First-generation Students' Experiences of the Classroom Climate in a Redesigned Gateway Math Course: A Mixed Methods Case Study

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Dedication

To my husband Jeff, whose love and support carried me through this process. Whether I needed someone to edit my writing, let me vent, or tell me I could do it, he was always there for me.

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Abstract

In U.S. higher education, there are large disparities in student persistence rates in the science, technology, engineering, and mathematics (STEM) fields along lines of race and ethnicity, gender, generation status, and class. Most underrepresented student attrition from STEM happens during the first year. Large, introductory science and math courses have been criticized for their unwelcoming and competitive classroom climates, and many scholars have argued that these courses act as gatekeepers for students with marginalized identities who wish to major in a STEM field. Many policymakers and researchers have called for these introductory courses to move away from a traditional lecturing model and towards active learning. In the STEM education literature, active learning is often presented as a panacea for closing disparities in STEM education outcomes. A critical approach to this topic challenges the assumption that the incorporation of active learning would transform these introductory courses into equitable spaces for students with marginalized identities.

I conducted a mixed methods case study of a large, introductory math course taught at a public research university. The lead course instructor had redesigned the course in order to move toward an active learning model, with the goal of better preparing students to take subsequent math courses. Using the influence of pedagogy on the classroom climate as my conceptual framework, I sought to understand how first-generation students experienced the classroom climate of the redesigned class, how pedagogy influenced the climate, and how first-generation students' experiences in the course affected their intentions to persist in STEM. My data collection methods were

classroom observation, a student survey (N = 171), interviews with first-generation students (N = 13), interviews with the two course instructors, and a review of the syllabus and other course materials.

I found that first-generation students described a classroom climate characterized by disengagement and collective confusion and frustration. Pedagogy negatively influenced the climate through a lack of structure, guidance, and communication at several levels; a test-based approach to assessment; and, in the case of one of the instructors, lecturing. The teaching assistants and one of the two instructors provided a high level of immediacy, which positively influenced the climate. Study participants varied in terms of whether the course had negatively or positively influenced their intention to persist in STEM, with about half of survey respondents saying the course had no impact.

I approached the study of pedagogy through the lens of three teaching and learning paradigms: traditional pedagogy, active learning, and inclusive pedagogy. While the pedagogy utilized in the pre-calculus class mirrored the active learning paradigm in several ways, it also aligned with some aspects of traditional pedagogy and inclusive pedagogy. The dominant trend in introductory science and math course reform is to move from traditional pedagogy to active learning, and I was interested in exploring whether active learning is sufficient for creating an equitable classroom climate or if inclusive pedagogy is needed. Inclusive pedagogy calls for instructors to contextualize math within its social and cultural context and to tie course content to students' experiences and goals. Conversely, the pre-calculus course presented math in a decontextualized manner. While inclusive pedagogues would argue that this decontextualization harms marginalized students, the class aligned with the first-generation interview participants' expectations that a math course would avoid issues of identity, inequity, and discrimination.

The study leads to several implications. A lack of structure was a main driver of the negative classroom climate. Under any pedagogical approach, a clear course structure should serve as a foundation on which to build a positive and inclusive classroom climate. Given that first-generation students benefited from the validation they received from the teaching assistants and one of the instructors, individuals who have a teaching role in introductory science and math courses should prioritize their position as someone who can provide validation to underrepresented students. I also discuss recommendations for institutional leaders and researchers who seek to bring about greater equity in science and math introductory courses and STEM education in general.

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Definition of Key Terms

Active learning: "Active learning engages students in the process of learning through activities and/or discussion in class, as opposed to passively listening to an expert. It emphasizes higher-order thinking and often involves group work" (Freeman et al., 2014, pp. 8413-8414).

Classroom climate: Ambrose, Bridges, Dipietro, Lovett, and Norman (2010) defined the classroom climate as the "intellectual, social, emotional, and physical environments" of a course (p. 170).

Factors that influence the classroom climate: There are seven classroom factors that influence the climate: professor-student interaction, student-student interaction, participation, discriminatory behavior, isolation and feelings of being invisible or too visible, inclusion of diverse backgrounds, and physical space. In my study, I explored teaching assistant-student interaction as an additional influential factor.

First-generation student: A college student for whom neither parent has completed a four-year baccalaureate degree.

Gateway course: Bauman (2005) defined a gateway course as one that "acts as a prerequisite for particular majors or programs or a generally required course for graduation, and a student's success or failure in such a course might limit his or her options or the ability to graduate" (p. 26).

Inclusive pedagogy: Inclusive pedagogy is an umbrella term for pedagogies influenced by critical theories, such as critical pedagogy, feminist pedagogy, and culturally relevant pedagogy (Tuitt, 2003, 2016). These methodologies explicitly recognize the history of racism, sexism, and classism in education; seek to share power between the instructor and students in the classroom; develop students as "reflective and active citizens" (Tuitt, 2003, p. 246); and seek to continuously tie content to students' lives (Tuitt, 2003).

Marginalized student: A term used interchangeably with the term underrepresented students (see below).

Predominantly white institutions (PWIs): A university where at least 50% of students are White.

STEM fields: STEM stands for science, technology, engineering, and mathematics. For this study I used the U.S. Immigration and Customs Enforcement's (2012) designation to inform which disciplines fall under the STEM umbrella. This list of disciplines includes biology, biomedical sciences, chemistry, computer science, engineering, environmental science, information technology, mathematics, physical sciences, and psychology.

Traditional pedagogy: Traditional pedagogy is based on an assumption that the instructor possesses expert, objective knowledge that can be transmitted to students. Traditional pedagogy is often associated with the lecture method, rote memorization, and an exam-based approach to assessment.

Underrepresented students: In STEM, underrepresented students include first-generation; low-income; and Black, Latinx, Native American, and Southeast Asian American (Cambodian, Hmong, Laotian, and Vietnamese) students. In some STEM disciplines, women are also underrepresented.

Chapter One: Introduction

With the lowest rate of intergenerational mobility among advanced nations, the United States is a country of severe and growing inequality (Carnevale & Strohl, 2013; Sommeiller & Price, 2018); the inequitable structures of higher education fuel this problem instead of remedying it. Parental education is now the strongest predictor of educational achievement, meaning that students whose parents did not earn a college degree are at a significant disadvantage (Carnevale & Strohl, 2013). In 2012, for individuals who were high school sophomores in 2002, only 14.7% of people whose parents had a high school degree or less had a bachelor's degree, compared to 21.7% for those with parents who had some college, 36.4% for those with parents with a bachelor's degree, and 44% for those with parents with an advanced degree (Snyder, de Brey, & Dillow, 2016). Because education level is a strong predictor of income and social class (Pell Institute for the Study of Opportunity in Higher Education, 2016), social inequality is reproduced from generation to generation. Since race, ethnicity, and class are intertwined in U.S. society, this means that individuals of color are disproportionately affected by this dynamic.

This study focused on one context that has been consistently criticized for exacerbating the role of higher education in reproducing inequity: large introductory courses in the science, technology, engineering, and mathematics (STEM) fields. More specifically, I examined how first-generation students experienced the climate of a pre-calculus course that had been redesigned in an effort to improve student persistence in STEM. This course is considered a gateway course because students who are placed into it need to receive a passing grade to take calculus, which is a required course for students majoring in a STEM field and other quantitatively oriented disciplines, such as business and economics. While varying definitions of first-generation exist, for the purpose of this study I define a first-generation (FG) student as a student whose parents have not completed a four-year baccalaureate degree (Verdin & Godwin, 2015). In this chapter I provide an overview of the critical issue of first-generation student persistence in the STEM fields, the role of large introductory courses, and efforts to reform pedagogy in those courses. In the subsequent chapters I examine the bodies of literature that informed my study, lay out the details of my study design, present my mixed methods findings, and discuss how my findings advance the literature on classroom climate, pedagogy, and introductory STEM courses.

First-generation Students in U.S. Higher Education

One way that postsecondary institutions could reverse inequity and become drivers of social change is to better address the needs and recognize the assets of first-generation students. Because of different definitions and statistical sources, it is difficult to determine the exact percentage of FG students in the overall student population. Using the definition provided above, FG students represent anywhere from 33% to 62% of the U.S. undergraduate population, including two-year and for-profit institutions (Jehangir, Stebleton, & Deenanath, 2015; Toutkoushian, Stollberg, & Slaton, 2015; U.S. Department of Education, 2014). At large, public research universities (characteristics that define my research site), this figure is somewhere between 22% and 47% (Soria & Gorny, 2012; U.S. Department of Education, 2014).

FG students are more likely than continuing-generation (CG) students to be low-income and students of color. According to the U.S. Department of Education (which has overall estimates of FG students that are higher than some other sources), 56% of White students and 54.8% of Asian students are FG, compared with 72.3% of Black students, 74.8% of Latinx students, and 68.1% of Native American students. Among students in the lowest income quartile, 72.2% are FG compared with 48.8% of students in the highest income quartile (U.S. Department of Education, 2014). This overlap is relevant because deep disparities exist in U.S. higher education along lines of race, ethnicity, and class – both in terms of access and persistence (Carnevale & Strohl, 2013; Riegle-Crumb, King, & Irizarry, 2019).

Higher education structures and cultures are especially unwelcoming to FG students in the STEM fields (Ferrare & Lee, 2014; Harackiewicz, Canning, Tibbetts, Priniski, & Hyde, 2015; Martin, Miller, & Simmons, 2014; R. E. Wilson & Kittleson, 2013). For instance, in some STEM disciplines, students who have a family member in that field are more likely to persist (Trenor, 2009). The issue of FG student persistence in STEM is situated within the ongoing dialogue around student retention in U.S. higher education. Student retention has been a leading area of scholarly and practitioner focus in higher education for over 40 years (Braxton, 2008; Rendón, Jalomo, & Nora, 2000; Tinto, 1975). Yet, only 68% of students who started at a four-year institution in 2012 graduated within six years (Shapiro, Dundar, Huie, Wakhungu, Bhimdiwala, & Wilson, 2018), and this rate is significantly lower for historically underserved students, including FG students (National Center for Education Statistics, 2016; Soria & Stebleton, 2012;

Verdin & Godwin, 2015). Scholars have traditionally focused on individual-level characteristics to explain why certain students are not successful at the postsecondary level, relying on explanations such as poor high school preparation (Rendón et al., 2000). However, a more convincing argument is that the structures of higher education are not set up to benefit certain students.

A large body of evidence on student persistence in the STEM fields suggests that FG students are less likely to persist in STEM compared to CG students (E. Anderson & Kim, 2006; Chen & Soldner, 2013; Dika & D'Amico, 2016; Shaw & Barbuti, 2010). Because of overlaps between generation status, race and ethnicity, and class, FG students are likely to encounter barriers and supports that have been documented in the broader literature on underrepresented students in STEM. In STEM, underrepresented students include FG; low-income; and Black, Latinx, Native American, and Southeast Asian American (Cambodian, Hmong, Laotian, and Vietnamese) students (Dika & D'Amico, 2016; Museus & Liverman, 2010). In addition, women are underrepresented in several STEM disciplines, such as the physical sciences and engineering (Dika & D'Amico, 2016).

Common barriers for underrepresented students in STEM include cultural incongruence; stereotypes, microaggressions, and other forms of discrimination; and feelings of isolation (Carlone & Johnson, 2007; Holmes, 2013; Strayhorn, Long III, Kitchen, Williams, & Stentz, 2013; Sue et al., 2007). Common assets include a *prove-them-wrong* mindset (i.e., a drive to succeed in response to low expectations) and strong familial and peer support (Fries-Britt, Younger, & Hall, 2010; Peralta, Caspary, &

Boothe, 2013; Yosso, 2005). In addition to these barriers and supports, because FG students often lack access to family members who can provide college advice and insight, they are more likely to lack the types of cultural and social capital that STEM education structures reward (Bourdieu, 1986; Martin et al., 2014). In order to address the educational structures and cultures that contribute to lower rates of FG student persistence in STEM, it is important to frame the issue within the national movement to reform STEM education.

Reforming STEM Education as a National Issue

Calls to reform STEM education in the United States began in the late 1960s; the current flood of appeals for improving underrepresented student persistence in STEM largely focuses on the need to make the U.S. economy more competitive (Basile & Lopez, 2015). Equally important to consider is economic equity. There is evidence that panic surrounding a shortage of STEM workers is overblown; the emergence of this apparent crisis is partially due to a desire among employers for an oversupply of labor to help lower salaries (Charette, 2013). Whereas the overall U.S. economy is relatively healthy, wide economic disparities exist (Stone, Trisi, Sherman, & Debot, 2015) that could be remedied in some measure by more equitable STEM education outcomes.

Scholars who study the economic benefits of education have long been interested in whether individual lifetime earnings differ more by education level (termed *vertical stratification*), institutional selectivity, or field of study (two forms of *horizontal stratification*). Ma and Savas (2014) demonstrated that field of study is a much stronger predictor of income differences compared to institutional selectivity; students who earn degrees in fields such as math, engineering, and business are well positioned for high earnings regardless of the perceived prestige of their institution. Field of study may even be more important than education level in explaining earnings gaps. Kim, Tamborini, and Sakamoto (2015) found that:

> The gaps in 40-year (i.e., ages 20 to 59) median lifetime earnings among college graduates by field of study are larger, in many instances, than the median gap between high school graduates and college graduates overall … the gap in cumulative 40-year earnings between a bachelor's degree in STEM versus education is *26 times larger* [emphasis added] than the gap between a bachelor's degree in education and a high school diploma. (p. 320)

Because field of study is such a strong differentiating factor, exploring the demographic representation of the various disciplines may help explain persisting economic inequities along lines of gender, race and ethnicity, and other identities.

Most of the majors associated with the highest lifetime earnings are in the STEM fields. Among the 20 college majors with the highest mid-career median salary, 18 are from the STEM disciplines (PayScale, n.d.). The number of available jobs in occupations related to STEM fields is projected to increase more quickly than in non-STEM related professions (U.S. Department of Education, 2015). While underrepresented students enter STEM fields at rates similar to majority students, they are more likely to leave STEM (Graham, Frederick, Byars-Winston, Hunter, & Handelsman, 2013). Studies have found that women and Black and Latinx students are underrepresented in the highest paying majors and overrepresented in the lowest paying majors (Ma & Savas, 2014). A stable income and adequate salary are key influential factors towards improving the welfare of individuals and their families. The structures and cultures of STEM that deter underrepresented students are reproducing economic inequity in the United States.

Increasing underrepresented student persistence in STEM may also improve wellbeing beyond the degree-earners. Underserved communities will likely benefit from a more diverse STEM workforce (Byars-Winston, 2014). For example, studies have found that underrepresented medical students of color are more likely to work in underserved communities compared to their majority peers (Saha, Guiton, Wimmers, & Wilkerson, 2008; Saha & Shipman, 2008). In addition, a more diverse STEM workforce is likely to result in a greater prevalence of research conducted on the problems that afflict low-income communities of color (Intemann, 2009).

Despite the current low unemployment rate (Eavis, 2019), many college graduates are entering an unfavorable employment landscape (Cunningham, 2016). It is estimated the 43% of college graduates are underemployed in their first job, meaning that their skills are underutilized, which leads to lower lifetime earnings (Korn, 2018) Technological innovation and globalization have polarized the job market – there is a large and growing divide between well-paying and low-paying jobs (Hanson & Gulish, 2016). As mentioned above, the STEM professions represent some of the highest-paying jobs. Unfortunately, the current STEM workforce is severely lacking in diversity and many women, people of color, and individuals from low-income backgrounds lack access to these professions. In 2010, 11.5% of the U.S. population was Black and 13.9% was Latinx, but only 4.6% of the science and engineering workforce was Black and only 5.2%

was Latinx. Conversely, White and Asian people were overrepresented in the science and engineering workforce (National Science Board, 2015). Diversifying the STEM workforce is a necessary step towards diminishing inequity in U.S. society, and much of this work must be done at the postsecondary level. The first year of college is an especially crucial stage that policymakers and institutional leaders need to address.

Importance of the First Year and the Role of Large Introductory STEM Courses

The first year of college is particularly important for retaining FG students and for retaining students in STEM (Dika & D'Amico, 2016; Jehangir et al., 2015). Griffith (2010) found that 52% of students who originally intended to major in STEM had left STEM by the 2nd year, whereas the attrition rate was 13% between the 2nd and 4th years. Students intending to major in STEM usually take several introductory science and math courses in the first year, and these courses have the potential to either attract or deter large numbers of students to or from STEM (Eagan Jr. & Jaeger, 2008). Evidence suggests that much of the first-year attrition from STEM is due to discouraging experiences in large introductory courses (e.g., introductory physics, chemistry, and math courses), which are characterized by competition, harsh attitudes from professors, and decontextualized learning (Daempfle, 2003; Seymour & Hewitt, 1997; Strayhorn et al., 2013; Tobias, 1990; Watkins & Mazur, 2013). In reviewing the literature on failure rates in these courses, Freeman, Haak, and Wenderoth (2011) claimed that "it appears common for one-third of students to fail in STEM gateway courses" (p. 175).

Instead of serving as a *gateway* course, these classes are often termed "gatekeeper courses [which] are designed to weed out students who cannot perform at the expectations of faculty" (Eagan Jr. & Jaeger, 2008, p. 40). According to Hurtado et al. (2011), the "single objective" of these courses is to "differentiate students' capacity for absorbing large amounts of information" (p. 573). In gatekeeper courses, students often struggle to earn a high grade even when they were successful in high school (Seymour & Hewitt, 1997). Chen and Soldner (2013) found that earning low grades in STEM courses was one of the primary drivers of students to non-STEM majors.

The field of higher education is lacking in large-scale quantitative studies identifying the reasons students attribute to leaving a STEM major. However, smaller quantitative studies and qualitative research provide convincing evidence that introductory STEM courses play a significant role. In Tobias' (1990) qualitative study, 40% of students left STEM after taking their first undergraduate STEM course. Barr, Gonzalez, and Wanat (2008) found that among students at Stanford whose interest in pursuing a medical degree declined during the first two years of college (who were disproportionately women and students of color), 75% identified course experiences as a cause of their lowered interest, often referencing the weed-out mentality of the classes. Seymour and Hewitt's (1997) seminal study that explored why students leave STEM cited poor experiences with introductory courses as one of the top reasons. Vivyan's (2016) qualitative study of introductory STEM courses found that students who reported introductory courses with competitive cultures, or cultures that induced anxiety, were more likely to leave STEM compared to students who reported a comfortable and informal classroom culture.

Lecturing is often identified as one of the main factors that contributes to negative experiences in introductory courses (Eagan Jr. & Jaeger, 2008). Many institutions are currently attempting to redesign introductory courses to move away from a *traditional* pedagogical model, characterized by lecturing, rote memorization, and a high stakes, exam-based grading approach (Danowitz & Tuitt, 2011). The traditional pedagogical model is most often replaced by an *active learning* model (Shuster & Preszler, 2014). Freeman et al. (2014) provided the following definition for active learning: “Active learning engages students in the process of learning through activities and/or discussion in class, as opposed to passively listening to an expert. It emphasizes higher-order thinking and often involves group work” (pp. 8413-8414). Active learning strategies are believed to greatly improve first-year student persistence in STEM; they may be especially beneficial for FG and other underrepresented students who suffer disproportionately from traditional lecture-based approaches (S. L. Eddy & Hogan, 2014; Freeman et al., 2014; Morales & Trotman, 2010; Nicol & Macfarlane-Dick, 2006; Prince, 2004).

Although efforts to incorporate active learning into large introductory STEM courses reflect a step in the right direction, the literature often erroneously treats active learning as a cure-all that will benefit all students (Gasiewski, Eagan, Garcia, Hurtado, & Chang, 2012; D. M. Riley, 2003). This is an incorrect assumption for at least two reasons. First, the effect of any one pedagogy on students will vary depending on their backgrounds, personalities, and experiences. For instance, Stephens et al. (2012) demonstrated that FG students performed better when a course stressed interdependent tasks, whereas CG students performed better when a course emphasized independent activities. Second, most of the literature on active learning in STEM avoids issues of underlying racism and inequity in the sciences (Holmes, 2013; A. Johnson, 2007; D. M. Riley, 2003). This tendency means that professors often incorporate active learning without considering issues of classroom climate.

Classroom climate is a complex concept that includes "racial climate, verbal and nonverbal communication between instructors and students, the nature and frequency of faculty-student interactions, students' comfort level with asking questions or seeking assistance, and course curricula" (Holmes, 2013, p. 24). In my study, I considered the following aspects that the literature has shown can influence the climate: interaction (professor-student interaction, student-student interaction, and participation), climate for diversity (discrimination, student feelings of isolation or being too visible, and inclusion of diverse backgrounds), and the physical space. Throughout this paper, I refer to these elements as "factors that influence the classroom climate." The classroom climate is one component of the larger campus climate, which encompasses the physical, psychological, and social environment of a campus (Strange & Banning, 2001). According to Gasiewski et al. (2012),

> The call for more active learning in introductory science courses has led to a burgeoning body of research known as the scholarship of teaching (Boyer 1990), conducted by the research scientists teaching these courses, that investigates student outcomes related to these strategies. Scholars, however, have not given as much attention to the *climate of introductory courses* [emphasis added] that

> students encounter during their first year of college, particularly in the STEM context. (p. 230)

As a result of this inattention to classroom climate, FG and other underrepresented students may continue to experience discrimination, isolation, and feelings that they do not belong despite taking a course that has replaced lecturing with active learning (Basile & Lopez, 2015; D. M. Riley, 2003).

STEM reform advocates operating from a more critical stance have called for the use of an *inclusive pedagogy* model that uses active learning but also explicitly recognizes the inequitable structures of STEM education and aims to create environments that are welcoming to historically underserved students. Tuitt (2003) coined the term inclusive pedagogy to include a wide range of approaches that seek to reverse power imbalances in education, including critical, feminist, and culturally relevant pedagogy. Inclusive pedagogues acknowledge that the STEM disciplines operate from Western, White, male norms and values; these educators seek to transform the disciplines instead of merely reproducing existing knowledge in students (Mayberry, 1998). The inclusive pedagogy paradigm places a strong emphasis on acknowledging students' experiential knowledge and unique reasons for pursuing STEM, especially for marginalized students (Hurtado, Alvarez, Guillermo-Wann, Cuellar, & Arellano, 2012).

Inclusive pedagogy uses several tenets of active learning but goes further. For instance, active learning calls for the instructor to serve as a facilitator of student learning rather than a transmitter of information. Inclusive pedagogies contend that *in addition,* the professor should play a validating role, conveying to students that they belong and can succeed in the course (Tuitt, 2016). Under the inclusive pedagogy paradigm, students are not only engaged in the learning process but also take on shared power and responsibility in the classroom (Tuitt, 2003). The distinctions between traditional pedagogy, active learning, and inclusive pedagogy are further explored in chapter two and are summarized in Appendix A. There is a lack of knowledge on how FG students experience introductory courses that have been reformed mainly under an active learning model, how active learning influences the climate, and whether inclusive pedagogies are needed to create equitable environments in introductory courses. My study addresses this gap in the literature.

Study Purpose

Differences in lifetime earnings by field of study in higher education significantly contribute to economic inequality in the United States. The STEM fields are associated with substantially higher lifetime earnings compared to most non-STEM fields, yet FG students persist in STEM at lower rates than their CG peers, thereby limiting economic mobility. Large, competitive, lecture-based introductory science and math courses have long been identified as a main factor that deters students from persisting in STEM, especially for FG and other underrepresented students. Institutions, aided by external funding, have begun to invest more in reforming introductory courses to incorporate active learning and move away from their traditional gatekeeper role; however, little is known about how FG students experience these redesigned courses, especially regarding the classroom climate.

Instead of assuming active learning will create more welcoming environments that encourage FG students to persist in STEM, it is important to gain an in-depth understanding of how students experience these environments. The purpose of this mixed methods case study was to understand how FG students experienced a large, gateway pre-calculus course that had been redesigned to incorporate active learning, how those experiences affected students' intentions to take additional math courses and persist in STEM, and how pedagogy influenced the classroom climate. The overarching research question guiding this study was: How do first-generation students experience a large STEM gateway course that has been redesigned to incorporate active learning?

It is critical to explore this question now due to growing economic disparities in the United States as well as the massive investment in STEM education reform at the postsecondary level. In 2012, the President's Council of Advisors on Science and Technology published a report entitled *Engage to Excel: Producing One Million Additional College Graduates with Degrees in Science, Technology, Engineering, and Mathematics.* This report cited the improvement of introductory STEM courses as one of the most important strategies for obtaining more STEM graduates. The report specifically referenced introductory math courses as ones that "often leave students with the impression that all STEM fields are dull and unimaginative" (President's Council of Advisors on Science and Technology, 2012, p. vi). Millions of dollars are being invested in reforming introductory courses. This funding comes from governmental agencies such as the National Science Foundation, private foundations such as the Howard Hughes Medical Institute (Howard Hughes Medical Institute, 2014) and individual institutions. At the same time, these entities are increasing investments in supporting FG and other underrepresented students (Mangan, 2015).

If these investments continue without recognition of underlying inequities or consideration of the classroom climate, the structures of higher education will remain the same and disparities in STEM education outcomes will not improve, reflecting a lost opportunity to reverse widening social and economic gaps in U.S. society. In the next chapter, I provide an overview of the literature pertaining to my research question, as well as my research paradigm and conceptual framework.

Chapter Two: Review of the Literature

I begin this chapter by outlining critical theory as my approach to this study. Critical Race Theory and Latinx Critical Race Theory are especially informative. Next, I explore the existing scholarship on underrepresented student persistence in STEM and first-generation students in STEM, which is helpful for understanding the larger context in which this study is situated. I then discuss the literature on the classroom climate and teaching and learning paradigms in STEM. Teaching and learning reform in STEM has largely followed the active learning paradigm without considering the classroom climate or whether a more radical approach that uses inclusive pedagogy is needed. My conceptual framework, the influence of pedagogy on the classroom climate, draws from these two bodies of literature. I then summarize efforts to reform introductory STEM courses in U.S. higher education through the lens of the teaching and learning paradigms. Finally, I discuss some aspects that are specific to the mathematics context, as well as considerations related to large, public research universities and predominantly White institutions, which reflect the context in which I conducted my study.

Paradigmatic Approach: Critical Theory

I am concerned with issues of power, structure, and agency in higher education, and aim to advance social justice through my work. As such, I approached this study through a critical lens. By drawing attention to the seemingly neutral rationalities and ideologies in the STEM classroom that mask discrimination and reproduce inequity, critical theory is the most effective paradigm for transforming the classroom into an equitable environment (Museus, 2011; Ochoa & Pineda, 2008; Tierney, 2000). Below I review the central tenets of this paradigm and of two branches of critical theory: Critical Race Theory and Latinx Critical Race Theory.

Central tenets. Although it has evolved substantially, critical theory has its origins in the 1800s and in the work of Karl Marx. Marx viewed society as that of an ongoing class struggle and as a conflict between capital and labor. The ruling class was not only dominant in economic terms, but also in terms of culture and ideas (Crotty, 1998). Critical theory is based in an ontology of "historical realism," claiming that "reality" has been constructed over time through social, political, and cultural forces that shaped a version of "reality" that is now taken for granted as objective truth (Guba & Lincoln, 1998, p. 205). The critical paradigm aims to both uncover and shift inequitable structures. Critical theory takes on a subjectivist epistemology, in which knowledge is socially constructed and knowledge creation is mediated by the values and beliefs of the researcher (Guba & Lincoln, 1998).

Power relations are central to the critical paradigm; according to Kincheloe and McLaren (1998), "All thought is fundamentally mediated by power relations that are social in nature and historically constituted" (p. 263). Power dynamics are most often hegemonic instead of overt; the dominant beliefs, values, and norms of a society or institution are portrayed in everyday discourse as ordinary and reflective of an objective reality, and thus remain unquestioned (Mumby & Stohl, 1991). A critical approach to my topic casts the low persistence rates of FG students (many of whom are low-income and students of color) in STEM as a structural issue instead of an individual problem and identifies the dominant discourse of STEM education reform as being potentially complicit in reproducing inequity (Benschop & Doorewaard, 1998; A. Johnson, 2007). Power relations and many other central focuses of critical theory have been strengthened and expanded by Critical Race and Latinx Critical Race theorists (Bernal, 2002; Hernández, 2016).

Critical Race Theory and Latinx Critical Race Theory. Critical legal scholars established Critical Race Theory (CRT) in the 1980s as a set of concepts that explained the perpetuation of racial inequities in the United States, partially in response to the perceived failure of critical legal studies to do so (Bell, 1988; Crenshaw, 1988; Delgado, 1990; Peralta et al., 2013). In 1995, Ladson-Billings and Tate argued for the use of CRT in education research. Latinx Critical Race Theory (LatCrit) is a branch of CRT that "is concerned with a progressive sense of a coalitional Latina/Latino pan-ethnicity" (Bernal, 2002, p. 108). LatCrit expands beyond racism to incorporate multiple forms of oppression, considering discrimination based on aspects such as immigration status, class, language, and ethnicity (Peralta et al., 2013). Several tenets of CRT and LatCrit informed my thinking and approach to the issues surrounding my study, including the centering of race, racism, and multiple forms of oppression; the questioning of claims to meritocracy and neutrality; the concept of interest convergence; and intersectionality (Gonzalez & Morrison, 2016; L. D. Patton, Harper, & Harris, 2015; Peralta et al., 2013). Below I discuss these concepts and how they apply to STEM education reform.

Centering of race, racism, and multiple forms of oppression and questioning claims to neutrality and meritocracy. CRT, LatCrit, and other branches of critical theory (e.g., TribCrit, AsianCrit) argue that racism is a part of everyday life in the United States, thus necessitating a central focus on race (Abes, 2016). Both theories, and especially LatCrit, recognize additional intersecting forms of oppression. In education, when scholars and practitioners fail to acknowledge race and racism, they obscure the fact that U.S. educational institutions were designed according to a White, Eurocentric, upper-class culture. While whiteness usually goes unacknowledged as a race and culture, higher education leaders must name it and recognize that it “provides the standard or the measure for which all ‘others’ are judged and critiqued” (Gonzalez & Morrison, 2016, p. 90). A failure to acknowledge that whiteness underlies higher education structures invalidates the feelings of cultural incongruence and isolation that students of color and other underrepresented students often experience (Mitchell, Donahue, & Young-Law, 2012; R. E. Wilson & Kittleson, 2013).

