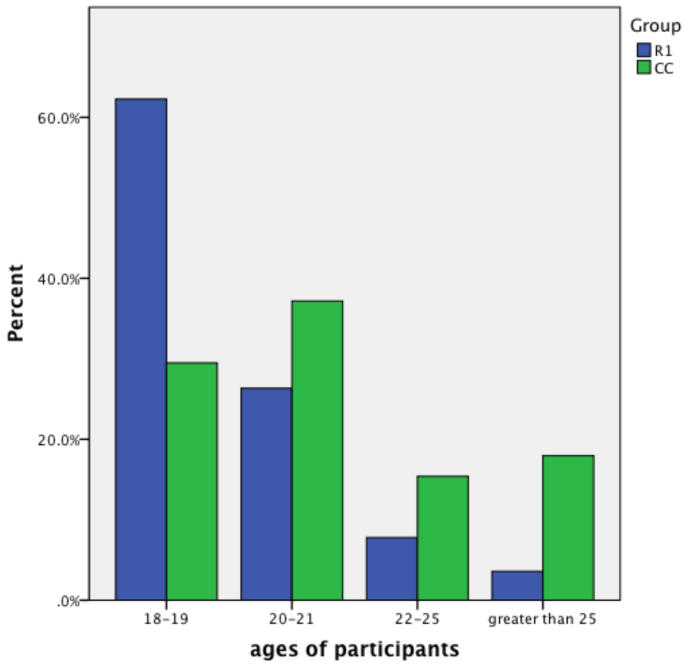

Figure 5.1. Students ages represented at both institutions reported as percentages. CC_S students are generally older than their $R1_S$ counterparts in this study.

Students in an introductory geology classroom at a R1 were more likely (0.43) to be a declared a STEM major (Earth Science or any other STEM) than at a CC (0.16). The probability of a STEM major in a R1 introductory geology classroom was 2.7 times more likely than at a CC. In addition, CC students were less certain about their major overall. The proportion of undecided majors at a CC was 0.5 versus 0.29 for R1 students in introductory geology classrooms. The probability of an undeclared major at a CC was 1.7 times more likely than at a R1.

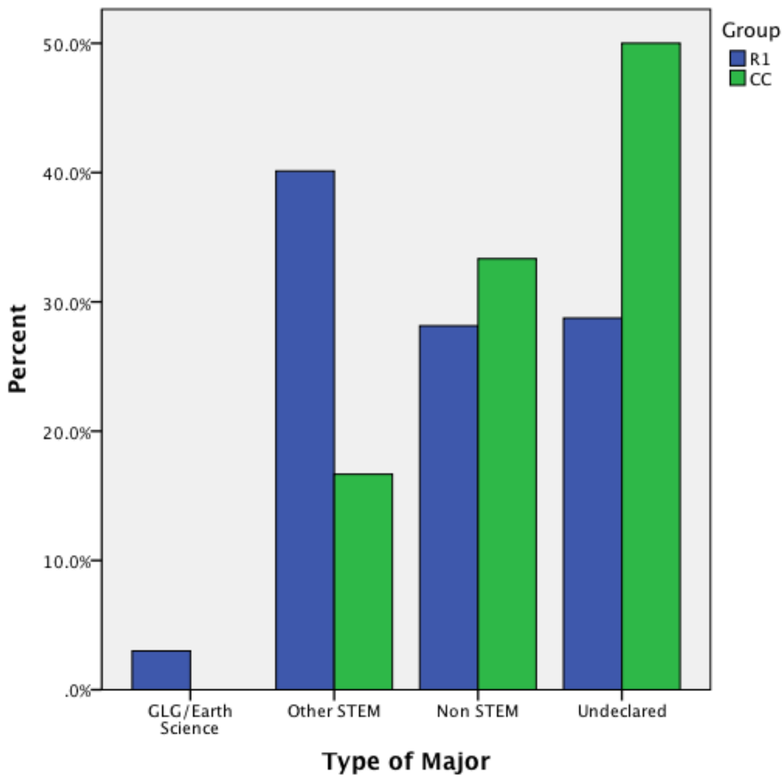

Figure 5.2. Students at the community college are more likely to be undeclared or non-stem relative to their R1 counterparts. R1 students are more likely to be declared STEM majors.

Because race had several occurrences of fewer than 5 cases, I chose to combine the non-white race into one category for a more accurate chi-square test. In that analysis, the proportion of nonwhite students at R1's versus CC's was 0.14 and 0.46, respectively. The probability of a non-white student attending a CC was 3.3 more times as likely (0.46/0.14) than at a R1.

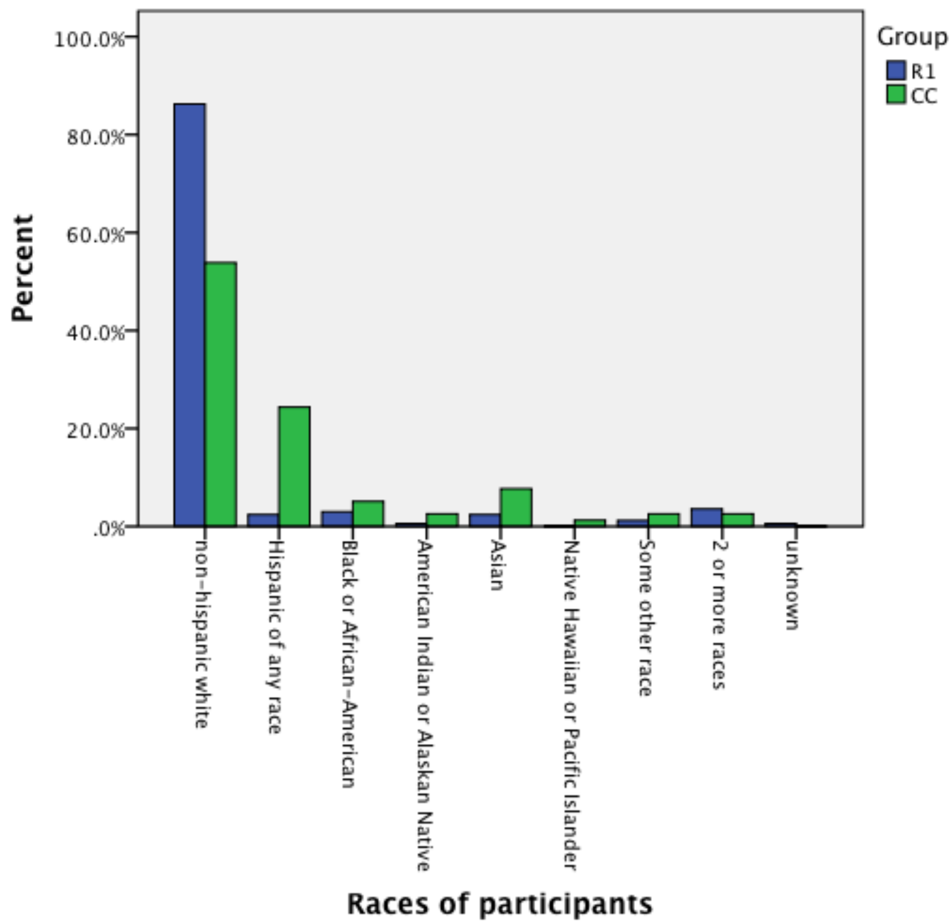

Figure 5.3. The range of races for participants in this study. While most of the participants are white from both institutions, students from community colleges are more likely to be non-white.

Comparisons of the nominal data of previous science and math courses are reported in table 5.6 (homogeneity of variance is not assumed due to some of the results as skewed and/or kurtotic, table 5.3). It appears that high school graduation requirements assure equal amount of science courses for all students, however, community college students had completed a significantly fewer number of math courses entering into college, and were more likely to be in one of their first college level science courses.

Table 5.6

Comparison of previous science and math courses taken by students enrolled at different institutions.

Courses	Institution	Mean	s.d.	*t*	*p*	*df*	*d*
College science	R1 CC	1.59 0.95	1.33 1.13	3.89	0.0001	176.5	0.59
High School math	R1 CC	3.64 3.36	0.80 0.76	2.68	0.008	158.5	0.43
High school science	R1 CC	3.44 3.33	1.28 1.53	0.55	0.59	130.4	0.096
College math	R1 CC	1.65 1.74	1.24 1.34	-0.50	0.62	150.6	0.081

Note: College science and High school math are statistically significant when applying Holm's Bonferonni test (Holm, 1979).

Comparing reasons students enrolled in their introductory geology courses, the overwhelming reason for enrollment for all students was to satisfy a general education requirement, which agrees with previous findings (Gilbert et al., 2012). Figure 5.4 illustrates the responses to each of the different categories. Students were able to select more than one response, so the sums are greater than the total N. Results are reported in table 5.7. The proportion of students who were more likely to enroll as a general education requirement at a R1 versus a CC was 0.70 versus 0.84, respectively. As a result, the probability of a CC student enrolling in an introductory geology class due to a general education requirement was 1.21 times more likely than a R1 student. In addition, the probability that students who anticipated that the class would be easier (than other general education requirements) at a R1 than a CC was 1.5 times more likely. However, the proportion of students at a R1 who were enrolling because they were more interested was higher at a R1 than at a CC (0.39 versus 0.24, respectively). As a result, the probability of a student interested in the topic was 1.6 times more likely than in a CC classroom. Both of these results have implications for student motivation and incoming expectancies and valuing of the course. A R1 student had a higher probability of capitalizing on social capital by entering in the course based on a recommendation (0.35 versus 0.19 for a CC student). The probability of a R1 student receiving a recommendation for taking the course was 1.8 times as likely than for a CC student. Lastly, it should be noted that students may have misinterpreted the option of "required for a major/minor," when examining the percent responses to choosing the course for a general education requirement and required for a major/minor, the total percent adds to more than 100% for both the R1 and CC response sets. Ideally, these two options should be an either/or situation, so it should not add to more than 100% responses. It is possible that some students were interpreting a requirement for graduation (general education requirements) as part of the requirement for their major.

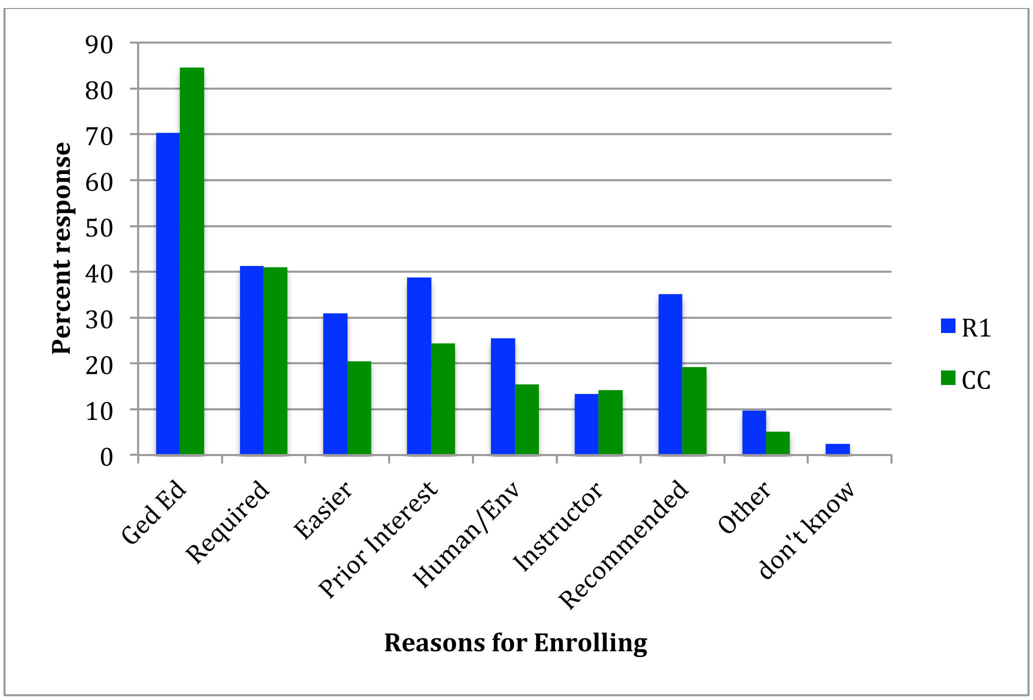

Figure 5.4. Reasons students selected to enroll in the course, most students are enrolled for general education requirements, but also have other reasons for enrolling.

Table 5.7

Reasons for students enrolling in the course.

Reason for enrolling	Institution[a]	N	proportion	X^2	df	p	ϕ
General Education	R1	116	0.70	5.77	1	0.02	0.15
	CC	66	0.85				
Required for Major/Minor	R1	68	0.41	0.001	1	0.98	-0.002
	CC	32	0.41				
Prior Interest	R1	64	0.39	5.05	1	0.03	-0.14
	CC	19	0.24				
Recommendation	R1	58	0.35	6.39	1	0.01	-0.16
	CC	15	0.19				
Easier	R1	51	0.31	2.87	1	0.09	-0.11
	CC	16	0.21				
Human-Env Interactions	R1	42	0.15	3.11	1	0.08	-0.11
	CC	12	0.15				
Instructor	R1	22	0.13	0.03	1	0.88	0.01
	CC	11	0.14				
Other	R1	16	0.10	1.46	1	0.23	-0.08
	CC	4	0.05				
Do not know	R1	4	0.02	1.92	1	0.17	-0.09
	CC	0	0.00				

Note: Question and stem options are in Appendix A, students could select multiple options.
[a]N for R1 = 165, CC = 78.

In comparing the student responses from different institutions for expectancy, math self-concept, interest and intent to persist there were significant differences between the CC_S and $R1_S$ sample (all the results assume non homogeneity of variance based on results from table 5.3). An independent t-test was used to determine if there were differences between $R1_S$ and CC_S responses for expectancy and math self-concept scores. There was no difference between the two samples for expectancy scores ($t_{\text{expectancy}} = 0.53$ (126.01), $p = 0.60$, $d = 0.10$), but there was a statistically significant difference in math self-concept between these two samples ($t_{\text{math self-concept}} = 2.55$ (142.50), $p = 0.01$, $d = 0.43$) with a moderate effect size. A chi-squared test was used to determine if there were differences between the two samples for interest and intent to persist scores. There was no difference in intent to persist (X^2_{intent} = 3.81 (*df* = 3, *N* = 244), *p* = 0.28, Cramér's V = 0.13, but there was a statistically significant difference in interest scores between the $R1_S$ and CC_S samples (X^2_{interest} = 22.79 (*df* =3, *N* = 244), *p* < 0.001, Cramér's V = 0.31) with a moderate effect size. Based on means and standard deviations for these populations (table 5.3), for both interest and math self-concept, the R1 sample had higher scores relative to their CC counterparts.