The STEM disciplines have a historical legacy of racism and sexism (Ong, 2005; Sosnowski, 2002). For example, in the first half of the 20th century, research institutions granted a small number of doctoral degrees in the sciences to women of color but refused to hire them as faculty (Haynes, 2014). At one time, “Scientific inquiry focused on connecting, classifying and categorizing race differences of people into various sub-levels of humanness” (Sosnowski, 2002, p. 128). Despite this history, these fields most often operate under a false claim to neutrality and objectivity (A. Johnson, 2007). This perceived objectivity elevates the STEM fields to a privileged status in a Western, White culture that values rationality. The field of mathematics in particular “imposes the rationality of the dominant power over all other kinds of forms of thinking and expression in non-Western, indigenous, colonized cultures” (Valero, 2008, p. 51).

CRT and LatCrit question claims to neutrality, meritocracy, and objectivity that are rooted in the STEM fields and in broader U.S. society. These assertions often serve as rationalizations for maintaining the status quo; if education is based on meritocracy, then any individual can achieve through hard work alone (Holmes, 2013). An appearance of meritocracy and objectivity also portrays racism and other forms of discrimination as individual acts and not part of a larger, systemic, historically-based system. This false representation may lead students to attribute challenges to individual shortcomings instead of systemic issues (Seymour & Hewitt, 1997). A failure to identify and address systemic inequities reinforces racism and other forms of discrimination in STEM education (Parsons, Rhodes, & Brown, 2011).

Interest convergence. Another central tenet of CRT and LatCrit is interest convergence: how the dominant group will promote the advancement of people of color and other marginalized groups only when it serves their best interest (L. D. Patton et al., 2015). It is not difficult to view the intense national focus on improving persistence rates of underrepresented students in STEM through an interest convergence lens. As I mentioned in the previous chapter, many industry and government leaders see the goal of improving persistence rates as one that will achieve a more competitive U.S. economy or that will bring down wages for STEM workers, rather than viewing it as an equity-oriented goal. Because an expanded STEM workforce (which will need to emerge from a more diverse population) will benefit industry leaders and policymakers, there has been a surge in attention to this issue (Basile & Lopez, 2015). Basile and Lopez reviewed 17 government documents published between 1994 and 2009 that called for diversifying

STEM; whereas 14 documents discussed the economic benefit of making the STEM workforce more diverse, only one document mentioned the "direct benefit to students of color" (p. 530). The intentions behind improving underrepresented student persistence in STEM makes it even more important to question and challenge the assumptions driving STEM reform efforts, including the assumption I will examine in this study: that active learning will automatically create more inclusive classroom environments.

Intersectionality. Intersectionality, a framework that emerged from Black feminist legal studies in the 1980s, highlights the ways in which different dimensions of identity intersect, overlap, and conflict with each other and affect individual experiences and identities (Cho, Crenshaw, & McCall, 2013; Crenshaw, 1989, 1991; Jones & Abes, 2013; Nash, 2008; L. D. Patton et al., 2015). Because multiple identities influence how a person experiences any given context, individuals cannot be considered along only one identity category; for instance, a FG student in STEM also holds identities related to race, ethnicity, gender, class, sexual orientation, etc. Such identities are not cumulative and some identities may be more salient in certain situations (Crenshaw, 1991; Nash, 2008). According to Hazari et al. (2013), studies focused on intersectionality are important "because the normative structures within science communities (e.g., classrooms, departments, fields) have created disadvantages for individuals of certain race, gender, ethnicity, etc., in intersecting and differing ways that are not necessarily additive" (p. 84). Intersectionality is useful for limiting the extent to which we essentialize students according to only one identity dimension (e.g., race, gender).

Studies that adopt an intersectional framework have been useful in demonstrating the nuances of student experiences in STEM classrooms. For instance, women of color in STEM are often in a “double bind” (Charleston, Adserias, Lang, & Jackson, 2014, p. 275) in which they experience discrimination due to both their gender and racial identities. Ong (2005) demonstrated that undergraduate women of color in physics often engaged in both “gendered passing and racial passing” (p. 595) in which they simultaneously downplayed their racial and/or ethnic minoritized status and took on masculine behaviors and appearances. Historically constituted systems of power, oppression, and privilege shape the unique experiences, opportunities, and challenges that students in STEM face.

Some closing thoughts on critical theory, CRT, and LatCrit. It is important to note that while critical theory seeks to shed light on the structures that perpetuate inequity, it also allows for individual agency (Tierney, 2013). Johnson et al. (2011) defined agency as “action that resists and undermines structural constraints resulting from a subordinate location in the matrix of oppression” (p. 343). Many underrepresented students succeed in STEM despite inequitable structures. However, Johnson et al. stressed that agency can at times be constrained; for example, if a professor is unwilling to validate certain students as future scientists, those students may be limited in the extent to which they can see themselves as scientists. In the next section, I review the literature on underrepresented student persistence in STEM and issues that are specific to FG students in STEM.

Underrepresented Student Persistence in STEM

Before introducing the literature on classroom climate and pedagogy, I discuss the larger body of research on underrepresented students in STEM, which includes studies that focus on the classroom and others that explore the influence of other actors and institutions. To understand the context of first-generation students in STEM, it is important to first consider the assets and challenges of underrepresented students more broadly. As I mentioned in the first chapter, in STEM underrepresented students include FG; low-income; Black, Latinx, Native American, and Southeast Asian American; and in some disciplines women students (Dika & D'Amico, 2016; Museus & Liverman, 2010). For decades, scholars have examined the disparities in STEM graduation rates between majority students and underrepresented (UR) students. UR students face the same challenges to persisting in STEM as majority students, but also face additional obstacles, such as cultural incongruence and feelings of isolation (Harper, 2013; Holmes, 2013). At the same time, these students utilize unique assets, such as the ability to navigate between different cultures and a strong motivation to better their communities and persist through difficult and unwelcoming conditions (Yosso, 2005). Given these dynamics, the persistence process of UR students in STEM is complex.

There are two main approaches to studying UR student persistence in STEM. One approach focuses on the barriers that keep students from earning STEM degrees. This focus is often criticized for its emphasis on student deficits. A strengths approach examines the strategies used by students who successfully navigate the STEM pipeline (Harper, 2010). Below I review both the barriers to and supports for UR student persistence in STEM, arguing that the two approaches are equally necessary and that many factors act as both obstacles and motivators. This approach allows higher education scholars to criticize structures while also recognizing student agency (Carlone & Johnson, 2007). I examine factors at several levels: individual, departmental and institutional, and peers and family.

Individual-level assets and barriers. Several factors related to individuals' backgrounds and characteristics can affect a student's trajectory in STEM. An analysis of the narratives of UR students in STEM reveals certain mindsets that are beneficial for persistence. For example, Espinoza (2013) found that Latinx students who entered STEM programs with a strong sense of academic self-efficacy were more likely to persist. Numerous studies on UR students in STEM have also identified a *prove-them-wrong* mindset, aligned with Yosso's (2005) notion of resistant capital, in which students are driven to prove they can succeed to those who have doubted them (Fries-Britt et al., 2010; Harper, 2013; E. Kim & Hargrove, 2013; Peralta et al., 2013). This mindset demonstrates that even though discrimination acts as a barrier, it can simultaneously harden students' intentions to succeed.

Students often must develop positive mindsets that strengthen their resilience because of contextual factors that can act as barriers. UR students are more likely to work long hours and/or work off campus, which is negatively associated with persistence (Tsui, 2007). UR students are also more likely to come from high schools that did not provide high-quality preparatory science and math courses (Perna et al., 2009; Seymour & Hewitt, 1997; Tsui, 2007). However, it is important to keep in mind that even for students who attended under-resourced schools, positive high school experiences, often related to supportive teachers, can be key elements for fostering resilience in UR students in STEM (Fries-Britt et al., 2010; Morales & Trotman, 2010; Russell & Atwater, 2005).

An additional individual factor that drives resilience is identity. The development of a *science identity,* or the extent to which a student identifies as a *science person,* is a crucial component of the persistence process (Carlone & Johnson, 2007; Hazari, Sadler, & Sonnert, 2013; Tate & Linn, 2005). Carlone and Johnson's study of successful women of color in STEM found that participants had constructed science identities, often related to conducting research or entering altruistic professions, which drove them to continue their studies. For these women, it was important that external actors, such as professors, affirm their science identities. Unfortunately, some participants' science identities were not affirmed by others. Those women persisted by "redefining their understanding of what it means to be in science and whose recognition is important to them" (p. 1210). This reframing highlights the power of individual agency. Yet, when "individuals must be able to engage in sophisticated levels of cultural production to find a peaceful niche for themselves within science" (Carlone & Johnson, 2007, p. 1202), there are clearly underlying inequities that must be addressed. Taken together, the individual factors discussed in this section demonstrate the importance of students' self-perceptions and the ways in which students frame their experiences for themselves.

Departmental and institutional supports and barriers. The literature has identified several sources of support provided by the institution or department, as well as barriers at this level. Institutions that foster familial or collectivist cultures on campus have generally enjoyed higher rates of UR student persistence in STEM (Museus, 2011; Perna et al., 2009; Seymour & Hewitt, 1997). Seymour and Hewitt found that student support services were most successful when offered at the departmental level, specific to the discipline, and offered to all students in the department, which reduced the stigma of using them. Experiential learning opportunities, such as conducting research with faculty or working as a lab assistant, also act as powerful sources of motivation for students to persist (Carlone & Johnson, 2007; Hurtado, Cabrera, Lin, Arellano, & Espinosa, 2009; A. Johnson, 2007; Perna et al., 2009). These findings demonstrate that institutions, especially at the departmental level, can provide meaningful sources of support to UR students.

Unfortunately, there are several ways in which institutions and departments can act as barriers. The cultures of STEM largely follow White, male, middle- and upper-class values, such as individualism, competition, and objectivity (Holmes, 2013). Consequently, UR students frequently experience cultural incongruence, impeding the incorporation of a science identity with students' other multiple identities (Carlone & Johnson, 2007; Holmes, 2013; Morales & Trotman, 2010). Through the use of words such as meritocracy and objectivity, claims of neutrality conceal innate cultural biases (Carlone & Johnson, 2007; L. D. Patton et al., 2015). The White male culture of STEM is associated with competitiveness and independence, attributes that have been associated with UR student departure from STEM (Museus, 2011). Seymour and Hewitt (2007) explained why this may be:

> [STEM] tests for qualities of character traditionally associated with 'maleness' in Anglo-Saxon societies and is based on motivational strategies understood by young men reared in that tradition. The cues are more likely to be missed, and the messages lost on students whose education was grounded in different normative systems. (p. 132)

This incongruence produces a need to constantly switch between cultures (Gonzalez & Morrison, 2016; Stephens, Fryberg, Markus, Johnson, & Covarrubias, 2012). Although developing this ability serves as an asset (Gonzalez & Morrison, 2016; Morales & Trotman, 2010), it can also be a burden to UR students that majority students do not experience (Stephens et al., 2012).

UR students, especially students of color, often encounter unwelcoming postsecondary climates characterized by stereotypes, microaggressions, and feelings of isolation. According to Harper (2013), stereotypes frequently emerge from a belief that UR students were given a place at the institution because of their minoritized status. In addition to overt stereotyping, UR students experience microaggressions, which are small and subtle acts of discrimination or exclusion (Sue et al., 2007). An example of a microaggression is when a student is mistaken for a different student of the same race or ethnicity (Harper, 2013). In addition, UR students are often confronted with a lack of other students or faculty of their racial, ethnic, gender, or class identity, which can lead to feelings of isolation (Davis et al., 2004; Harper, 2013; Seymour & Hewitt, 1997; Strayhorn et al., 2013). Cultural incongruence and unwelcoming climates represent subtle dynamics that may influence UR students to switch to a non-STEM major or leave college altogether.

The role of peers and family. Family and peers play a significant role in the persistence process for most UR students. Strong relationships with peers are drivers of persistence (Fries-Britt et al., 2010; Harper, 2013; Seymour & Hewitt, 1997). Brandt (2008) documented how indigenous women in science collectively created “comfort zones” that “were locations of possibility where Indigenous students could imagine how to bring their university education back to their communities” (p. 718). Family support and expectations are among the most significant external sources of support noted in the literature (Peralta et al., 2013; Russell & Atwater, 2005). This finding challenges earlier notions, based on Tinto’s (1975) work, that students needed to separate from their home lives in order to succeed in college (Museus, 2011; Rendón et al., 2000). However, the family does not always represent an encouraging element. Seymour and Hewitt found that the familial expectations and commitments of many UR students conflicted with the high demands of STEM courses. Therefore, family can play both a positive and negative function in the persistence process (Peralta et al., 2013; Russell & Atwater, 2005; Seymour & Hewitt, 1997). In addition to the dynamics reviewed in this section, there are contextual factors specific to the FG experience that affect FG students’ experiences in STEM.

First-generation Students in STEM

FG students enroll in STEM majors at rates similar to CG students, but are more likely than CG students to leave STEM (Dika & D’Amico, 2016; Shaw & Barbuti, 2010).

Several studies have demonstrated that students with parents who possess higher levels of education are more likely to persist in STEM (Dika & D'Amico, 2016). Despite these findings, FG students have been an overlooked group in the literature on underrepresented students in STEM (Harackiewicz et al., 2015). The literature that *has* addressed FG students in STEM has tended to focus on social and cultural capital.

Because their parents have limited or no experience with college, FG students often lack the cultural and social capital that is utilized by CG students to navigate postsecondary contexts. Cultural capital represents familiarity with the implicit and explicit cultures, assumptions, and processes of higher education (Jehangir, 2010). Entering college without this capital means that FG students are often confronted with a "second curriculum" they must learn in order to be successful (Strayhorn, 2012, p. 29). Martin et al. (2014) found that engineering FG students were "less likely to utilize or have more difficulty in recognizing university support resources because they have little practice in doing so" (p. 823). Needing to navigate unfamiliar cultures places an additional strain on FG students.

Social capital refers to the knowledge and resources individuals obtain through their social networks (Bourdieu, 1986). Social capital is passed on within families to new generations; as a result, FG students often lack social capital that is relevant to succeeding in college and in their post-baccalaureate careers (Soria & Stebleton, 2012). Martin et al. (2014) discussed how engineering is often viewed as a "closed club" (p. 822); not having family members who are knowledgeable about the discipline is a significant disadvantage and lowers the likelihood that a student will pursue engineering.

Trenor (2009) referred to this tendency as "occupational inheritance" (p. 1). FG students possess cultural and social capital, but often not the type that will lead to success in the context of STEM and higher education.

FG students possess several other forms of capital they have accumulated throughout their lives. For example, Martin et al. (2014) demonstrated that FG students are more likely to rely on emotional support from their families. FG students often view their education as a family goal instead of an individual one, and are driven by a desire to support their families and give back to their communities (Espinoza, 2013; Harackiewicz et al., 2015). However, too often higher education does not recognize or reward those types of capital (Jehangir, 2010; Yosso, 2005). Dika and D'Amico (2016) explained the complexity of this issue: "It seems, however, that many FGCSs [FG college students] fall into a catch-22—needing social capital to pursue a major that may result in the social and economic capital that they need to be successful in a STEM major" (p. 371). It is imperative that STEM programs and departments work to provide FG students with opportunities to develop college-relevant social and cultural capital and also recognize and validate the unique forms of capital FG students possess.

There are some limitations to the research on FG students in STEM. Much of the literature is quantitative (e.g., Harackiewicz et al., 2014; Martin, Miller, & Simmons, 2014), and while the studies illuminate important issues, they do not capture the lived experiences of FG students in STEM. Research in this area tends to treat FG students as one homogenous group, which various scholars have demonstrated is not true. While it is challenging to discuss FG students while maintaining the diversity of this group, scholars cannot pretend that all FG students share similar experiences. Further research that incorporates a qualitative component and addresses the complexities of student identities is needed. There is an especially urgent need for this work at the classroom level, where research can examine how classroom climate influences FG student persistence.

Classroom Climate

Scholars attempting to understand student retention have traditionally focused mainly on out-of-class student success interventions, such as mentoring programs and student support groups. However, first-generation and other underrepresented students are more likely to have jobs, live off-campus, and be unaware of these extra services, and are consequently less likely to benefit from them. Thus, the in-class experience may be especially important for the persistence of FG students (Barefoot, 2004; Nelson Laird, Chen, & Kuh, 2008; Tinto, 2012; Volkwein & Cabrera, 1998). Classrooms are spaces in which student identities are either affirmed, ignored, or rejected, and in which inequities in broader society are either perpetuated or challenged. Unfortunately, UR student identities are often not affirmed through the in-class experience and patterns of power and inequity are reinforced (A. Johnson, Brown, Carlone, & Cuevas, 2011; Tierney, 2000).

The concept of classroom climate captures the affective side of learning; when students experience a negative climate, they are likely to feel that they do not belong in the course (and associated discipline), or that the course is not aligned with their experiences and values. Hall and Sandler's (1982) finding that science classrooms often had a "chilly climate" (p. 3) for women fueled much of the scholarly attention to this concept. Ambrose et al. (2010) defined the classroom climate as the "intellectual, social, emotional, and physical environments" of a course (p. 170). Classroom climates vary in terms of the degree to which they are intentionally created by the instructor versus emerging organically through interactions (Vivyan, 2016).

Because of its subjective nature, students experience the classroom climate in different ways; certain elements will be more salient to some students than others. In addition, the instructor often perceives the climate differently than students (Ferrare, Benbow, & Vivyan, 2014). Research has demonstrated that the classroom climate matters for student persistence and that FG and other underrepresented students often experience the classroom differently than majority students (Booker, 2007; Swaminathan & Alfred, 2001; Vivyan, 2016; Wolfe, 2000). Vivyan (2016) found that, in the context of introductory STEM courses, the type of climate most associated with leaving STEM was one characterized by a weed-out or competitive culture, and women were more likely than men to describe courses in this way. Vahala and Winston Jr. (1994) found that students in laboratory science courses reported a more negative climate compared to students in English and behavioral science courses.

Classroom climates have been portrayed in diverse ways. Vivyan (2016) qualitatively explored how students described the cultures (a concept similar to climate) of their introductory STEM courses; the most common themes were "weed-out and competitive," "STEM anxiety," "comfortable and informal," and "uncomfortable and formal" (p. 61). Barker and Garvin-Doxas (2004) determined that the introductory computer science courses they observed "can be characterized as impersonal, an environment in which it is easy to remain relatively anonymous and socially distant" (p. 132). Ambrose et al. (2010) discussed a study by DeSurra and Church (1994) on LGBT college students that placed the classroom climate on a continuum. The categories on the continuum were explicitly marginalizing (of LGBT identities and issues), implicitly marginalizing, implicitly centralizing, and explicitly centralizing. DeSurra and Church found that the most common classification was implicitly marginalizing. The literature in this area reveals a lack of uniform language around the classroom climate.

Factors that influence the climate. Elements of a course that are especially salient in shaping the climate are interaction (professor-student interaction, student-student interaction, and patterns of participation), climate for diversity (discrimination, feelings of isolation or being too visible, inclusion of diverse backgrounds), and the physical space. Below I describe each of these elements.

Professor-student interaction. The role of the professor in encouraging (or discouraging) persistence cannot be underestimated. Rendón's (1994) theory of validation provides a framework for understanding this role. According to Rendón, students strengthen their resilience when other people in their lives send them subtle or overt messages that they matter and can be successful in their education. Rendón found that professors often took on a validating role by providing meaningful feedback, showing genuine concern for their students, and taking extra time to work with students individually. Cantú (2012) explored the experiences of Chicana women in STEM who had succeeded academically. Cantú commented, "Time and again, these authors tell of sympathetic professors or caring teachers who gave of their time and energy to protect, sustain, and offer a different kind of scaffolding" (p. 480).

Professors play an important function in shaping the classroom climate. By the time students enroll in college-level STEM courses, they have been socialized to act a certain way in the classroom. Oftentimes students believe they should remain passive and not ask for clarification or feedback, and the professor needs to signal that students can and should play an active role (Garvin-Doxas & Barker, 2004). Students pick up on "cues" from the professor that signal how approachable they are (Hurtado et al., 2011, p. 555). Professors not calling students by their name is an example of a cue that indicates a lack of approachability (Garvin-Doxas & Barker, 2004).

Students of color often form validating relationships with professors of color (Espinosa, 2011; Harper, 2013; Holmes, 2013; Hurtado, Eagan, et al., 2011; Rendón, 1994), demonstrating the importance of diverse faculty. In the context of STEM, this is a concern because underrepresented faculty of color make up only 6% of all STEM professors, an underrepresentation that is unlikely to change in the near future due to a lack of diversity among STEM Ph.D. students (Holmes, 2013). Nonetheless, educators of all backgrounds who realize the importance of their validating role can make a difference.

Unfortunately, professors do not always provide validation. Especially in STEM, many professors take on harmful attitudes and behaviors including sarcasm and an unwillingness to discuss non-science topics with students, shaping a negative climate (Daempfle, 2003; A. Johnson, 2007; Seymour & Hewitt, 1997). These harmful behaviors create barriers to persistence because students often take them as indicative of their own self-worth (Fries-Britt et al., 2010; A. Johnson, 2007; Rendón Linares & Muñoz, 2011). Many professors likely do not realize their effect on students, perhaps because they once experienced and persisted through the same attitudes. Institutional leaders aiming to improve student persistence must stress the critical role of their teaching faculty.

Student-student interaction. Student-student interaction is one of the most frequent activities across postsecondary contexts (Holmes, 2013). Especially in courses that emphasize collaboration, students take on a greater role in shaping the classroom climate (Sohn, 2016). A component of many courses is students working in small groups. Some scholars believe that group work leads to increased interdependence among students and feelings of community, which could be especially beneficial for FG students (S. L. Eddy & Hogan, 2014). However, collaboration among students does not always create a welcoming climate. Students of color often perceive that their peers avoid working with them when they are told to work in groups (Holmes, 2013; Stebleton & Aleixo, 2016). Swan (2012) summarized findings from several studies on engineering courses indicating that women often feel undervalued by men in small groups. The research suggests that student interaction should be intentionally designed, especially when considering interactions between majority and underrepresented students (Rankin & Reason, 2005; Stebleton & Aleixo, 2016). The instructor has an important role to play in ensuring that certain students do not feel marginalized or isolated through patterns of student-student interaction.

Patterns of participation. According to Hirschy and Wilson (2002), each class has:

> Norms of discourse [that] shape the patterns of participation, that is, who participates and who does not (Sykes, 1990), whether one feels free to disagree with the instructor or other students, how to deal with conflicts, what kinds of questions are acceptable, and, in general, how to act appropriately in a classroom. (p. 87)

Oftentimes, classroom participation is limited to a small proportion of the students in a class (Sohn, 2016). If a professor responds to a student's questions in an unsupportive manner, that student may decide to remain silent in future classes (Garvin-Doxas & Barker, 2004). FG students, as well as students from certain underrepresented cultures, are more likely to have been socialized to respect and defer to authority, and thus might feel less comfortable challenging the instructor or other students (Jehangir et al., 2015).

Ochoa and Pineda (2008) argued that students who have had prior educational experiences that affirmed their identity are more likely to feel confident in a classroom setting, which is reflected in the tendency of White men to participate more than women or students of color. In a study on women of color in STEM, Johnson (2007) found that White men were the most likely to ask or answer questions in front of the class. Eddy, Brownell, and Wenderoth (2014) studied participation in 23 introductory biology courses. Despite women representing 60% of the students in the courses, on average, they accounted for only 40% of student participation. In an examination of introductory computer science courses, Garvin-Doxas and Barker (2004) found that certain men asked questions that were not genuine questions; rather, the inquiries were designed to demonstrate the students' superior knowledge of coding concepts. This behavior, which the authors termed “strutting” (p. 13), created a hierarchy among students and negatively impacted women’s intentions to persist in computer science. Instructors must pay attention to patterns of participation, disrupt negative student behaviors such as strutting, and avoid assuming that certain students are not participating because they have nothing to contribute.

Discriminatory behavior. Faculty and students enact both overt and subtle forms of discrimination in the classroom. This behavior is often in the form of microaggressions, such as majority students avoiding sitting near a student of color or the professor acting surprised when a UR student is a top performer in the class (Harper, 2013; A. Johnson, 2007). Unfortunately, because courses are often taught by majority faculty, it may be difficult for them to perceive when microaggressions are occurring or when they themselves are carrying out microaggressions (Sue, Torino, Capodilupo, Rivera, & Lin, 2009).

Stereotype threat occurs when a student experiences anxiety out of fear that they will confirm a negative stereotype associated with a group to which they belong; this anxiety in turn leads to lowered performance (Chang, Eagan, Lin, & Hurtado, 2011). According to Ambrose et al. (2010), “The activation of a stereotype does not need to be intentional, and in fact seemingly innocuous comments can trigger stereotype threat” (p. 174). Instructor practices that can activate stereotype threat include giving certain students disingenuous praise or not providing diverse examples that incorporate individuals from underrepresented backgrounds (M. K. Brown, Hershock, Finelli, &

O'Neal, 2009). Experiencing microaggressions and stereotypes represent two common and subtle forms of classroom-based discrimination.

Chang et al.'s (2011) study of first-year students of color in the biomedical and behavioral sciences found that even for students who were deeply committed to their discipline, a higher frequency of negative racial experiences was associated with a stronger likelihood of leaving those fields. When UR students feel silenced and experience microaggressions and other forms of discrimination, it is not surprising that they perceive a harsh classroom climate and feel they do not belong. In addition, the anger students experience in response to discrimination can impede cognitive processes, making the learning process more difficult (Ambrose et al., 2010).

Isolation and feelings of being too visible or invisible. UR students often feel isolated in the classroom due to high proportions of majority students and uneven power dynamics (Davis et al., 2004; A. Johnson et al., 2011; Strayhorn et al., 2013). Strayhorn et al. documented how Black and Latinx students in their study felt "virtually invisible" (p. 6) in their STEM classes, and how heavily those feelings impacted their experiences. Alternatively, UR students, especially students of color, frequently feel too visible due to their perceived difference from other students (Davis et al., 2004; Holmes, 2013; A. Johnson et al., 2011). Davis et al. termed this as a feeling of "supervisibility" (p. 427).

Feelings of both invisibility and supervisibility disempower students to define their own identity (Davis et al., 2004). For instance, a Latina student in a mathematics course of mainly White students and instructors may struggle to envision herself as a future STEM professional. If she constantly feels that others in the classroom notice and react negatively to her perceived difference from them, this feeling of supervisibility will create tension between her science identity and her ethnic and racial identities. These dynamics may be more present in active learning settings that stress interaction among students and between the instructor and students (Cooper & Brownell, 2016). As such, careful consideration of classroom dynamics is necessary for creating a welcoming climate and encouraging the persistence of FG and other underrepresented students.

Inclusion of diverse backgrounds. This category reflects the extent to which students feel their backgrounds are acknowledged and integrated into the course. This includes recognizing the experiential knowledge that students bring to the course, as well as students' cultural backgrounds and unique reasons for taking the course. Especially in STEM, courses often stress the accomplishments of White men from a European background. A failure to acknowledge the contributions of women and people of color, or doing so in a tokenizing manner, leads UR students to feel alienated and to perceive that the groups to which they belong are devalued (A. Johnson, 2007; Killpack & Melón, 2016; Marchesani & Adams, 1992). A lack of diverse viewpoints and examples can also reinforce in students the pervasive image of scientists as "old men in lab coats" (Killpack & Melón, 2016, p. 3). When students do not see themselves reflected in what they are studying, it becomes more difficult for them to believe they can be successful in that context (Carlone & Johnson, 2007; Schinske, Perkins, Snyder, & Wyer, 2016).

UR students often possess goals of using their STEM degree to give back to their communities, frequently through a health profession, and they may leave STEM if their coursework does not make a clear connection between introductory content and their long-term aims (Seymour & Hewitt, 1997; Strayhorn et al., 2013). In STEM there is a tendency to avoid discussing issues of race, class, and gender, which may prohibit professors from understanding and incorporating the reasons that different students are pursuing the discipline (A. Johnson, 2007). A course that only represents the dominant culture will create a climate in which UR students feel they do not belong.

Physical space. The physical space is an important element of any environment. Large-enrollment courses often take place in auditorium-style classrooms, which creates an impersonal atmosphere and hinders students' interaction with the professor and other students. The physical separation of the professor from students also reinforces unequal power dynamics (Trees & Jackson, 2007). Scholars and practitioners have argued for making these auditorium-style spaces more collaborative, such as having students turn to their neighbor and discuss a problem (Walker, Cotner, Baepler, & Decker, 2008). Universities are increasingly engaged in the creation of "active learning classrooms" that diverge from this traditional classroom setup (Park & Choi, 2014, p. 749).

A popular active learning classroom model is based on the "Student-Centered Active Learning Environment for Undergraduate Programs (SCALE-UP)" project, which began at North Carolina State University and has been replicated by over 250 institutions (Park & Choi, 2014, p. 752). These large-enrollment classrooms include round tables throughout the room for students to work in groups, a station at the center of the room for the professor(s), and whiteboards and audiovisual equipment placed along the walls (Langley & Guzey, 2014). The hope is that this type of design will create a more collaborative and less hierarchical environment (Park & Choi, 2014). Based on students' preconceived expectations of what type of activity happens in different kinds of spaces, being in an active learning classroom may prime students for interaction and collaboration (Hodges, 2018). Yet it is important to note that even in collaborative classroom spaces, professors may teach in a traditional manner, and subtle or overt forms of discrimination can occur (Brooks & Solheim, 2014; Lester, Yamanaka, & Struthers, 2016). In any type of physical setting, the classroom climate is a malleable construct that can be influenced through the actions of the instructor and students.

Studying classroom climate. The classroom climate has been a common focus of inquiry in education research for the last several decades. Momentum for this approach began in the 1980s; however, most of this work has been at the K-12 level (B. J. Fraser, 2012). In addition to classroom climate, this unit of analysis can be referred to as *classroom culture* or *classroom environment*. Researchers who examine the classroom climate often approach the task by studying the student experience in a course. Both quantitative and qualitative researchers have studied classroom climate, and disagreement exists as to the best method.