In order to compare the different items proposed in the structural equation model, a bivariate regression analysis was run using Spearman rho for ordinal values and Pearson product-moment correlation for values that only involved continuous variables. Based on the previous analysis of normality, the assumptions of these analyses were violated, however, it is a first pass at determining relationships. Results are reported in table 5.8. While intent to persist was not directly related to math self-concept in either population, it was related to other subscales, and as such merits a more detailed examination of how these different scales work together to predict intent to persist.

Table 5.8

Bivariate correlations among items used for SEM analysis with R1[a] and CC[b] students (in bold)

	Intent to Persist	Interest	Control of Learning Beliefs (CLB)	Self-Efficacy (SE)	Math Self-Concept (MSC)
Intent	---	**0.54*** **	**0.18**	**0.34** **	**0.04**
Interest	0.40***	---	**0.18**	**0.36** **	**0.08**
CLB	0.19*	0.25**	---	**0.71*** **	**0.22**
SE	0.28***	0.48**	0.64***	---	**0.32** **
MSC	0.04	0.20*	0.10	0.27**	---

[a] N = 166 ($R1_S$), [b] N = 78 (CC_S)
* = p < 0.05, ** = p < 0.01, *** = p < 0.001

SEM Analysis

Prior to SEM analysis, I initially ran the variables from the CC_S and $R1_S$ samples in a measurement model CFA to examine the relationships of the items and chose to parcel the self-efficacy items and the math self-concept items. I chose theoretically logical pairings, and for those that didn't have an obvious pairing, I chose them based on the modification indices, and paired the low with the high (Little et al., 2012). Table 5.9 illustrates the pairing and indicates which were parceled based on content and which where parceled based on modification indices.

Table 5.9

Parceling of subscale items for SEM analysis

Subscale	Statements	Parceled item
Self-Efficacy	I believe I will receive an excellent grade in this class I expect to do well in this class	1 6 [a]
	I'm certain I can understand the most difficult material presented in readings for this course I'm confident I can understand the most complex material presented by the instructor in this course	2 4 [a]
	I'm confident I can understand the basic concepts taught in this course I'm certain I can master the skills being taught in this class	3 [b] 7
	I'm confident I can do an excellent job on the assignments and test in this course Considering the difficulty of this course, the teacher, and my skills, I think I will do well in this course.	5 [b] 8
Math Self-Concept	I find that mathematical problems interesting and challenging I have never been very excited about math	1 10 [a]
	I have hesitated to take courses that involve	2

math	3 [a]
I have generally done better in math courses than other courses	
Math makes me feel inadequate	4
At school, my friends always come to me for help in math	9 [a]
I am quite good at math	5
I have always done well in math	7 [a]
I have trouble understanding anything that is based upon math	6
I never do well on tests that require math	8 [b]

[a] parceled based on theoretical similarities, [b] parceled based on modification indices

In comparing the relationship between SE, CLB, interest and students intent to persist in another geology class, I conducted a SEM using the WLSMV estimator. Because this initial analysis did not contain math self-concept as an item, I used the CC_F and $R1_F$ populations. Figures 5.5 and 5.6 illustrate the models from this analysis for CC_F and $R1_F$. In all models, variance, co-variances and pathways are all values that are significant at $p < 0.001$ unless otherwise noted. The initial structural analysis revealed that $X^2_{\text{difftest}} = 205.43$, $df = 2$, $p = 0.00$; $N = 536$; RMSEA = 0.09 (0.08-0.10); CFI = 0.88; WRMR = 0.71. Since these values generally did not meet the cutoff criterion (table 4.2), a post hoc analysis revealed a shared error variance between two variables in control of learning beliefs increased the overall fit of the model, $X^2_{\text{difftest}} = 253.75$, $df = 3$, $p = 0.00$; $N = 536$; RMSEA = 0.06 (0.04-0.07); CFI = 0.95; WRMR = 0.50. Since this model was right at the cutoff criteria, I proceeded to share error variance with two items in the self-efficacy subscale, which was the next recommended change in the modification indices. After this last test, the final model produced a strong fit, $X^2_{\text{difftest}} = 206.60$, $df = 2$, $p = 0.00$; $N = 536$; RMSEA = 0.04 (0.02-0.06); CFI = 0.98; WRMR = 0.39.

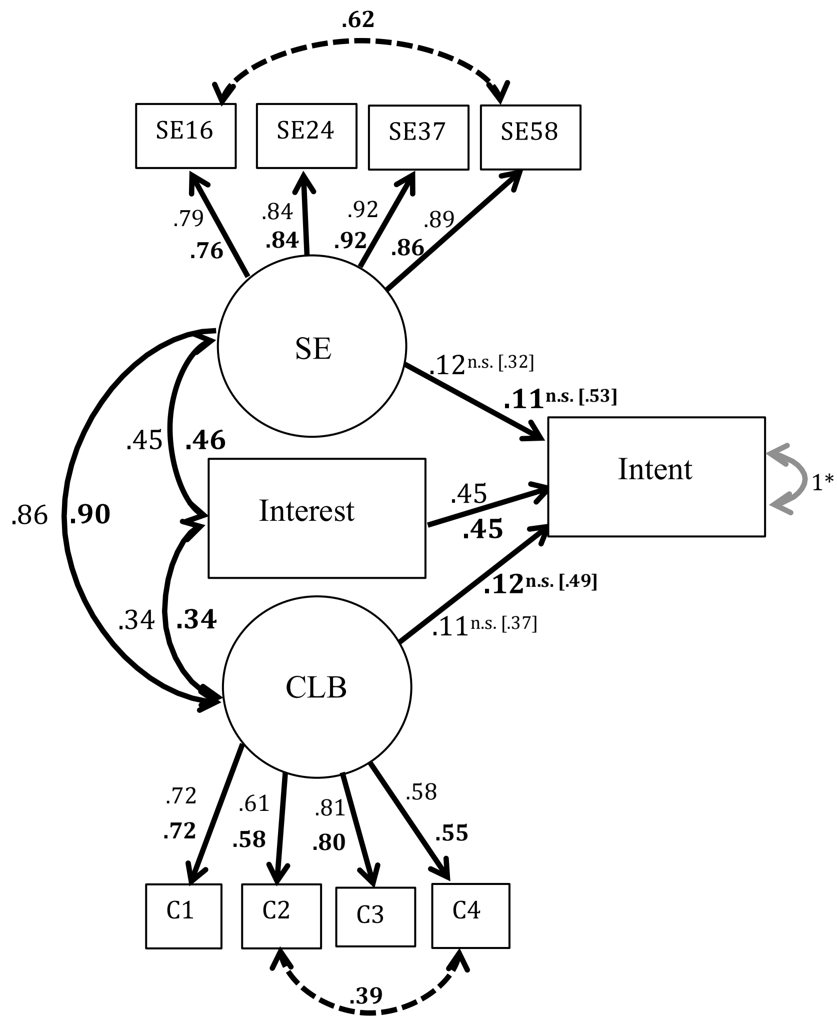

Figure 5.5. Structural model for CC_F responses predicting intent to persist based on self-efficacy (SE), control of learning beliefs (CLB) and interest.
Note: Post hoc analysis additional co-variances are indicated by dashed lines. New values are bolded. The gray arrow on intent indicates a fixed construct variance of 1.0, all construct variables were fixed at 1.0.
n.s. = not significant, p values in brackets.

The first model for the $R1_F$ population also did not meet the cutoff criterion, $X^2_{\text{difftest}} = 988.33$, $df = 2$, $p = 0.00$; $N = 2505$; RMSEA = 0.09 (0.08-0.09); CFI = 0.89; WRMR = 1.35. As a result, I also did a post-hoc analysis for this model, however, in order for the models to be comparable, after examining the modification indices, I chose to co-vary the same subscales without creating a secondary model. The final model produced a strong fit, X^2_{difftest} = 999.56, df =2, p = 0.00; N = 2505; RMSEA = 0.04 (0.03-0.04); CFI = 0.98; WRMR = 0.58.

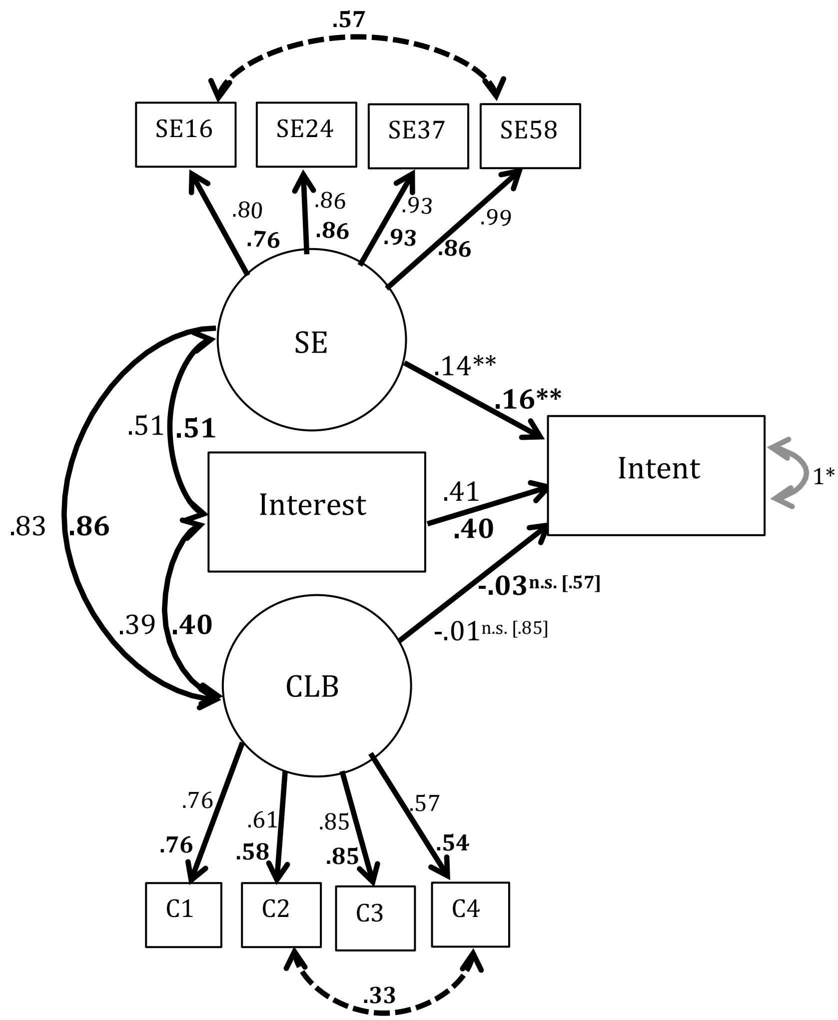

Figure 5.6. Structural model for $R1_F$ responses predicting intent to persist based on self-efficacy (SE), control of learning beliefs (CLB) and interest.
Note: Post hoc analysis additional co-variances are indicated by dashed lines. New values are bolded.
n.s. = not significant, p value provided in brackets, ** = p < 0.01.

Both of these models, once adjusted for shared error variance within self-efficacy and control of learning belief items, predicted intent. Control of learning beliefs did not predict intent to persist in either of these models. Whereas, self-efficacy was a predictor of intent for the R1 population only. Interest was the strongest predictor for success with both populations, predicting at least 40% of the variance in intent to persist.

In comparing instructor pedagogy, I compared high vs. medium RTOP categories for the CC_F population and all categories for the $R1_F$ population in omnibus tests similar to an invariance test. The results for these analyses are reported in table 5.10. These results indicate that there was likely a difference between the RTOP classrooms as the ΔX^2 values did not indicate a difference, but the CFI comparisons do. Comparing the CC classrooms, $\Delta X^2 = 17.2$, ΔN (substituting for df) = 71, p =1.0, but ΔCFI = -0.08, which was not within the accepted cutoff value of 0.01. Because the ΔX^2 is less reliable, I looked to the ΔCFI for a more reliable measure of comparison across classrooms when there was disagreement. As a result, it appears that there was a difference between these two populations. Similar comparisons existed at the $R1_F$ classroom comparisons, where $\Delta X^2_{(high\text{-}middle)} = -77.65$, $\Delta N = -314$, p =1.0, and ΔCFI = 0.08; $\Delta X^2_{(middle\text{-}low)} = 111.84$, $\Delta N = 252$, p =1.0, and ΔCFI = -0.07; and $\Delta X^2_{(high\text{-}low)} = 34.19$, $\Delta N = -62$, p =0.998, and ΔCFI = 0.01. These results indicated that there were differences between the classrooms, although the differences between the high and the low were minimal, since they were right at the CFI cutoff value of 0.01.

Table 5.10

Results of CFA comparisons between different RTOP classrooms.

Institution	RTOP	$X^{2\,a}$	df	N	CFI
	High	469.95	3	686	0.94
R1	Middle	547.60	3	1000	0.86
	Low	435.76	3	748	0.93
CC	High	153.57	3	286	0.85

	Middle	136.37	3	215	0.93

Note: Separation of categories is based on categories established by Budd et al., 2013 where a low RTOP represents a traditional classroom (RTOP < 30), middle RTOP represents a transitional classroom (RTOP 30-50), and high RTOP represents a student-centered classroom (RTOP > 50).
[a] Results are reported as the chi-squared difftest from MPlus due to the WLSMV estimator used for categorical variables.

When comparing the SEM models for these different classrooms, a nested chi-squared comparison revealed that, again, there were differences in these populations. However, none of the originally proposed models was a strong predictor of intent to persist. None of the models were within the accepted cut off values, as revealed in table 5.11. Post-hoc analysis revealed that when the same items in control in learning beliefs and self-efficacy co-varied as from the first models (figures 5.5 and 5.6), these models became significant (figures 5.7-5.11). Figures 5.7 and 5.8 represent the CC_F population, and figures 5.9-5.11, the $R1_F$ population.