Quantitative approaches. Extensive survey-based research on STEM classroom learning environments exists, although mainly in the K-12 realm. Fraser (2012) outlined 11 different instruments that have been designed to measure classroom climate, with two of them being appropriate for higher education. Most of these surveys measure the climate through a post-positivist lens instead of a critical one; as a result, questions about the enactment of overt or subtle forms of discrimination by students or the instructor are limited. Trees and Jackson (2007) employed a quantitative approach to measuring the classroom environment in large courses that used student response systems. The authors administered a survey at the end of the semester; the survey included items related to students' expectations of large courses, attitudes toward learning, classroom involvement, and motivation. The classroom involvement category came the closest to the idea of classroom climate as it asked questions about the class culture.

Qualitative Approaches. Sohn (2016) criticized the tendency of some researchers to reduce the classroom climate to a Likert-type item on a survey, arguing that the construct is too complex and multidimensional to be measured in that way. Sohn and several other researchers have opted to use a qualitative approach to measuring classroom climate. These studies usually employ a case study design. Swan (2012) used Bronfenbrenner's (1979) ecological model to study women students' experiences in introductory engineering courses that used project-based learning; the classroom climate was placed at the microsystem level. Swan employed classroom and group observations, semi-structured interviews and focus groups, and a review of course documents.

Benbow and Vivyan (2016) used a comparative case study approach to examine students' experiences in two gateway computer science courses that may influence persistence. Many of the factors on which Benbow and Vivyan focused were entwined with the concept of classroom climate: "instructional methods, social interaction, gendered and disciplinary stereotypes, and students' sense of belonging" (p. 3). The authors' analysis included student and instructor focus groups and classroom observations. Sohn (2016) used a phenomenological case study approach to examine the "student experience of other students," (p. 72) arguing that most researchers of classroom climate focus on the role of the professor and place too little emphasis on dynamics among students.

Strengths and limitations to the research on classroom climate. The classroom climate literature adds a previously missing component to research on UR student persistence in STEM, demonstrating the significance of the affective side of learning and the importance of studying the in-class experience. However, classroom experience and climate studies tend to group all UR students together, which is problematic because their results can falsely lead to "one-size-fits-all" solutions (Eddy & Hogan, 2014, p. 454). Even studies that attempt to disaggregate students are in danger of making false generalizations if they do not recognize variations within subpopulations (Museus & Griffin, 2011).

Surprisingly, to my knowledge there have been no mixed methods studies that examine the classroom climate in undergraduate STEM courses. There is an opportunity to use mixed methods so that the weaknesses of one method are addressed by the other (Creswell & Plano Clark, 2011). To address these gaps, my study employed mixed methods to examine FG students' experiences in a reformed introductory STEM course. In any classroom study, the prevailing teaching and learning paradigm the instructor uses will be highly significant in shaping the climate.

Teaching and Learning Paradigms in STEM

In this section I first provide an overview of the three main teaching and learning paradigms that have been discussed in the STEM education reform literature: traditional pedagogy, active learning, and inclusive pedagogy. The second paradigm (active learning) is phrased differently than the other two, reflecting the ways they are discussed in the literature; however, all three approaches imply a *pedagogy*, with expectations for both the professor and students. While all three paradigms are present in the STEM reform discourse, the first two are far more prevalent than inclusive pedagogies. These paradigms overlap along certain dimensions and are not meant to be considered as mutually exclusive. For example, both active learning and inclusive pedagogies assert that the student should be actively engaged in the learning process. After introducing these concepts, I discuss the three main components of pedagogy (teaching approaches, curriculum, and learning assessment) and how each paradigm addresses them.

Teaching and learning paradigms.

Traditional pedagogy. Traditional pedagogy is most often associated with the lecture method, where the instructor transmits information to an audience of passive learners. The lecture dates to the Middle Ages, before the invention of the printing press, and its original use was not knowledge transmission but rather the preservation of texts. At that time, reading rarely occurred individually but rather out loud in groups. Over the centuries, lecturing gradually shifted away from the recitation of texts and became more focused on the expertise of the lecturer. With the advent of modern media forms (e.g., PowerPoint, Smartboards), the lecture again shifted to representing “textually enabled dramaturgical effect” (Friesen, 2011, p. 101). Friesen argued that the lecture has survived not because of inertia or resistance to change (as its critics would argue) but because of the ability of the lecture to adapt to “changes in media and technology as well as in culture and epistemology" (p. 100). The active learning paradigm represents the approach most often promoted by critics of traditional pedagogy.

Active learning. The active learning paradigm has emerged as an alternative to traditional pedagogy, and its proponents argue that lecturing is ineffective for developing students' conceptual understanding. Active learning, in which students mentally engage with course content to construct their own understanding and knowledge (Freeman et al., 2014), has been positively linked to student learning and persistence (Braxton, Bray, & Berger, 2000; Pascarella, Seifert, & Whitt, 2008). Active learning encompasses a diverse range of strategies, including lab-based activities, problem-based learning, and case-based learning (Prince, 2004). Many of these strategies have been developed especially for large courses (Twigg, 2005b). This paradigm is based in constructivist theories of learning, and its advocates have used studies grounded in cognitive science to document the benefits of active learning for students (Mayberry, 1998; D. Riley & Claris, 2009).

The large body of evidence supporting active learning implies that the widely used lecture method is detrimental to student persistence and learning (Watkins & Mazur, 2013; Wieman, 2014). Increasingly, scholars and practitioners are calling the use of the lecture method (when used without any incorporation of active learning) unethical because of its perceived ineffectiveness in terms of both learning and persistence (Mulnix, Vandegrift, & Chaudhury, 2016; Penner, 2018). However, several studies have found that students sometimes reject active learning approaches, demonstrating that active learning is far from being a panacea (Garcia, Gasiewski, & Hurtado, 2011; A. Johnson, 2007; R. E. Wilson & Kittleson, 2013).

Inclusive pedagogies. Numerous pedagogies have emerged as alternatives to the active learning paradigm; proponents of these pedagogies argue that active learning is a step in the right direction but ultimately maintains the status quo because of its failure to address underlying inequities and power imbalances in education. This category includes critical pedagogy, feminist pedagogy, and culturally relevant pedagogy. Tuitt (2003, 2016) used the concept *inclusive pedagogy* as an umbrella term for these approaches, although the author is most influenced by the critical pedagogy scholars Freire (1973, 2000), Giroux (1988), hooks (1994), and McLaren (1998). These methodologies explicitly recognize the history of racism, sexism, and classism in education; seek to share power between the instructor and students in the classroom; develop students as "reflective and active citizens" (p. 246); and seek to continuously tie content to students' lives (Tuitt, 2003). Drawing on Yosso's (2005) community cultural wealth framework, this approach also explicitly recognizes the strengths of UR students instead of focusing on deficits (Gonzalez & Morrison, 2016).

The emergence of inclusive pedagogies has occurred as some scholars and practitioners have rejected the dominance of cognitive psychology as the theoretical basis for teaching and learning, instead turning to fields such as sociology, anthropology, and cultural psychology (Lerman, 2000; Valero, 2008). In the context of mathematics education research, Lerman called this movement the "social turn" (p. 8). Whereas the active learning paradigm treats educational disparities as a technical or methodological issue, inclusive pedagogies acknowledge the greater social and historical contexts that have shaped inequity (Bartolome, 1994).

While I have not included Universal Instructional Design (UID), a framework for designing learning environments that are inclusive to students with disabilities, under the umbrella of inclusive pedagogies, it is important to note that there is substantial overlap between UID and inclusive pedagogies. For example, both encourage the use of student voices and the sharing of authority between the instructor and students (J. R. Johnson, 2004). Moreover, power imbalances between people with disabilities and able-bodied people represent one form of inequity that inclusive pedagogies seek to address. However, there are also important differences: “Although most UID scholars address UID as part of the movement for inclusion, their focus is pluralism without specifically examining manifestations of power” (J. R. Johnson, 2004, p. 147). Because UID does not explicitly address issues of power and oppression, I do not consider it as an inclusive pedagogy for the purpose of this study. I now turn to the three main components of pedagogy – teaching approaches, curriculum, and assessment – and how each paradigm addresses them. The table in Appendix A summarizes the distinctions and overlaps between the three paradigms.

Components of teaching and learning.

Teaching approaches. Teaching approaches refer to the ways in which the instructor structures a course’s learning activities. In the traditional pedagogy paradigm, students listen and take notes while the professor lectures (Wieman, 2014). In active learning, students are cognitively engaged with course content instead of passively processing it. Active learning can take on myriad forms; in the STEM context, popular methodologies include project-, problem-, and team-based learning (Gehrke & Kezar, 2016; Helle, Tynjälä, & Olkinuora, 2006; Parmelee & Hudes, 2012). Active learning can occur individually but often involves collaboration among students. Practitioners frequently rely on the scientific teaching literature, which attempts to identify the most effective teaching methods through experimental studies, to determine which teaching approach to use (Dehaan, 2005).

Inclusive pedagogies are similar to active learning in that they actively engage students in the learning process, yet they acknowledge that specific teaching methodologies will depend on the cultures and backgrounds that students bring to the course (Bartolome, 1994). Practitioners using inclusive pedagogies maintain an explicit focus on power relations. According to Riley and Claris (2009),

> The focus on power relations applied to epistemology creates a focus on power/knowledge – that is, the Foucauldian idea that knowledge is not independent of structures of power, but indeed power structures have a role in creating knowledge, and vice versa. (p. 44)

Inclusive pedagogues thus aim for shared power in the classroom, encouraging students to question and challenge dominant knowledge and take responsibility for their learning. Finally, in addition to serving as facilitators of learning, inclusive pedagogues seek to validate classroom members as competent students who belong and can be successful in the discipline (Rendón, 1994; Tuitt, 2003).

Curriculum. Course content, or *what* is being taught, is an important factor in the teaching and learning process. In both the traditional and active learning paradigms, content represents the prevailing concepts and facts associated with the discipline. In traditional pedagogy, there is often a focus on rote memorization of facts that are decontextualized from any real-world application. A perceived lack of relevance leads to boredom and low intrinsic motivation; Morales and Trotman (2010) explained why this can be especially harmful for UR students:

> While it appears that most wealthy white students also lack intellectual curiosity at that stage, the difference is that often they can excel anyway due to both their cultural capital, and the engrained academic expectations with which they and their peers were raised. (p. 54)

The active learning paradigm stresses conceptual learning over memorization and encourages real-world applications of content (Dehaan, 2005). While active learning stresses content that is germane to students, establishing relevance is "often done only from a white male perspective, and may or may not have relevance for white women and people of color" (D. M. Riley, 2003, p. 2).

Inclusive pedagogies push back against the prevailing theories, concepts, and values of a discipline. In traditional pedagogy and active learning, content is falsely presented as neutral or value-free (Holmes, 2013). A failure to critically examine what is included in the curriculum reproduces existing systems of power and oppression (Mayberry, 1998). Basile and Lopez (2015) argued that in the context of STEM, UR students, especially students of color, are assimilated into a professional community that does not have their best interests in mind:

> In the past 40 years, we have seen corporations systematically move industry and production jobs overseas, away from U.S. urban centers (Levine, 2011), leaving

> large numbers of Peoples of Color in these areas unemployed. Combined with a continued lack of access to innovations in health care and technological advancement, it is difficult to see the benefits that corporate economic gain and STEM innovation have delivered to Communities of Color. (p. 535)

Inclusive pedagogies promote content that relates to students' lives (especially the lives of women and students of color) and develops students' abilities to criticize what they study and analyze broader societal implications (Hurtado et al., 2012; D. Riley & Claris, 2009). Instructors using this approach recognize that they must prepare students to enter the STEM fields even as they criticize them; learning to navigate this contradiction is a principle challenge in using inclusive pedagogies for both professors and students (D. Riley & Claris, 2009).

Assessment. Assessment is perhaps the most important element of the learning process, as students prioritize assessment requirements over any other course component (Gibbs, Simpson, James, & Fleming, 2004). First-semester GPA is among the strongest predictors of persistence in STEM; low grades, even in a course where the majority of students do not receive an A or B, send messages to students that they cannot be successful in the corresponding discipline (Crisp, Nora, & Taggart, 2009; Dika & D'Amico, 2016; Harackiewicz et al., 2014; Whalen & Shelley, 2010). Receiving a low grade in a first-year course can be an especially shocking and negative experience when the student was accustomed to receiving high grades in high school (Seymour & Hewitt, 1997). Traditional pedagogy is most often associated with a testing approach to assessment, frequently prioritizing students' abilities to memorize large quantities of information (Dehaan, 2005). In introductory STEM courses, exams are often coupled with harsh grading policies such as grading on a curve, which can be detrimental to student persistence (Gibbs et al., 2004; Seymour & Hewitt, 1997).

Both active learning and inclusive pedagogies encourage formative and authentic assessment and stress that assessment is a crucial part of the *learning process itself* and should not be seen purely as a way to *evaluate* learning (Harlen, 2005). The feedback element of assessment is critical. High-quality feedback is important not only for learning, but also for student motivation and self-efficacy. Evidence suggests that formative assessment, which generates a feedback loop between the professor and students throughout a course, fosters resilience (Cole, 2008; Yorke, 2003). Authentic assessment, in which students receive feedback on their performance of real-world tasks, is especially effective because students are able to envision themselves as future professionals in the field (Morales & Trotman, 2010; Van Dinther, Dochy, & Segers, 2011). In the context of STEM, this visualizing process is crucial for science identity development (Carlone & Johnson, 2007).

Regarding assessment, the literature does not strongly differentiate between active learning and inclusive pedagogies. Similar to teaching and curriculum, inclusive pedagogues would more closely examine for *whom* the assessment is authentic and consider the power dynamics of the process (D. M. Riley, 2003; Tuitt, 2003). Unfortunately, educators often see assessment and instruction as separate instead of parts of the same process. In many cases, instructors reform their teaching but maintain a traditional, test-based approach to assessment (Shepard, 2000). When assessment does not change along with teaching, an essential part of the learning and persistence processes is missing. I now turn to my conceptual framework, which connects the literature on pedagogy with the concept of the classroom climate.

Conceptual Framework: The Influence of Pedagogy on the Classroom Climate

My conceptual framework for this study is the influence of pedagogy on the classroom climate. The relationships between these concepts are displayed in figure 1. As discussed above, the factors that influence the classroom climate have a direct effect on the overall climate of the course, which is displayed on the right-hand side of the diagram. The three components of pedagogy, in turn, influence these factors. Figure 1 indicates the specific ways in which teaching approaches, curriculum, and assessment affect the factors. For example, assessment influences the inclusion of diverse backgrounds but does not tend to influence the physical space.

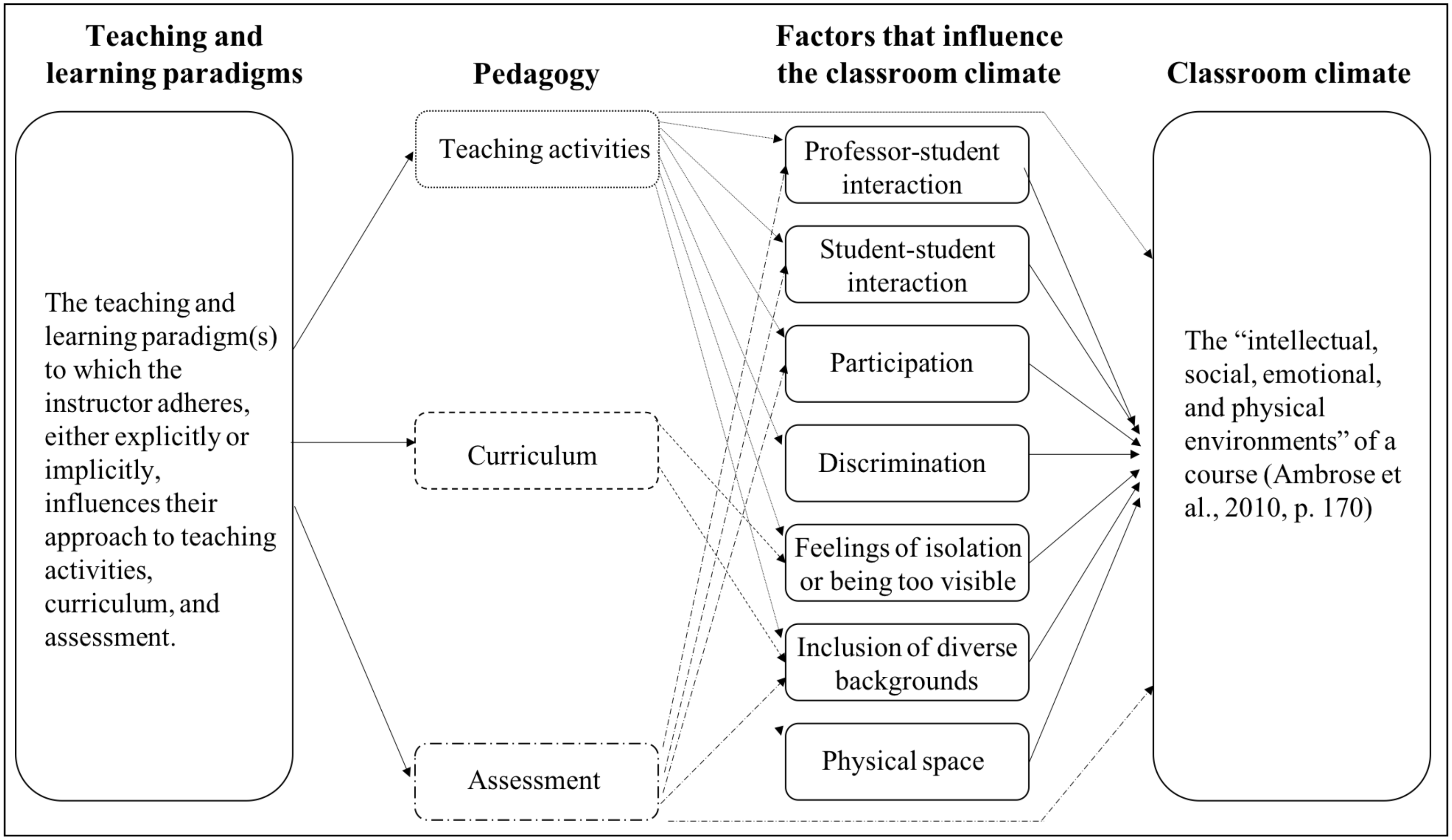

Figure 1. Conceptual framework

Teaching approaches can affect all seven factors that influence the classroom climate. Teaching approaches play a large role in determining the amount of interaction that students have with the professor, as well as the nature of those interactions. Teaching and learning activities also structure (or fail to structure) the interactions that students have with other students, how much students participate, and how comfortable or uncomfortable underrepresented students feel participating. Through designing learning activities in a careful and thoughtful manner, instructors can limit the amount of discrimination that occurs in the classroom and can prevent underrepresented students from feeling isolated or too visible (Tanner, 2013). When the professor incorporates details about their own backgrounds and those of students into teaching and learning activities, students are more likely to feel that diverse backgrounds are represented (Tuitt, 2003). Finally, teaching approaches influence students' perceptions of the classroom space. For instance, when the professor moves around the room instead of standing in one place, students may feel more comfortable with the classroom's physical layout (Seidel & Tanner, 2013).

Curriculum influences the classroom climate through its effect on the feelings of isolation or being too visible and inclusion of diverse backgrounds factors. The decision of which content to include determines whether students perceive that diverse backgrounds are represented or if only one perspective is present. If content only represents a White male perspective, students with marginalized identities may feel isolated; conversely, the use of diverse examples in a tokenizing way risks making students feel too visible (Marchesani & Adams, 1992).

Assessment can affect several factors that influence the classroom climate. In addition to teaching strategies, grading policies influence both the quantity and quality of interaction that students experience with the professor and other students. A grading system based on frequent and formative assessment, for instance, will likely lead to greater levels of professor-student interaction compared to a test-based system. The provision of authentic feedback will also likely create opportunities for the instructor to provide validation to students (Gasiewski et al., 2012). Through making students more accountable to their groups or teams, the use of peer assessment can improve student-student interaction (Hodges, 2018). Including a participation grade and offering multiple ways that students can meet participation expectations (e.g., giving students the option to submit written questions or answers instead of speaking in front of the class) is a method for equitably encouraging participation (Tanner, 2013). Finally, assessment strategies that make connections to students' backgrounds and goals, or that draw on examples from underrepresented individuals, will positively influence the inclusion of diverse backgrounds factor (Schinske et al., 2016).

Figure 1 shows that in addition to their effect on the factors that influence the classroom climate, teaching approaches and assessment can also directly influence the overall climate of the course. For example, regarding teaching approaches, a professor who calls on students who have not raised their hand may produce an anxious classroom environment, whereas a professor who uses humor and examples from their personal lives may encourage an informal climate (Vivyan, 2016). Regarding assessment, a high-stakes, test-based grading policy can produce a competitive classroom climate, whereas a grading system based on authentic and formative assessment may lead to an engaged and participatory climate (Seymour & Hewitt, 1997; Vivyan, 2016).

The teaching and learning paradigms are positioned on the left-hand side of figure 1, as an instructor's overall beliefs and approaches to pedagogy will influence the decisions they make regarding teaching strategies, curriculum, and assessment. There are many findings from the literature that connect the teaching and learning paradigms to the classroom climate.

Connections between the teaching and learning paradigms and the classroom climate. Several studies have highlighted ways in which aspects of the three teaching and learning paradigms affect the classroom climate. Extensive research has documented the negative effects of traditional pedagogy on the climate, especially in the context of introductory STEM courses (Eagan Jr. & Jaeger, 2008; Holmes, 2013; A. Johnson, 2007; Tobias, 1990). Lecturing creates distance between the instructor and students and limits interactions between students, creating an impersonal atmosphere (Barker & Garvin-Doxas, 2004). If an introductory course is exam-based and grades on a curve, the course will become highly competitive (Hurtado et al., 2009). If students receive harsh feedback that is not focused on continuous improvement, they may believe the instructor thinks they cannot be successful (Rust, 2002).

Proponents of active learning argue that increased engagement in the learning process will create a more welcoming climate compared to traditional pedagogy. According to Braxton, Jones, Hirschy, and Hartley III (2008), "Active learning practices that faculty use shape in students the perception that their college or university is committed to their welfare in general and their growth and development in particular" (p. 81). Holmes (2013) documented that Black women physics students were more likely to feel valued as scientists when they were in collaborative classroom settings.

Yet active learning does not always improve the climate. For example, some students may appreciate the anonymity of a lecture course and feel more exposed in active learning settings (Trees & Jackson, 2007). Such exposure could increase the likeliness of experiencing stereotype threat (Tsukada & Perreault, 2016). Colbeck, Cabrera, and Terenzini (2001) found that women's perceptions of gender bias were greater in courses that used collaborative learning compared to ones that used traditional pedagogy. These findings underlie the fact that there is nothing inherent in active learning approaches that leads the professor to consider the student-professor relationship or the existence of microaggressions, for example (Dewsbury, 2018). Conversely, it is possible (although difficult) for a lecture course to create a supportive classroom climate (Garvin-Doxas & Barker, 2004).

Critical scholars believe that inclusive pedagogies are needed to create a truly welcoming climate for underrepresented students. When teaching and learning activities recognize inequities in STEM education, underrepresented students are more likely to feel that their experiences of marginalization are acknowledged (A. Johnson, 2007). By performing a validating role for students, professors instill in students a belief that they belong and can be successful in the course (Rendón, 1994; Rendón Linares & Muñoz, 2011). Acts of validation can be as simple as learning students' names; Tanner (2011) demonstrated that learning students' names in a large course greatly improved the connections that students felt to the professor. And, by linking content to the life experiences of students, UR students will feel that their backgrounds are represented and that the experiential knowledge they bring to the course is valued (Gonzalez & Morrison, 2016).

Scholars who promote inclusive pedagogies acknowledge that these approaches are complex and difficult to apply in the real world (J. R. Johnson, 2004). Some studies of inclusive pedagogies in non-STEM courses demonstrate how these strategies do not always meet their intended purposes. Alemán and Gaytán (2017) used critical race pedagogy in an ethnic studies course. The authors found that some students of color resisted the pedagogical approach, often using claims to meritocracy to deny the effect of racism on their lives. Alemán and Gaytán noted that "even the presence of one to two students who consistently challenge the material in class can result in an adverse environment antithetical to the goals of critical race pedagogy" (p. 134).

Ochoa and Pineda (2008) used critical pedagogy in their education classroom, engaging students in discussions about the reproductive function of education as they collectively learned about the education of Latinx students in the United States. However, the authors were disappointed to find that Latinx students, who were overrepresented in the course, did not participate as much as the White minority. In their comments, White students tended not to acknowledge their own privilege and how they had benefited from the education system. The silence among Latinx students represented a reluctance to be seen as speaking for all Latino/as, as well as a sense of not being able to "talk like the middle- and upper-middle-class White students" (p. 50). The power dynamics in greater society were not deconstructed, as the authors had hoped, but were rather reproduced (Ochoa & Pineda, 2008). Riley and Claris (2009) summarized some of the challenges in using inclusive pedagogies to create more equitable learning environments:

> Students will not always behave as expected, and will not always be thrilled with the upending of power dynamics, particularly when it means more work for them; some remain silent and decline to participate. Institutional constraints such as grading requirements can reinforce problematic power relations that must be continually questioned. (p. 42)

Just as active learning is not a panacea for improving UR student persistence in introductory STEM courses, neither are inclusive pedagogies.

Nuances. There are many nuances to the discussion of teaching and learning and its effect on the classroom climate. The teaching and learning paradigms are not mutually exclusive, and many professors use elements of multiple paradigms. As mentioned above, instructors often incorporate active learning activities but maintain a test-based approach to assessment, which is more aligned with traditional pedagogy. A professor who gives a lecture on sexism in the STEM fields may be using strategies from both traditional and inclusive pedagogies. Instructors often combine “mini-lectures” with active learning activities, representing a fusion of the traditional pedagogy and active learning paradigms (R. E. Wilson & Kittleson, 2013, p. 822). While it is possible to differentiate between teaching and learning paradigms, the strategies that any given instructor uses will rarely stay within the boundaries of only one. Nonetheless, it may be possible to indicate the *main* paradigm a professor uses.

An additional nuance is that students react to teaching and learning practices in complex ways that are difficult to predict. FG students are more likely to have communal (i.e., working with and helping others) goals, and researchers have cited the inability of STEM programs to stress communal activities as one factor that discourages FG students from persisting in STEM (Allen, Muragishi, Smith, Thoman, & Brown, 2015). However, in a biology course that encouraged group work, collaboration and peer assessment created a negative climate for Jamie, a first-generation student:

> Jamie noted that this situation resulted in students giving high grades to each other at the mid-point and then awarding each other low grades for the final assessment in order to come out on top ... After this course, Jamie avoided all classes, regardless of her interest level, that were structured in that way because she did not like the behind-your-back competitive behavior that it incited in her peers. *Therefore, an instructor's effort to increase student engagement through social learning ended up making Jamie feel more frustrated than included* [emphasis added]. (Wilson & Kittleson, 2013, p. 812)

In their comparative case study of two introductory computer science courses, Benbow and Vivyan (2016) further described this complexity, documenting how expectations of independence were simultaneously "intimidating and liberating for students" and how teaching illustrations "linked lessons to examples relevant and irrelevant to students" (p. 29). These examples demonstrate the inherent paradoxes of the teaching and learning process.

Personality is an additional dimension that affects perceptions of the learning environment. For example, introverted students may be especially appreciative of student response systems (e.g., clickers) that allow them to participate without speaking in front of the entire class (Holmes, 2013). The incorporation of any new teaching and learning practice will have differing effects on the classroom climate depending on each student's background and preferences. Given the importance of large introductory STEM courses for UR student persistence, more research is needed on how FG and other UR students experience various teaching and learning contexts in these courses. Researchers should contextualize these studies within the ongoing movement to reform first-year science and math classes.

Teaching and Learning Paradigms in the Context of Reforming Introductory STEM Courses

In this section, I provide an overview of efforts to improve introductory STEM courses, which have mainly used the active learning paradigm.

Overview of the reform movement. Calls to reform STEM education in the United States began in the late 1960s due to an emerging realization that U.S. students were less prepared for STEM careers than their international counterparts (Mayberry, 1998). However, reform at the postsecondary level was sluggish until the mid-1980s, which coincided with the publication of national reports urging the country to do more in its quest for global scientific and military dominance (e.g., the 1983 *Nation At Risk* report) and for STEM education to move towards a more collaborative and evidence-based learning model (Basile & Lopez, 2015; Heyman, 2016; Mayberry, 1998). In the higher education context, the fields of mathematics, physics, and chemistry were quickest to act on the plea for reform, thus becoming early leaders in changing college teaching and learning in STEM (Stokstad, 2001).

The specific role that introductory STEM courses play in the STEM persistence process has long been a point of scholarly concern. In 1990, Tobias published a study in which students were asked to record their experiences auditing introductory physics and chemistry courses. The study identified several issues, including cold and condescending attitudes of professors, an overwhelmingly fast pace of content delivery, and professors' disinterest in helping students to develop an understanding of underlying concepts. Since Tobias' study, researchers have continued to demonstrate ways that these "gatekeeper" (Gasiewski et al., 2012, p. 229) courses discourage students from persisting. The courses often operate on a weeding out mentality and grade on a curve, giving the class a highly competitive climate (Eagan Jr. & Jaeger, 2008; Holmes, 2013; Hurtado et al., 2009; Seymour & Hewitt, 1997). These hostile environments are especially detrimental to the persistence of UR students (Holmes, 2013; A. Johnson, 2007).

Examples of reform. The strategies institutions have used to reform introductory STEM courses have mainly fallen under the active learning paradigm. Strategies have included an increased use of laboratory-based activities (Buncick, Betts, & Horgan, 2001), small-group workshops (Shuster & Preszler, 2014), and educational technologies including learning analytics (Twigg, 2005b; Wright, McKay, Hershock, Miller, & Tritz, 2014). There is considerable variation in terms of the extent to which the courses have shifted towards active learning and away from lecturing. Walker, Cotner, Baepler, and

Decker (2008) concluded that a "mixed-format approach that blends structured active-learning exercises with mini-lectures" (p. 361) was more effective than a complete elimination of lectures in the context of a large introductory biology course. Conversely, Buncick et al. (2001) described physics courses that used "full studio models … [in which] there is little or no lecture and the students spend the entire time exploring physical concepts with laboratory equipment" (p. 1240). There is a lack of consensus around whether a full embrace of active learning has any benefits (or downsides) compared to a modified lecture approach.