Table 5.11

SEM regression results for different RTOP ranked classrooms in both original analyses and post-hoc (ph) results.

Institution	RTOP	$X^{2\,a}$	df	N	RMSEA	CFI	WRMR
R1	High	357.19	3	686	0.08	0.92	0.71
	High ph	282.11	2	686	0.03	0.99	0.39
	Middle	481.55	3	1000	0.10	0.84	1.04
	Middle ph	390.71	2	1000	0.05	0.97	0.52
	Low	382.09	3	748	0.08	0.91	0.71
	Low ph	306.42	2	748	0.03	0.99	0.37
CC	High	127.56	3	286	0.10	0.83	0.65
	High ph	100.57	2	286	0.06	0.95	0.39
	Middle	115.30	3	215	0.07	0.92	0.42
	Middle ph	89.75	2	215	0.04	0.98	0.30

[a] Results are reported as the chi-squared difftest from MPlus due to the WLSMV estimator used for categorical variables.

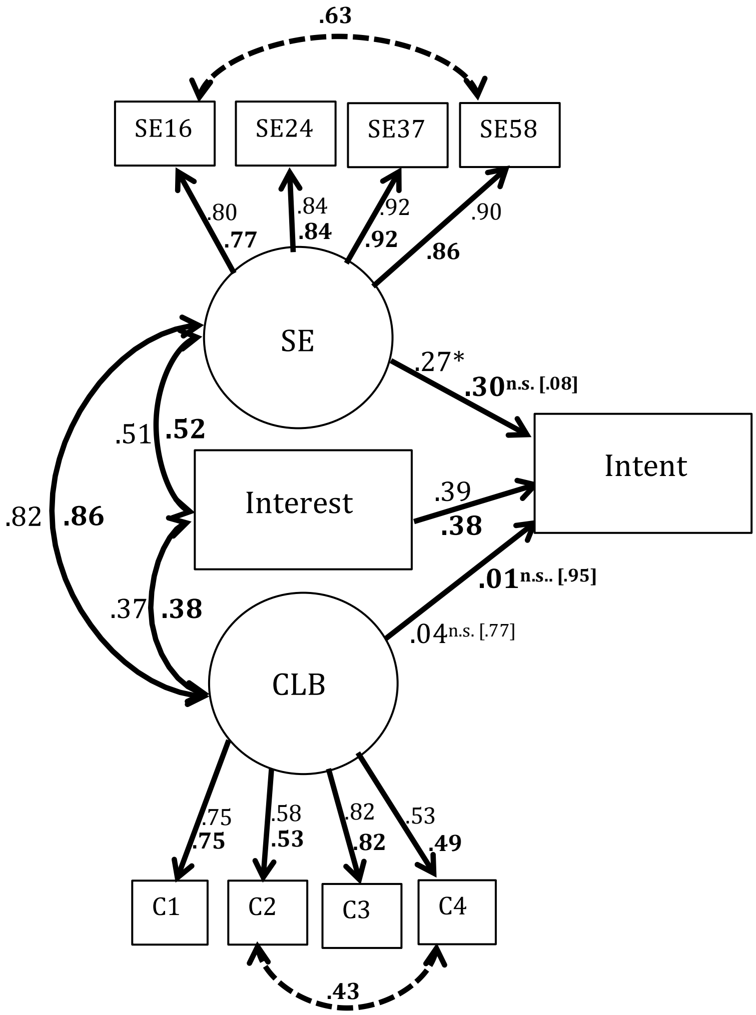

Figure 5.7. SEM for high RTOP CC_F classrooms.
Note: Post hoc analysis additional co-variances are indicated by dashed lines. New values are bolded. While not indicated on the diagram, construct variance was fixed to 1.0 for all construct variables.
n.s. = not significant, p values in brackets, * = p < 0.5.

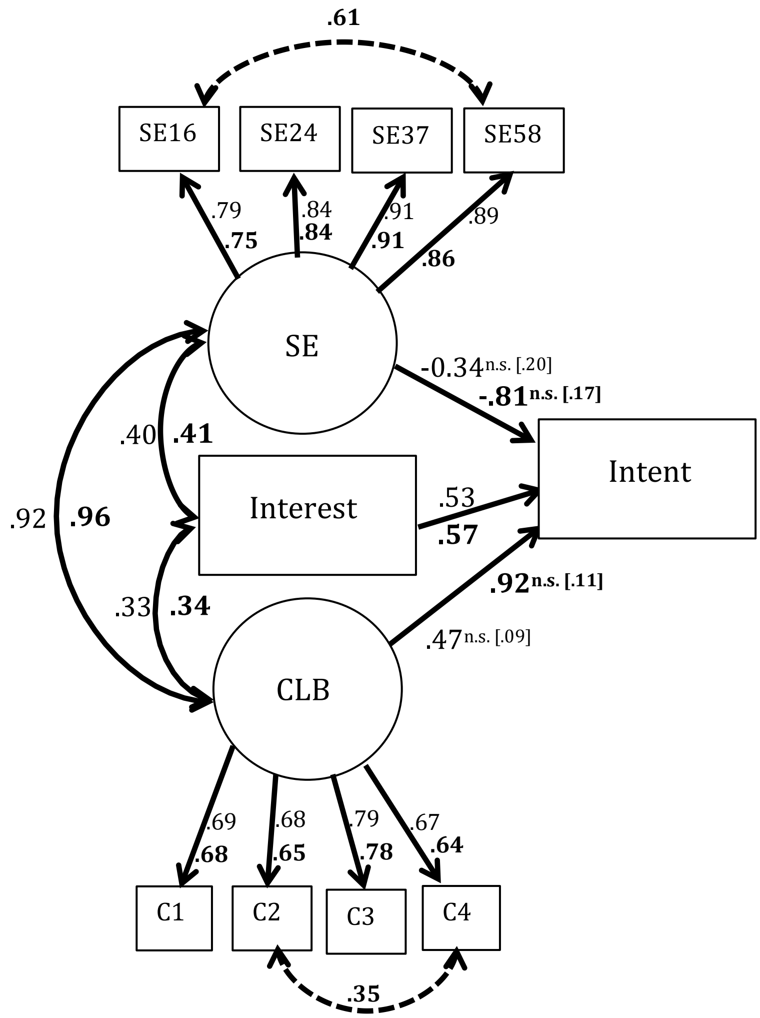

Figure 5.8. SEM for middle scoring RTOP CC_F classrooms.
Note: Post hoc analysis additional co-variances are indicated by dashed lines. New values are bolded.
n.s. = not significant, p values in brackets.

For both models at the community college (figures 5.7 & 5.8), interest continued to be the only predictor of intent to persist. However the % of variance that interest predicted in intent to persist varied between these two models, where the middle scoring RTOP classrooms had a higher percent explained than the high RTOP classrooms.

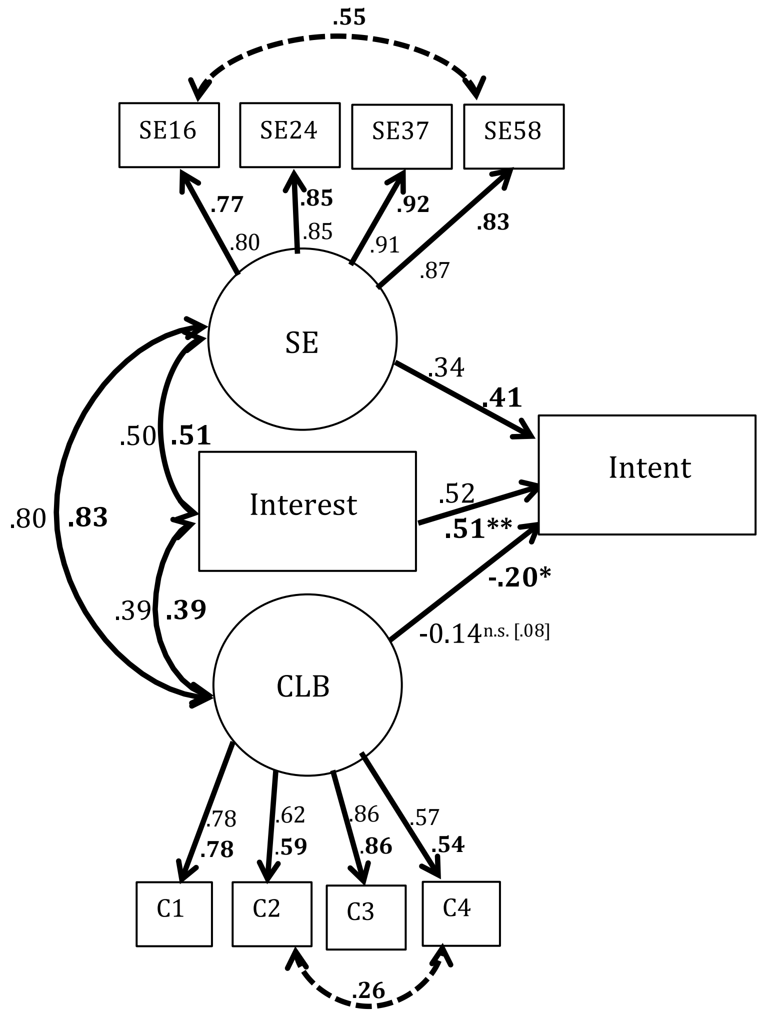

Figure 5.9. SEM model for high scoring RTOP $R1_F$ classrooms.
Note: Post hoc analysis additional co-variances are indicated by dashed lines. New values are bolded.
n.s. = not significant, p values in brackets, * = p < 0.5, ** = p < 0.01.

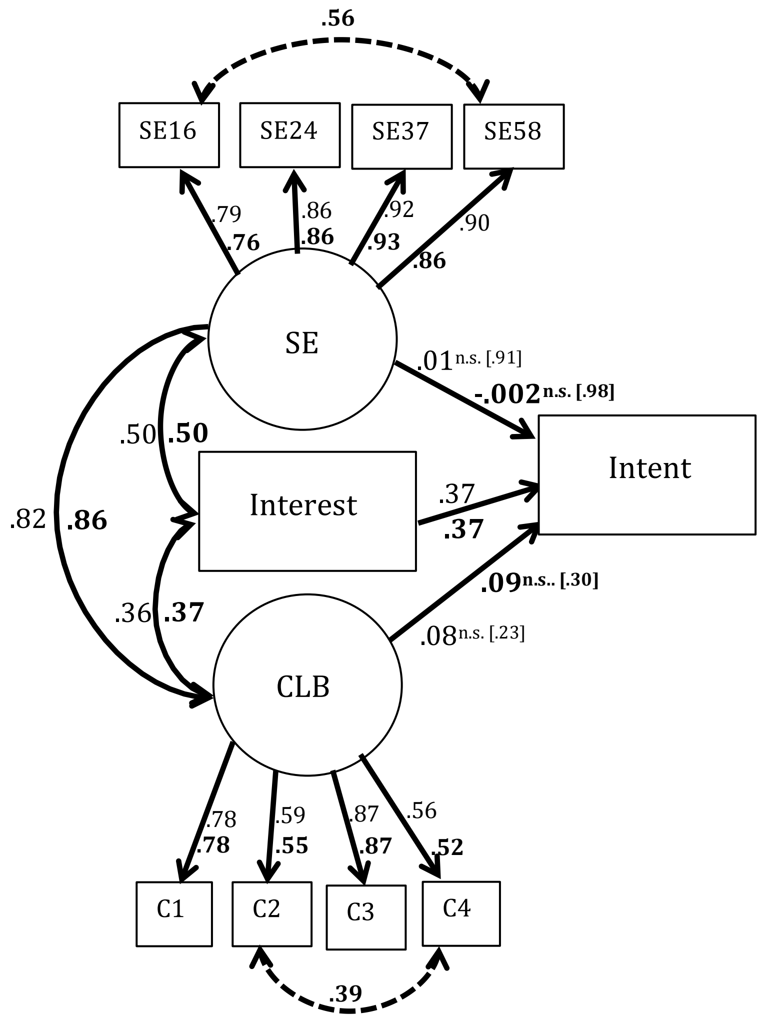

Figure 5.10. SEM for middle scoring RTOP $R1_F$ classrooms.
Note: Post hoc analysis additional co-variances are indicated by dashed lines. New values are bolded.
n.s. = not significant, p values in brackets.

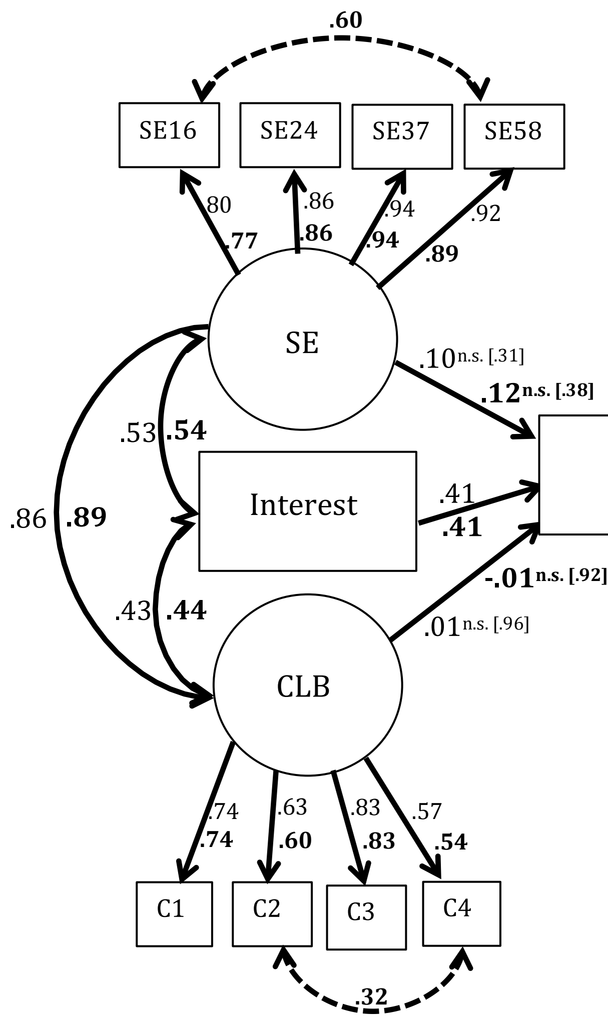

Figure 5.11. SEM for low scoring RTOP $R1_F$ classrooms.
Note: Post hoc analysis additional co-variances are indicated by dashed lines. New values are bolded.
n.s. = not significant, p values in brackets.

In each of these models, interest consistently predicted intent to persist. However, at R1 institutions, in high RTOP scoring classrooms only, self-efficacy also directly predicted intent to persist and control of learning beliefs negatively predicted intent to persist (figure 5.7). Other than high RTOP classrooms in R1 institutions, as the classroom became more teacher-centered, interest became a stronger predictor of intent to persist, which would indicate that students would need to have a strong interest if they were not engaged in the classroom to want to persist. The one exception, high RTOP classrooms at the R1 (figure 5.7), had many different variables that contributed, which lessons the impact that interest alone would need to predict.

In order to determine if CLB, SE, and MSC should be loaded as a second order factor of geology expectancy, I ran a CFA with just the continuous variables on their own in order to compare to the second order factor model. Results for $R1_S$ and CC_S are below in table 5.12 and in figures 5.12 and 5.13. When running the 2^{nd} order factor model, the self-efficacy factor loaded with a negative residual variance, which resulted in an impossible model. This held consistent even in post-hoc analyses. As a result, there was no evidence that a second order factor model would strengthen the results of the model. As a result, in the final model, they were treated as separate latent constructs. However, it should be noted that self-efficacy and control of learning beliefs consistently co-vary to a very high degree (ranges from 83-96% in all models analyzed), and as a result, the previous assumption for testing t-tests of self-efficacy and control of learning beliefs as a greater expectancy construct was appropriate, it is just not possible to test a SEM with only two latent constructs on a single second order factor, as the model would be just identified which would not change the interpretation of individual models (Byrne, 2012). However, the CFA model illustrated a strong fit for these variables.

Table 5.12

CFA results for continuous variables of Self-Efficacy, Math Self-Concept and Control of Learning Beliefs.

Institution	N	$X^{2\,a}$	*df*	*p*	RMSEA	CFI	SRMR
R1	166	122.87	62	0.000	0.08	0.95	0.05
CC	78	91.28	62	0.009	0.08	0.95	0.07

[a] X^2 values are not modified based on non-normality of the data, may not be reliable

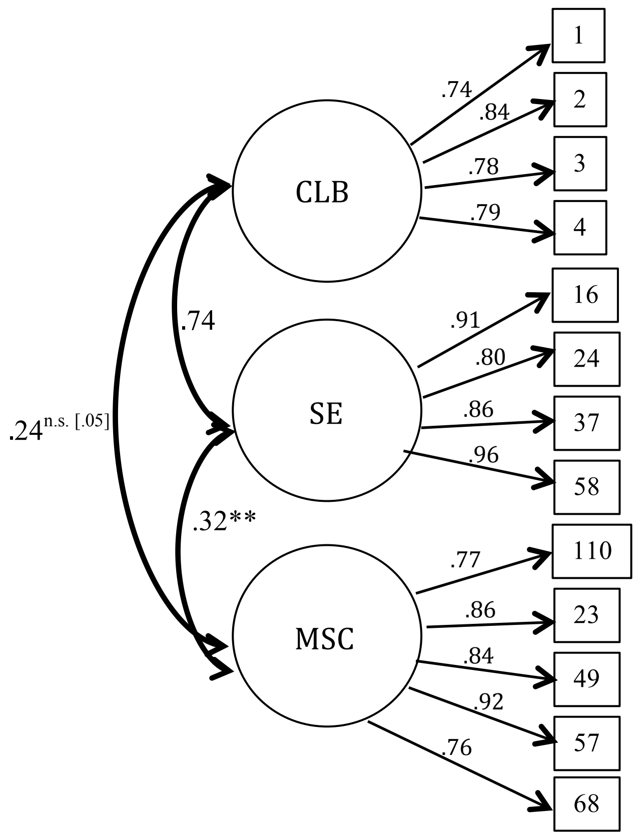

Figure 5.12. CFA model for CC_S sample of just continuous items.
Note: Unless otherwise noted, all variances and co-variances are p < 0.001
** p < 0.01, n.s. = not significant, p value in brackets.

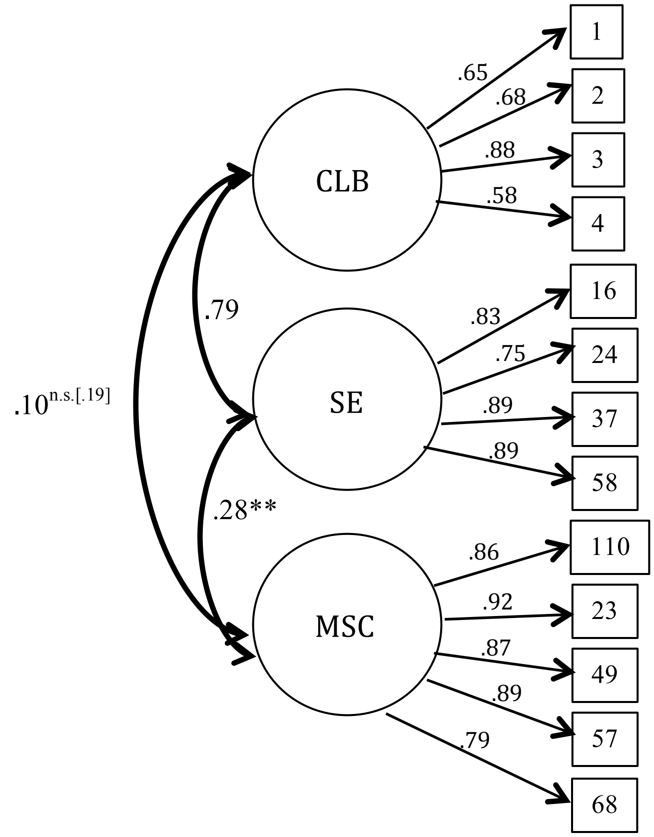

Figure 5.13. CFA model for $R1_S$ sample of just continuous items.
Note: Unless otherwise noted, all variances and co-variances are $p < 0.001$
** = $p < 0.01$, n.s. = not significant, p value in brackets.

In comparing the final proposed model, I did a SEM that included math self-concept. Results are reported in table 5.13 and in figures 5.14 and 5.15. Neither of the original models were statistically significant. As a result, a post-hoc, EFA analysis was done to determine the best-fit model for the data in each of these populations. The CC_S model did not have any possible modifications, it was already as complete of a model as presented, however, a post-hoc analysis of $R1_S$ was possible. The post hoc analysis of this model revealed that the best alteration for the data were if the control of learning beliefs shared variance with one item in math self-concept, both of which were items that include a control of learning aspect to the statements (“I have trouble understanding anything that is based upon math” and “I never do well on tests that require math”). Because the math self-concept items were only collected in the spring semester, it is possible that the CC_S model is simply underpowered, as it is right at the CFI cut off value, and the RMSEA and WRMR values are within acceptable range. Because SEM analyses are subject to variation based on sample size and normality, it is ultimately up to the researcher to determine the acceptability of a model (Byrne, 2012), as such, I think that the CC_S model with the math self-concept variable included is likely a relatively good representation of the student’s intent to persist at community colleges. In comparing the two original models of $R1_S$ and CC_S, the ΔCFI = -0.02, and the $\Delta X^2 = 5.9$, ΔN = 88, p = 1.0, which would indicate that these models are not invariant, which indicates that how math self-concept plays a role in these models differs.

Table 5.13

SEM regression results for the full model of Interest, Self-Efficacy, Math Self-Concept and Control of Learning Beliefs in predicting intent to persist.

Institution	*N*	X^{2} [a]	*df*	*p*	RMSEA	CFI	WRMR
R1	166	17.91	3	0.001	0.05	0.93	0.56
R1-post hoc	166	14.89	3	0.001	0.03	0.97	0.46
CC	78	12.01	3	0.007	0.04	0.95	0.41

[a] chi-squared test results from “difftest” in MPlus software calculation

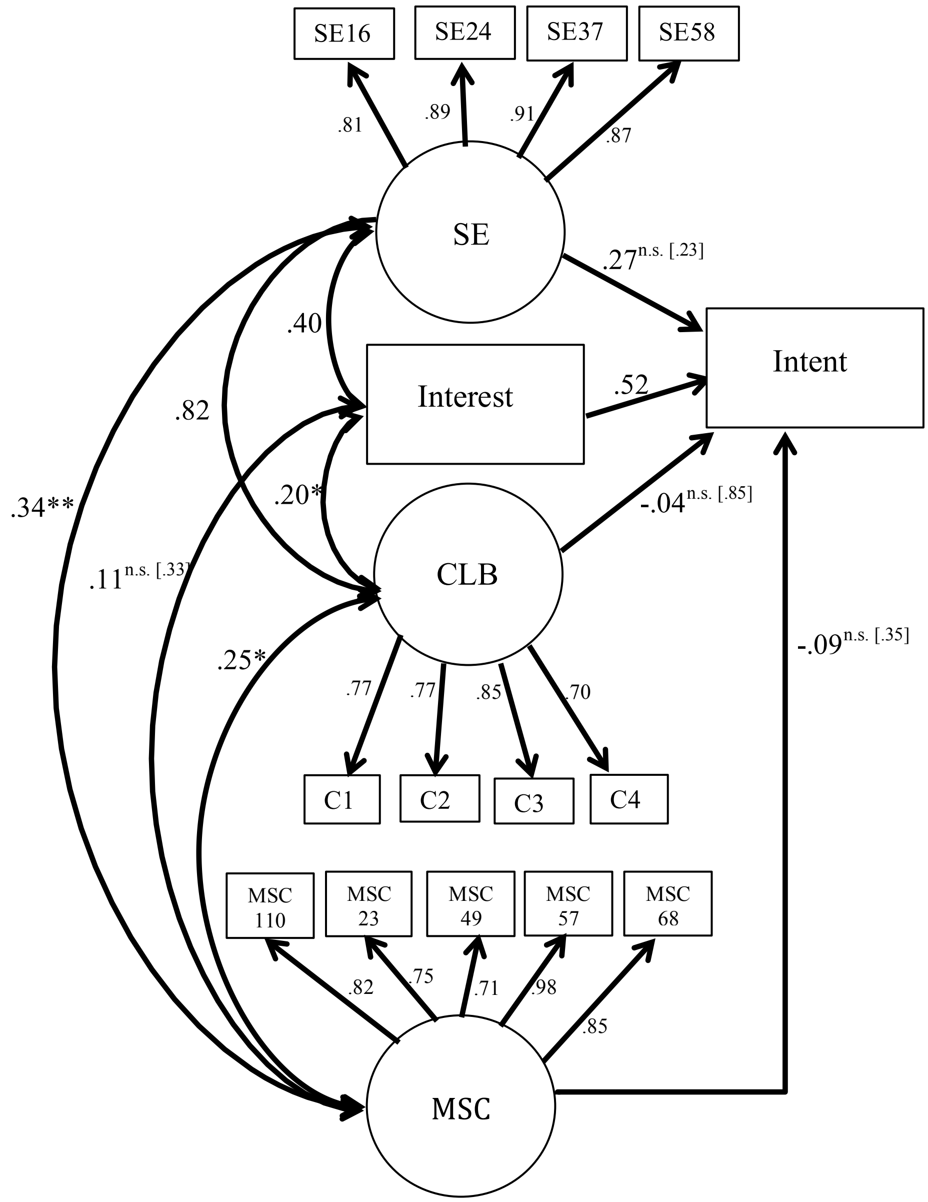

Figure 5.14. Final SEM for CC_S classrooms.
n.s. = not significant, p values in brackets, * = $p < 0.05$, ** = $p < 0.01$.

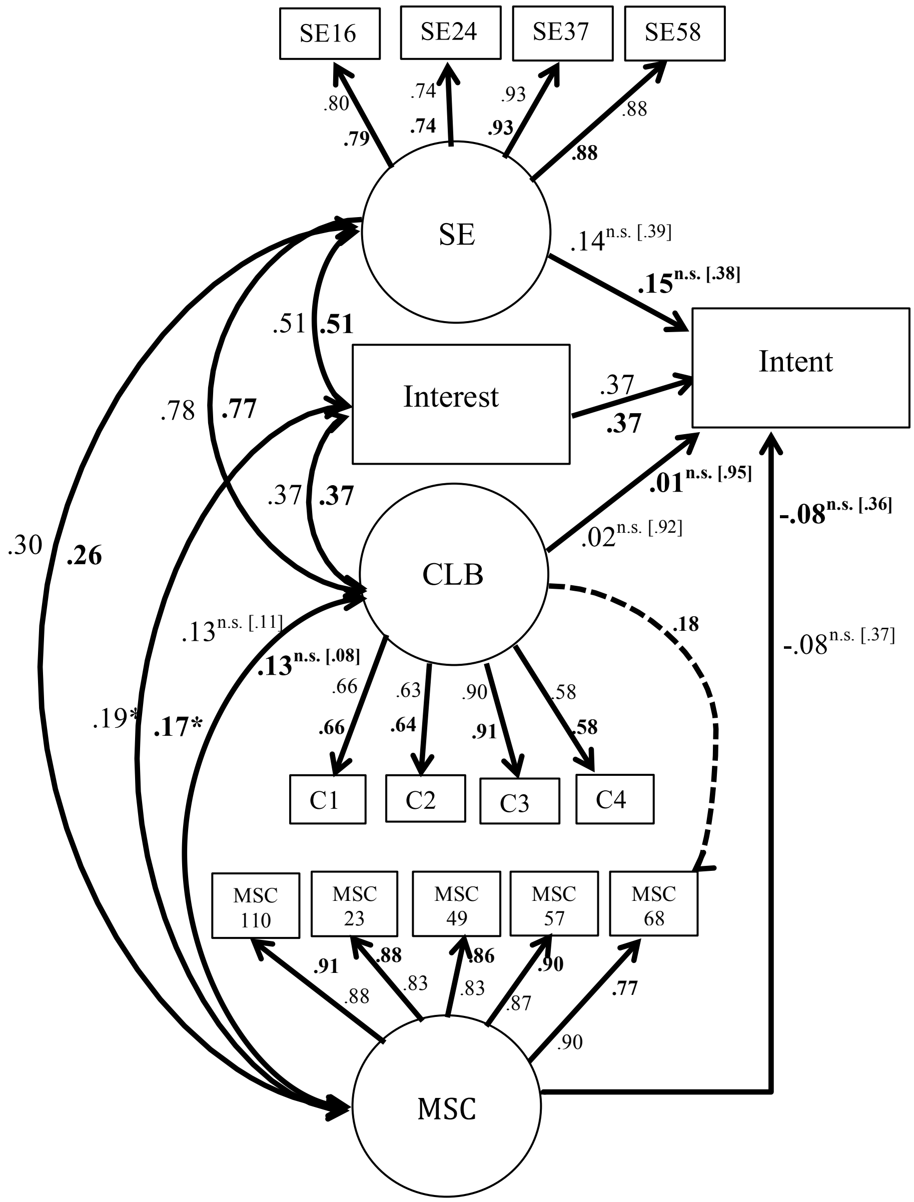

Figure 5.15. Final SEM for $R1_S$ classrooms.
Note: Post hoc analysis additional shared variance is indicated by dashed lines. New values are bolded.
n.s. = not significant, p values in brackets, * = $p < 0.05$.