Many reform efforts have focused on changing course content or on changing the physical space. As I mentioned above, some institutions have opted to create active learning classrooms that facilitate collaboration and encourage the instructor to act as a co-constructer of knowledge rather than a gatekeeper (Rogers, Keller, Crouse, & Price, 2015). Gentile et al. (2012) described an effort to create a first-year interdisciplinary course that integrated concepts from five different STEM disciplines in order to contextualize learning and facilitate students' conceptual linkages across disciplines. Many of the efforts reviewed in this section have yielded positive results including improved learning outcomes (Rogers et al., 2015; Shuster & Preszler, 2014; Walker et al., 2008; Wright et al., 2014), increased student participation (Buncick et al., 2001), and improved student persistence (Gentile et al., 2012; Twigg, 2005a). While these studies were not carefully controlled experiments, the results nonetheless bolster the argument for reforming introductory STEM courses.

Barriers to change. Despite the numerous publications highlighting changes to first-year STEM courses, Kezar, Gehrke, and Elrod (2015) argued that these reforms have only affected a small proportion of the STEM student population and that comprehensive change is still needed. A study of over 2,000 STEM classes at North American universities, with over half of the classes being introductory, found that 55% of the courses were taught using conventional lecturing, 27% were interactive lectures, and only 18% placed a heavy emphasis on active learning (Stains et al., 2018). Addis et al. (2013) discussed several barriers that hinder large-scale change. When professors themselves could succeed in a largely lecture-based education, they may not agree with the need for change. Reforming pedagogy is also time-intensive; especially at universities with research-based incentive structures, professors feel substantial pressure to focus on their research instead of teaching. Addis et al. argued that resistance is especially high for large courses, as professors may not see alternatives to the lecture approach. Finally, Stokstad (2001) demonstrated that change efforts are sometimes stalled because professors are reluctant to reduce the amount of content they cover. Given these extensive barriers, it is perhaps not surprising that more widespread reform has not been achieved.

Criticisms of mainstream reform efforts. While the reforms described above represent well-intentioned efforts, they follow a line of reasoning that will fail to bring about true equity. Riley (2003) would claim that most of the research aligned with the active learning paradigm is representative of mainstream pedagogical reform in STEM. This mainstream research was written from a post-positivist lens that assumes that the success of interventions can be measured by primarily quantitative and objective means.

These reforms rely on technocratic solutions that "apply a private sector cost-benefit analysis using a simple input/output quantitative measure to determine success" (Anderson, Barone, Sun, & Bowlby, 2015, p. 259). Neoliberal thought, based on the extension of economic logic to the social realm (Gildersleeve, Kuntz, Pasque, & Carducci, 2010), evidently serves as an underlying framework for much of the research on pedagogical reform in STEM. For example, instead of stressing the individual benefits of earning a STEM degree, most of the authors using a mainstream approach argue that as the country becomes increasingly diverse, UR students are needed to fill workforce needs that will maintain U.S. competitiveness (Basile & Lopez, 2015).

Critical scholars aligned with inclusive pedagogies have taken issue with the workforce argument and criticized the tendency in STEM to avoid issues of underlying racism and inequity. This avoidance is conveniently concealed by claims that the sciences are neutral and value-free disciplines, and that educational disparities can be addressed through purely technical solutions (Bartolome, 1994). The failure to recognize that these disciplines are based on White male European cultural norms produces a view, held by educators and students themselves, that UR students struggle in STEM due to individual problems and not systemic issues (Holmes, 2013; A. Johnson, 2007; Joseph, 1987; D. M. Riley, 2003). When educators *do* acknowledge the biases inherent in STEM, students will likely believe that their feelings of cultural incongruence have been affirmed instead of ignored (A. Johnson, 2007).

As I have mentioned, much of the mainstream literature on pedagogical reform in STEM references *high-impact* or *evidence-based* practices that will allegedly raise achievement for all students (e.g., Brown, Hershock, Finelli, & O'Neal, 2009; Twigg, 2005). Riley (2014) took issue with this tendency, claiming that it is an inappropriate attempt to transfer medical research practices to education. According to Basile and Lopez (2015), the "'one-size-fits-all' approach to science and mathematics education … ultimately works to maintain and reproduce the racialized structures and outcomes already in place" (p. 533). STEM education reformers must be aware that students will react in different, and sometimes opposing, ways to the changes they implement.

Scholars critical of the mainstream approach have argued that student-centered pedagogical strategies are a step in the right direction, but do not go far enough (D. M. Riley, 2003). The discipline of physics provides concrete evidence that mainstream approaches are not sufficient; physics has been one of the leaders in adapting active learning (Stokstad, 2001), but remains one of the least diverse STEM disciplines (Hazari et al., 2013). Through their focus on disrupting the status quo and addressing underlying inequities, inclusive pedagogies have a greater potential than mainstream pedagogies based in the active learning paradigm to address the alarming disparities in STEM education.

Inclusive pedagogies are more prevalent in non-STEM fields and there are fewer examples in the literature of their use in the STEM context. Chamany (2006) described using case studies based on scientists with humanitarian interests and inclusion of politically charged topics to teach basic science principles. In an engineering thermodynamics course, Riley (2003) had students write reflections relating thermodynamics to their lives, assigned case studies that dealt with ethics issues in thermodynamics, and included examples from thermodynamics that challenged the perceived objectivity of science. Despite these examples, a larger body of literature examining students' experiences with inclusive pedagogies in STEM courses is needed. Research in this area should consider the institutional and disciplinary context of any given course.

University and Disciplinary Context

Just as student experiences and strategies differ according to their unique identities and backgrounds, there is also variation related to institution type and discipline. Studies have associated large research universities and predominantly White institutions (PWIs) – qualities that characterize my research site – with poor persistence rates of FG and other underrepresented students in STEM (Espinosa, 2011; Fries-Britt et al., 2010; Harper, 2013; Seymour & Hewitt, 1997). In addition, disciplinary cultures within STEM vary significantly. In this section I review these contextual factors.

The disciplinary context of mathematics. There is substantial variation across STEM disciplines with respect to culture, historical context, climate, demographics, and persistence rates. For example, persistence rates for underrepresented students are lower in the computer science, math, physical science, and engineering majors compared to other STEM disciplines (Dika & D'Amico, 2016). Math is a field that cuts across STEM disciplines as well as many non-STEM ones; student success in a sequence of math courses, often culminating in calculus, is necessary for advancing in STEM majors and many business and other quantitatively oriented majors (Gainen, 1995). The topic of math education reform at the postsecondary level has a long history in the United States.

Calls for reform have ranged from remedial math courses that are focused on pre-college algebra (most often taught at community colleges) to calculus (Joiner, Malone, & Haimes, 2002; Markman, 2016). There was a strong movement to revise calculus courses in the late 1980s and 1990s. Such reforms were focused on tying math to real-world problems, incorporating group work and class discussions with lecturing, and the use of graphing calculators and other technologies (R. Wilson, 1997). However, critics have questioned the effectiveness of those changes (McGowen, 2006; Worthley, 2013).

In the United States, an increasing percentage of students are deemed unprepared to take calculus and are placed in remedial math or pre-calculus courses – often courses they have already taken in high school (McGowen, 2006; Sonnert & Sadler, 2014). There is evidence that pre-calculus, which usually focuses on college-level algebra and trigonometry, serves as a gatekeeper for students trying to enter a quantitative major (McGowen, 2006). Sonnert and Sadler (2014) found that only 30 to 40% of students who pass pre-calculus go on to enroll in a calculus course. This aligns with McGowen's finding that an increase in pre-calculus enrollment has occurred in parallel with decreased enrollments in calculus. In other words, the increased focus on providing instruction to students who are deemed unprepared for calculus has not ultimately produced a larger body of students who complete the sequence of math courses that is required for majoring in STEM.

Introductory math courses have been highly criticized for their instructional approach. A common criticism of gatekeeper math courses is that they are taught in exceedingly abstract ways. Sonnert and Sadler (2014) commented:

> All too often, mathematics is taught as a set of concepts developed by mathematicians pursuing goals of beauty and abstraction, when in reality many students might be more interested in solving knotty, concrete technical problems rooted in the real world. (p. 1204)

According to critical scholars, the field of mathematics in particular is portrayed as "skills-based knowledge that is socially, politically and ethically neutral" – even though in reality the mathematics curriculum has been created through "socio-political practices in Western Europe in the past three-hundred years" (le Roux, 2016, pp. 51, 54). Practitioners who use the active learning paradigm most often maintain this notion of math as an objective and neutral subject, creating a belief that there is a rational structure of mathematics that can be recreated in the individual mind (le Roux, 2016).

These underlying beliefs and practices produce climates that may be unwelcoming to students who do not identify as White middle- or upper-class men. Struggles in primary and secondary math classes often instill in students a negative reaction to mathematics – and this is disproportionately experienced by women and students of color (Peters, 2013). Consequently, UR students often enter introductory mathematics courses with negative associations to the subject and then experience a context that further alienates them. Researchers who examine math courses must keep this context in mind.

Large research universities. It may be especially difficult to improve introductory courses at large research universities because these courses tend to enroll high numbers of students and faculty have a strong incentive to focus on their research instead of teaching (Garcia et al., 2011). These dynamics can lead to a situation where the lecture method is over-utilized and students' access to professors is limited (Garcia et al., 2011; Soria & Stebleton, 2012). This type of institution is also more likely to utilize competitive grading practices (Espinosa, 2011). Soria and Stebleton argued that because FG students often lack relevant social capital, the limited access to professors and other institutional agents at large research universities is especially detrimental to them.

Predominantly white institutions. PWIs, which are institutions where at least 50% of students identify as White, are often characterized by unwelcoming campus and classroom climates for students of color and other underrepresented students (Holmes, 2013; Stebleton & Aleixo, 2016). Fries-Britt et al. (2010) found that students of color enrolled in physics programs were more likely to describe a communal environment at historically Black colleges and universities (HBCUs) compared to PWIs. Perna et al. (2009) remarked that "of the top 20 leading producers of African American bachelor's degrees in STEM fields, all but three are HBCUs" (p. 5). Researchers studying STEM courses at PWIs should keep in mind that there are likely broader campus climate issues that affect student experiences. The variations described in this section point to the importance of research on underrepresented student persistence in STEM to situate itself in a specific context(s).

Conclusion

There is currently growing momentum to reform introductory STEM courses at U.S. universities. However, there is a mismatch between the narratives of FG and other underrepresented students in STEM and the scholarly discourse surrounding mainstream pedagogical reform. For example, the mainstream literature suggests that increasing course structure can have positive effects on persistence (S. L. Eddy & Hogan, 2014). Yet, a professor not operating from an equity framework (Bensimon, 2005) might improve course structure without changing patterns of participation or addressing microaggressions. Students have agency and many will persist, but FG and other UR students will not be equally represented in STEM until there is transformative change. If transformation is achieved, first-year introductory classes can provide environments in which FG students develop science identities, feel validated by their peers and professors, and believe that they fit within the culture of STEM. Unfortunately, most of the literature regarding the reform of introductory STEM courses is based on post-positivistic research and encourages the use of mainstream pedagogical practices, rooted in the active learning paradigm, that do not address structural inequities. This simplistic framing of the issue does not challenge educators to question their underlying assumptions and frameworks regarding equity and the cultures of STEM, leading to the reproduction of inequity.

Due to recent scholarship that has considered the role of the classroom, it is clear that the in-class experience matters greatly for student persistence, and that the classroom climate is highly influential. Yet, as Holmes (2013) argued, “Considering the importance of classroom experiences in academic outcomes, we know very little about what actually happens in the classroom, and how students perceive the interactions therein” (p. 24). This is in part due to the predominant use of survey research that does not capture student or faculty narratives (Garcia et al., 2011). Most work that *has* attempted to gain an in-depth understanding has focused on courses that are taught through the lecture method.

Much less has been done in courses that have been reformed or redesigned in an attempt to improve student persistence and learning.

There is a clear need for further research that examines the experiences of FG and other underrepresented students in redesigned introductory STEM courses and how those experiences affect persistence. Scholars must critically examine the active learning paradigm and consider whether inclusive pedagogies are needed. To address this gap in the literature, I conducted a mixed methods case study of a large, gateway pre-calculus course that had been redesigned mainly using the active learning paradigm, although there were also aspects of traditional and inclusive pedagogies. I explored how FG students experienced the classroom climate and how the professors' teaching and learning strategies shaped the climate. I aimed to determine the extent to which pedagogical elements aligned with the three teaching and learning paradigms created a welcoming or unwelcoming climate for FG students, and whether a greater incorporation of inclusive pedagogies may have been more effective in that regard. In the next chapter, I provide an overview of the methods I used to answer my research questions.

Chapter Three: Methods

In this chapter I discuss the methods I used to conduct my study. After presenting my research questions, I discuss my positionality and explore the paradigmatic considerations of this research project. I then discuss how my study aligns with an explanatory sequential mixed methods approach that is embedded within a single case study design. Next, I provide details on my research site, sample, instruments, and data collection and analysis. I end the chapter by discussing the strategies I used to ensure the rigor and quality of the study.

Research Questions

My overarching research question was: How do first-generation students experience a large STEM gateway course that has been redesigned to incorporate active learning? The following specific research questions guided the study:

1. How do FG students perceive the classroom climate?
    a) How do FG students describe the classroom climate?
    b) Are there differences between FG and continuing-generation (CG) students' perceptions?
    c) How do FG students' multiple intersecting identities inform their perceptions of the climate?
    d) How do racism, sexism, classism, and other intersecting forms of discrimination influence FG students' experiences of the climate?
    e) What factors not related to pedagogy influence climate perceptions?
2. How does pedagogy reinforce or disrupt classroom power dynamics that affect the experiences of FG students?

a) How does the course pedagogy align with traditional pedagogy, active learning, and/or inclusive pedagogy?

b) How does pedagogy influence the classroom climate?

3. How do FG students' experiences in the course influence their intentions to take additional mathematics courses and persist in STEM?

Positionality

Especially when studying marginalized populations, it is essential for researchers to consider and reflect on their own positionality (Merriam, 2015). In writing about reflexivity, Pillow (2003) challenged researchers "not to situate reflexivity as a confessional act" (p. 177) but to embrace "uncomfortable reflexivity" (p. 188) that acknowledges the complexity and contradictions embedded in the various subjectivities of both the researcher and the research participants. I attempted to reflect on these subjectivities while acknowledging that at the same time, we cannot truly know or understand them (Pillow, 2003). As a White woman from a middle- to upper-class background, I was limited in the extent to which I could truly empathize with my study participants, many of whom (in the study's qualitative strand) were low-income and students of color. I am deeply committed to reversing inequitable structures in higher education, yet I have also benefited and continue to benefit from those structures.

In the section below I discuss the ways in which CRT and LatCrit influenced my study design. I approached the use of these theories with some hesitance. CRT and LatCrit are two branches of critical theory created by Black scholars and Latinx scholars, respectively (L. D. Patton et al., 2015; Peralta et al., 2013). Although I am committed to dismantling racism and other forms of discrimination in education, I do not know what it is like to be an individual who has been marginalized by others because of racism or classism, and at times I unintentionally perpetuate inequities. I feared that using CRT or LatCrit risked appropriating or co-opting the theories (Bergerson, 2003). However, although I risked appropriation, to use the concepts of these theories without naming them and giving credit to their founding scholars would have been worse.

Sunstein and Chiseri-Strater (2011) (as quoted in Saldaña, 2016, p. 23) urged scholars to continuously ask themselves the following questions as they conduct research: "What surprised me? (to track your assumptions); What intrigued me? (to track your positionality); What disturbed me? (to track the tensions within your value, attitude, and belief systems) (p. 115)." In keeping a journal throughout the data collection and analysis process, I attempted to keep these considerations in mind. By continuously acknowledging the complexity of our subjectivities and by checking my assumptions and interpretations with myself and my study participants, I have attempted to recognize the tenuous nature of my findings while also engaging in the "real work to be done" (Pillow, 2003, p. 192). I now turn to discussing some paradigmatic considerations of my study design.

Paradigmatic Considerations

The design of this study was informed by CRT, LatCrit, pragmatism, and critical quantitative studies. Below I discuss the aspects of each paradigm that influenced the study.

Application of CRT and LatCrit to research methods. As discussed in the previous chapter, CRT and LatCrit are useful in exploring the underlying inequities that have led to disparities in STEM education outcomes, and for highlighting the role of the classroom climate of introductory courses. In addition to providing a lens for understanding the issues that were central to my inquiry, there are several ways in which the tenets of these theories informed my study design. First, it was vital that the study acknowledge and center the existence of racism and other forms of oppression in higher education and STEM education in particular. It was especially important to maintain this perspective during the quantitative phase, as surveys designed to assess the classroom climate often do not address the existence of both overt and subtle forms of discrimination. Patton et al. (2015) described this tendency:

> Not captured on surveys are students' interactions with classroom environments in which they are the lone representatives of their racial/ ethnic groups, where the professor either commits or permits racial microaggressions, where the threat of confirming racist stereotypes about them is high, and where all the authors of class assignments are white. (p. 209)

I incorporated aspects of several existing classroom climate surveys, and supplemented them with additional items where needed, to ensure these dynamics were incorporated.

Second, given the importance of including the voices and stories of underrepresented students, it was necessary for my study to incorporate a qualitative component based around student interviews. According to Patton et al. (2015), "When the experiences and knowledges of people of color are shared, the process allows for a more authentic and unique understanding of how they experience racist, oppressive structures" (p. 197). The need for authentic voices means that scholars must listen to those who have experienced racism, classism, sexism, and other forms of discrimination

(Iverson, 2007). The inclusion of a qualitative strand allows for a marginalized student's narrative to emerge as an alternative to the dominant narrative (Ladson-Billings & Tate IV, 1995; Peralta et al., 2013). For example, according to the dominant narrative, a FG student would be less prepared to seek out academic support resources such as office hours or tutoring services. While some of my interview participants discussed feeling less prepared, one student felt that being first-generation made her more prepared because she had not been able to rely on her parents for help with math during her K-12 education.

I invited students to participate whose voices are normally silenced in the largely positivistic and quantitatively-driven field of STEM education research (D. M. Riley, 2003). In the interviews, I asked some guiding questions but allowed for students to speak at length about their classroom experiences. Most importantly, I listened (Bernal, 2002). When analyzing my qualitative data, I shared my interpretations with my research participants to see if there were any areas where I had misunderstood or misinterpreted what they said. Through these steps, I aimed to provide a more authentic interpretation of the classroom climate than what my interpretation alone would provide.

Paradigmatic issues in the use of mixed methods. One issue mixed methods researchers encounter is at the paradigm level, as quantitative and qualitative researchers often operate from different worldviews. During the "paradigm wars" (Donmoyer, 2006, p. 18) of the 1980s, researchers argued that different research paradigms, such as post-positivism and constructivism, were incommensurable and thus could not be used in the same study. This led to a false notion that a researcher needed to choose either quantitative or qualitative methods (Donmoyer, 2006). While critical theory has traditionally been associated with qualitative research (Giddings & Grant, 2009), I argue that one can conduct a mixed methods, or even purely quantitative, study that is informed by the critical paradigm. Critical quantitative studies provide some helpful reasoning for how researchers attempting to take a critical stance can use quantitative methods. I will also use some of the concepts from pragmatism to explain my justification.

Pragmatism. Pragmatism is one of the leading paradigmatic frameworks used in mixed methods research (Muncey, 2009). In pragmatism, the problem being studied is prioritized over questions of the nature of reality (Creswell, 2009). The pragmatist view is not meant as equivalent to practicality or expediency, but rather reflects an intersubjective approach that rejects the existence of a dichotomy between objectivity and subjectivity (F. L. Bishop, 2015; Morgan, 2007). Pragmatists recognize that there can be both "an external world independent of the mind as well as that lodged in the mind" (Creswell, 2013, p. 11), and appreciate diverse paradigms such as post-positivism and constructivism without attempting to merge them (Crotty, 1998; Sandelowski, 2000). For example, there likely exist general trends in students' perceptions of the classroom climate that can be captured (although imperfectly) through a survey. At the same time, students' interpretations of the classroom climate are subjective and at times nebulous, which lends itself to a qualitative approach.

Pragmatists value transferability over generalizability, arguing that findings can and should be informative for other similar contexts (Morgan, 2007). While the findings from my study are not generalizable to a broader context (e.g., I cannot say that all FG students will perceive a certain classroom climate in reformed introductory courses at all four-year institutions), educators and researchers interested in improving the climate of introductory STEM courses may find my conclusions useful for their own practice.

Pragmatism supports the view that the shortcomings of quantitative research can be alleviated by the strengths of qualitative research, and vice versa (Yoshikawa, Weisner, Kalil, & Way, 2013). Sohn (2016) argued that "typical classroom climate research uses survey instruments that, while designed to measure student perceptions, fail to help educators realize the meaning of classroom climate for students" (p. 13). In my study, survey data provided a general understanding of FG students' perceptions of the classroom climate but did not allow me to understand the specific contexts that led to those perceptions. In a similar vein, interview data could not point to general trends, but it could provide me with answers to the *why* questions.

Quantitative critical studies. Quantitative criticalists (i.e., critical theorists who use quantitative methods) share the pragmatist view that the research question is most important (Stage, 2007). Dixson and Rousseau (2005) argued that "CRT scholarship in education is neither inherently 'qualitative' nor 'quantitative'. Rather, such scholarship should employ 'any means necessary' to address the problem of inequity in education" (p. 22). In critical quantitative research, the methods are quite similar to those of post-positivistic approaches; however, the *motivation* behind the research is more equity-driven and focused on questioning the assumptions of post-positivist models (Stage, 2007). Quantitative criticalists also stress the disaggregation of data. Instead of examining central tendencies, these researchers are interested in disparities among different groups of students as well as those students who are on the margins (Bensimon, 2004; Dika & D'Amico, 2016). Where I differ from quantitative criticalists is that I did not attempt to explore large data sets or produce generalizable findings; I am more concerned with transferability than with generalizability (Stage, 2007).

Putting it together. As a researcher interested in incorporating a critical perspective, my main goal is to challenge and reverse inequitable structures and systems (Giddings & Grant, 2009). I strongly believe that mixed methods is well situated for this goal, and that pragmatism and critical theory are both useful for my aims. According to Stage (2007), "The qualitative studies provide details on how subtle experiences color students' lives; the quantitative studies provide the persuasion of numbers" (p. 12). Through reporting quantitative results, I seek to sway those policymakers who are influenced by numbers. If such decision makers (e.g., institutional leaders, grantmakers) become convinced that active learning does not automatically produce welcoming climates, and that climate matters for student persistence, they might invest in studying classroom climates as they continue to advocate for the reform of introductory STEM courses. The qualitative findings honor my participants' voices and provide contextual details and explanations of the quantitative results. Student narratives also serve as powerful stories that may influence policymakers (Pluye & Hong, 2014). I now turn to the specific design I used.

Research Design

The quantitative and qualitative methods I used were embedded within a case study design. In this section I first describe the case study approach, and then provide information on the type of mixed methods design I used.

Case study approach. Yin (2014) argued that a case study is appropriate when the researcher is studying a bounded system such as a classroom, the study involves a *how* or *why* question, the researcher has no control over individual behavior or events, and the study is focused on contemporary events. My study matched these criteria, making this research design appropriate. The case study approach is useful for studying a complex phenomenon, such as the classroom climate, in its real-world context – especially when an understanding of the context is crucial to the researcher's interpretation. Case studies take a holistic approach, which is aligned with my interest in understanding the influence of pedagogy on the classroom climate not only from students' perspectives, but also from that of the instructor as well as my own. Case studies aim for "analytic generalization" instead of "statistical generalization," where the goal is to "shed empirical light about some theoretical concepts or principles" (Yin, 2014, p. 40).

Through this study, I sought to *shed empirical light* on the concept of classroom climate and the influence of pedagogy on climate, as well as the distinctions and overlaps between traditional pedagogy, active learning, and inclusive pedagogy. The study results are informative for other practitioners and researchers attempting to improve underrepresented student persistence in STEM through teaching and learning reform. I also aim to influence the larger policy discussion around student retention in STEM by demonstrating that simply moving away from lecturing and toward active learning is not sufficient for making STEM more welcoming to students.

I used a mixed methods embedded single case study approach (Creswell & Plano Clark, 2011; Yin, 2014). The unit of analysis was the course, and I was especially focused on the various teaching and learning approaches utilized (both the professor's intentions behind their use and students' perceptions of them) and their influence on the climate. An embedded design means that within each case, there are sub-units of analysis (Yin, 2014). Students and the course instructor were the sub-units of my study, as I analyzed their perceptions of and reactions to the classroom climate. The case was three sections of a pre-calculus course at a large, public, four-year research university. One section was taught by the professor who had led the redesign of the course and the other two sections were taught by a professor who had not taught the course before in its redesigned format. I used the critical case rationale in selecting this course, in which the case represents "a significant contribution to knowledge and theory building by confirming, challenging, or extending the theory" (Yin, 2014, p. 51). Extensive research exists on students' experiences of introductory courses that use a lecture-based approach; studying a course where the professors incorporated non-lecture elements offered greater potential to expand the literature on underrepresented students' experiences in introductory courses.

Yin (2014) urged case study researchers to "bound" the case to clarify what will and will not be examined as part of the study (p. 26). For my study, the course included what happened in the classroom during class time (including smaller discussion sections), as well as student engagement with the course outside of the classroom (e.g., meetings with the professor, using the course's website and online videos, working on homework). Although larger issues (e.g., the *campus* climate, experiences in other courses) likely influenced students' experiences of the course, I did not explicitly include them as part of the study – although I knew those aspects may emerge during student interviews. I collected data on the classroom through observations, analysis of the syllabus, a student survey, and interviews with the instructor and a sub-sample of first-generation students. While the study included data collected from the instructor as well as my own observations, the central focus was on FG students' experiences in the course, and I used a sequential explanatory mixed methods design to collect student data.

The sequential explanatory mixed methods design. In this design, a quantitative phase provides the researcher with initial information that it used to design a subsequent qualitative phase (Creswell & Plano Clark, 2011). Kerrigan (2014) argued that "case studies should have a feedback loop that informs research design" (p. 347), and the sequential explanatory approach naturally creates this cycle. During the first phase, a student survey measured students' overall perceptions of the classroom climate and the pedagogical strategies utilized by the instructor. During the second phase, student interviews allowed me to further explore the survey results, and also captured additional, subtler, elements of the climate. In addition to informing the interview protocol, I used the survey results to guide my sampling process for the student interviews. Because of my focus on using interviews and course observations to provide a rich, contextual understanding of the climate that built on the initial quantitative results, this study prioritized the qualitative phase (Creswell & Plano Clark, 2011). The diagram in figure 2 provides a visual explanation of the research design.

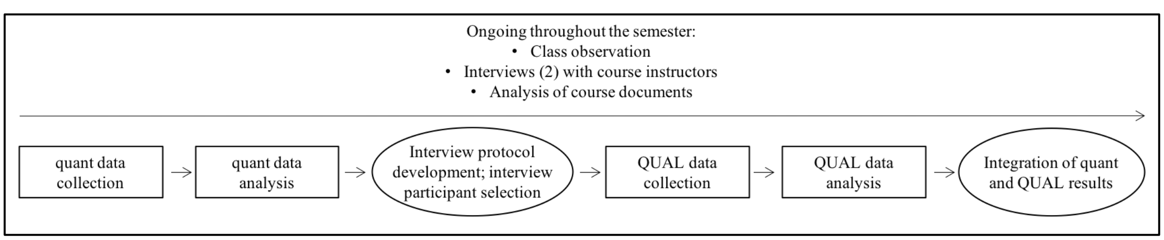

Figure 2. Study design

Research Site

The criteria I used for selecting my research site (a pre-calculus course) was that the course enrolled over 100 students, was taken mainly by first-year undergraduate students, used a teaching and learning approach mainly aligned with the active learning paradigm, and was considered a gateway STEM course (i.e., serves as a prerequisite to more advanced science and/or math courses). Additionally, the lead course instructor (referred to as Dan, a pseudonym) was dedicated to continuously improving the course and had expressed an interest in participating in the study.

In my preliminary conversations with him, Dan had estimated that on average, roughly half of the students taking the course intended to major in a STEM field, and most of the other half intend to major in either business or economics. While all students were included in the survey phase, I interviewed only first-generation students who were at least considering pursuing STEM. I also knew from Dan that most students who took the course intended to eventually take calculus as a requirement of their intended major. As such, even for the non-STEM students, I could assess the influence of the course on their intentions to take further mathematics courses.

The pre-calculus course was taught in an active learning classroom; students sat at round tables, whiteboards were on walls throughout the classroom, and the instructor had a station at the center of the room. The course covered algebra, analytic geometry, exponentials, and logarithms. Trigonometry was taught in a separate math course.

I studied all three sections of the class. Section one was taught by Dan and enrolled 94 students. Sections two and three were taught by the second professor (referred to as Isaac, a pseudonym) and enrolled 86 and 72 students, respectively. Each section met as a whole class for 50 minutes on Mondays, Wednesdays, and Fridays. Section one began at 8:00 AM, section two started at 12:20 PM, and section three began at 3:35 PM. In this paper, I sometimes refer to these sections as the "large class sections."

In addition to the professor, each large class section had two graduate-level teaching assistants (TAs) and four undergraduate TAs who had taken the course previously. There were discussion sections that met once a week on Tuesdays and were led by a graduate TA; these sections enrolled a maximum of 20 students. Each student was also required to attend a review session with the same small group that met on Thursdays and were led by undergraduate student tutors – referred to as peer instructors in this paper - who had taken the course before (separate from the undergraduate TAs). In this paper, I refer to these Tuesday and Thursday sessions as the TA- and peer-led sections.

Dan, who identifies as a White man, is a non-tenure-track Assistant Professor in the math department. He was hired by the university with the charge of improving student preparation for calculus. At the time of the interview, he had been working at the university for six years. Previous to his time at the university, Dan taught math at the high school level. Dan moved the course to a flipped model, where students first learn routine math skills through reviewing online videos before coming to class, and then work on applying the concepts to math problems in the large class sections. The flipped classroom model has come to prominence over the last 10 years. Proponents of this approach argue that with technological advances, much of the learning that used to occur through lectures can now happen online, and in-class time can be reserved for the application of course content to concrete problems (J. L. Bishop & Verleger, 2013). I observed the class during the fall semester of 2017, which was the second time that Dan had taught the pre-calculus class using the flipped classroom approach. He had also taught other introductory math courses in the department using a flipped model.