These models reveal that while MSC does not predict intent to persist in either model, it did co-vary with self-efficacy and interest with the R1 population and with SE and CLB in CC classrooms. MSC is playing an indirect role in the persistence model, albeit one that is not immediately clear.

Interest was consistently the most reliable predictor of intent to persist in all of the models for this research. This held true even though the variable was a more global measure of interest, rather than course specific interest. Initial regression analysis prior to any SEM indicated that self-efficacy significantly predicted intent to persist with both samples, and control of learning beliefs predicted intent to persist with the $R1_S$ sample (table 5.8). As a result, I tested the role that self-efficacy and control of learning beliefs played in predicting intent to persist in each of the SEM models to determine if interest was acting as a possible mediator for any of these populations. Figures 5.16 and 5.17 illustrate the structural models for CC_F and $R1_F$ models similar to those from figures 5.5 and 5.6.

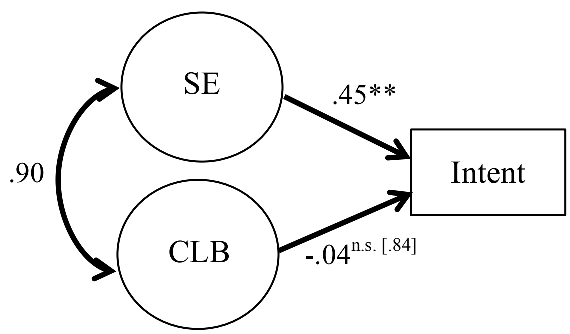

Figure 5.16. Structural model for CC_F with interest removed.
Note: SE = Self-Efficacy, CLB = Control of Learning Beliefs, Intent = Intent to persist
n.s. = not significant (p value in brackets), ** = $p < 0.01$, otherwise $p < 0.001$

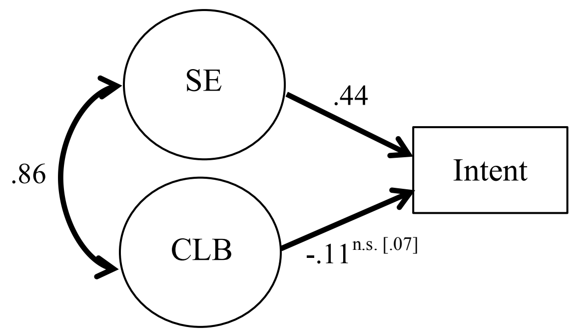

Figure 5.17. Structural model for $R1_F$ with interest removed.
Note: SE = Self-Efficacy, CLB = Control of Learning Beliefs, Intent = Intent to persist
n.s. = not significant (p value in brackets), otherwise $p < 0.001$

These figures illustrate that when interest was removed, self-efficacy replaced interest as the predicting variable for intent to persist, in both cases, it predicted almost the same amount as interest did in the original models (table 5.14). Both of these models were built from the final post-hoc models where self-efficacy and control of learning beliefs shared error variance. The fit indices for both of these models still indicates a good fit, where the CC_F model was $X^2_{\text{difftest}} = 139.53$, df = 1, p = 0.000, RMSEA = 0.04, CFI = 0.98, WRMR = 0.34 and the $R1_F$ model was $X^2_{\text{difftest}} = 681.60$, df = 1, p = 0.000, RMSEA = 0.04, CFI = 0.98, WRMR = 0.61.

Table 5.14

SEM results when interest variable was removed from original models

Institution	% interest predicted in original model	What predicts when interest was removed	% predicted
CC_F	45%	Self-Efficacy	45%
$R1_F$	40%	Self-Efficacy	44%

The story becomes a bit more complex when the role of instructor is considered as a function of RTOP. Re-examining these models when interest is removed reveals a slightly more nuanced result, however, in general, self-efficacy tends to replace the role of interest (figures 5.18 and 5.19 for CC_F structural models and 5.20-5.22 for $R1_F$ structural models).

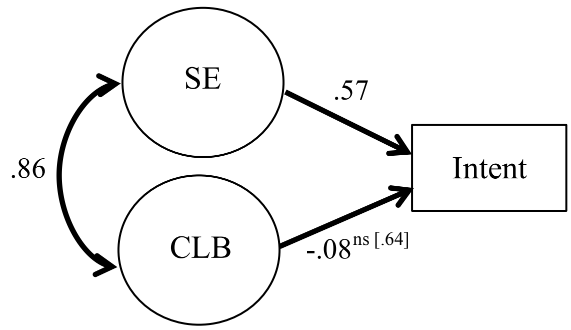

Figure 5.18. Structural model for CC_F with interest removed in high RTOP classrooms
Note: SE = Self-Efficacy, CLB = Control of Learning Beliefs, Intent = Intent to persist
n.s. = not significant (p value in brackets), otherwise $p < 0.001$

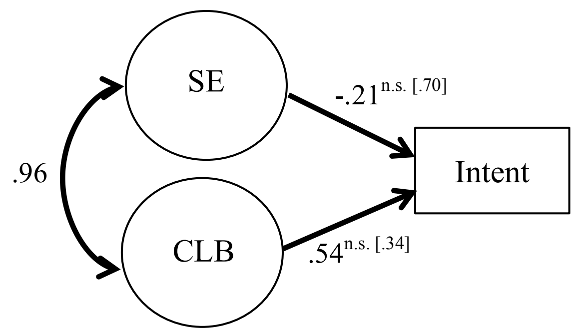

Figure 5.19. Structural model for CC_F with interest removed in middle RTOP classrooms
Note: SE = Self-Efficacy, CLB = Control of Learning Beliefs, Intent = Intent to persist
n.s. = not significant (p value in brackets), otherwise $p < 0.001$

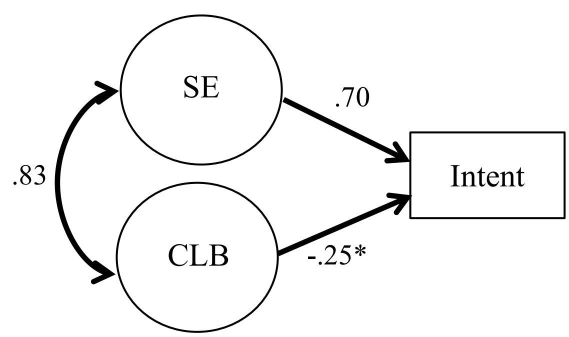

Figure 5.20. Structural model for $R1_F$ with interest removed in high RTOP classrooms
Note: SE = Self-Efficacy, CLB = Control of Learning Beliefs, Intent = Intent to persist
n.s. = not significant (p value in brackets), * = $p < 0.05$, otherwise $p < 0.001$

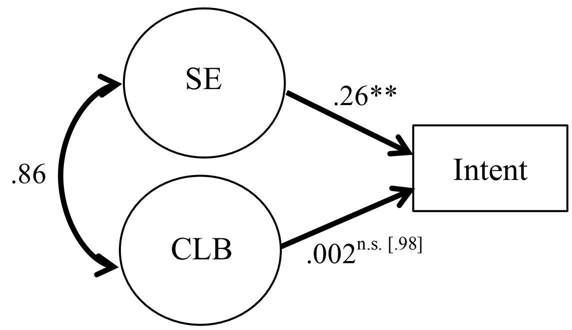

Figure 5.21. Structural model for $R1_F$ with interest removed in middle RTOP classrooms
Note: SE = Self-Efficacy, CLB = Control of Learning Beliefs, Intent = Intent to persist
n.s. = not significant (p value in brackets), ** = p < 0.01, otherwise p < 0.001

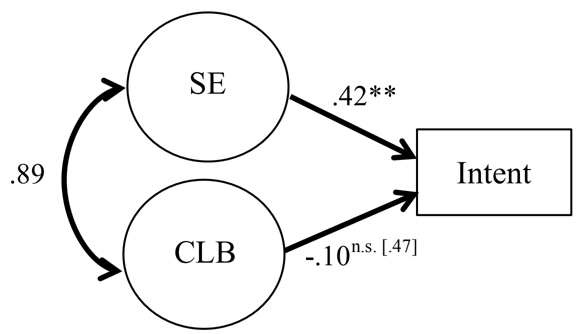

Figure 5.22. Structural model for $R1_F$ with interest removed in low RTOP classrooms
Note: SE = Self-Efficacy, CLB = Control of Learning Beliefs, Intent = Intent to persist
n.s. = not significant (p value in brackets), ** p < 0.01, otherwise p < 0.001

In this case, the high scoring RTOP CC_F model illustrates that self-efficacy is an even stronger predictor for intent to persist when interest is removed, whereas with the middle RTOP CC_F classroom, there was nothing that significantly predicted interest. With the $R1_F$ classrooms, the predictors are more consistent with previous results, Self-efficacy and negative control of learning beliefs continues to predict interest, with an increased weight to each individual variable, and self-efficacy replaces predicting interest in the $R1_F$ middle and low RTOP classrooms with fairly consistent levels of replaced % variance explained (table 5.15).

Table 5.15

SEM results when interest was removed from RTOP classroom models

RTOP scale	Institution	% Interest predicted	What predicts intent after interest is removed	% predicted
High	CC_F	38	Self-Efficacy	57
Middle	CC_F	37	Nothing	--
High	$R1_F$	51	Self-Efficacy, Control of Learning	70, -25 (respectively)
Middle	$R1_F$	37	Self-Efficacy	26
Low	$R1_F$	41	Self-Efficacy	42

As with the other interest-removed models, the fit indices indicated a strong fit for each of these models (table 5.16).

Table 5.16

SEM regression results for different RTOP ranked classrooms where interest was removed.

Institution	RTOP	$X^{2\,a}$	df	N	RMSEA	CFI	WRMR
$R1_F$	High	189.55	1	686	0.04	0.98	0.38
	Middle	271.64	1	1000	0.05	0.97	0.50
	Low	208.76	1	748	0.04	0.98	0.40
CC_F	High	65.27	1	286	0.06	0.95	0.36
	Middle	62.58	1	215	0.03	0.99	0.25

Note: all fit indices were based on post-hoc models from original models prior to interest removal where self-efficacy and control of learning beliefs shared error variance.
[a] Results are reported as the chi-squared difftest from MPlus due to the WLSMV estimator used for categorical variables.

In the final model, when interest was removed, self-efficacy again becomes the consistent predictor that replaces interest in predicting intent to persist. Figures 5.23 and 5.24 illustrate these new structural models for CC_S and $R1_S$, respectively. Table 5.17 compares the original model predictor of interest to the new models.

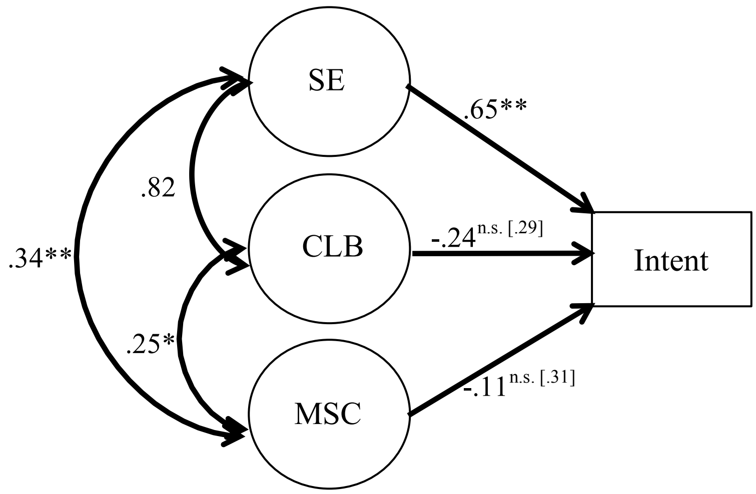

Figure 5.23. Final structural model for CC_S with interest removed
Note: SE = Self-Efficacy, CLB = Control of Learning Beliefs, MSC = Math Self-Concept, Intent = Intent to persist
n.s. = not significant (p value in brackets), ** p < 0.01, otherwise p < 0.001

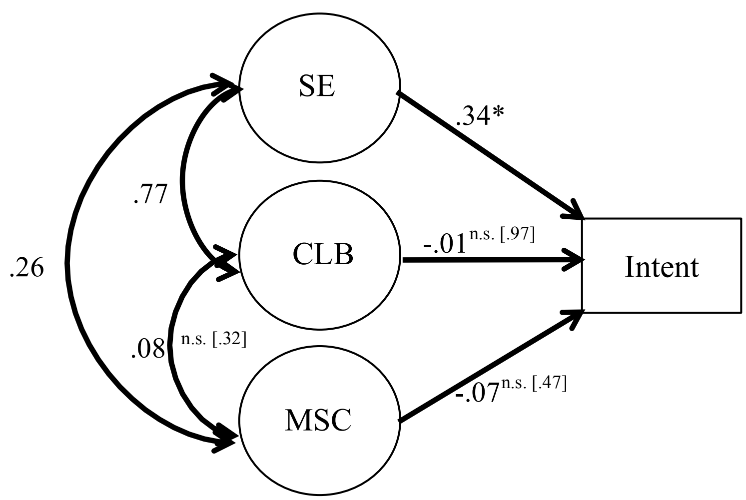

Figure 5.23. Final structural model for $R1_S$ with interest removed
Note: SE = Self-Efficacy, CLB = Control of Learning Beliefs, MSC = Math Self-Concept, Intent = Intent to persist
n.s. = not significant (p value in brackets), * p < 0.05, otherwise p < 0.001

In these final models, the fit indices were similar to those of the original models prior to the removal of interest. The CC_S sample was close to the cut off with CFI, but within acceptable cut-off ranges for RMSEA and WRMR values, $X^2_{\text{difftest}} = 9.58$, df = 2, p

= 0.008, RMSEA = 0.04, CFI = 0.94, WRMR = 0.42. The post-hoc interest-removed model for the $R1_S$ sample was a good fit, $X^2_{difftest}$ = 10.98, df = 2, p = 0.004, RMSEA = 0.03, CFI = 0.98, WRMR = 0.46.