Isaac, who identifies as a White man, had been working for the university for 10 years as a Teaching Specialist. He had used the lecture method in the past, but was ready to start trying new teaching methods, as he had become convinced that the lecture method was ineffective. The semester during which I studied the course was the first time that Isaac was attempting to use a non-lecture teaching approach. He was expected to follow the flipped classroom format that Dan had established.

The large class sections tended to follow the same weekly structure. At the beginning of each Monday session, students were given a list of problems to solve in small groups. Students were not assigned to groups and ended up working with the other students at their table. During class time, the professor and six TAs circulated the class and helped groups that were stuck on a problem. The Wednesday sessions were similar but were more focused on individual problem solving. The Friday sessions were usually reserved for quizzes or exams.

There were three levels of the course's assessment system. In order to be eligible to receive a passing grade, students had to pass 10 quizzes that tested their basic skills; these quizzes comprised "level one" of the grading system. Students could retake each quiz as many times as they needed until they passed. For "level two" of the grading system, 60% of students' grades was based on test scores. Thirty percent was based on participation and the remaining 10% was based on online homework and quizzes. Finally, there was a “level three” of assessment that students had to complete to receive an A or A- in the course. The syllabus explained:

> If you have completed the Basic Material by certain deadlines, and earned grades of ‘B+’ or better on exams, you will be eligible to do extra material. These topics will not be on the final, but are related to other topics in the course. The extra material is not designed as ‘extra credit’ for students who wish to improve their grade. Students who have not perfected the basic material should continue to improve on the basic material.

Students who did not pass level one would not pass the course. Students who completed level two but not level three would receive a grade between a C- and a B+. Students who successfully completed all three levels would receive an A- or A.

The course was taught at a large, public, research-intensive PWI located in an urban area in the upper Midwest region of the United States. The racial/ethnic breakdown of the institution’s undergraduate student population at the time of data collection was 68% White, 10% Asian, 9% international, 5% Black, 4% Latinx, 4% multi-racial, less than 1% Native American, and less than 1% Hawaiian. The vast majority of students (93%) attended on a full-time basis and were under the age of 25, and women were slightly overrepresented (52%).

Sample

Quantitative sample. For the quantitative phase, I invited all students in the course (N=252) to complete the survey (CG students were included to compare their answers to FG students). I asked students to provide informed consent before beginning the survey, and only those students who gave consent completed the survey (see Appendix B). The usable sample is reported in the section on data collection.

Qualitative sample. For the qualitative phase, I used homogenous purposeful sampling (M. Q. Patton, 2014) to identify, from the survey demographic data, first-generation students who were either majoring in a STEM field or considering going into a STEM field. On the survey students provided their email address if they were interested in participating in an interview. Out of those who expressed an interest, 22 met the above criteria (7 in Dan's section and 15 in Isaac's sections). All 22 students were invited via email to do an interview, and I sent up to two reminder emails to those who did not respond initially. Thirteen students completed an interview. Information on these students is provided in Table 1.

Table 1

Interview participant demographics

Name (pseudonym)	Professor	Gender	Race/Ethnicity	Year at the institution	Pell/NBS/Loan status*	Intended major or field of study
Alexis	Isaac	Woman	Black	1st	SL	Child psychology, pre-med
Amina	Isaac	Woman	Somali, Black	1st	PE, NBSE	Undeclared, leaning toward physiology
Caitlin	Isaac	Woman	White	1st	PE	Theater arts, economics (also considering pre-med)
Devin	Isaac	Man	White	1st	--	Computer science
Hafsa	Dan	Woman	Somali, Black	1st	PE, NBSE	Pre-med
Hanh	Dan	Woman	Laotian, Vietnamese	1st	PE, SL	Biology
Jake	Isaac	Man	White	1st	SL	Pre-med
José	Isaac	Man	Latino, American Indian	1st	PE, NBSE, SL	Psychology, neuroscience
Laura	Isaac	Woman	White	1st	SL	Kinesiology
Maria	Dan	Woman	Latina	2nd	NBSE	Biology
Matt	Isaac	Man	White	1st	SL	Chemistry or math
Nour	Isaac	Woman	North African, Black	2nd	SL	Genetics
Ying	Isaac	Woman	Hmong	1st	PE	Education, considering medical school

* NBSE = eligible for the institution's need-based scholarship; PE = eligible for a Pell grant; SL = has taken out student loans

Instruments

Quantitative. The main aims of the student survey were to assess perceptions of the classroom climate, student perceptions of the instructor's pedagogy, the influence of the course on students' academic plans, and student demographics. The final survey items are included in Appendix C. To develop the survey, I engaged in expert and peer review, conducted survey think-alouds with students who are representative of the study's target population, and ran a pilot of the survey with 23 students enrolled in a similar math class to tailor the instrument to my population and to minimize item non-response and measurement error (Dillman, Smyth, & Christian, 2014). The survey took students approximately 15 minutes to complete.

Classroom climate scales. Quantitatively measuring the classroom climate *itself* would be difficult due to the complex nature of the concept (Sohn, 2016). However, I could gain a sense of students' perceptions of the factors that influence the classroom climate, which I reviewed in the previous chapter (e.g., participation, feelings of isolation). To measure these factors, I combined Likert-type items from four existing classroom climate surveys with additional items that I created. In some cases, the response choices were modified to ensure they were on the same four-level rating scale (strongly disagree, somewhat disagree, somewhat agree, strongly agree).

The *What is Happening in this Class?* (WIHIC) survey was created by Fraser, McRobbie, and Fisher (1996) and has been used extensively to assess classroom climates across various educational levels, subjects, and countries. Several studies have provided evidence that WIHIC is a valid and reliable instrument (Aldridge, Fraser, & Huang, 1999; den Brok, Fisher, Rickards, & Bull, 2006; B. J. Fraser, 2012; Martin-Dunlop & Fraser, 2008). I used three of its nine scales (each containing seven to eight items) to assess professor-student and student-student interaction, and I slightly modified the items to align it with a college course (e.g., substituting professor for teacher).

I used modified items from two scales to assess perceptions of discrimination in the classroom. Cabrera and Nora (1994) created the *Perceptions of Prejudice and Discrimination* (PPD) scale to assess students' experiences with discrimination at both the classroom and campus levels, and found evidence of validity and reliability among their survey sample. I included two PPD items in the discrimination scale. The Higher Education Research Institute created a classroom climate module as part of its larger *Diverse Learning Environments* (DLE) survey (Higher Education Research Institute, 2016). The latest version of the module was recently created and at the time of data collection, to my knowledge its factor structure and reliability had not been examined, but my analysis included factor analysis and measures of internal consistency to ensure the appropriateness of its use for my population, along with the rest of the classroom climate items. I used two DLE items in the discrimination scale, four items in the inclusion of diverse backgrounds scale, and three items in the participation scale.

Rovai's (2002) *Classroom Community Scale* (CCS) measures perceptions of cohesiveness in the classroom. Through factor analysis and calculating measures of internal consistency, Rovai demonstrated evidence of the scale's validity. I used the connectedness sub-scale, consisting of 10 items, to measure students' feelings of isolation, being too visible, or invisible. I could not find an existing survey that explored the physical aspect of the classroom climate, so I created six Likert-type items to measure perceptions of the physical space. I also created Likert-type items for other dimensions of the classroom climate that were only partially addressed in existing surveys. I created three items for the participation scale, four items for the discrimination scale, two for the isolation or being too visible scale, and five for the inclusion of diverse backgrounds scale. I used evidence-based item writing guidelines throughout (Dillman et al., 2014). The items for each scale are provided in Appendix D.

Students' perceptions of pedagogy. To collect information on students' perceptions of each pedagogical strategy, I first needed to create an inventory of the strategies in use. I did this through reviewing the course syllabus and interviewing the professors about their specific approaches to learning activities, course content, and assessment. This process produced a list of 11 pedagogical strategies, six which were teaching-related (e.g., small group work) and five which were assessment-related (e.g., exams). The survey included 11 Likert-type items asking students how effective or ineffective they perceived each strategy to be for their learning.

Influence of the course on students' academic plans. To assess the influence of the course on students' intentions to persist in STEM, I asked about their intended major at the beginning of the semester (open-ended question), whether their current plans had changed (multiple choice question), and if so, what their current intended major was (open-ended question). I also included two Likert-type questions asking students whether the course had positively or negatively impacted their intentions to major in STEM and take additional math courses.

Student demographics. The survey collected information on students' gender, race, ethnicity, and first-generation status. Three financial variables were also included in order to assess students' level of financial hardship: whether they were eligible for a Pell grant, whether they were eligible for the institution's need-based scholarship, and whether they had taken out student loans.

Qualitative.

Student interviews. For my interviews with students, I created a semi-structured interview protocol designed to expand on survey findings and capture additional contextual elements of the course experience. I reviewed the protocol with one university professor who has a background in teaching and learning in higher education. The protocol began with general questions about the students' background (e.g., where they are from, why they chose to attend the institution, why they were taking the course). The interview then moved to questions about their experiences in the course. I aimed to gain an understanding of their overall perceptions of the climate, allowing themes to emerge that are not necessarily aligned with factors that influence the classroom climate that I identified from the literature. For instance, I asked: "Each course takes on a general atmosphere. For example, students may sense that a course has an overall tone of competition, student indifference, or high student energy. What are some words you would use to describe the general atmosphere of this course? What aspects of the course do you think have shaped its overall atmosphere?" Next, I explored student identities, asking them to describe the identities that were most salient to them and whether they felt the course provided a welcoming space to those identities.

Following a general exploration of each student's experience in the course, I asked participants about their perceptions of the factors that influence the classroom climate (e.g., "How would you describe your interactions with the professor?"). I also explored the nature of students' interactions with the graduate and undergraduate TAs, who took on a pedagogical role in the class. I then had students discuss their perceptions of the different teaching and learning strategies utilized by the professor.

I also asked students to discuss their academic plans and whether the course had had any impact on their plans, both in terms of taking additional mathematics courses and what they intended to select as their major. In accordance with the explanatory sequential mixed methods design, I used the survey results to refine the interview protocol. For example, my preliminary analysis of survey data showed a large amount of variation among student respondents about the quality of student-student and professor-student interaction. I ensured that the interviews explored in-depth students' experiences with these types of interaction, in order to explain why the large range of variation existed. Appendix E provides the final interview protocol that was used.

Professor interviews. I interviewed each professor at the beginning of the semester and again toward the end of the term. I designed the first interview protocol to confirm the specific pedagogical strategies being utilized by the professors (a preliminary list had been compiled through syllabus review and informal conversations with Dan). I sought to understand the intention behind each strategy, to later determine whether the strategy produced its intended effects. The first interview also explored each instructor's teaching and learning philosophy. Questions included, "What do you think the role of the professor should be in the course?" and "Do you think that math education is structured in a way that benefits certain students over others?" I kept in mind that the professors' philosophies would likely include views that fall under more than one pedagogical framework. Finally, I asked the instructors about the type of course climate they were trying to create.

The second interviews were designed to fill in information that had not been captured during the first interview and to see how the professors felt the semester had gone. Understanding their perspectives at the end of the semester was important in order to have a more holistic understanding of what had occurred in the course. For example, as discussed in chapter five, many of the students I interviewed were frustrated by a perceived lack of guidance. However, the professors believed it was important for students to guide themselves and take on greater responsibility for their learning. In this example, the professors' arguments do not take away from the frustration felt by the students, but this tension demonstrates the complexity of using a pedagogy in which students are expected to take a more active role. Appendix F provides the professor interview protocols.

Observation protocol. Observation allows the researcher to witness a naturally occurring context instead of removing the participant from that context (Cotton, Stokes, & Cotton, 2010). To gain a better understanding of how the different teaching and learning strategies were implemented and what influence they had on the climate, it was necessary to see the context first-hand. I observed the course throughout the semester and took on the role of a passive, overt observer (Fyfe, 1992) – students were aware of my presence but I did not actively participate in course activities. I rotated between three different observation protocols. For one of them, I focused on student-student interaction, observing a section of four tables (the entire classroom had fourteen tables). For the second, I focused on professor-student interaction, also observing four tables. For the third, I focused on half of the class (seven tables) and made minute-by-minute notes of how much help each table received from the professor and TAs, as well as how often students raised their hands. For each observation, I noted the perceived demographic patterns of the tables I was observing, acknowledging that a student's race or gender may be different from what I perceive it to be. I was conscious of focusing on different areas of the classroom so that I was not singling in on any one physical section. For each observation, I also included the following question prompts:

- What did the overall "vibe" or atmosphere of this class feel like?
- How did this session seem to go for students?
- Who had power?
- Who did not have power?
- Did I see any evidence of systems of power and oppression? (e.g., sexism, racism)
- Did I see any evidence of student resistance to systems of power and oppression?

Data Collection

Quantitative. I administered the survey in class during the seventh week of the semester, once the students had had sufficient exposure to the course. I employed strategies from social exchange theory to maximize the response rate (Dillman et al., 2014). At the beginning of the semester, I introduced myself to students, explained the study, and mentioned that there would be an in-class survey. On the day of the survey, as it was being passed out, I stressed to students the importance of the study in terms of improving student persistence in STEM. Students were also informed that if they completed the survey, they would have the option to enter into a drawing for one of four $50 Amazon gift cards. I clarified, both through an announcement to the class and in the informed consent information, that the survey was voluntary. I manually entered the paper survey data into the online Qualtrics version.

On the day of the survey, students were also taking an in-class quiz. The survey and the quiz were passed out at the same time, and the instructors told students that they could complete the quiz first. Sixty-six students in section 1 (taught by Dan), out of roughly 75 who were in attendance that day, completed the survey. Forty-six students out of approximately 72 in attendance in section 2 (taught by Isaac) completed the instrument, and 31 students out of approximately 61 in attendance filled it out in section 3 (taught by Isaac). The in-class response rates may have been lower for sections two and three because in addition to the quiz that all students were asked to take, students had the option to retake past quizzes at that time. As a result, some students spent the whole class time taking quizzes. In addition, throughout the semester I observed that students in section three tended to leave class early; there were no consequences for doing this and the timing of the section late in the afternoon made it more likely. On the day of the survey, many students in section 3 took the quiz and then left class instead of staying and completing the survey.

During the week following in-class administration, students were emailed (via Dan) an online version of the survey. The online survey was targeted towards students who had not been in class on the survey administration day or who had been in class but preferred to use the online version. An additional 28 students filled out the survey online (14 from section 1, 7 from section 2, and 7 from section 3). In total, 171 students completed the survey for a response rate of 68% (see table 2). Table 3 presents the demographics of the sample, for all respondents as well as just the FG students.

Table 2

Student Survey Response Rates by Course Section

Section	Student enrollment	Number of survey respondents	Survey response rate
Section 1 (taught by Dan)	94	80	85%
Section 2 (taught by Isaac)	86	53	62%
Section 3 (taught by Isaac)	72	38	53%

Table 3

Distributions of Survey Respondent Demographic Indicators

Category		All students (n = 171)	FG students (n = 66)
Student status			
	Full-time	155 (95.09%)	61 (92.42%)
Gender			
	Agender/non-binary	1 (.61%)	1 (1.52%)
	Gender queer/gender non-conforming	1 (.61%)	1 (1.52%)
	Man	52 (31.90%)	23 (34.85%)
	Woman	109 (66.87%)	41 (62.12%)
Race/ethnicity			
	Asian – non-URM	13 (8.02%)	2 (3.03%)
	Asian – URM	21 (12.96%)	17 (25.76%)
	Black/African American	11 (6.79%)	10 (15.15%)
	Latinx/Hispanic	11 (6.79%)	6 (9.09%)
	Mixed race	10 (6.17%)	3 (4.55%)
	Native American	1 (.62%)	0
	White	89 (54.94%)	22 (33.33%)
	Something else	5 (3.09%)	5 (7.58%)
	Prefer not to answer	1 (.62%)	1 (1.52%)
URM/non-URM			
	URM	44 (30.14%)	33 (57.89%)
International student status			
	Needs visa to attend	15 (9.26%)	8 (12.12%)
Transfer student status			
	Transfer student	28 (17.18%)	11 (16.67%)
Transfer students – length at prior institution			
	Less than 1 year	5 (17.86%)	1 (9.09%)
	1 to 1.99 years	14 (50.00%)	5 (45.45%)
	2 to 2.99 years	8 (28.57%)	4 (36.36%)
	3+ years	1 (3.57%)	1 (9.09%)
Number of semesters at current institution			
	1-2	149 (90.86%)	59 (89.39%)
	3-4	12 (7.32%)	5 (7.58%)
	5-6	1 (6.10%)	1 (1.52%)
	7+	2 (1.22%)	1 (1.52%)
Pell grant eligibility			
	Eligible to receive Pell grant	44 (26.83%)	34 (51.52%)
Institution's need-based scholarship eligibility			
	Eligible to receive scholarship	36 (21.95%)	24 (36.36%)
Student loans status			
	Has taken out student loans	73 (44.79%)	35 (53.03%)

Table 4 presents a comparison of the sample demographics with the demographics of the whole course, for the demographic indicators that the university's Office of Institutional Research (OIR) was able to provide. The survey sample was roughly representative of the whole course with regard to the percentage of first-generation, White, and Pell grant-eligible students. Full-time students, women, and Asian students were overrepresented in the survey sample, whereas Black/African American, Hispanic/Latinx, and Native American students were underrepresented. However, the differences in the racial and ethnic composition between the survey sample and the whole class may be partially due to the different ways in which this information was collected. For instance, the OIR did not have a "mixed race" category while my survey did. The OIR included international students as a race/ethnicity category, while my survey did not.

Table 4

Comparison of Distributions of Survey Respondent Demographic Indicators with Distributions of Demographic Indicators for All Students in the Course

Category		Survey respondents (n = 171)	All students in course (N = 252)
First-generation status			
		66 (38.60%)	93 (36.90%)
Student status			
	Full-time	155 (95.09%)	223 (88.49%)
Gender			
	Agender/non-binary, gender queer/gender non-conforming, or unknown	2 (1.22%)	2 (0.79%)
	Man	52 (31.90%)	106 (42.10%)
	Woman	109 (66.87%)	144 (57.14%)
Race/ethnicity			
	Asian	34 (20.98%)	34 (13.49%)
	Black/African American	11 (6.79%)	27 (10.71%)
	Latinx/Hispanic	11 (6.79%)	21 (8.33%)
	Mixed race	10 (6.17%)	--
	Native American	1 (.62%)	8 (3.17%)
	White	89 (54.94%)	145 (57.54%)
	Something else	5 (3.09%)	17 (6.75%)
	Prefer not to answer	1 (.62%)	--
Pell grant status			
	Eligible to receive Pell grant	44 (26.83%)	--
	Pell grant recipient	--	66 (26.19%)

Qualitative.

Interviews. Twelve 30 to 60-minute in-person semi-structured student interviews occurred during weeks 11 through 14 of the semester. In addition, one student was not available to participate in the interview during that semester, and participated in a phone interview during the second week of the following semester. On the survey, students indicated whether they were interested in participating in a follow-up interview. Using the methods described in the sampling section, I invited students who met my sampling criteria. I gave each student who completed an interview a $25 gift card; the gift card acted both as an incentive to participate as well as recognition of their time. I also conducted 60 to 90-minute interviews with the instructors at the beginning and end of the semester. All interviews were recorded and transcribed for analysis. The student consent form is provided in Appendix B and the professor consent form is provided in Appendix G.

Observation. I observed the Monday session of the class several times throughout the semester. I observed 9 sessions of Dan's section and 11 of Isaac's (alternating between the two that he taught). I rotated between the three observation protocols (e.g., one day I observed professor-student interaction and the following week I observed student-student interaction), taking notes on paper and then transcribing them into a Microsoft Word document for analysis.

Document review. I reviewed the course syllabus in order to gain additional context about the course and the specific teaching and learning strategies that were utilized. Because much of the initial student learning occurred online, it was necessary to watch the online videos that students were expected to watch before class. I was granted access to the course's website, which hosted these documents and resources. I also received the emails that Dan sent to students with updates, which provided additional context.

Data Analysis

In this section I first provide some general notes on my approach to quantitative and qualitative analysis. Because most of my research questions were addressed through both quantitative and qualitative methods, for the sake of clarity I have organized the rest of the section by each research question.

General quantitative approach. I downloaded the survey results from Qualtrics into an Excel file, which I then uploaded into the R statistical software package, which I used to perform all quantitative analysis. Before conducting the specific analyses described below, I examined the data for any potential errors, recoded the variables for analysis (e.g., converting yes/no answers to 1 and 0), and calculated descriptive statistics for all variables. My R code is included in Appendix H.

General qualitative approach. For the qualitative analysis I employed simultaneous coding, where I applied several first-cycle coding procedures to the data. I kept a research journal, using the memoing process to capture emerging ideas and themes as I conducted the interviews and coded the data. After first-cycle coding, I grouped the codes into categories and sub-categories, and then generated themes from those categories (Saldaña, 2016). I used the NVivo qualitative coding software so that as I coded, a directory of the codes was automatically created. I now turn to the specific analysis strategies I used to answer each research question.

RQ1. How do FG students perceive the classroom climate?

RQ 1a: How do FG students describe the classroom climate? The quantitative analysis for this question involved summarizing students' responses about the factors that influence the classroom climate. The first step was to use confirmatory factor analysis (CFA) and measures of internal reliability (i.e., Cronbach's alpha) to create continuous classroom climate scales. It was important for the CFA that each cross-tabulation of variables did not have any cells with zero values. As such, some variables were recoded by collapsing values (e.g., coding 1 and 2 as 1) until there were no empty cells. Next, I performed an item analysis based on classical true test (CTT) score theory for each scale and removed items with low correlations to the rest of the scale, or where Cronbach's alpha would go up if the item was removed.

I then performed a CFA. I examined several CFA fit indices. T. A. Brown (2006) suggested the following criteria for these indices:

> (1) SRMR [standardized root mean square residual] values are close to .08 or below; (2) RMSEA [root mean square error of approximation] values are close to .06 or below; and (3) CFI [comparative fit index] and TLI [Tucker-Lewis Index] values are close to .95 or greater. (p. 87)

The weighted root mean square residual (WRMR) should also be under 0.9 (Yu, 2002). In addition to these fit indices, I examined the residual correlations, which should be between +/-.1. When these criteria were not met, I removed the item that had either the lowest factor loading, the lowest R-squared, or the greatest number of residual correlations greater than +/-.1. I then re-ran the CFA and continued to remove items until all criteria were met. I calculated Cronbach's alpha for the final set of items to ensure that it was above .7. I also looked at correlations between scales (e.g., is there a correlation between students' interactions with the professor and perceived discrimination?). Since each scale measures an aspect of classroom climate, there would be some level of correlation between them. However, anything above .8 is problematic (T. A. Brown, 2006).

The final factor solution resulted in seven scales. The isolation and student-student interaction scales were combined because they were highly correlated and it made substantive sense to combine them. For instance, one item from the student-student interaction scale was “I cooperate with other students on class activities,” and one item from the isolation scale was “I trust others in this course.” The scale was renamed “student-student interaction and cohesion”. The other six scales were: discrimination, inclusion of diverse backgrounds, participation, physical space, professor-student interaction, and TA-student interaction. Each final scale had between three and eight items. In Appendix D, the final items that were retained for each scale are marked with an asterisk.

I created a composite score for each scale by taking the mean of its items. For all scales, there were no extreme violations of homogeneity of variance or normality, and no extreme outliers for both first-generation and continuing-generations students. For five of the scales, the skew was also between +/- 1, and the skew was in the same direction for FG and CG students. For two of the scales, TA-student interaction and student-student interaction/cohesion, the skew was close to but over +/- 1. For these two scales there were no extreme violations of normality, but for the MANOVA and other analyses I used square root transformations in order to reduce the number of multivariate outliers. To respond to the research question, I examined the mean and standard deviation of each scale in order to gain a sense of how each factor that influences the classroom climate was perceived by FG students.

For the qualitative analysis, I focused on the interview questions that examined students’ experiences of the course, both in terms of broad perceptions (e.g., *What are some words you would use to describe the general atmosphere of this course?*) and the factors that influence the classroom climate (e.g., *How would you describe your* *interactions with students in the course?*). Concept coding is a macro approach to coding that seeks to draw larger ideas or concepts from specific experiences. I used concept coding when I believed an example provided by a student indicated a larger theme related to the climate. For instance, a quote from Laura in which she described students looking at each other and asking "What's going on?" was coded as a collective sense of confusion. Because the classroom climate is related to the affective dimension of learning, I used emotion coding to identify the feelings that students experienced during the course. Similarly, values coding captured my participants' "values, attitudes, and beliefs" about their experiences in the course (Saldaña, 2016, p. 131).

While the coding strategies described thus far are inductive in nature, I also used deductive coding, mirroring my strategy for allowing themes related to classroom climate to emerge while also identifying aspects of a course that can influence the climate prior to the start of the study. Using provisional coding, in which the researcher uses a predetermined set of codes (Saldaña, 2016), I coded interview data for the factors that influence the classroom climate (e.g., discrimination, participation).

Analysis of my observation data provided me with additional context and insights regarding the climate. I read through my observation notes and summarized the main themes and wrote memos about the overall atmosphere of the course, as well as student-student interaction, professor/TA-student interaction, and gender and race dynamics.

RQ 1b: Are there differences between FG and continuing-generation (CG) students' perceptions? I compared FG and CG students on each of the seven classroom climate scales. I conducted a multivariate analysis of variance (MANOVA), in which the classroom climate scales are treated as multiple dependent variables (D. C. Howell, 2013). Three multivariate outliers were removed. As noted above, I used square root transformations for the TA-student interaction and student-student interaction and cohesion scales. Using G-Power, I calculated that if there was a small difference (f=.1) between the two groups, I would need a sample of 190 students to have a 90% chance of calculating a statistically significant difference (α=.05) if such a difference existed. If there was a medium difference (f =.25), I would need a sample size of 82. Because my sample size of 163 was below the number needed to detect a small difference, I decided that if the result of the MANOVA was statistically significant (α=.05) or *approaching* statistical significance ($p<.15$), I would then conduct individual t-tests comparing FG and CG survey respondents for each classroom climate scale.

While this question is primarily quantitative, since my qualitative sample did not include CG students, I did analyze interview data related to students' experiences in the course as FG students. I applied emotion and values coding to the question: "Do you think being first-generation has affected your experiences in this course at all?"

RQ 1c: How do FG students' multiple intersecting identities inform their perceptions of the climate? For this question, I wanted to explore whether any social identities were especially salient in terms of explaining differences in climate perceptions. I first examined correlations between the classroom climate scales and student demographic variables for the first-generation survey respondents. I also included which professor each student had in order to account for any differences along that dimension. The demographic variables I included were:

- Gender: Because there were only two survey respondents who identified as agender/non-binary or gender queer/gender non-conforming, I used a dichotomized gender variable with the categories man and woman.
- Race and ethnicity: The race and ethnicity variable was first put into the following categories: Asian URM (Hmong, Laotian, and Vietnamese), Asian non-URM (all other Asian students), Black/African American, Latinx/Hispanic, mixed race, Native American, prefer not to answer, something else, and White. For the analysis, I needed to further collapse the categories because there were small numbers of students in some of them (e.g., only six Latinx/Hispanic FG respondents). I did this by combining groups that tended to respond similarly on the classroom climate scales, resulting in three categories: Black and Asian URM, Latinx and mixed race, and non-URM Asian and White. Each of these categories was introduced as a dummy variable in the analysis (e.g., Black and Asian URM = 1, non-Black and Asian URM = 0).
- Financial hardship: Each of the three binary measures of financial hardship was coded 0 = No, 1 = Yes, and the three measures were summed to create a discrete quantitative variable. This variable ranged from 0 to 3. A score of 3 reflected a student who was eligible for both a Pell grant and the institution's need-based scholarship and who also had taken out student loans. A score of 0 reflected a student who was not eligible for either scholarship and who had not taken out any student loans.

In addition to examining correlations, I performed multivariate regression analysis, using each scale as a dependent variable and the demographic variables as predictors. For the student-student interaction/cohesion and student-TA interaction scales, the transformed variables were used. This analysis allowed me to see whether any of the demographic variables were statistically significant predictors of differences in the classroom climate scales while holding the other predictors constant. The results of each regression were examined to ensure that there were no extreme violations of the assumptions of homogeneity of variance, linearity, and normality of residuals.

My qualitative analysis centered on the interview questions related to how identity influences course experiences: *Do you feel that this course is a welcoming space to those identities [students had previously discussed which social identities were most salient to them]? How do you think sense of belonging in this class might be different for students with marginalized identities, if at all? Do you see any pattern in terms of how students interact with each other related to gender, race, or other aspects of identity? How has the experience been of being a student of color in a class of mainly White students [for interview participants who were students of color]?* Given the subjective and affective nature of identity, my analysis of these questions centered on emotion and values coding (Saldaña, 2016).

RQ 1d: How do racism, sexism, classism, and other intersecting forms of discrimination influence FG students' experiences of the climate? While the analysis of this question was primarily qualitative, I revisited correlations between the discrimination scale and the other classroom climate scales in order to gain a preliminary understanding of the association between a sense of discrimination in the classroom and other classroom climate factors. Regarding the qualitative analysis, I used the same analyses process as I did for RQ1c, although I focused more on issues that students brought up that may have been representative of structural dynamics. I also reviewed my observation notes to see whether I had detected any gendered or racialized patterns of interaction.

RQ 1e: What factors not related to pedagogy influence climate perceptions? The analysis of this question was exclusively qualitative, as it allowed for non-predetermined aspects to emerge as being influential. I used concept, emotion, and values coding to analyze passages from student interview transcripts in which they discussed how non-pedagogy factors (e.g. individual personalities, past experiences with math) had influenced their subjective experiences of the course. I also employed causation coding, which allows the researcher to search for the "antecedent conditions (i.e., pre-existing or initiating factors) [and] mediating variables (i.e., causes, contexts, actions)" that students attribute to the classroom climate (Saldaña, 2016, p. 192).

RQ2 How does pedagogy reinforce or disrupt classroom power dynamics that affect the experiences of FG students?

RQ 2a: How does the course pedagogy align with traditional pedagogy, active learning, and/or inclusive pedagogy? I aimed to qualitatively understand how the pedagogical strategies being utilized aligned with the three teaching and learning paradigms. In using provisional coding to analyze the transcripts of the interviews with the professor, I coded for the different elements of pedagogy identified in the literature (underlying theory of learning; goal; issues of racism, sexism, classism, and other forms of oppression; role of the professor; role of the student; content; and assessment). In addition, values coding allowed me to focus on the attitudes and beliefs that guided the instructors' teaching and learning approaches. Provisional coding of the syllabus, as well as the memos from my observation notes, provided further evidence of the pedagogical elements in use and the beliefs and values that guided them. I then compared each teaching and learning strategy to the chart in Appendix A to determine whether it fell under the traditional pedagogy, active learning, or inclusive pedagogy paradigm. There were some strategies that fell under more than one paradigm.

RQ 2b: How does pedagogy influence the classroom climate? I used both quantitative and qualitative analysis to gain an understanding of students' perceptions of pedagogy and how they felt that pedagogy affected the climate. For the survey questions about perceptions of pedagogy, I calculated frequencies as well as correlations between perceptions of pedagogy and classroom climate scales (e.g., are students who view group work as effective more likely to hold positive views of their interactions with other students?). The qualitative analysis centered on student answers to questions about their perceptions of pedagogy and its influence on the course experience. Causation coding was useful in mapping linkages that students made between pedagogy and classroom climate. I also used emotion and values coding to capture students' reactions to pedagogy.

RQ3. How do FG students' experiences in the course influence their intentions to take additional mathematics courses and persist in STEM? For the quantitative analysis, I first computed descriptive statistics for the questions: *To what extent, if any, has your experience in this course influenced your intention to major in a STEM field [for those interested in STEM]?;* and *To what extent, if any, has your experience in this course influenced your intention to take additional math courses [for those who took the course with the intention of taking additional math courses]?.* I also examined FG survey respondents' intended major at the beginning of the semester and whether the intended major had changed, and classified them as "STEM throughout," "non-STEM throughout," or "left STEM or considering leaving STEM" (there were no FG respondents who went from non-STEM to STEM).

I compared the "STEM throughout" (STEM stayers) with the "left STEM or considering leaving STEM" (STEM leavers) on how they had responded to questions about the influence of the course on their intention to major in a STEM field and their intention to take additional mathematics courses. I also compared STEM stayers and leavers on which professor they had as well as key demographic indicators. Finally, I was interested to know whether leavers differed from stayers in terms of the classroom climate scales. I did not have an adequate sample size to perform a MANOVA (n = 49), so I performed individual student t-tests for each scale. I used a Bonferroni adjusted alpha level of .007 in order to guard against committing a type 1 error. I also calculated the mean of each scale for stayers and leavers and calculated effect sizes that reflected the difference in means. Qualitative analysis centered on the interview question: *Has this course had any impact on what you plan to study going forward? How so?* Similar to research question two, I used causation, emotion, and values coding to analyze the interview data.

Validity and Trustworthiness

Mixed methods researchers have struggled to gain consensus on how to address issues of rigor. Dellinger and Leech (2007) argued that the typical approach of treating validity issues of quantitative and qualitative strands separately lacks an overarching mixed methods framework. In their Integrative Model of Inference Quality, Tashakkori and Teddlie (2008) proposed that mixed methods researchers use one set of quality criteria for the qualitative strand and a separate set for the quantitative strand, as well as a third set for the integration of the two strands. Below I discuss how I have addressed each set of criteria.

Validity of the quantitative phase. By following guidelines based in social exchange theory (e.g., introducing myself to students and personally asking them to complete the survey), I minimized survey non-response. In designing the survey, I adhered to evidence-based item writing guidelines and engaged in expert and peer review, think-alouds, and piloting, which minimized item non-response and measurement error (Dillman et al., 2014). To ensure reliability, I used factor analysis to construct survey scales and tested for the internal consistency of each scale. I reached statistical conclusion validity by ensuring that my data met the assumptions of each statistical test used (Tashakkori & Teddlie, 2008). Regarding external validity, I compared the demographic makeup of my survey respondents to the demographic makeup of the entire class, using data obtained from the Office of Institutional Research, to see whether my survey sample was representative of the course population. I did not seek broader generalizability through this study.

Trustworthiness of the qualitative phase. For the qualitative phase, I carefully documented my data analysis steps, noting any places where I diverged from my analysis plan. To enhance the transferability of my findings, I have provided a rich description of the course that allows scholars and practitioners to gauge the relevance of my findings for their own practice. By triangulating the multiple data sources and engaging in member checking with some of my student participants, I enhanced the credibility of my findings (Toma, 2011). My approach to member checking was to e-mail the 13 interview participants a one-page document summarizing my main qualitative findings. Four students responded saying that they found the summary to accurately reflect their experiences, and the rest did not respond. I also reached out to the two instructors to share my findings with them, but they did not respond to these communications.

Integrative efficacy. Integrative efficacy is “the degree to which inferences made in each strand of mixed methods study are effectively integrated into a theoretically consistent meta-inference” (Tashakkori & Teddlie, 2008, p. 23). As such, for each mixed methods research question (each question except for 1e and 2a), I provide meta-inferences that incorporate findings from both the quantitative and qualitative strands of the study (Tashakkori & Teddlie, 2008). Giddings and Grant (2009) urged a certain kind of integration for critical mixed methods: “The point of credible triangulation is that the research design seeks ‘counter patterns’ (Lather 1986: 67) as well as the convergence that is sought in the postpositivist and interpretivist paradigms” (p. 130). For each meta-inference, I elaborate on whether the two strands agree with each other (convergence) or reveal different aspects of the same phenomenon (complementarity). Another possibility is that “one set of inferences provides the conditions for the applicability of the other (elaboration, conditionality)” (Tashakkori & Teddlie, 2008, p. 24). I also note where there is divergence between the quantitative and qualitative findings.

Chapter Four: Describing the Classroom Climate

This chapter shares findings that respond to the following research questions:

RQ1: How do first-generation (FG) students perceive the classroom climate?

RQ 1a) How do FG students describe the classroom climate?

RQ 1b) Are there differences between FG and continuing-generation (CG) students' perceptions?

RQ 1c) How do FG students' multiple intersecting identities inform their perceptions of the climate?

RQ 1d) How do racism, sexism, classism, and other intersecting forms of discrimination influence FG students' experiences of the climate?

RQ 1e) What factors not related to pedagogy influence climate perceptions?

I begin this chapter with two vignettes that describe my experience observing the class, as a way of contextualizing the course's day-to-day interactions for readers. I then begin the presentation of my findings by describing FG students' perceptions of the classroom climate, which I explored both inductively and deductively. I first present findings from the inductive analysis of interview participants' descriptions of the climate. Two themes emerged: (1) a collective sense of confusion and frustration and (2) a disengaged atmosphere. I then share the quantitative and qualitative findings from the deductive analysis that was centered on students' perceptions of each of the seven factors that influence the classroom climate discussed in chapter two. Next, I discuss how FG students' identities influenced their course experiences. This includes quantitative and qualitative data on the influence of students' first-generation status, as well as how their other multiple identities shaped their experiences. Finally, I share three individual-level student characteristics that affected how interview participants experienced the climate: previous exposure to content, individual personality, and personal attitudes toward and experiences with math. At the end of the chapter, I provide mixed methods meta-inferences for each research question.

My Experience Observing the Course

The classroom was large, containing 14 round tables, each with an average of six or seven students. This meant that during any given observation, I focused on either four or seven tables, depending on the type of observation I was doing that day. On the first day of class, I introduced myself to each section and described the purpose of my study. Students seemed to quickly grow accustomed to my presence on Mondays and would mostly ignore me as I walked around the periphery of the classroom and took notes.

In all three sections, I was often struck by how different the tables were along a range of characteristics. Some tables had only three students and others had as many as ten. At certain tables, students tended to interact and work in groups of two or three (with individual students being on their own at times), whereas others were characterized more by whole group interactions. The level of noise generated by each table varied substantially. Some appeared to be homogenous in terms of gender and others were more mixed. Certain tables appeared to be all-White and others appeared to be more racially integrated.

Vignette one: A typical experience observing Dan's section. Dan's section meets at 8:00 in the morning, and my energy level mirrors that of the students, many of whom yawn and appear not fully awake. Dan provides a contrast, speaking and moving around the room in a way that exhibits a higher energy level. He begins by addressing the whole class to give announcements (date of the next exam, a new resource on the course's website) and work through one problem on the projector. As he speaks to the whole class, he slowly turns so that he faces each section of the room. He pauses and asks if there are questions, but is met with silence.

By 8:05, Dan has put a worksheet of problems on the projector, which is displayed on the screens located throughout the room. Students are largely quiet, looking around at the other students at their table. They slowly start working on the problems, mainly on their own at first. Dan instructs each TA to go to a different section of the room, and he himself goes up to a table and sits down. I overhear him asking, "Hi I'm Dan, what's your name? Can you show me how you did the first problem?" Some TAs ask students if they have questions and start going over problems on the nearest whiteboard. Other TAs appear more reluctant, lingering by a certain table, waiting for a student to raise their hand or wave them over.

The class gradually grows louder as time goes on. It is 8:30, and students at one table are quietly working in two groups of three, their bodies turned toward each other. At another table, students are laughing and loudly talking about their weekend. At the next table over, some students appear to be working individually on the problems, one with a TA looking over their shoulder, whereas other students are scrolling through their phones. When Dan visits a new table, students tend to pay attention to him and re-focus on the problems. Some TAs have asked students to go to the whiteboard to work through a problem in front of the other students at their table, while others continue to quietly linger or work one-on-one with students. At 8:40, Dan goes to the center of the room and interrupts the class for a few minutes to go through a problem on the projector that has been challenging for students. When 8:50 arrives, students begin to pack up their bags and filter out of the classroom.

Vignette two: A typical experience observing Isaac's section. I am observing section three, which starts at 3:35 in the afternoon. Before the class starts, most students are scrolling through their phones or talking with the student next to them. There are a few louder tables where students are engaged in a livelier group conversation. At 3:35, Isaac begins with the same announcements that Dan had given. His voice through the microphone is noticeably quieter than Dan's. Isaac then starts to go through some math problems, writing them out line by line on the projector. Unlike Dan, he goes through several problems. As he does so, he looks down at the projector, looking up only once to ask if there are any questions. One student raises their hand, but Isaac has already looked back down and does not see.

At 3:55, Isaac is still going through problems and the classroom is otherwise silent. I look around the room and see that most students and TAs are either staring off into the distance, doing something on their laptop, or scrolling through their phone. I notice that I myself have lost track of what Isaac is covering. At 4:00, Isaac puts a worksheet on the projector, and he and the TAs go to different sections of the room. Similar to Dan's section, students look around at each other and slowly start going through the problems. Student activity ranges from working on their own to working as a table. Also similar to Dan's section, some TAs are proactive and ask students to show them how they solved a problem, while others are more passive and wait for a student to ask for help.

At 4:05, all of the students at two tables stand up and leave the classroom. Isaac appears to notice them leaving but does not say anything. Isaac stands over the shoulders of two students, silently observing them go through a problem. Students continue to leave the class, and by the end of the class session, around half of the class is present. At 4:25, the remaining students notice the time and pack up their bags and filter out of the classroom.

I now turn to the presentation of my findings, describing the classroom climate from the perspective of my study participants.

Describing the Overall Atmosphere of the Course

Two themes emerged from my inductive analysis of the student interview data, in which I searched for overarching themes related to the classroom climate: (1) a collective sense of confusion and frustration, and (2) a disengaged atmosphere.

Collective sense of confusion and frustration. Twelve out of the thirteen FG interview participants discussed a shared sense of confusion and frustration among students in the class. Participants were confused about what was happening in the course and also felt lost in terms of understanding the content. The participants described this as a collective experience instead of feeling as though they were the only ones experiencing it. This theme has three sub-themes: confusion about the instructors' actions and expectations of students; confusion about the order of content; and feeling lost with the content.

Confusion about the instructors' actions and expectations of students. The participants described a common classroom scene of the professor presenting something to the class, or the TAs handing out worksheets to everyone, and the students looking around at each other in confusion. Jake, a White man planning to attend medical school, described:

> Sometimes [the professor] just throws that worksheet on the screen and okay, what do we do, what ones because there are different sections on that worksheet. Sometimes he's clear about that but other times some of the kids at our table are just like “what are we doing, what ones are we doing?” And we ask him questions and he's like, “you don't need to do that one.” [And we say] “Okay, [but] we [already] did it.”

According to José, a Latino man studying psychology and neuroscience, this confusion had become so common that students accepted it as a regular feature of the course:

> A lot of students, the majority of students I talked to, they suffered from the same things, like not understanding what we needed to do or understanding the direction of the professor … it just felt like every day when we went there, it was a norm to feel confused. That became normal. You didn't know why you were there and you didn't know what was going on.

Laura, a White woman studying kinesiology, described having difficulties following along with Isaac, not knowing why he was covering a certain topic:

> Sometimes he goes really fast and is not taking the time to say “this is why we're learning this.” So sometimes I get confused as to why we're even talking about that because I don't know if it's going to be on the test on Friday, don't know if I should study it. Sometimes I just feel like I don't really know what's going on in lecture. I feel a lot of people feel the same way.

In all three of these examples, there is widespread confusion about the intentions behind the instructors' actions, as well as the expectations of the students.

Confusion about the order of content. Interview participants often described the class as "jumping all over the place" between different content areas. Alexis, a Black woman who was pre-med and studying child psychology, described a sense of frustration related to the way in which topics were sequenced:

> I kind of really can't maneuver when to ask questions … because I'm like, okay we're going to have homework on this [topic] tonight. Then the homework is confusing and I come back [the next class] learning a whole different thing and I don't even want to go asking questions and go backwards.

Alexis was also taking an introductory chemistry course, where she felt that the content was more difficult but was better structured:

> Chem is harder but it's like the understanding is kind of there. I can understand as soon as she says something. Whereas like in math I would have to go back and forth to what he's doing, to the videos or the homework. I'll have to use all those things to try to understand it.

For Alexis and other students, a great deal of mental energy went into making sense of how the different course components fit together.

The going back and forth between topics was stressful for students partially because they were unsure about which topics would be on the upcoming test. According to Maria, a Latina woman studying biology:

> Sometimes we get confused, especially people I talk to, where we're all over the place especially when we get behind, I think because we were learning things for

> another test but we hadn't taken the previous one … we were confused about if that was going to be on the upcoming tests.

Laura described a similar sense of test-related anxiety:

> A lot of the time we don't even know what is going on in lecture because we don't know what's going to be on the test and it's kind of frustrating in that sense because we just want to be prepared for the test … we're all just like, "what's going on?"

Uncertainty about how to prepare for exams was a clear source of frustration for many of the students I interviewed.

Feeling lost with the content. Participants also felt lost when it came to understanding the content, even when they were investing a considerable amount of effort. Nour, a north African, Black woman studying genetics, described this as feeling as though something were missing:

> There are some topics that even if I do the homework, I do them with the video and I pay attention in class, I feel like I'm still missing a part of it and I feel that I'm not the only one who is feeling that way. I think that sometimes I vocalize my opinions and then people are like, "yeah I feel the same way" and it just takes someone to say it.

Caitlin, a White woman who was planning to major in economics and theater, but was also considering being pre-med, felt that despite her efforts, it was not possible to be prepared in the class:

> I've tried coming into class fully prepared on a topic and you get to it and you're like this isn't what the video said we're supposed to be doing. And I've tried just

> going to get a clean slate, okay, I'll pick up on this as I go along. No, this still isn't working! I've tried Google, I've tried looking at Google beforehand. Maybe this way will do it, more like actual sense. This didn't work either. So I really can't go in prepared.

Caitlin described a common occurrence in the class: “Isaac puts the problems on the TV, we usually look at it and think okay, what is going on, this isn't what he just described.”

Amina, a Somali, Black woman who was undeclared but leaning toward majoring in physiology, explained that the sense of disjunction often led to a collective sense of frustration: “It's just the days where we all kind of get frustrated because we haven't necessarily learned, we haven't been taught anything, we haven't learned anything and we just kind of walk away from like a wasted day.” Many of the interview participants felt that they were gaining little from the time and energy they were putting into the class.

I picked up on the confusion and frustration during my observations. I myself often became confused with what the students were supposed to be doing. For example, one day in Isaac’s class, after 10 minutes of students doing group work, Isaac put a new problem worksheet up on the projector. He went over a problem, addressing the whole class, but then trailed off and stopped talking. At that point, it was unclear what students were supposed to be doing. I assumed they were supposed to start working through the worksheet, but explicit instructions were never given. In both Dan and Isaac’s classes, I overheard students expressing frustration with the format of the class. In Dan’s class one day, a student sighed loudly and said, “Why don’t they say ‘here’s how you do this, now do it.’ It’s so dumb.” These negative experiences likely led students to disengage from the class. A disengaged atmosphere was the other overarching classroom climate theme that emerged from my analysis.

Disengaged atmosphere. All 13 participants spoke about the disengaged climate of the course during their interview. When I asked students to describe the general atmosphere of the class, the phrases “zoned out,” “checked out,” and “low energy” were common. Caitlin described what this looked like:

> You try to follow along but when you stop and look around there's kids who are asleep, there's kids on their phones, there's kids doing homework for other classes, I mean it's a noon class you really shouldn't have people falling asleep.

Laura explained that students would gradually stop paying attention or making an effort over the course of a class session:

> Sometimes Isaac puts a lot on [the projector]. We just kind of get sick of it. After ten problems it’s like, we're done so we just chat. I think that’s what a lot of people do honestly … after a while people just stop paying attention. It's not just my table, I think it's most tables.

Interview participants described the class as being quiet and lacking energy. Maria commented, “I think [the class is] kind of low energy, I don't know, nobody really talks to each other in the classroom.” Laura described the class in a similar way: “It's pretty quiet and everybody's just listening or zoned out. So it's pretty low energy.”

Not all of the class settings were the same in this regard. For instance, Matt, a White man planning to major in either chemistry or math, described the large section as much more disengaged compared to the smaller TA- or peer-led sections:

> [In the larger section] we'll all just goof off a little bit and then we'll finally get the assignment and we didn't pay attention to what he was talking about and it's like a daily thing because everyone depends on [the smaller section] the next day where we actually discuss what we learned. Monday, Wednesday, Friday it's more so just like you can listen, you can try to listen but a good majority of everyone is just goofing off.

Whereas Maria described Dan's section as "low energy," Caitlin believed that Dan's class was more engaged than Isaac's:

> I remember one time I had to take an exam in a different lecture and I took it with [Dan] at 8am and that was a whole new experience for me because I was like oh, 8am, I've never had to take one of these before, expecting everyone to be really groggy and show up in their pajamas but everyone was bright, chipper, and alert. They were actually really involved.

The extent of disengagement was not even across the different settings of the course.

The tables and individual students also varied with regard to their level of engagement. According to Devin, a White man studying computer science, the students who lacked motivation could get away with being disengaged: "If the student wants to learn they'll be competitive, if they don't then they're just going to check out." Hafsa, a Somali, Black woman who identified as pre-med, described a setting which was at times more engaged and at times more passive:

> 50% of the time if people are struggling … another person would jump in and say "this is how you do it." But the other 50% of the time people would sit down, quietly waiting on [the TA] or someone to explain it to us.

While the level of engagement or disengagement varied, interview participants seemed to feel that the overall atmosphere tended toward disengagement.

The confusion and lack of engagement fueled each other. Caitlin explained how students' lack of attention led to more confusion:

> 90% of the time people are on their phones or talking. [Isaac is] not a very commanding person. One time during lecture someone discovered that the little writing tables have microphones that you can use to speak and they were making burping noises into it and the teacher doesn't say anything … then [the professor is] like "okay, do the problem" and everyone's like "what do you mean?"

José described how the confusion also caused engagement to drop:

> So we're like, okay, what's the point of doing this, I don't understand it, I'm not getting any help and my group doesn't understand it so what's the point of even continuing, there's like 20 minutes left of class so might as well go on Facebook.

The sense of confusion and frustration even resulted in groups of students leaving class early. Nour explained that when Isaac would finish addressing the whole class and pass out worksheets for students to work on:

> People just get up and leave … I know people who do it just because [they think], "I'm not learning anything from this, he's just been talking to himself" … Personally, I get frustrated so I just pack my stuff and leave sometimes.

The more confused and frustrated that students felt, the more they disengaged, which in turn led to more confusion.

The interview participants' descriptions of the disengaged atmosphere reflected what I saw during my observations. It was common for students to stop going through the problems midway through class, and students were often on their phones or computers, or were listening to something on their headphones. It did not seem like students felt the need to hide their lack of engagement, especially in Isaac's sections. For example, one day I observed a student leave early during group work. He came back in to retrieve something he had left behind as Isaac was addressing the whole class, and then immediately walked out again despite being more visible because the class was silent. However, there were some students who stayed focused on the class throughout, and the overall level of student engagement seemed higher on some days, especially in Dan's section. I now turn to describing students' perceptions of the factors that influence the classroom climate.

Describing the Factors that Influence Classroom Climate

In addition to an inductive exploration of the climate, I engaged in deductive analysis in which I explored FG students' perceptions of the factors that influenced the classroom climate. Below I present the quantitative and qualitative findings that resulted from that process.

Quantitative findings. As discussed in the previous chapter, the confirmatory factor analysis produced seven scales: professor-student interaction, TA-student interaction, student-student interaction and cohesion, participation, discrimination, inclusion of diverse backgrounds, and physical space. The student-student interaction and cohesion scale combined items from two scales that were originally separate: student-student interaction and student feelings of isolation or being too visible. Figure 3 displays boxplots of the scale distributions for FG students. The items were kept on their original scales ranging from 1 to 4 for ease of interpretation.

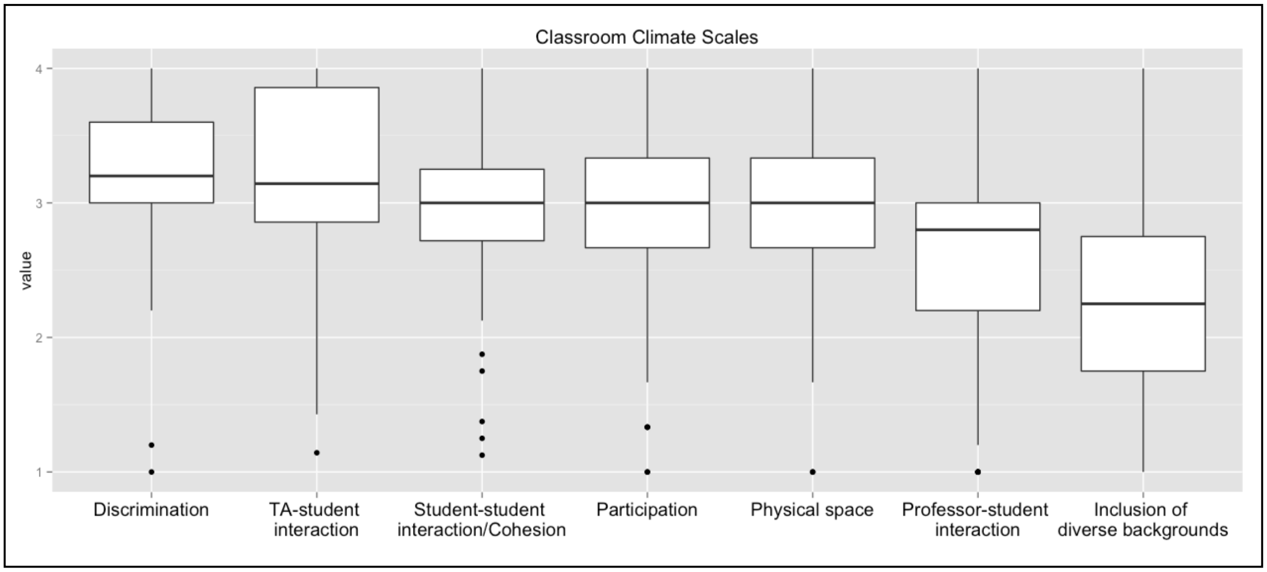

Figure 3. Boxplots of classroom climate scales for FG students

On average, the factors that influence the classroom climate viewed most positively by FG respondents were discrimination (a high score indicates that the respondent felt there was a lack of discrimination) and their interactions with the TAs. The factors viewed least positively were interactions with the professor and inclusion of diverse backgrounds. There was also the most variability (as measured by standard deviation) for those two factors, as well as the participation factor. In other words, most respondents enjoyed interacting with the TAs and did not believe that discrimination was present in the course, whereas their interactions with the professors were not as enjoyable, and they did not believe that multiple perspectives and backgrounds were represented. Means and standard deviations of the scales are reported in table 5.

Table 5

Mean Response on Classroom Climate Scales among FG Respondents (n = 65)

Scale	Mean	Standard deviation
Discrimination	3.18	.60
Inclusion of diverse backgrounds	2.24	.70
Participation	2.82	.73
Physical space	3.01	.63
Professor-student interaction	2.56	.76
Student-student interaction and cohesion	2.94	.61
TA-student interaction	3.19	.66

For some of the scales, there were meaningful differences by professor (see figure 4). Table 6 reports the mean value for each scale and each professor, as well as the difference in means and the effect size of the difference (Cohen's *d*). FG survey respondents who had professor 2 (Isaac) scored lower on the inclusion of diverse backgrounds scale, and the effect size representing this difference was approaching the cutoff value for a large effect size (d = .77). Respondents who were in Isaac's sections also scored lower on the professor-student interaction scale, and this difference was medium in magnitude (d = .52). Respondents with Isaac scored lower on the physical space scale and higher on the TA-student interaction scale, and these differences were small in magnitude (d = .35, .27, respectively). There was not a meaningful difference between the two professors for the discrimination, student-student interaction/cohesion, and participation scales.

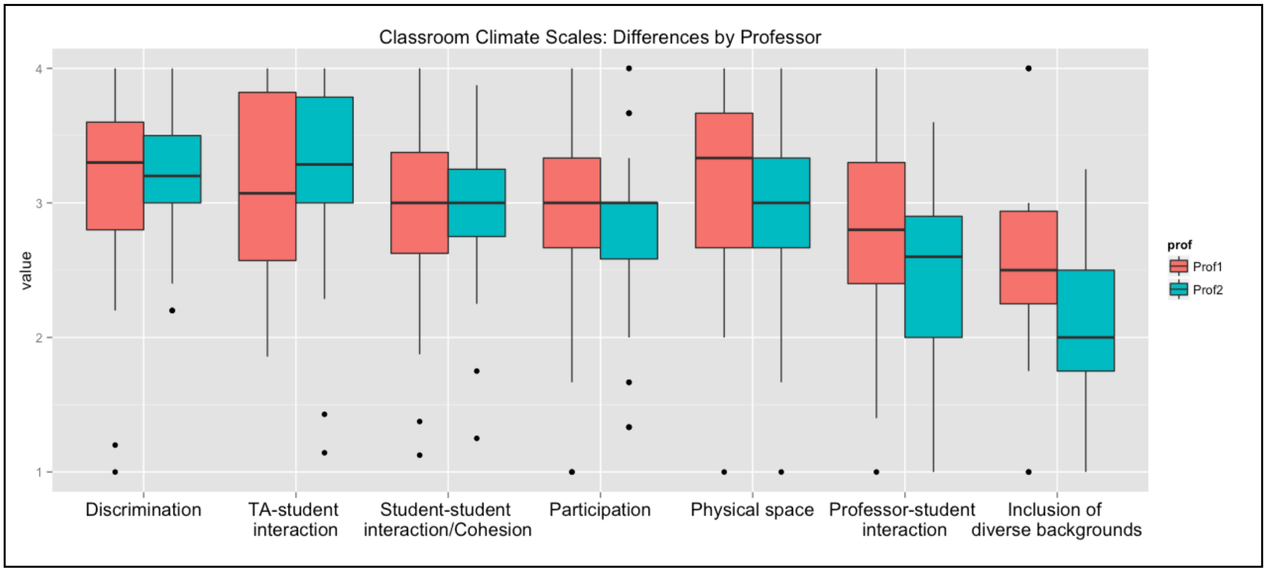

Figure 4. Classroom climate scales: Differences by professor

Table 6

Mean Response on Classroom Climate Scales for FG Students by Professor (Prof 1: n = 26, Prof 2: n = 39)

Scale	Mean (SD) for prof 1 (Dan)	Mean (SD) for prof 2 (Isaac)	Difference in means	*d*
Discrimination	3.13 (.76)	3.21 (.46)	-.08	.12
Inclusion of diverse backgrounds	2.55 (.76)	2.04 (.59)	.51	.77
Participation	2.9 (.8)	2.77 (.68)	.13	.18
Physical space	3.14 (.68)	2.93 (.58)	.21	.35
Professor-student interaction	2.79 (.77)	2.41 (.72)	.38	.52
Student-student interaction and cohesion	2.93 (.73)	2.95 (.52)	-.02	.04
TA-student interaction	3.08 (.67)	3.26 (.65)	-.18	.27

Because research question 1d is centered on how the experience of discrimination affects FG students' experiences of the classroom climate, I calculated correlations between the discrimination scale and the other classroom climate scales. There was little to no correlation between the discrimination scale and the TA-student interaction, professor-student interaction, student-student interaction/cohesion, and inclusion of diverse backgrounds scales. There were small correlations between the discrimination scale and the participation and physical space scales (*r* = .2 and .23, respectively). While these correlations were not statistically significant, they approached significance (p = .12, .08 respectively). This provides weak evidence that FG survey respondents who believed that discrimination was not present in the classroom were more likely to feel comfortable participating in class and were more likely to feel physically comfortable in the classroom.

Qualitative findings. Below I discuss what interview participants shared with me regarding the factors that influence the classroom climate.

Professor-student interaction. Students in both Dan and Isaac's sections had much more interaction with the TAs compared with the professors. In most cases, interview participants said they were much more likely to ask a TA for help or clarification rather than the instructor. Nonetheless, students spoke about cues they received from the professors' actions, which produced beliefs about how invested the instructors were in the students' learning and wellbeing. For this question, I analyzed the data from students who were in Dan's section separately from the students who were in Isaac's class.