Table 5.17

SEM results when interest was removed from the final model

Institution	% Interest predicted	What predicts intent once interest is removed	% predicted
CC	52	Self-Efficacy	65
R1	37	Self-Efficacy	34

All of the interest-removed models indicate a relationship between self-efficacy and interest. In some cases, self-efficacy replaces the role of interest in an almost exact amount of variance. In other cases, there is more or less variance explained by self-efficacy than was by interest alone. As a result, this may be an indication of possible moderating relationships taking place within these models.

Discussion

The results from this research reveal several possible implications for community college students, and students in introductory geology classrooms in general. In particular, are the impacts that an instructor may play a role in student interest and the possible implications for student persistence in the geosciences.

In this research, I was examining the role that self-efficacy, control of learning beliefs, interest and in some cases, math self-concept played in predicting a student's intent to persist in taking another geology course. For this study, self-efficacy, as measured on the MSLQ as a student's self-evaluation of how well they expect to do in their geology course. Control of learning beliefs also measured by the MSLQ as a measure of a student's perception of how well they are in control of their grade and their ability to learn the geology content. Because these measures were from the last third of the semester, it is likely to be a more accurate gauge of these measures than their incoming scores because they had been able to calibrate their expectations to the actual classroom experience (Zusho et al., 2003). The combination of self-efficacy and control of learning beliefs was operationalized as expectancy within portions of this research (Appendix B). Math self-concept was measured from the SDQ III as a measure of a more global aspect of how students feel about their ability to do math and their preference for doing so (Appendix C). Interest and intent to persist were both measured with individual items from the GARNET demographic survey (Appendix A).

Differences between Community College and University Students

There were measureable differences between community college students (CC_S) and university students ($R1_S$) both demographically and affectively. Students enrolled in introductory geology classes at the community college were more diverse, older, had fewer STEM majors (including the geosciences), more undeclared majors, had less incoming interest, but also fewer expectations of the course as an easy course. In addition, CC_S students had fewer prior math courses and were more likely to be in their first college-level science course. Many of these findings support national trends in which CC students are more diverse and older, and may lack the prior experiences to be able to gauge what to expect from a college level course (NCES, 2001; NSF, 2009; AACC, 2012).

In addition to demographic differences, there were also measureable differences between CC_S and $R1_S$ students with regards to math self-concept and interest. $R1_S$ students were leaving geology classrooms with a higher math self-concept and a greater interest in science. These findings were consistent with the demographic measures. If $R1_S$ students have had more math courses prior to entering the introductory science courses, it is likely their math self-concept will be higher. In addition, since more $R1_S$ students entered the course with interest, it is likely that there will be more leaving the course interested. However, these differences have not been documented in the literature prior to this research.

Lastly I hypothesized that there would also be differences between CC and R1 students with regards to intent to persist and expectancy for success in the course, and these differences were not found to be true. These results counter previous findings of students in other STEM disciplines at the community college. For example, student self-efficacy in introductory engineering classrooms were found to be lower in community college classrooms than in R1 institutions (Baker, Wood, Corkins & Krause, 2012). If interest and math self-concept were lower with community college students, but intent to persist was not, this may indicate that even with lowered interest, CC students may be willing to consider taking another geology course.

With both samples, the negative skew in intent to persist indicated that there were fewer numbers of students reporting continuing on to take another geology class. This was an unfortunate result, because our greatest chance of capturing students is not in the first course they take, but in subsequent courses. Wilson's recent report on geoscience graduates indicated that the second year of coursework was the highest likelihood of when students decide to become geology majors (Wilson, 2013). This would mean that the chances of capturing geology majors in the introductory geology courses is low, but if they choose to take more geology courses, their likelihood of becoming a major increases.

Role of Expectancy and Interest in Predicting Intent to Persist

There was a significantly positive relationship between expectancy, interest and intent to persist with both CC_F and $R1_F$ populations. In the CC_F population, interest was the only direct predictor, predicting 45% of the variance in intent to persist. Both self-efficacy and control of learning beliefs (expectancy) played an indirect role in this model as they significantly co-varied with interest, but were not direct predictors of intent to persist. Within the $R1_F$ population, both interest and self-efficacy predicted intent to persist, explaining 56% of the variance. Again, while control of learning beliefs did not directly predict intent, it did significantly co-vary with both interest and self-efficacy.

Interest was measured as a global measure of interest, rather than specifically identifying a type of situational or individual interest as described by Hidi and Renninger (2006) or even as a subject specific measure. And yet, in this research, it was the most consistent predictor of intent. It predicted 45% of the variance in intent to persist with the CC_F population and 40% in the $R1_F$ population. This finding is consistent with what Harackiewicz and colleagues (2000) found with introductory psychology students.

Students who were most likely to take another psychology course were those who had the greatest interest.

Role of the Instructor

In this research, the Reformed Teaching Observation Protocol (RTOP) was used to measure the instructor pedagogy as classified by the degree to which they created an environment that allowed for students to interact with each other as much as with the instructor (Appendix D). Due to limitations in the number of classrooms involved in this project, the RTOP was broken down into three different categories based on the degree of student interactivity. From this process, it became clear that that the degree of student interactivity in the classroom played a role in predicting student intent to persist, however, the relationships were nuanced and complex. Table 6.1 breaks down the relationships with the different classrooms.

Table 6.1

Predictors of intent to persist in different RTOP classrooms

Institution	RTOP ranking [a]	Direct predictors of intent	% predicting intent
CC_F	High	Interest	38
	Medium	Interest	57
$R1_F$	High	Interest, Self-Efficacy, Control of Learning Beliefs	51, 41, -20 (respectively)
	Medium	Interest	37
	Low	Interest	41

[a] Rankings based on recommendations by Budd et al., 2013.

In all of these models, other than the high RTOP classrooms at the $R1_F$, the results were consistent with the previous models where interest was the only direct predictor of intent to persist. Ignoring the high RTOP $R1_F$ classroom, a general trend of increasing level of interest as a predictor of intent to persist becomes apparent. This trend may indicate that instructors were supporting students in other ways not measured in this model that helped to predict intent to persist in classrooms where there was greater interaction between both classmates and the instructor. Classrooms that were more instructor-centered, students needed to maintain their interest in order to persist in taking another geology course, as a result, interest played a larger role in predicting intent to persist.

In the high RTOP $R1_F$ classroom, the relationship became much more complex. Self-efficacy and interest both positively predicted intent to persist and control of learning beliefs negatively predicted intent to persist. This indicates that students who had a high self-efficacy were almost as likely to persist as those with high interest. The fact that a decline in control of learning beliefs positively predicted intent to persist is a bit concerning. This indicated that as students had less control over their own learning, the more likely they were to take another geology course. This may have some negative consequences for long term persistence with majors. If students think they are simply good at doing geology, rather than thinking that they have worked hard to become proficient, when faced with future challenges, could result in a decline in persistence.

With all of these models, there was a clear indication that instructor played a role in a student's intent to persist. This is in contrast to the initial calculation that there was greater variance between students within a classroom than between different classrooms. However, because classrooms within a given RTOP range were taught in similar ways (Budd et al., 2013), this discrepancy may be as a result of the commonalities within certain RTOP ranges.

While the findings may not reveal what other factors in the classroom may contribute to supporting students intent to persist, previous work has illustrated other benefits from more student-centered classrooms. Students are more likely to learn in student-centered classrooms, this has been demonstrated in work like that of Hake's seminal work in Physics college classrooms (Hake, 1998). In addition, Zusho et al., (2003) demonstrated that in general, student self-efficacy declined through the course of the semester in other introductory science courses, but students with a high self-efficacy, were more likely to perform better in the course. Our recent GARNET findings have confirmed these same results of increased learning gains and high self-efficacy predicting performance with introductory geoscience courses. In addition, we have found that student-centered classrooms were more likely to minimize the need for expectancy (as measured by self-efficacy and control of learning beliefs) to predict performance and learning (van der Hoeven Kraft et al., 2013). Highly student-centered classrooms help support student learning, support their self-efficacy, and based on my research may also minimize the role that interest is needed to persist.

Role of Math Self-Concept in Expectancy for Success

Expectancy has been measured in this research as combining self-efficacy and control of learning beliefs, however in SEM analysis, creating a second-order factor of expectancy from two sub-constructs does not contribute to the interpretation of the model. This is because at a local level within the model, expectancy would be just-identified and as such, limits model interpretations (Byrne, 2012). However, I hypothesized that the expectancy factor would include math self-concept for the $R1_S$

population and not for the CC_S population, as I predicted that math self-concept would play a greater role on it's own with the CC_S population due to their higher need for developmental courses. However, when I added math self-concept to self-efficacy and control of learning beliefs as contributors to a larger second order construct of expectancy the model fell apart for both $R1_S$ and CC_S populations. As a result, math self-concept was a more powerful predictor as it's own variable than it was as a larger expectancy construct. With that being said, these variables as separate latent constructs still created a strong measurement model where math self-concept and self-efficacy shared variance, but control of learning beliefs only shared variance with self-efficacy.

These findings are consistent that self-efficacy and self-concept measure similar constructs, but are distinctly different measures. Bong and Clark (1999) argued that self-concept is a reflective way of viewing ones self and self-efficacy is a predictive future path. In my research, the consistent high level of covariance of self-efficacy and control of learning beliefs supports previous work that expectancy is an appropriate larger second-order construct encompassing self-efficacy and control of learning beliefs (Hilpert et al., 2013).

Role of Math Self Concept in Predicting Intent to Persist

By adding math self-concept to the predictive model, I had hypothesized that not only would it increase the strength of predicting the model in predicting intent to persist, but that it would also be different in the pathways of how it predicted between $R1_S$ and CC_S populations. Math self-concept did not play a significant role in predicting intent to persist in either model. However, the models that included math self-concept were significantly different from one another in how math self-concept interacted with other variables in the model. The complexities of interactions within each model indicated that the more parsimonious model without math self-concept may be missing some important variables, and that there are other possible variables that should be considered in predicting persistence. Table 6.2 illustrates the ways that the models vary with the newly added variable of math self-concept.

Table 6.2

Relationships in SEM models with Math Self-Concept

Institution	% of intent predicted by interest	What co-varies with math self-concept
CC_S	52	Control of Learning Beliefs, Self-Efficacy
$R1_S$	37	Interest, Self-Efficacy

In the CC_S model, a high degree of interest was required when predicting intent to persist with the math self-concept variable added into the model. In addition, math self-concept co-varied with self-efficacy and control of learning beliefs, but not with interest. In contrast, the $R1_S$ model indicated that interest played less of a role in predicting intent to persist and math self-concept co-varied with interest and self-efficacy. So while both models were predictive of intent to persist, and math self-concept did not play a role in directly predicting intent to persist, how it interacted with the different variables did differ between different types of institutions. In particular, when interest was removed from the model, self-efficacy predicted a much higher amount of variance than interest did. These results suggest that math self-concept may have played a moderating role in interest in science and self-efficacy for the community college population, but not for the R1 population.

The relationships between math self-concept, self-efficacy and interest are not clear based on these models, however, a math self-concept role of moderation has implications for the likelihood of community college student persistence in the geosciences. In particular, if students at a community college lack the cultural capital of access to prior math courses, it may increase the challenges students face in overcoming the hurdle of persisting. This is not to say that CC students have a lowered likelihood of persisting because they are CC students, rather the students who are more likely to attend a CC are those who lack the background content which may impact their responses to math self-concept. Previous research has indicated that math self-efficacy was mediated by math self-concept (Miller & Pajares, 1994). Because the measures in this research were geology self-efficacy and math self-concept, there may not be as direct of a relationship, but these latent interactions may be influencing the outcome of interest on intent to persist.

Interest as a Possible Mediator

Interest was consistently the most reliable predictor of intent to persist in all of the models for this research. This held true even though the variable was a more global measure of interest, rather than course specific interest. When interest was removed from the different models, self-efficacy most consistently replaced the role of interest in predicting intent to persist. This indicates that for those students who had a high self-efficacy, must also be interested in the subject in order to persist in the discipline. In cases where self-efficacy predicted the same amount that interest predicted, it would indicate that self-efficacy was mediated by interest. However, for those classrooms where self-efficacy did not predict the same amount as interest could that in addition to mediation, another variable is moderated by interest.

The original framework posed for the model in this research was applying the Expectancy x Value theory (Wigfield & Eccles, 2000) in which I had predicted that both expectancy (as measured by self-efficacy and control of learning beliefs, and possibly math self-concept) and value (as measured by interest) would collectively predict intent to persist. It appears that this model may not be the most appropriate framework for this research. If interest was serving as a mediator, this more strongly supports Hidi & Renninger's work (2006, 2010) in which they argue that other variables may be mediated by interest. This is supported in other research where the relationship between self-efficacy and interest has been examined. Brown and Lent (1996) described how faulty efficacy perceptions influenced ones interest and career choices. These perceptions would prevent someone from pursuing a career path of interest because they did not perceive themselves capable. Gehlbach et al. (2008) found that interest in a subject was mediated by a declining self-efficacy. Which meant that as student's self-efficacy declined through the course of the semester, they were more likely to become interested in the subject. While initially this may seem counter-intuitive, they proposed that if the classroom activities were more closely matched to challenging a student at an optimal level (Locke & Latham, 2002), then interest would be promoted. This would indicate the importance of student-centered instruction where students are forced to confront their own understanding of the content as they collaborate with classmates in negotiating content.