All three participants in Dan's section felt that he cared about students in the class, and provided concrete examples of how he demonstrated this care. Maria was struck by the effort he put into making sure students understood the content:

> When [Dan is] talking to the classroom as a whole, he's like, "I want you to understand this, this is an easy way to do this." He's good at teaching in a way that

> everyone can understand. If someone actually has a question he'll answer it for you.

Hafsa felt similarly:

> So whenever you go up to him and ask a question, he doesn't just give you a vague or brief answer. He'll ask, "how did you try to do this problem," or, "show me the steps you did" … Even when you're retaking quizzes or something like that, he'll be like, "this method is good but then this one isn't. Just throw it out, don't do it anymore." He will re-shift the way you were taught before. Which can be hard but I feel like he's trying, he's trying.

Hanh, a Laotian and Vietnamese woman studying biology, also believed that Dan went well beyond the amount of effort that was required:

> He seems pretty passionate about when he's explaining things. When he explains things he explains them very clearly. I think he makes a point about, "if you don't understand something you can talk to a TA or talk to me," and I think that indicates that he cares about people doing well in his class.

Hafsa inferred from Dan's actions that he was working to reduce the math-related anxiety that some students felt: "He's trying to reshape the way people think of math. That concept of, 'oh my God, I was never a math person, I'm not going to do well.' He wants to get rid of that stigma." While Hafsa, Hanh, and Maria did not have extensive interactions with Dan, they were able to conclude that he cared about students being successful in the class.

The participants who were in Isaac's section had more varied perceptions. Four of the participants felt positively about him, saying that his efforts to communicate expectations and check to see if students were understanding sent messages that he cared. When I asked Laura if she thought Isaac cared about students in the class, she responded, “I think so, yeah. He always gives us, he'll send out emails reminding us about tests and which problems we should be doing which really helps.” Ying, a Hmong woman studying education but also considering medical school, provided another example of his efforts: “I like how after he gives the lecture, just a few people have questions but then afterwards he walks around and talks to students and checks if they're doing it right.” Matt described out-of-class interactions with Isaac that were positive:

> I've talked to him in the office hours, he helps me out, tries to, if you don't understand the full concept and how to apply it. Plus he always, whenever I have a question he gives me the answer and then some so I always find that really helpful.

These students saw Isaac making an effort to improve students’ understanding of concepts, which led to generally positive impressions of him.

Four other interview participants who were in Isaac’s section had a more negative perception. Nour found him to be aloof and detached: “He's not in touch with the class, he does his best to walk around but it's just to peer what people are doing.” Nour’s experience with Isaac was similar to those she had with other STEM professors, who she found to be generally less relatable or approachable: “It definitely feels like there's a pattern with my STEM classes … the professor is kind of passive, kind of not really there, kind of info dumps every lecture and then leaves.” José perceived that Isaac had a difficult time relating to students, which made him seem unapproachable:

> I think he's a very smart man but to the point where he's too smart necessarily to be able to relate to someone. I know a lot of people they didn't want to ask him questions sometimes because he was very knowledgeable in his field obviously, the answers may have seemed obvious to him they weren't necessarily obvious to us.

When explaining why she would not go to the professor if she needed help, Caitlin said, “Yes the professor will definitely know the answer most likely but he really wouldn't care why I would want to know that question or anything. I'm more likely to go find other routes.” There was a distance between these students and Isaac that resulted from a perceived lack of caring or aloofness on his part. The remaining two participants who were in Isaac’s section said they had very little interaction with him and did not seem to hold positive or negative attitudes about him.

Through observing the class, I saw dynamics that demonstrated the difference between Dan’s interactions with students versus those of Isaac. When Dan worked with students at the tables, he would start the interaction in a personal way. For example, he might say “Hi I’m Dan, what’s your name?” or “You emailed me the other day didn’t you?” Conversely, interactions between Isaac and students tended to be impersonal. Caitlin explained,

> [Isaac] walks around but it's never like “oh, what's your name? Well Johnny, here's how you do this, here's how we can make this better” … the interaction between him and the students is very limited. He's usually talking to one of the TAs or something, checking his notes.

It was common that when Isaac went around to different tables, he would stand over a student's shoulder without saying anything. Students would often talk over Isaac as he lectured, signifying a lack of regard for him. Whereas students had varied perceptions of the professor, they tended to have more consistent opinions about their interactions with the TAs.

TA-student interaction. The interview participants had overwhelmingly positive views of the TAs in the course. Through making a strong effort to help students, the TAs sent a message that they cared. Hafsa explained,

> [The TA] tries to get everyone more involved and more energized and excited about the topic, [rather] than just going up there and going, "I'm a TA, I'm not going to care." She really is passionate about it. I like working with her.

The TA that Nour interacted with the most was so invested in her success that he inspired her to take on a similar role in the future:

> I don't think I have a word to describe it but the way that he interacts with me is something that very much makes me want to keep going and become a professor, become a TA, become a professor. Kind of do the same thing that he's doing to me, give it to somebody else.

While there was one TA that Nour tended to go to for help, if he was not available, she felt that the other TAs would jump in and help: "They'll walk by and ask, 'are you guys doing alright, you guys look kind of confused.' They're all pretty cool with that." Most of the interview participants used similarly warm language to talk about the TAs.

Many of the participants perceived that the TAs went above and beyond what they were required to do. Laura explained that the TA who led her discussion section had "emailed us plenty of times saying please come into my office hours, I'm always here, I'm here to help you. She's very inviting with that kind of thing." Some participants thought that the TAs went to such efforts because they understood how confused students were in the course. José explained:

> There was like a trust and there was a student to teacher bond between us because they were empathetic and they knew the struggle of the class was real. They understood that what we're going through was, I wouldn't say unfair but they understood that it wasn't necessarily functioning as it was supposed to and because of that, they worked a lot harder to teach us material as much as they can.

Students seemed to feel that the TAs were "on their side" to a greater extent than the professors.

The students I interviewed described the TAs as relatable and approachable, partly because the TAs were closer in age and had more recently gone through the same math education. José explained, "I think that it helped that they were recently educated on [the content]. I think it helps that they were in a similar generation where they could relate different things to us." Devin felt that the main TA that helped his table was relatable because of a similar background: "He probably talks the same as all the guys on my table, he comes from a somewhat similar background, similar personality. So probably similar culture that he grew up in." Caitlin's description of an interaction with a TA demonstrated that she felt comfortable enough with the TA to admit that she had gotten off topic:

> Then there's this other [TA] who comes over every once in a while. It's usually when we're not doing anything at all when we're very off topic they'll come by

> and we'll ask him about his weekend and then he's like "oh yeah, it was pretty cool," and then, "why aren't you doing [the problem]?" And we'd be like "we don't understand it" and he's like, "we're going to make you understand it."

This anecdote shows not only a high comfort level, but also an effort by the TA to get the students back on track in a friendly, non-intimidating way.

Student-student interaction. Interview participants mainly discussed interactions with other students in terms of the interactions they had at the tables where they sat. Although seating was not assigned, all of the interview participants said they stayed at the table where they had sat the first day, and that the student composition of the table did not change after the first day. The interview participants did not report any sort of negative interaction, although some talked about a *lack* of interaction. Conversely, six of the interview participants described a tight-knit bond that had developed with the other students at their table. Nour was one of the participants who described her table as tight-knit:

> There's girls from every background, every state. Someone's an international student, couple of them are transfers from different schools, couple are from out of state, couple are from in state. You know we have a girl that speaks Spanish, a girl who speaks Chinese and then me who speaks Arabic and French … and we're all very close friends at this point in the semester and I think that we all very much mingle very well and we're very close with each other.

While the interactions at Nour's table were initially mainly about the class, they evolved into broader friendships: "We exchanged phone numbers for all the assignments that were expected and then we started deviating away from the topic of math and getting to know each other as people." As a commuter, the close bonds with the other students at his table was the reason that the class was one of Matt's favorites that semester:

> I don't live in a dorm so having an opportunity to actually talk to my classmates and essentially make friends, I think that's huge. I feel if I didn't have that, it wouldn't be one of my more favorite classes.

For some interview participants, they had formed meaningful relationships with other students in the course, which had a significant impact on their overall course experiences.

There were three participants who sat at tables with little interaction among the students. Hanh was one of those participants, and she wished that there was more interaction. When I asked Hanh how her table worked on problems, she responded:

> I would say for the most part we all work individually unless someone has a problem with one of the questions, like one of the math problems or we're asked to work together and write something on the board. Otherwise, we pretty much keep to ourselves … I would say the ideal method for this class is for us to be more cooperative and work together more and bounce off of each other's ideas and what does this math mean, how do you do it and that kind of thing.

Hafsa explained that some students were more eager to interact and collaborate than others: "Some people don't want to communicate at all and some people will attempt to and some people are just like, 'I know what we're doing, I'll show you what we're doing, I'll take the lead.'" Maria was also at a table that lacked interaction, saying that "we don't really talk to each other … I think it's kind of early in the morning [and] some of them might be shy." When I asked Maria if she wished there was more interaction with other students, she expressed wishing she had sat by someone she knew from her discussion section. Notably, even though there was not assigned seating, Maria did not feel that she could move to the table where that person was.

The other four participants described a moderate level of interaction with the other students at their table. The interactions were mainly about what was happening in the class, and these participants did not describe their table as being tight-knit. Ying sat at a table with three other students and explained, “We didn't talk a lot at first but if we struggled with something we would talk about it … we don't talk a lot but we do interact.” Caitlin’s table had become more interactive during the semester, which she attributed to a chance encounter. When I asked her what had caused an increase in interaction, she said,

> I think the biggest one was one of the girls at the table and I, we were at TA [office] hours, we went separately but we ended up there at the same time and right after that we walked to class together and we sat by each other … everyone just automatically scooted closer. So I think it's just the little shifts that kind of happen maybe. One person making a small change then everyone shifts, “okay I can do that,” it's a more socially acceptable thing.

Table dynamics seemed to vary along two dimensions: how interactive they were and how close the students felt with one another.

In observing the class, I noted that there was a variety of different table dynamics. I was struck by how much the tables differed in terms of their noise level and number of students. Tables ranged from having three to ten students. Students worked almost exclusively on their own at some, whereas at others, the whole table seemed to be working together. At others, pockets of two to three students would huddle together and work on problems. Sometimes it seemed like certain students were left out.

Some of the participants spoke about gendered patterns of student-student interaction in the class. According to Maria, "Girls mostly talk with the girls and the boys mostly talk with the boys." Caitlin observed, "I notice that most of the time the genders are separate. Like men tend to sit with men and females tend to sit with females." Laura described feeling more comfortable sitting with other women: "If it would have been a bunch of guys that I don't know [sitting at my table], I probably would have been a little too scared to say 'hey, I don't understand, this could you help.'" Some of the men participants also commented on this pattern.

The participants also observed some patterns of interaction based on race and ethnicity. Caitlin said, "I do kind of see that there are some tables where there are more variety of races than others or where people, one race will stick together more than dispersing with others." Hanh observed:

> I would say in general people tend to congregate in groups of people that are like them. I mean the classroom is predominantly White so I would say that people of color tend to migrate in areas where they also see people that are like them. It's very subconscious but I do notice it.

Some students commented on certain tables that seemed to be all-White. Amina observed, "Well I kind of noticed … a table nearby us where it's like a group of White guys and they seem like they kind of coagulated together I guess." Ying had noticed that some of the fuller, louder tables were predominantly White:

> There are two tables close to us and they're all full usually … I think they all interact well with each other because I feel when they start talking you can hear a lot of talking coming from their side so I feel that they get along really well … from what I saw those tables are more White people or one or two Asian or people of color just sitting there.

Many of the participants seemed to be aware of demographic patterns of interaction that were occurring in the class.

In my observations, I noticed similar gender and racial patterns of interaction. In almost every class session that I observed, there were tables that appeared to be only one gender (all men or all women), as well as some tables that appeared to have only White students. In one section there was also a table where all of the students appeared to be Asian. Other tables appeared more diverse in terms of gender, race, and ethnicity. I noticed that women of color would often cluster together in pairs or triplets. For example, Latina students or Black women who wore the hijab would often sit together.

There were also certain tables where the groups seemed to be exclusive. I observed some full tables that appeared to be all men and predominantly White, where at least some of the students seemed to be athletes based on their apparel (e.g., wearing clothing that was worn by the University's football team, carrying gym bags). These tables took up space, both physically and in terms of noise. The students would stretch out in their chairs and sigh loudly. At one of these tables in one of Isaac's sections, the students would make fun of Isaac and talk over him. Also in Isaac's sections, there were some full tables made up of White men and women. The students seemed to know each other from outside of class because more students were packed in than the table space allowed for. These students would usually leave the class early as a whole group. My subjective interpretation was that these tables seemed to give off a certain feeling of exclusivity. Matt and Caitlin made comments that seemed to reflect the same phenomenon. Matt said, “I have noticed that the frats sit with the frats, the jocks sit with the jocks, and I think that gets pretty exclusive for the most part.” Caitlin said, “they look like they were the popular kids in high school. It just kind of has that look to them.” Taken together, it seemed like students often sat by other students like them.

Participation. Regarding participation in the large sections, it was rare for students to raise their hands and ask or answer questions in front of the whole class. Participation was more centered around students’ work at their tables, and included going to the whiteboard to solve a problem and, more commonly, raising their hand to gain the attention of a TA. Much of the participation was supposed to happen in the smaller TA- and peer-led sections. According to some of the participants, students were reluctant to participate in the smaller sections. Amina described an uncomfortable atmosphere regarding participation in her smaller discussion section, which was led by Isaac:

> [Isaac will] have us go through on the whiteboard and individually pick on people. That's why we avoid the eye contact. He'll pick on people and then even if you don't know you have to go up to the whiteboard anyway and work it out and I feel that's so much more, just because we're just a smaller group and we are in his eye we're more quiet and reserved.

However, other students described the smaller sections as being participatory. According to Alexis, “A lot of people participate in the discussion because it's a smaller group but in the lecture, it's not really [participatory]. People don't really use the whiteboards in the lecture or raise their hand a lot." Some interview participants seemed to have interactive, participatory discussion sections, whereas others described a more quiet, reserved atmosphere.

Some of the participants were more comfortable participating in the large and smaller sections than others. None of the participants attributed uneven participation rates to gender, racial, or other identity dynamics, seeing it instead as natural that some students are more comfortable participating than others. Through my observations, I noticed that in the large sections, it seemed like men, and especially White men, were more likely to raise their hands to get the attention of a TA or the professor. In the nine class sessions during which I was doing minute-by-minute observation tracking, I made note of whenever a student raised their hand. I counted 11 times that a student who appeared to be a White man raise their hand, 7 times that a man of color did, 6 times that a White woman did, and 5 times that a woman of color did. This is especially notable given that 57% of the students in the course were women, based on data from the institution's Office of Institutional Research. While the interview participants did not observe any demographic patterns of participation, it is possible that students with dominant identities felt more comfortable participating, whereas students with non-dominant identities felt comfortable participating less.

Discriminatory behavior. The interview participants overwhelmingly believed that the class was welcoming to students of diverse backgrounds and that discriminatory behavior was not present. José expressed,

> I mean you didn't care, you honestly didn't care about a person's race or their identity or anything. All you cared about was that you guys were a team on the

> table and you need to get this assignment done so that hopefully you could pass the test.

As a Black student who had attended a predominantly Black high school, Alexis intentionally planned to attend a PWI:

> My city and my high school were mostly Black … I didn't want to go to a predominantly Black college, I wanted to go to a PWI for the experience … So I knew what I was getting myself into.

Alexis's experience at the university at the time of the interview was going better than she had anticipated. She explained, "My experience coming here was better than I thought it would be. There haven't been any issues with anything. Everybody is really welcoming." Alexis also felt that the math class was welcoming: "They don't look at people differently in that class. I don't see that. Everybody has the opportunity to speak." Alexis's and José's beliefs that there was no unequal treatment were echoed by the rest of the interview participants.

A common belief among the students I interviewed was that social identities were less relevant in math and other STEM classes, and consequently there were fewer opportunities for discrimination to occur. Ying was aware of the class being predominantly White, but did not feel bothered by it:

> I do notice that there's a majority of White people but then it doesn't bother me, I'm not sure if it's because we only work with numbers and not social like talk about political or social stuff … it's just math. There's not going to be any argument over political stuff.

Devin had a similar reaction to an interview question about whether certain students may feel less welcome in the class:

> I think one of the nice things about STEM classes is that not only are they always welcoming to people of all different backgrounds and identities, but it's almost like irrelevant what your background is. I think, yes, of course, it's welcoming as far as I've heard from TAs, teachers and fellow students, but I don't even think it's like a thing that comes up. I don't even think people care.

Amina echoed the idea that identity was irrelevant in the context of the class: "Our identities don't really impact our course of learning. I feel it's much more, you have the material and you learn it and that's it." Students seemed to see the content of the course as devoid of a social and political context, which led to the belief that the class was a non-discriminatory space.

In my observations, I did not detect a difference in the amount of attention students received from the TAs and professors by gender or race. Regarding the question of who had power in the class, one subtle dynamic I noticed was that White men often appeared to be the most comfortable in class. For instance, they were often more willing than other students to explicitly not pay attention in front of the professor. I would also see men – especially White men – stretching out and taking up a large amount of space with their bodies. During one of my observations, a White man held his hand up continuously until a TA came and helped him. By contrast, most other students tended to raise their hand for a brief amount of time, put it down, and then raise it again later if they had not received help. In another observation, a table of all White men kept raising their hands, which seemed to keep the TAs from visiting other tables. Based on these behaviors I observed, it seemed like White men took up a disproportionate amount of space in the class.

Isolation and feelings of being too visible or invisible. None of the interview participants reported feeling isolated, too visible, or invisible because of their identities. Students had mixed views on whether the class was diverse or not. Some participants described it as predominantly White, whereas others believed it to be racially diverse. Maria perceived the class to be diverse, which helped her to feel that she fit in and was not discriminated against:

> I've lived in Minnesota for a long time but I'm originally from Mexico so I'm an immigrant you could say. I don't feel like there's any discrimination against me especially since there are a lot of different people … that I see, they're from different backgrounds and international students and they always participate and ask things.

While Maria acknowledged that most students in the class could not relate to certain parts of her background, it did not seem to bother her:

> The only thing that will be different [as one of the only Latinas in the class] will be, I can't talk to someone and relate them to an experience of mine, let's say, if we were just talking about what we did over the weekend, they might not understand. But everyone is always open to hearing what you have to say.

The other interview participants seemed to feel similarly; while many of them had underrepresented backgrounds and identities, they did not report feeling isolated or too visible. This may have been tied to students' claims, described above, that identity was not relevant in the course because the content did not touch on social or political issues.

Inclusion of diverse backgrounds. Students spoke about this factor mainly in terms of whether they thought the course was aligned with their interests and professional goals. Most students saw some sort of a connection. Sometimes students saw an explicit connection to a field or profession of interest. For instance, Caitlin shared, “We did something on [the topic of] interest and it was like something relatable to me, something I can use.” José talked about a conversation he had with Isaac about his interests:

> We were talking basically about the idea of how psychology has changed in every single culture and how different cultures identify different psychological disorders … after that I was talking about what I was interested in and what I was pursuing and then he was telling me how mathematics could be needed in those fields.

In other cases, there was not an explicit connection but students still saw ways in which the course was useful. Maria appreciated the inclusion of word problems, because although students often do not like them, she thought they were preparing her for her future profession:

> I just know for science you're always going to need math and problem-solving and I know the professor always wants you to solve problems without having to think so much, especially word problems. He wants you to learn how to solve them faster and easier than before because everyone seems to hate math word problems. So I find that interesting because not everything is going to be A+B.

Other students did not see the class as being relevant to their goals. Nour commented, “I think that there's not much of a connection between what I want to do [and the class].” Amina also did not see how the course was relevant for her goals, and explained that she was only in the class because she was required to take it.

Students' experiential knowledge and cultural backgrounds were not addressed in the class. There was never any discussion of race, gender, or other identities, nor an exploration of the contributions of people of diverse backgrounds to the field of mathematics. As discussed above, the inclusion of math topics that were devoid of a social context was aligned with students' expectations and attitudes toward the field of mathematics.

The professors did not share details about their own backgrounds. For Nour, this contributed to her feeling disconnected from Isaac: "I think that even learning a little bit about somebody makes it easier to learn from them." Most students did not think that Dan or Isaac knew anything about their background. Caitlin said, "I'm fairly certain [Isaac] knows nothing [about me]. I'm just another face." Some students felt that there was more of a personal connection with the TAs. Ying explained,

> Students are in [the discussion section] five minutes before or a bit early before class starts so [the TA] will make small talk, like "how was your day, how's your other classes, what do you guys going to do for Thanksgiving or Christmas." So I would say he knows enough about me outside of school.

While some students felt that their identities and backgrounds were recognized by other students and the TAs, the class largely took on an impersonal atmosphere in which individual experiences were not seen as important.

Physical space. The interview participants were varied in terms of whether they had a positive or negative view of the active learning classroom. Many of the participants appreciated the layout. Ying explained how the environment facilitated learning and interaction:

> With [the professor] being in the center I think it's really helpful and then all these screens so you can see, you don't have to look way over there to see what he is projecting. So I think that's really helpful and just facing everyone on your table is really helpful. Yeah, I think it's positive.

Laura appreciated the decentralized layout of the classroom:

> There's a lot of whiteboards hidden in the corner which is nice, so if somebody wants to go up and try to explain it to your table, it's not on display for everybody else, so it's a more private way to do it.

Hanh felt that the layout made the professor more accessible to students: "I think that having direct contact with your professor, being able to see them the entire time is important." These students seemed to believe that the classroom layout made interactions easier and more comfortable.

Other students had a negative perception of the classroom space. One issue was being able to see and hear the professor. Nour did not believe that the space was accessible:

> At one point in the first couple weeks I didn't come to class on lecture days because it was like, I'm not gaining anything from Isaac because I can't hear him first of all, I can't see him and because I'm visually impaired I can't see the board even if I scoot close to it. And I can't ask him to slow down because his back is to me … learning how to accommodate in that class was definitely a challenge especially with the way it's laid out.

Amina's experience demonstrated that where one ended up sitting affected their experience in the course:

> I went to the wrong class the first day so I turned up a bit late so I kind of took the only open seat that was left I mean at the very end. The seat that I ended up taking was facing away from the professor so I kind of just sat there. I feel like it’s been pretty terrible.

For Nour and Amina, the active learning classroom layout did not lessen the distance between students and the professor. Notably, both Nour and Amina had Isaac as their professor. One difference I observed between Dan and Isaac’s use of the physical space was that when Dan was addressing the whole class, he tended to turn around as he talked so that the whole class was addressed for a portion of time. In contrast, Isaac would either look down while he talked or stare forward without turning around, thereby only addressing one section of the class.

Other criticisms of the space were centered on a lack of interaction. Maria did not think that the space facilitated interaction:

> At first I thought it was kind of cool, the classroom … [but] no one really talks, no one really uses any technology so I don't know if a lecture room would have been better because you're sitting closer to people, you might be forced to talk to them more.

Maria was also taking an introductory chemistry course that was taught in a lecture hall, which she felt facilitated more interaction with other students: “It's in a lecture hall so I think I know people better because I sit next to them all the time and we actually talk to each other.” Caitlin experienced difficulties interacting beyond her table: “The tables are so far away from each other. I feel that when I'm there I'm confined to my table and that's it. This is my whole world, it's this little table and that little TV screen that I can see.”

Maria and Caitlin seemed to think that the amount of space between students, or between tables, hindered interaction. I now turn to my mixed methods findings related to students' multiple identities.

Identities

In both the survey and student interviews, I explored how students' various social identities influenced their experiences in the course. Below I report quantitative and qualitative findings on the influence of being first-generation and the influence of other social identities (e.g., gender, race). I also report qualitative findings about other individual-level student characteristics that affected course experiences.

The influence of being first-generation.

Quantitative findings. I conducted a MANOVA that compared FG and CG students on the seven classroom climate scales. The omnibus F-statistic was not statistically significant for the effect of type of student, although it was approaching significance ($p = .14$). Because the lack of statistical significance could be due to the relatively small sample size ($n = 149$ after missing values and multivariate outliers were removed) and because it was approaching significance, I examined the results of the univariate ANOVAs for each scale. There was a statistically significant difference between FG and CG students for four of the dependent variables: discrimination, participation, physical space, and student-student interaction/cohesion. Table 7 reports the means and standard deviations for each scale for FG and CG students, as well as the Cohen's *d* effect size for the difference between the means. Scales were kept in their original, untransformed scales for ease of interpretation.

Table 7

Mean Response on Classroom Climate Scales for CG (n = 95) and FG (n = 65) Respondents

Scale	Mean (SD) for CG	Mean (SD) for FG	Difference in means	*d*
Discrimination	3.37 (.43)	3.18 (.6)	.19	.37
Inclusion of diverse backgrounds	2.3 (.6)	2.24 (.7)	.06	.1
Participation	3.11 (.64)	2.82 (.73)	.29	.44
Physical space	3.23 (.44)	3.01 (.63)	.22	.41
Professor-student interaction	2.63 (.77)	2.56 (.76)	.07	.09
Student-student interaction and cohesion	3.14 (.46)	2.94 (.61)	.20	.37
TA-student interaction	3.21 (.66)	3.19 (.66)	.02	.03

CG students scored higher than FG students on all of the scales. The difference between the two groups represented small effect sizes for the scales that had statistically significant univariate ANOVAs: participation, physical space, discrimination, and student-student interaction and cohesion (d = .44, .41, .37, and .37, respectively). Because the effect sizes for the other three scales were too small to represent meaningful differences between CG and FG survey respondents, I ran another MANOVA with just the participation, physical space, discrimination, and student-student interaction and cohesion scales. The omnibus F-statistic for that MANOVA was statistically significant ($p = .02$). These results provide tentative evidence that in the course, on average CG students felt more favorably about participation, physical space, a lack of discrimination, and student-student interaction/cohesion compared to FG students.

Qualitative findings. In the interviews, I asked students whether they thought their first-generation status affected their experiences in the course. Most participants felt that being first-generation influenced their overall college experiences, but not those specific to the pre-calculus class. In terms of the general college experience, many participants talked about not having received knowledge or support around how college works. Maria explained, for example:

> It was always hard. I didn't really have anyone to ask questions like, "Oh, what happens here? What does this mean?" Even with registration I didn't know how that worked for classes. You don't really have anyone to ask like, "Oh, do you think this schedule is a good idea since you've been to college?"

Most participants felt that even if their overall college experiences were different as first-generation students, the challenge of being first-generation did not carry over to the specific math course. For some students, like Maria and Ying, they felt this way because much of the course was a repeat of what they had learned in high school.

Some of the participants, however, did feel that their FG status affected their course experience. Laura believed that she had become more resourceful because her parents had historically not been able to help her with math, which made her more comfortable seeking out help in the pre-calculus class:

> I never got to ask [my parents] for help in math so it's made me more open to asking for help, because I'm used to going to teachers on my own time and asking, "I need help with this" instead of just having my parents do it or help me.

José felt that being first-generation was tied to his past educational experiences that had been less student-centered, meaning he was less prepared for the flipped classroom approach: "I never was in a class where … you would get tidbits of information and from that information they wanted you to, they tried to scaffold you to find a solution. I kind of was unprepared for that." Caitlin also felt less prepared as a FG student. When I asked her whether being first-generation had affected her experience in the course, she said:

> I think in a way it has because it's just not knowing what to expect and then you have to take the punches and roll with it. I never really learned study stuff in high school so I've got to figure out how to study, there's no, I never got those tips, "okay show up to your teacher's TA, show up to the professor [office] hours so you can get more help" or "do this and this to make you more likeable so they can actually pay attention to you. This is the best seat in the class so you can learn the most," you just don't pick up on all those tricks as easy as everyone else does.

Whereas most of the interview participants did not believe their FG status affected their course experiences, a few students believed that it had made them either more or less prepared to navigate the class. Next, I turn to findings related to the study participants' other social identities.

How FG students' multiple identities informed climate perceptions.

Quantitative findings. Table 8 presents the correlations between the classroom climate scales, demographic variables, and the professor variable for FG students. For the most part, the demographic variables did not have statistically significant correlations with the classroom climate scales. However, there were negative, moderate, statistically significant correlations between the Latinx/mixed race variable and the inclusion of diverse backgrounds and professor-student interaction scales. There was also a negative, moderate, statistically significant correlation between the professor variable and inclusion of diverse backgrounds scale, meaning that students with professor 2 (Isaac) were more likely to score lower on the scale.

Table 8

Pearson Product-moment Correlations Among Climate Scales and Demographic Variables for FG Students (n = 66).

	Discrim.	Partic.	Physical	TA-stud	Stud-stud	Dv. back.	Prof-stud
Discrimination		0.2	0.23	-0.02	0.03	-0.06	0
Participation			0.33**	0.33**	0.45***	0.31*	0.32*
Physical space				0.26*	0.51***	0.41**	0.44***
TA-student interaction					0.55***	0.22	0.34**
Student-student interaction/ cohesion						0.44***	0.46***
Inclusion of diverse backgrounds							0.68***
Professor-student interaction							
	White / Asian	Latinx / Mixed	Black / Asian	Professor	Gender	Fin. Hardship	
Discrimination	0.15	0.07	-0.23	0.14	-0.2	0.03	
Participation	0.25	0.1	-0.19	-0.05	-0.11	-0.07	
Physical space	0.21	-0.14	-0.09	-0.13	-0.05	-0.02	
TA-student interaction	0.06	-0.12	-0.06	0.19	0.02	0.07	
Student-student interaction/ cohesion	0.08	-0.17	0.03	0.04	0.18	0.22	
Inclusion of diverse backgrounds	0.14	-0.40**	0.08	-0.38**	-0.09	-0.05	
Professor-student interaction	0.2	-0.44***	0.01	-0.18	-0.16	-0.05	
White / non-URM Asian		-0.29*	-0.67***	0.04	-0.4**	-0.50***	
Latinx and Mixed Race			-0.31*	-0.01	0.17	0.31*	
Black and Asian URM				-0.11	0.29*	0.29*	
Professor					-0.15	0.01	
Gender (woman = 1, man = 0)						0.31*	
Financial hardship							

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

Table 9 reports the results of the multiple regressions that used the classroom climate scales as the dependent variables and the demographic and professor variables as the independent variables. In terms of race and ethnicity, being White or non-URM Asian was associated with an increase of .45 points (about one standard deviation) on the participation scale ($p<.05$), holding all other predictor variables constant. On average, Latinx and mixed race students scored .77 points lower (about 1.5 standard deviations) on the professor-student interaction scale ($p<.01$) and scored .59 points (about 1.25 standard deviations) lower on the inclusion of diverse backgrounds scale ($p<.05$). In other words, White and non-URM Asian FG respondents felt more comfortable participating in class whereas Latinx and mixed race FG respondents felt relatively less positive about their interactions with the professor and were less likely to feel that diverse backgrounds were included. On average, students who were in Isaac's sections scored .34 points (about .7 standard deviations) lower on the inclusion of diverse backgrounds scale ($p<.05$), meaning they were less likely to believe that multiple perspectives were incorporated into the class.