The exceptions to this model of mediation were how instructor may have played a role in student intent to persist. For example, in the high RTOP CC_F classroom, self-efficacy predicted more than just interest, 38% of intent to persist was predicted by interest, but 57% of intent to persist was predicted by self-efficacy when interest was removed. In the high RTOP $R1_F$ classrooms, self-efficacy already predicted intent to persist independent of interest, but it loaded more strongly once interest was removed. This may indicate that classrooms that are more student-centered are creating an environment where student's self-efficacy is strongly supported and they are sufficiently challenged to support their interest in the subject. In other words, students self-efficacy is mediated by interest and moderating by classroom student-interactions. On the other extreme, in middle RTOP CC_F classrooms, when interest was removed, the model was no longer predictive of interest. This would indicate that the only factor that predicts intent to persist is interest, and once removed, students have no intent to persist in the geosciences. The more avenues we can create for students to persist in the geosciences, the higher the probability of increasing retention over time. As Harakiewicz and her colleagues (2000, 2008) found with their research, the more classes a student takes in a given subject, the more likely that interest is to become internalized.

Limitations of the Study

Ideally, for SEM analysis, there should be 200 of each groupings of students (for both R1 and CC) minimum, in order to assure enough power (Tabachnick & Fidell, 2001). In collecting data for the MSC items, there was only data for 78 students in the community college setting. As a result, the ability to make broader generalizations may be limited. However, since the data set were part of the larger GARNET data set, and the bootstrapping indicated that the Spring 2013 dataset was statistically similar in other responses to the larger dataset, particularly for the CC population, I feel confident that the final model in this analysis was likely close to representing the larger population, however, it may be underpowered as a result of the smaller Spring 2013 sample size.

In addition, there are other factors that may be playing a role in determining STEM choices including Future Time Perspective (Husman & Lens, 1999) and values, particularly utility value (Hulleman & Harackiewicz, 2009; Packard, Tuladhar & Lee, 2013) which were not measured in this project in the interest of assuring a tightly constrained project where I did not overburden students with too many different survey items. In addition, all of these methods were based on quantitative data, as a result, the reasons for these responses are left unanswered. This type of question would require a qualitative approach, and is something currently under investigation by others within the GARNET project (Lukes, 2013).

This methodology was highly dependent on self-report. While commonly targeted as problematic since it is based on the perception of the individual and not necessarily reality, self-reports commonly reported as less reliable measures. However, research consistently demonstrates that self-reports are highly predictive of behavior and are not biased when in a low-stakes setting (Ross, 1996; Chan, 2009). To avoid concerns of stereotype threat when answering questions about math and science, all demographic questions occurred after the survey itself (Steele, 1997).

The measure of intent to persist is not the same as actual persistence. In particular, CC students face tremendous obstacles in persisting based on course preparation, job, family, and finances (Nunez & Cuccaro-Alamin, 1998; NCES, 2001; Parsad & Lewis, 2004; Horn & Nevill, 2006; AACC, 2012). With that being said, Barnett (2011) initially measured student's intent to persist in her research with community college students, but followed with a measure of actual persistence at the institutional level rather than the class level and found there to be a moderate correlation of 0.47. Because her measure of persistence was at the institutional level rather than at the class level, she did not include students who were enrolled in other institutions rather than the community college where she conducted her research. Previous research on intent to persist versus actual persistence with the community college population, also at the institutional level, indicated a high predictive correlation of 66% and higher depending on what other variables were considered for interaction (Voorhees, 1987).

Another important limitation was the data itself. While each response was nested within each classroom and each campus, it was treated as a larger data set in order to make a meaningful comparison across populations. While analysis of variance of within versus between classroom variance indicated that multilevel modeling was not needed for the individual classrooms, the RTOP analysis was underpowered as a result of making it an ordinal value rather than continuous variables at a higher level. Becuase there were instructor effects when applying the RTOP model indicates a need to re-visit the multilevel modeling approach.

While there is not a lot of agreement on how to best measure interest, a global measure of interest in science is not the strongest way to predict interest as it does not determine whether this measure is one that is situational or individual (Hidi & Renninger, 2006). So while interest was a strong predictor of intent to persist in this model, it was difficult to discern where and when that interest developed and how stable it was.

Lastly, there were limitations with examining students choosing to enroll in another geology class because there may be more than one reason for persisting. For example, some schools have programs where they continue in a block of two classes for completing their science credits. Other schools may have limited courses in options for additional geology courses as available on campus. Although, it should be noted that this was about measuring the student’s intent, not necessarily what options actually existed for the student.

Next Steps & Implications

The importance of this research is because it helps add to the literature on what factors predicting persistence in the introductory science courses, in particular, the geosciences. While this is only one course, the ability for students to persist from one class to the next is the first step. As determined by Harackiewicz et al. (2000), the more courses a student enrolls in a given topic, the more likely s/he is to take another future course.

Because math self-concept played an indirect relationship to intent to persist, it is possible that there were other variables or better predicting variables that may help predict intent to persist than the ones presented in these models. While it is generally the goal to make as parsimonious of a model as possible, it is also best to find a model that explains the phenomena as accurately as possible (Byrne, 2012). Further research in examining intent to persist may include self-regulatory components (e.g., metacognition and effort regulation), performance and learning gains, and geology self-concept (as a global measure rather than a class-specific focused self-efficacy). Carlone & Johnson (2007) argued that a science identity was critical for the success of women of color in persisting in STEM fields, and as such, this may be an important variable to measure and consider, particularly for the URM's in science. Lastly, all of these data should be tracked and analyzed longitudinally. In particular, Maxwell & Cole (2007) argue that mediation can not be measured in cross-sectional data, so in order to test the mediation model, it should be tested over time. Demographic and background experiences that students bring to the classroom including race, sex, and background knowledge would also merit further investigation, while these are factors that instructors can not control, they can inform models of that may help to determine best practices for all students.

Even though there were differences across the populations and models in this research, a consistent theme was that the environment created by the instructor did make a difference in a student's intent to persist. So while R1 and CC students were different demographically and in background experiences, a key recommendation would be to implement a greater emphasis on student-centered instruction if institutions are serious about increasing majors in STEM (at least for the geosciences). This recommendation is in line with both the President's Council of Advisors on Science and Technology (Holdren & Lander, 2012) and Graham and colleagues (Graham, Frederick, Byars-Winston, Hunter & Handelsman, 2013) in which the argument is made that if we do not improve instruction at the introductory science level in colleges and universities, we will not be able to increase the number of STEM majors for the purposes of creating a larger STEM workforce.

With that being said, while RTOP served as a good proxy for student-centered instruction in the classroom, it did not capture the intricacies of what was said in the classroom. The fact that the high RTOP CC_F classroom did not have similar results to the high RTOP $R1_F$ classroom may be due to what was specifically discussed in these classrooms and how that may impact students at community colleges, more so than at R1 universities. Recent work by Packard and others (Packard et al., 2013) found that the more STEM community college faculty used class time to discuss the transfer process to a four-year institution, the more likely students were to be successful at transferring to a four-year institution in STEM. This could extend to the persistence within a discipline, if faculty encourage students to consider more coursework in the geosciences and are transparent about the transfer pathways, it is possible that this dialogue could play a role in student persistence in the geology pathway. In particular, Packard and other (2013) identify the advice provided during class time as addressing a utility value for students. Utility value was not measured in this research, but could provide insight into how much students valued the content within the course and even what the instructor discussed that may not have been course specific (for example, transfer pathways).

The consistent shared co-variance between the control of learning belief items 2 & 4 and the combined variables of self-efficacy of 16 and 58 (Appendix B and table 5.9), would indicate that something within these variables is interpreted differently from how the original authors intended. While there are no perfect models, the reasons for this consistent variance may warrant further investigation.

Because the CC_S sample was underpowered due to the small sample size, I hope to compare these results with a new set of participants in the GARNET population in the future to see if the models still holds true and consistent across semesters.

Lastly, while intent to persist for one semester is a start to measuring the greater persistence model, this research should be extended to a larger longitudinal analysis. What is the relationship between intent to persist and actual persistence with regards to self-efficacy and interest? What role does math self-concept play in choosing to become a major? Are there instructional settings that predict persistence for more than one semester? Are there certain programs that are doing a better job and supporting student's persistence and what is different within those institutions versus those who are not? There are many questions that can build toward supporting a stronger model in determining how to best support student persistence in the geosciences and ultimately STEM as a whole. While following students from a community college poses its challenges, if we are serious about our commitment to increasing a more diverse STEM workforce (NRC & NAE, 2012), we need to determine what factors lead to success and what aspects institutions and faculty can play a role in supporting students for that success. The work in this research is a small step down a long and important path.

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APPENDIX A

GEOSCIENCE AFFECTIVE RESEARCH NETWORK (GARNET) ITEMS

After completing the MSLQ survey, students will then be asked the following questions on a separate page:

Pre survey (response stems are in parentheses):

- Age (17 or younger, 18-19, 20-21, 22-25, >25)
- Gender (Male, Female)
- Race/Ethnicity (Non-Hispanic White, Hispanic of Any Race, Black or African American, American Indian or Alaskan Native, Asian, Native Hawaiian or Other Pacific Islander, Some Other Race, Two or More Races, Unknown)
- Field of Declared Major (Geology/Earth Science, Other Natural Science, Engineering, Technology, Math, Arts, Humanities, Social Science, Open Option/Undeclared)
- If Changing Major, to what area? (Not Changing Major, Geology/Earth Science, Other Natural Science, Engineering, Technology, Math, Arts, Humanities, Social Science, Open Option/Undeclared)
- In general, how interested in science are you? (Very interested, Somewhat interested, Not very interested, Not interested at all)
- How likely is it that you will major in a natural science (i.e., physics, chemistry, biology, geology, etc)? (I have already declared a natural science as a major, Very likely I will switch to a natural science, Somewhat likely, Not very likely, Definitely not)

- In a class like this, which of the following teaching methods are most effective in helping you learn the material and your instructor's expectations? (Formal lecture (instructor delivering information using chalkboard, overhead, and/or laptop), Instructor-led class discussions, conversation, and/or collective class review, Students working together in groups and/or student led discussions, Other)
- Number of Full Academic Year High School Math and Science Courses Completed:
  - Full-Year High School Earth Science Courses: (0, 1, 2, 3 or more)
  - Other Full-Year Natural Science High School Courses (0, 1, 2, 3 or more)
  - Full-Year School Math Courses (0, 1, 2, 3, 4 or more)
- Number of Full Term (Semester or Quarter) College Math and Natural Science Courses Completed (Prior to the present semester or term):
  - Term-Length College Geology Courses (0, 1, 2, 3 or more)
  - Other College-Level Term-Length Natural Science Courses (e.g., Astronomy, Biology, Chemistry, Meteorology, Physics, Physiology): (0, 1, 2, 3 or more)
  - College Math Courses: (0, 1, 2, 3, 4 or more)
- Reasons for Enrolling in This Class (Please check all that apply): (Satisfy a General Education Requirement, Required for Major or Minor, Easier than other Science Classes, Prior Interest in the Subject, Interest in Human/Environment Interactions, Reputation of Instructor(s), Recommendation of Friend or Advisor, Other Specific Reason, Don't Know)

Post Test Items (Response stems in parentheses)

- Did you take a lab (either optional or required) in conjunction with this class? (Yes, No)
- In general, how interested in science area you? (Very interested, Somewhat interested, Not very interested, Not interested at all)
- Do you plan to take another geology class after this one? (Very likely, Somewhat likely, Not very likely, Definitely not)
- How likely is it that you will major in a natural science (i.e., physics, chemistry, biology, geology, etc)? (Very likely (or have already declared a natural science as a major), Somewhat likely, Not very likely, Definitely not)
- In a class like this, which of the following teaching methods are most effective in helping you learn the material and your instructor's expectations? (Formal lecture (instructor delivering information using chalkboard, overhead, and/or laptop), Instructor-led class discussions, conversation, and/or collective class review, Students working together in groups and/or student led discussions, Other).

APPENDIX B

MOTIVATED STRATEGIES FOR LEARNING QUESTIONNAIRE (MSLQ) ITEMS

Determine how each of these statements is 1 = not at all like me to 7 = very much like me.

Control of Learning Belief Items

1. If I study in appropriate ways, then I will be able to learn the material in this course.
2. It is my own fault if I don't learn the material in this course.
3. If I try hard enough, then I will understand the course material.
4. If I don't understand the course material, it is because I didn't try hard enough.

Self-Efficacy Items

5. I believe I will receive an excellent grade in this class.
6. I'm certain I can understand the most difficult material presented in the readings for this course.
7. I'm confident I can understand the basic concepts taught in this course.
8. I'm confidence I can understand the most complex material presented by the instructor in this course.
9. I'm confident I can do an excellent job on the assignments and tests in this course.
10. I expect to do well in this class.
11. I'm certain I can master the skills being taught in this class.
12. Considering the difficultly of this course, the teacher, and my skills, I think I will do well in this course.

APPENDIX C

MATH SELF-CONCEPT ITEMS

Math Self-Concept items:

Please determine how much you agree or disagree with the following statements about your feelings toward math in general. 1 = definitely false and 8 = definitely true

1. I find many mathematical problems interesting and challenging
2. I have hesitated to take courses that involve mathematics*
3. I have generally done better in mathematics courses than other courses.
4. Mathematics makes me feel inadequate*
5. I am quite good at mathematics
6. I have trouble understanding anything that is based upon mathematics*
7. I have always done well in mathematics classes
8. I never do well on tests that require mathematical reasoning*
9. At school, my friends always came to me for help in mathematics
10. I have never been very excited about mathematics*

* = negative items

APPENDIX D

REFORMED TEACHING OBSERVATION PROTOCOL (RTOP) SCALE

Lesson Design and Implementation (What Teacher Intended to Do)				
1) Instructional strategies and activities respected students' prior knowledge and the preconceptions inherent therein (what's happened before this class)				
Never occurred 0	Lesson is designed to inform students what they already know 1	Lesson is designed to assess student's prior knowledge based on student input, but not to adjust. 2	Lesson is designed to use prior knowledge to build on and add value to content already provided 3	Lesson is designed to activate student prior knowledge (before any content delivery), and introduce content based on that input (and adjust if needed) 4
Comments:				
2) The lesson was designed to engage students as members of a learning community				
No evidence 0	Lesson has limited opportunities to engage students. (e.g., some clickers, rhetorical questions with shout out opportunities, clarification questions) 1	Lesson is designed for continual interaction between teacher and students 2	Lesson is designed to include both extensive teacher-student and student-student interactions 3	Lesson was designed for students to negotiate meaning of content primarily through student-student interaction 4
Comments:				
3) In this lesson, student exploration preceded formal presentation (students asked to think or do **prior to** content introduction)				
No exploration occurred 0	Lesson starts with an abstract exploration opportunity (e.g., what do you think about…) 1	Lesson designed with an initial, short exploration opportunity (students do something) 2	Lesson is designed to engage students in an active exploration experience 3	Major focus of the lesson is for students to spend time exploring, in detail. 4
Comments:				
4) This lesson encouraged students to seek and value alternative modes of investigation or of problem solving (questions have more than one right possible answer)				
No alternative modes explored 0	Lesson designed for instructor to ask divergent questions 1	Lesson designed for students to ask divergent questions, but not investigate 2	Lesson designed for students to engage in alternative modes of investigation, but without subsequent discussion 3	Lesson designed for students to engage in alternative modes and a clear discussion of these alternatives occurs 4
Comments:				

5) The focus and direction of the lesson was often determined by ideas originating with students (is there a clear plan to incorporate student ideas?)				
Lesson is entirely instructor directed 0	Lesson plan accommodates instructor pausing for student questions and ideas 1	Lesson plan call for student generated ideas 2	Lesson plan designed for adjustments based on student input. 3	Lesson plan is entirely student directed, with content guided by instructor, but has allowances for different ideas, and questions 4
Comments:				

Content: Propositional Knowledge (What the Teacher knows, and how well they are able to organize and present material in a learner-oriented setting)				
6) The lesson involved fundamental concepts of the subject (Is *content* concept-oriented?)				
No clear focus, just a series of random facts 0	A suggestion of concepts, but not obvious and mostly facts rather than overall concepts 1	Concept taught, but not necessarily within a conceptual framework. Topic is bogged down in term definitions 2	Concepts are presented within a conceptual framework, but still contains miscellaneous details/facts and/or tangents 3	Instructor ties concepts to conceptual framework without any tangential material that potentially confounds 4
Comments:				
7) The lesson promoted strongly coherent conceptual understanding (Presented in a logical and clear fashion—*how it's presented*; does the lesson make sense, general flow)				
Not presented in any logical manner, lacks clarity and no connections between material 0	Lesson is disjointed and not consistently focused on the concepts 1	Lesson is may be clear and/or logical but relation of content to concepts is very inconsistent (or vice versa) 2	Lesson is predominantly presented in a clear and logical fashion, but relation of content to concepts is not always obvious 3	Lesson is presented in a clear & logical manner, relation of content to concepts is clear throughout and it flows from beginning to end. 4
Comments:				
8) The teacher had a solid grasp of the subject matter content inherent in the lesson				
Teacher had no clear understanding of content 0	Teacher has some of the fundamentals, but lesson is still wrought with errors 1	Mistakes are common, but fundamentals are sound 2	May have minor mistakes, overall accurate delivery 3	No mistakes, all information presented is accurate. 4
Comments:				
9) Elements of abstraction (i.e., symbolic representations, theory building) were encouraged when it was important to do so (variety of media and whether it improves the lesson)				
Only text/facts with no alternate delivery 0	Teacher uses some diagrams/images in addition to text, and does not explain them at all 1	Teacher uses a variety of media throughout the lesson, but does not explain them in a manner than supports/develops the content 2	Teacher uses a variety of media throughout the lesson, and occasionally explains them in a manner that supports/develops the content 3	Variety of representation were used to build the lesson and used to support/develop the content. 4
Comments:				
10) Connections with other content disciplines and/or real world phenomena were explored and valued				

No connection to anything beyond a list of facts 0	Some connection to real world made in passing, but generally abstract or not helpful for content comprehension 1	Teacher makes a deliberate effort to connect to real world/ other disciplines, but teacher does all the talking 2	Teacher makes a deliberate effort to make connections to real world/ other disciplines, by promoting student thinking 3	Teacher sets up concept, makes initial connections and then, asks students to explore. 4
Comments:				

Content: Procedural Knowledge (What students did)				
11) Students used a variety of means (models, drawings, graphs, symbols, concrete materials, manipulatives, etc.) to represent phenomena (quantity and time with materials)				
Students are not asked to do anything 0	Students are asked to represent or interpret phenomena using just one means through the course of the class 1	More than 2 different media are employed to assist student learning 2	Students manipulate more than 2 media at least 25% of the class time 3	In any given moment during the class, students are more likely working with a variety of media than listening (to instructor or other students) 4
Comments:				
12) Students made predictions, estimations, and/or hypotheses and devised means for testing them				
No opportunities for any predictions (students explaining what happened, does not mean predicting) 0	Teacher may ask class to predict as a whole, but doesn't wait for a response (first shout out, no wait time). No means for testing. 1	Teacher may ask students to predict and wait for input (class as a whole or as pairs, etc). No means for testing. 2	Students discuss predictions. Means for testing is highly prescribed. 3	Students guide questioning and can predict before explore a means for testing predictions. 4
Comments:				
13) Students were actively engaged in thought-provoking activity that often involved the critical assessment of procedures (quality)				
Students completely passive 0	Students engage in simple activities that are factually based (i.e., term recall, summarizing content) 1	Student activity requires some form of application (i.e., apply content to a new situation) 2	Student activity requires an analysis of a situation (i.e., compare and contrast competing ideas) 3	Student activity requires critical evaluation of content. Students negotiate meaning of content and may synthesize into something new. 4
Comments:				
14) Students were reflective about their learning (what do you think, and how do you know?)				
No reflection 0	Students may ask questions that indicates a thinking that goes beyond immediate content (trying to make intentional connections) 1	Teacher sets up opportunities for students to reflect (what do you think…), but doesn't follow through with how this helped their connection to learning	Students provided time to reflect on what they've learned. Some limited connections to their learning occur, but not a lot of follow through. 3	Students have specific opportunities to determine what they've learned, asked to make connections to their learning and processed as a class.

		2		4
Comments:				
15) Intellectual rigor, constructive criticism, and the challenging of ideas were valued (negotiating meaning/ debating ideas)				
Students were not asked to demonstrate rigor, offer criticisms, or challenge ideas 0	At least once the students respond (perhaps by shout out”) to teacher’s queries regarding alternate ideas, alternative reasoning, alternative interpretations. 1	Students participate in a teacher directed whole-class discussion (debate) involving one or more of the following: a variety of ideas, alternative interpretations, or alternative lines of reasoning. 2	Students engaged in a teacher-guided but student driven discussion (debate) involving one or more of the following: a variety of ideas, alternative interpretations, or alternative lines of reasoning 3	Students debate ideas (in small group settings) through a negotiation of meaning that results in deliberate use of evidence/ arguments to support claims. 4
Comments:				

Classroom Culture: Communicative Interactions (Student-Student Interaction)				
16) Students were involved in the communication of their ideas to others using a variety of means and media (variety of types and scales of delivery)				
No student communication 0	At least one type of student-student communication (i.e., brainstorming, drawing pictures to convey ideas, mathematically) 1	Either more than one type of student-student communication, but not at a variety of scales (i.e., pairs, small group, group to group, whole class) or vice versa 2	Multiple types of student-student interactions, at multiple scales, but not at all scales of potential interaction 3	Focus of the class is based on student-student interactions through a variety of interactive scales and types (typically includes a whole class processing) 4
Comments:				
17) The teacher's questions triggered divergent modes of thinking (by students)				
No divergent modes 0	Students listen to teacher present an example of more than one answer or interpretation, but student thinking limited to individual questions about the material. 1	Students interact in response to teacher-framed question(s) that has/have more than one answer or interpretation, but the directions ask for just one "right" response 2	Students work on problems that may have more than one solution, but not obvious that this is the goal 3	Opportunities provided for students to ask divergent questions of each other and encouraged to pursue alternative solutions 4
Comments:				
18) There was a high proportion of student talk and a significant amount of it occurred between and among students (quantity of interactions)				
No student-student talk 0	Students talk to each other at least once (about lesson content) 1	Student-student talk occurs at least 10% of the time during the course of the class 2	Student-student talk occurs more than 25% of the time during the course of the class 3	In any given moment during the lesson, students are more likely to be talking to each other than the teacher (>50% student to student) 4
Comments:				
19) Student questions and comments often determined the focus and direction of classroom discourse (quality of student interactions)				
No student input 0	Student conversations are short and limited to "the answer," no	Student conversations are brief but do involve some	Student conversations are in depth examinations of a problem	Student conversations are detailed, multi-faceted

	negotiation of meaning 1	negotiation of meaning 2	3	examinations of recent and previously learned content that is student directed 4
Comments:				
20) There was a climate of respect for what others had to say				
No ideas beyond instructor are heard 0	Student-student interactions occur, but they are not needed 1	Some student-student interactions include voicing of ideas, opinions, and are well received and assist in the conversation 2	Most student-student interactions involve talking and listening to one another and the ideas are heard and considered/ needed 3	Every voice is equitably heard, respected, and valued. Student talk is critical for success. 4
Comments:				

Classroom Culture: Student/Teacher Relationships				
21) Active participation of students was encouraged and valued				
Entirely instructor directed, no student questions 0	Some student questions, may be opportunities to "shout out" ideas 1	Some student questions/ input are encouraged, and they appear to shift the direction of the lesson 2	Many students engaged some of the time in valuable conversations that leads to class discussions that appears to shift the direction 3	All students are actively engaged in meaningful conversation that guides the direction of the lesson from beginning to the end. 4
Comments:				
22) Students were encouraged to generate conjectures, (or) alternative solutions, and/or different ways of interpreting evidence				
Instructor may present interpretations, conjectures, etc., but asks students to do nothing 0	At least one time, students were asked to consider an alternate solution, make a conjecture, or interpret evidence in more than one way. 1	Teacher-student interactions lead students through a very directed format that considers alternate solutions, and/or conjectures and/or evidence 2	Teacher-student interactions facilitate students through a flexible format that considers alternate solutions, and/or conjectures, and/or evidence 3	Whole lesson is dedicated to students discussing, exploring and critiquing/ considering alternate solutions, and/or different ways of interpreting evidence, with minimal teacher guidance 4
Comments:				
23) In general the teacher was patient with the students (mostly about wait time)				
No opportunity to assess or teacher was not patient (no wait time, answers own questions). Unwanted behavior is tolerated/ ignored 0	There is a bit of wait time after asking a question, instructor avoids answering his/her own questions. Or instructor works with student(s) to clarify their vague question 1	Clear wait time (waiting for multiple student thoughts, waiting for all students have a chance to consider the question; not just taking the first raised hand or "shout out"). 2	Providing some time for student-student interaction (still on task), but may not be enough time for all to achieve goals. 3	Instructor provides adequate time for meaningful conversations to occur between students (enough time to achieve goal) 4
Comments				
24) The teacher acted as a resource person, working to support and enhance student investigations (activity beyond answering a question)				
No investigations (activity that	Very teacher directed, limited	Primarily directed by teacher with	Students have freedom, but	Students are actively engaged

engages students to apply content through problem solving) 0	student investigation, very rote 1	occasional opportunities for students to guide the direction 2	within confines of teacher directed boundaries 3	in their own learning process, students determine what and how, teacher is available to help when needed 4
Comments:				
25) The metaphor "teacher as listener" was very characteristic of this classroom				
Teacher was the only "talker" 0	At least once, teacher listened, and acknowledged or validated an idea presented. 1	Teacher is listening throughout (from beginning to end), but doesn't act on any ideas (but does acknowledge) 2	Teacher listens from beginning to end of lesson, but doesn't necessarily act on ideas throughout 3	Teacher listens and acts on what students are saying from the beginning to the end of the lesson (from gaining prior knowledge all the way to assessing student understanding). 4
Comments:				

APPENDIX E

HUMAN SUBJECTS APPROVAL FROM MARICOPA COUNTY COMMUNITY COLLEGE DISTRICT AND ARIZONA STATE UNIVERSITY

Maricopa County Community College District
2411 West 14th Street
Tempe AZ, 85281
TEL: (480) 731-8701
FAX: (480) 731 8282

DATE:	January 13, 2012
TO:	Kraft, Katrien, Geosciences
	Wilson, Merry, Geosciences, Matheney, Ronald
FROM:	MCCCD Institutional Review Board
PROTOCOL TITLE:	Geoscience Affective Research NETwork (GARNET) 2
FUNDING SOURCE:	National Science Foundation
PROTOCOL NUMBER:	2010-08-053
FORM TYPE:	AMENDMENT
REVIEW TYPE:	EXEMPT

Dear Principal Investigator,

The MCCCD IRB reviewed your protocol and determined the activities outlined do constitute human subjects research according to the Code of Federal Regulations, Title 45, Part 46.

The determination given to your protocol is shown above under Review Type.

You may initiate your project.

If your protocol has been ruled as *exempt*, it is not necessary to return for an annual review. If you decide to make any changes to your project design which might result in the loss of your exempt status, you must seek IRB approval prior to continuing by submitting a modification form.
If your protocol has been determined to be *expedited or full board review*, you must submit a continuing review form prior to the expiration date shown above. If you make any changes to your project design, please submit a modification form prior to continuing.

We appreciate your cooperation in complying with the federal guidelines that protect human research subjects. We wish you success in your project.

Cordially,
MCCCD IRB

Knowledge Enterprise Development

Office of Research Integrity and Assurance

To:	Jenefer Husman EDB
From:	Mark Roosa, Chair Soc Beh IRB
Date:	05/01/2013
Committee Action:	**Exemption Granted**
IRB Action Date:	05/01/2013
IRB Protocol #:	1304009127
Study Title:	Geoscience Affective Research Network (GARNET)

The above-referenced protocol is considered exempt after review by the Institutional Review Board pursuant to Federal regulations, 45 CFR Part 46.101(b)(1) (2) .

This part of the federal regulations requires that the information be recorded by investigators in such a manner that subjects cannot be identified, directly or through identifiers linked to the subjects. It is necessary that the information obtained not be such that if disclosed outside the research, it could reasonably place the subjects at risk of criminal or civil liability, or be damaging to the subjects' financial standing, employability, or reputation.

You should retain a copy of this letter for your records.