Table 9

Parameter Estimates (SE) and Model Summary Statistics for Regression Models with Classroom Climate Scales as the Dependent Variable

	Dependent variable:						
	Prof-stud int	TA-stud int	Stud-stud int	Partic	Discrim	Diverse back	Physical
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
White/non-URM Asian	-0.091 (0.209)	0.109 (0.166)	-0.136 (0.133)	0.454* (0.213)	0.025 (0.153)	-0.034 (0.209)	0.255 (0.221)
Latinx/ mixed race	-0.773** (0.243)	0.220 (0.192)	0.166 (0.154)	0.404 (0.246)	-0.010 (0.182)	-0.590* (0.243)	-0.101 (0.256)
Black/URM Asian	-0.281 (0.206)	0.208 (0.163)	0.029 (0.131)	0.218 (0.209)	-0.117 (0.150)	-0.157 (0.206)	0.004 (0.218)
Professor 2	-0.191 (0.109)	-0.118 (0.086)	-0.005 (0.070)	-0.042 (0.110)	0.051 (0.080)	-0.337** (0.109)	-0.111 (0.115)
Gender: woman	-0.105 (0.123)	-0.105 (0.097)	-0.153 (0.078)	-0.047 (0.124)	-0.111 (0.090)	-0.081 (0.123)	-0.002 (0.130)
Financial hardship	0.101 (0.068)	-0.025 (0.054)	-0.102* (0.044)	0.013 (0.069)	0.060 (0.050)	0.065 (0.068)	0.091 (0.072)
Constant	2.794*** (0.236)	0.494* (0.187)	0.736*** (0.150)	2.510*** (0.240)	3.062*** (0.172)	2.578*** (0.236)	2.897*** (0.250)
Observations	63	63	61	63	62	63	63
R^2	0.258	0.080	0.171	0.121	0.106	0.265	0.086
Adjusted R^2	0.179	-0.018	0.079	0.027	0.008	0.186	-0.012
Residual Std. Error	0.413 (df = 56)	0.327 (df = 56)	0.261 (df = 54)	0.419 (df = 56)	0.301 (df = 55)	0.413 (df = 56)	0.436 (df = 56)
F Statistic	3.247** (df = 6; 56)	0.817 (df = 6; 56)	1.856 (df = 6; 54)	1.283 (df = 6; 56)	1.087 (df = 6; 55)	3.364** (df = 6; 56)	0.878 (df = 6; 56)

Note: *p<0.05; **p<0.01; ***p<0.001

Finally, students with higher financial hardship scored higher on the student-student interaction/cohesion scale ($p<.05$). The student-student interaction/cohesion variable was transformed, so to interpret the regression coefficient, I calculated the predicted transformed value for a student with a median value for financial hardship and subtracted that from the predicted transformed value for a student with an additional unit of financial hardship. I then reverse transformed the difference in order to return it to the original scale. Holding all other predictor variables constant, a one-unit increase in financial hardship was associated with an increase of .06 points (about .2 standard deviations) on the student-student interaction/cohesion scale. This means that respondents with more financial hardship felt slightly more positively about their interactions with other students in the class.

There were no statistically significant findings for the Black/URM Asian and gender variables. Because the White/non-URM Asian variable had a large correlation with the Black/URM Asian variable (r = .67) and a noticeable correlation with the gender variable (r = .4), I re-ran the regressions without the White/non-URM Asian variable to see if collinearity was affecting the results. However, the coefficients and statistical significance for the remaining predictor variables were not meaningfully different.

The R-squared was the highest for the models predicting professor-student interaction and inclusion of diverse backgrounds scales (.26 and .27, respectively), suggesting that these factors that influence the classroom climate may be experienced the most differently by students depending on their various identities. The R-squared was the lowest for physical space and TA-student interaction (.09 and .08, respectively), suggesting that those factors were experienced less differently by students of different identities. In other words, out of the seven classroom climate scales, students' identities related to gender, race and ethnicity, and financial hardship were the most predictive of respondents' feelings about professor-student interaction and inclusion of diverse backgrounds, and were the least predictive of respondents' feelings about the physical space and TA-student interaction.

Qualitative findings. As discussed above, some students noted gendered or racial patterns of interaction among students. Beyond this, the interview participants did not seem to believe that course experiences were different based on identities such as gender, race, or ethnicity. Many participants felt that social identities were less salient in a math class that did not touch on social issues, and that as a result there were fewer opportunities for discrimination to occur. In my observations, I noted that men – and especially white men – seemed to be more comfortable participating and taking up space in the class.

Individual factors that affected FG students' perceptions of the climate. In the next chapter, I will explore the influence of pedagogy on the classroom climate. In the interviews, some individual factors related to past experiences and personalities emerged as also affecting their subjective experiences of the course. For several participants, much of the content was repeat, which led to a more positive experience. For Maria, while she still needed to adapt to the way the course was taught and was dealing with confusion related to expectations and processes, her familiarity with the content helped her with the overall experience:

> The first test was kind of hard just because I didn't know [the professor's] format. I felt I knew the material but I didn't do so well. Now I don't find the class challenging or anything, I think I'm doing pretty good.

By contrast, Hafsa was being introduced to the material for the first time, which made the pace of the course feel relentless:

> It's all new to me. So I feel like it takes a little bit more work and … we either have a quiz every week or an exam so there is always something happening each week. So I feel like I'm always preparing for something, so I would say it's really time consuming.

A lack of previous exposure to the course content made it more likely that students would have a negative experience in the class.

Another individual-level factor was the students' individual personalities. For instance, Nour felt that her outgoing personality had made it easier for her to develop close relationships with the other students at her table:

> I think it's personality that also plays into it because I'm somebody who's very sociable and I can make a friend out of anything, I'd like to think, but I do know that there are people who keep to themselves, who have never had, a friendship has never been offered to them and they've never offered.

Nour also acknowledged that being outgoing made it easier for her to seek out help, and that students who were less inclined to do so were at a disadvantage: "If you aren't almost extroverted and you aren't progressively chasing down the help you need, if you need it, it's very easy for me to understand how somebody could fall behind." For Nour, her outgoing personality facilitated positive interactions with other students as well as a high level of comfort in asking others for help.

The third individual-level factor was students' personal attitudes towards and experiences with math. It was easier for the participants who enjoyed math or felt they had a natural ability in the subject to find the course enjoyable. Ying was intrinsically interested in math, which facilitated her enjoyment of the course: "I like math and this course was fun, I enjoy reviewing and remembering what I learned in the past and just knowing more math." Hanh expressed a similar sentiment: "I really do enjoy math. Math is cool, I like the class and I enjoy doing math problems." There were other interview participants who described themselves as not being "math people." For Hafsa, this meant having to work harder and experiencing frustration:

> I always felt that math wasn't a strong subject for me or I didn't have a good math teacher in high school. So I always feel like I have to put in extra work or do more problems … sometimes I get a little frustrated.

Because math is taught throughout K-12 education, it is not surprising that students enter a college-level math course with preconceptions of what math means to them.

Mixed Methods Meta-inferences

As discussed in chapter three, a key strategy for pursuing validity in mixed methods studies is to provide meta-inferences that are based on an integration of the quantitative and qualitative findings (Tashakkori & Teddlie, 2008). On the following page, I include a table with mixed methods meta-inferences for the five research questions addressed in this chapter, indicating where the findings from the two strands were convergent, divergent, or complementary, or where the qualitative findings elaborated on the quantitative analysis. This synthesis helps the reader to understand how the results from each strand fit together to tell a larger story about the classroom climate of the pre-calculus course.

Table 10

Mixed Methods Meta-inferences for Research Questions 1a through 1e

Research question	Meta-inference
1a. How do FG students describe the classroom climate?	*Convergent:* • Both strands demonstrated high satisfaction with TA-student interactions and a belief that the course was not a discriminatory space. • Survey respondents and interview participants in Dan's class were more positive about professor-student interactions. • There was a high degree of variation in the survey data with respect to the inclusion of diverse backgrounds. There was also some variation in the qualitative data. Some interview participants saw a connection between the course and their goals, although there was no sharing of students' or the professors' personal backgrounds and how they related to the course. • On average, survey respondents felt positively about physical space and participation, although there was a significant amount of variation. In the interviews, students expressed varying degrees of comfort with participating in class, as well as mixed views of the physical space. Through my observations, I noticed that men, and especially White men, seemed to feel most comfortable participating in the class and also tended to take up more physical space. *Divergent:* • The quantitative data suggested that respondents felt positively about student-student interaction and cohesion and that there was minimal variation from the mean. Interview participants described a greater range of experiences in terms of interactions with other students. Some reported tight-knit and collaborative relationships while others reported a lack of interaction. Interview participants also discussed gendered and racial patterns to student interactions. • The quantitative data suggested that while, on average, students felt very positive about their interactions with the TAs, there was a high degree of variation on the scale. In the interviews, students were more uniformly positive about their interactions with the TAs.

	Complementary: • In addition to examining the factors that influence the classroom climate, the study's qualitative strand explored overarching themes related to the classroom climate. FG interview participants experienced an atmosphere of collective confusion and frustration, as well as disengagement. *Elaboration:* The qualitative findings provided contextual details that elaborate on some of the quantitative findings: • Regarding the differing views of Dan and Isaac, participants in Dan's section felt that he cared about students and went above and beyond to support them, whereas some students in Isaac's sections believed that he lacked a caring attitude. • Regarding the positive views of TA-student interactions, interview participants perceived that the TAs tried hard to help students, cared about their learning, and were relatable and approachable. • Regarding the perceived lack of discrimination in the course, interview participants partially attributed this to their view that issues of identity were not relevant in a math course that did not touch on social issues.
1b. Are there differences between FG and continuing-generation (CG) students' perceptions?	*Divergent:* • There was tentative quantitative evidence that, on average, CG students felt more favorably about participation, physical space, a lack of discrimination, and student-student interaction/cohesion compared to FG students. However, in the interviews, most participants felt that being first-generation influenced their overall college experiences, but not those specific to the pre-calculus class.

1c. How do FG students' multiple intersecting identities inform their perceptions of the climate?	*Convergent:* • Overall, survey respondents' gender, race and ethnicity, and class were not very predictive of differing views toward the factors that influence the classroom climate. Other than noticing some gendered and racial patterns of interaction among students, the interview participants did not seem to believe that course experiences were different based on identities such as gender, race, or ethnicity. • White and non-URM Asian survey respondents scored higher on the participation scale. In my observations, I noted that men – and especially white men – seemed to be more comfortable participating in the class. *Complementary:* • Latinx and mixed race survey respondents scored lower on the professor-student interaction and inclusion of diverse backgrounds scales. This specific dynamic did not emerge from the qualitative data. • The R-squared was the highest for the regression models predicting the professor-student interaction and inclusion of diverse backgrounds scales, suggesting that the way that students experienced these factors that influence the classroom climate may have been more influenced by students' identities compared to the other factors.
1d. How do racism, sexism, classism, and other intersecting forms of discrimination influence FG students' experiences of the climate?	*Convergent:* • There is weak quantitative evidence that students who felt more positively about a lack of discrimination in the classroom tended to feel more comfortable participating in class and tended to feel more comfortable in the physical space of the classroom. There is no evidence that students' feelings about discrimination in the course were correlated with other aspects of the classroom climate. Interview participants did not believe that there was any discrimination in the course.

1e. What factors not related to pedagogy influence climate perceptions?	Qualitative only: • Non-pedagogy factors that influenced the climate were students' previous exposure to the course content, individual personalities, and personal attitudes towards and experiences with math.

Chapter Five: Pedagogy and its Influence on the Classroom Climate

This chapter responds to the following research questions:

RQ2: How does pedagogy reinforce or disrupt classroom power dynamics that affect the experiences of first-generation (FG) students?

RQ 2a) How does the course pedagogy align with traditional pedagogy, active learning, and/or inclusive pedagogy?

RQ 2b) How does pedagogy influence the classroom climate?

I first examine the different elements of Dan and Isaac's pedagogy and how they align with the three teaching and learning paradigms. I then explore quantitative and qualitative evidence of FG students' perceptions of course pedagogy. Finally, I present quantitative and qualitative findings about the different ways in which pedagogy influenced the classroom climate. Five themes emerged from the qualitative analysis related to how pedagogy negatively influenced the climate: a lack of structure and organization, communication, guidance, and facilitation around group work; and a negative effect of lecturing. One theme emerged related to how pedagogy positively influenced the climate, which was the positive impact of the smaller TA- and peer-led sections. After discussing these themes, I examine a tension that was present in the professor and student interviews regarding the amount of responsibility that the instructors needed to assume versus the amount of responsibility the students had for their learning and success in the class. I end the chapter by presenting meta-inferences for research questions 2a and 2b.

Examining the Different Elements of Pedagogy in the Course

Through interviews with the two professors, as well as analysis of the syllabus and my classroom observation notes, I sought to gain a deep understanding of the pedagogy being utilized in the course. I was interested in both the espoused beliefs and ideas and what was implemented in day-to-day classroom interactions. Below I explore each element of pedagogy from the table in Appendix A, comparing them with the three teaching and learning paradigms.

Underlying theory of learning. Both Dan and Isaac had espoused theories of learning that fell under the active learning paradigm. They believed in learning by doing. Dan explained:

> I do the analogy of, you're in the woods, and you have to find your way through the woods. So one way to teach is, I just grab their hand and take them to where they're going. Okay? We get to where we're going, but the next day when I'm not there, they don't know how to get there. That it's better if they explore the woods, and learn more about where they are and, "Oh, I went this way, and that's not the right way." Going down wrong paths is a good learning experience. You learn more about the woods because you've explored the wrong paths, rather than just the right path.

Isaac said, "ultimately learning is experiential … all I can do [as the teacher] is I can help you out but you have to get the experience yourself." Both professors rejected the notion that knowledge can simply be transferred from the instructor to the student.

Dan also thought that learning through problem solving was important, and he stressed having students going through specific problems until they arrived at a general formula they can use:

> Instead of me telling the students how to get the formula, I give the students the skill so that they can figure out the formula for themselves. Here's a specific

> problem, calculate a numerical answer. And they stumble around for a while, but they eventually figure out how to get that numerical answer. But they don't understand yet. So now's the second problem. Now there's a third problem that has a little twist to show them the differences. And then there's a fourth problem. And okay. "Now that you've done these four problems, do you see a pattern?"

Isaac also stressed going from specific problems to general principles: “Basically the way we're sort of putting it is the idea that you do the individual cases to look for a pattern.” Dan believed that conceptual understanding was key for students to ultimately succeed in the course and in future math courses:

> Instead of just getting answers by using a formula they don't understand, they now, and you could see it happen, you could see the light bulbs turn on, like, "Oh, I think I get this now." … And maybe it's not perfect, but they'll be describing something that shows their conceptual understanding. And I think those [students] are the ones that succeed.

Whereas both professors espoused an underlying theory of learning that was based on learning by doing, problem solving, and conceptual understanding, not all of their actions aligned with these beliefs. As I discuss further below, in practice, especially for Isaac, it seemed that at least some of the actions were based on a theory more aligned with traditional pedagogy, in which knowledge can be transferred from the professor to the student.

Goal. For both professors, the goal of teaching and learning fit most closely with the active learning paradigm. They wanted students to learn the discipline’s prevailing concepts rather than to question and transform the field; this goal is aligned with the traditional and active learning paradigms. They both also stressed conceptual learning rather than rote memorization, which is aligned with the active learning and inclusive pedagogy paradigms. In addition, both professors were very focused on the goal of preparing students for their future professions. Dan used this goal as part of the justification for focusing on conceptual learning:

> When they're gonna use math in the future, they're gonna use a machine to do the computation. What's gonna be useful for them is, can they read in their discipline? Can they be reading biology and realize, "Oh, what's underlying this is a math problem. And if I use my math skills and the appropriate technology, I can get the answers that I need in order to do my biology." So I think the biggest thing is just to focus on the conceptual parts of things, more than we focus on the computational skills.

Both Isaac and Dan hoped that students would learn prevailing math concepts, which they saw as important preparation for successful careers.

Issues of racism, sexism, classism, and other forms of oppression. In the interviews, I asked Isaac and Dan about whether they thought that math education in the U.S. was structured to benefit certain groups over others, and to what they attributed disparities in math education outcomes. Dan used his own family as an example in talking about inequities in how K-12 education is funded, which he believed caused a pipeline issue:

> My family chose to live where we're currently living because of the quality of the school that my daughter would go to high school at … This is not talking about

> the students and their abilities. This is talking about the building that they're in, and other things that lead to success.

Dan explained that part of the reason the course had been redesigned was based on issues of inequity in STEM education:

> We have underrepresented populations that want to progress by winding up in careers in STEM fields. So how do we help them in that process? Well, their background coming in can differ greatly from the background of the mainstream students. So how do we address those issues?

Dan used a metaphor of running to explain why he believes the lecture method fails underrepresented students and why he had moved away from the lecture:

> It's somewhat akin to my experience as a distance runner, that when you move from junior high where it's just, "Yeah, we're just everybody running," to a high school varsity sport where it's, "Yeah, okay. You have to run faster." And there's some people that just, the pace is too fast to keep up. To doing it in college. "Okay, you're beyond me now. You're asking me to run at a pace that I'm not capable of running, and this is the end for me." That I think the way that we've typically taught math is, the lecture format sets the pace ... We put you on the treadmill and your legs go as fast as they can go. And if they don't go that fast, you have to get off the treadmill.

Dan seemed to feel strongly that inequities in math education at the postsecondary level were largely caused by inequities at lower levels of education. He believed that active learning was better than the lecture method for bringing underprepared students up to the level they needed to reach in order to progress.

Like Dan, Isaac believed there was unequal access to math education: “Some people have been promoted much more than others. Others have either obstacles in a way that they just give up or it's not made as accessible.” Isaac also acknowledged the cultural biases of the discipline of math:

> [Math is] a particular offshoot of western culture and that order doesn't automatically work in a way that just integrates it into a lot of people's other social experiences. But there are a lot of other things people do that they do not automatically integrate it into that either and they work with that too.

While Isaac saw that the prevailing way math is taught comes from a particular culture, he seemed to suggest that students who do not identify with that culture needed to adapt to it, rather than the way math is taught adapting to students’ diverse cultural backgrounds.

While both Dan and Isaac acknowledged that there were inequities in math education, neither professor acknowledged specific types of discrimination (e.g., sexism, racism) or specific groups within the population that are affected by inequitable structures. The course TAs were diverse in terms of gender, race, and ethnicity, and I asked Dan whether this was intentional. He explained that while he valued their diversity, it had happened by chance:

> Yeah, so each semester, it's like a week in where I think, "Oh you know what? Maybe I should be thinking about the underrepresented populations and making sure we're including them in these positions." And then I look through my list and go, "Oh, it accidentally happened without me thinking about it."

While there was recognition of disparities in math education, there were no actions being taken by either Dan or Isaac to challenge inequities beyond the belief that active learning would be better for underrepresented students than lecturing. This approach is most closely aligned with the active learning paradigm.

Role of professor. Per the woods metaphor mentioned above, Dan saw himself as a facilitator of learning. He described his approach:

> Some of it is just observing what [the students are] doing, and then, again instead of just then pointing them in the right direction, it's about the conversation about, "Okay. What did you do?" Maybe even, "Why did you dream that up? Why did you head that direction? What did you find out? What did you learn from it?" And then build on it.

Isaac saw himself as "trying to guide [students] toward showing what they're doing." Isaac believed that being a guide was better than simply giving students an answer: "I'm trying to give you enough so that you can think about what I told you rather than just getting a yes or no answer." Both Dan and Isaac saw their role as facilitators, which is aligned with the active learning and inclusive pedagogy paradigms.

Through my observations, I saw that in reality, Isaac mixed lecturing in with the group work component. Dan would usually speak to the whole class for about five minutes at the beginning of class in order to give announcements and set up the group work. He would sometimes interrupt the class to go over a problem, but those interruptions were usually brief. At the beginning of the semester, Isaac followed a similar pattern, spending five to ten minutes at the beginning of class to address all students. However, during the second half of the semester, this had increased to 25 to 30 minutes, which was at least half of the total class time. Isaac may not have been aware of the extent of his lecturing. In his second interview at the end of the semester, he said,

> I had said a number of times that I'm not supposed to lecture here. I'm going to try and cover some things that I think people need some clarification on but I'm not going to be spending 50 minutes sitting here just talking at you.

There was a gap between what Isaac believed his role should be and the role he actually played.

Through my observations, I noticed that Dan was more of an active facilitator of learning. He would encourage a student to explain something to another student, and would signal to the TAs when it was time to move to a new table. Instead of responding to a student's question by showing them how he would solve the problem, Dan would ask the student to show him what they had done. In Isaac's sections, I did not see him encouraging students to explain problems to him or to other students. He also did not ask the TAs to move to the next table if they had been at a table for a long time; the TAs had more autonomy over what they did compared to Dan's section. Dan would sometimes engage the class in problem solving as a large group. He would have one student from each table go to their whiteboard and start a problem, then hand off the marker to the next student, and so on. Isaac would not do this, sticking to a mix of lecturing and handing out problems and worksheets for students to do as individuals or in groups. Dan was also more explicit with students about the intentions behind his actions. For example, he would explain to students that he was focused on their conceptual learning and that he wanted them to go from doing specific problems to having a more generalized understanding of an underlying process.

Dan believed that an important part of an instructor's role is to send students messages that they could succeed. He told a story about a student who was struggling in the class at the beginning of the semester but had ultimately succeeded: "I think the biggest thing for her was the fact that she worked with her TA, she felt that her TA thought that she could do this and as a result, she kept working and she succeeded." Dan believed that an active learning model allowed for this validating role to exist:

> The student can see two things, whether or not they think they can be successful and whether or not I think they can be successful. In the lecture style class that second one is non-existent. They have no idea whether or not I, what I think about them, wherein this active learning where you're interacting with the students a lot more, I think when you ask a student whether or not I think they can succeed, they now believe that they can at least answer the question.

Dan believed that an important part of his job was to validate students, and in this way his pedagogy was aligned with the inclusive pedagogy paradigm. However, I also noticed that Dan had a somewhat fixed view of math ability. At several points during the interviews, he talked about how the students taking the pre-calculus class were not among the "best" math students. Dan explained:

> When I was a high school teacher, I probably was teaching at a more advanced level than I'm teaching now, because in high school I had some students that were at the top, that were going to go on to be engineers. Here, by and large, those students are beyond the courses that I teach. The students I'm teaching are maybe that second quarter of the students, where they're okay at math, they're gonna be

> dealing with math in their careers, but they're not the formal mathematical, scientific thinkers.

When Dan mentioned a certain area of mathematics that was more advanced, he expressed, “That's not where these students are at. That's not where these students are ever going to be at.” While Dan recognized the importance of sending students messages that they could succeed in the course, his views of ability as being somewhat fixed may have meant that he did not send them messages that they could succeed in math beyond the course. This static view of ability is more aligned with the traditional paradigm.

Role of students. The syllabus stated that students were expected to have an active role in the class: “Students should do their best to experiment, draw pictures, represent the problem, ask questions, answer questions, and explain answers to others.” In the interviews, both professors discussed how students needed to engage actively in the learning process, which aligns with the active learning and inclusive pedagogy paradigms. Dan explained, “You've gotta get over that fear of participation, and you need to be willing to engage in the material.” Students had the responsibility to collaborate with other students in solving problems. In class, Dan said,

> I told [the students] that, “You know, it's getting kind of loud in here, and I'm still uncomfortable because it's not loud enough. You're kind of hesitantly talking to each other. You need to be having conversations. You need to be talking about this with your group mates. You need to be talking about this with the other instructors. And this should sound like a coffee shop, where people are talking and carrying on conversations.”

Dan believed in students having an active role and also regularly communicated this expectation to students.

Isaac wanted students to take responsibility for their learning, but felt that many students were not fulfilling this role:

> You're now telling [the students], “Hey, we're making passing much more of the responsibility for your learning to you that we're telling you what you can go to and we're telling you if you want to use other resources that's fine too. But the thing is that you're expected to come in ready to work,” and a lot of people didn't apparently see it that way.

Isaac observed many students leaving class early and also suspected that students were not working on the problems during group work time and were not studying on their own outside of class. He explained, “I'm doing this though with the intent of meeting [the student] half way, not 90% of the way.” Isaac seemed to feel powerless when it came to students who lacked motivation: “There's no method of education that works for a person who doesn't know what they want to be, don't really see why they should spend their time this way.” In Isaac’s view, students were not meeting him halfway, and he was at a loss for how to get students to take on more responsibility.

In both Dan and Isaac’s sections, I observed that the goal of group work was often not met. Students would work on their own or only briefly check in with other students at their table. Or, students would be on their phone or computer engaging in non-class-related activities (e.g., homework for another class, social media). In reality, most students were not as actively engaged in the learning process as the syllabus and both professors stated they should be.

Content. As the lead instructor, Dan was in charge of deciding which content was included in the course. Dan seemed to be conscious of striving to include content that students would need for future math classes and/or professions. Dan talked about the importance of students making connections between the content and other disciplines:

> That's one of the other things that's nice about the active learning classroom, is that we were doing something on Wednesday and a student said, "Oh, this is like the Punnett square in genetics." "Okay. Let's talk about genetics for a while." Because it is. It's an important connection … Once the students are in the conversation, they will say things that are from their perspective, and the instructors can react to that and, yeah. They will say something that relates to their career choice, and we can talk about how the math connects to that.

In observing the class, I noted that some real-world examples were interspersed, but that more often the content was presented without a practical application. Also, most of the real-world application (topics such as compounding interest and radioactive decay) came at the end of the semester instead of being covered throughout. In the syllabus, the content was presented in a decontextualized manner: “Topics include a discussion of functions (function notation, domain/range, inverse functions, composition of functions, graphs of functions); general techniques of graphing and graph transformations; equations of lines, polynomial and rational functions; exponential and logarithmic functions.” As such, the course content was sometimes aligned with the traditional paradigm in that it was decontextualized from its real-world application, and sometimes aligned with the active learning paradigm in that there was some discussion of real-world application, although no questioning of for whom the content was relevant, nor any linking of content to students' life experiences.

Assessment. The grading methods were a mix of summative and formative assessment, blending components of all three teaching and learning paradigms. Regarding the 10 quizzes that comprised "level one" of the assessment system, there was a feedback component to them because students could take the quizzes as many times as necessary to pass. If they did not pass the quiz the first time, they would often seek help from a TA or professor before attempting it again. However, Isaac did not feel that students were necessarily learning through taking the quizzes. Because students could take them at any point during the semester, a significant number of students waited until the last minute. He explained:

> I have to really wonder if somebody tries to bomb through somewhere between four and in a couple of cases eight quizzes in under two weeks, how much do you figure that they really have learned about those topics?

As such, the quizzes varied from student to student in terms of providing feedback versus being purely summative.

Regarding "level two" of the grading system, the online homework and quizzes (10% of the grade) were done through an online system where students would submit answers but only be told if it was right or wrong, with no additional feedback. Thus, the 70% of their grade that was either test scores or online homework/quizzes aligned with the traditional pedagogy paradigm. The participation grade, which was the remaining 30% of the level two grade, came closer to formative assessment. Each student received their participation grade from the TA that led their Tuesday discussion section. The grade was based on their contributions to group work in the larger class as well as their contributions during the smaller TA- and peer-led discussion sections. The participation grade also included the written assignments, for which students received minimal feedback. Because these components involved collaboration and feedback, the participation grade was more aligned with the active learning and inclusive pedagogy paradigms.

For the "level three" problems that students needed to complete in order to receive an A, students were allowed to work with others on the problems and were allowed to ask for help from a professor or a TA, so there was an opportunity for feedback. However, because the feedback was not a built-in feature but would rather require students to seek out help, the "extra material" was closer to the traditional pedagogy paradigm.

The "level three" assessment was communicated to students in a way that suggested that there were different tiers of students. For example, the instructions were listed on the course's online site as "extra topics for 'A' students." In an email reminder that Dan sent out to the students, he stated that "Students in the 'B' and 'C' range should concentrate on preparing for the final exam" rather than attempting the extra material. When I interviewed Dan at the end of the semester, he stated that only a very small number of students had successfully completed the extra material: "How many of my students have proven to me that they're A students? Less than 5%." These dynamics again reflected a fixed view of student abilities, in which most students were not viewed as capable of being "A students."

When I spoke with Dan about how students were assessed in the course, he explained that his goal was to have a mix of formative and summative assessment, and that he believed the exams motivated students. Dan believed that exams made sense as a form of assessment within the context of math:

> You want students to walk away from a course with something. And the last day of class, you've got three hours in which students can demonstrate all that they've learned throughout the semester, and I think it's good to have some sort of culminating experience ... And I understand in other departments, in an English department, your culminating experience is going to be, "Write something big." You're not gonna do that in three hours. You're gonna do that over a period of weeks. But in math, yeah, [exams] make more sense.

Because exams carried more weight in determining students' final grades than any other assessment technique, the assessment approach was closer to the traditional paradigm than the active or inclusive pedagogy paradigms. In addition, there was no component of authentic assessment (which is encouraged in the active and inclusive pedagogy paradigms), as students were not carrying out math-related tasks that mirrored what they might be asked to do in a real-world setting.

Student Perceptions of Pedagogy

Quantitative findings. Table 11 reports frequencies reflecting FG respondents' perceptions of each of the 11 teaching and assessment strategies that were included on the survey. Overall, perceptions among FG students were positive. A majority of FG respondents reported that each of the 11 pedagogical elements were either very effective or somewhat effective for their learning. With regard to teaching strategies, 89% of respondents said that the TA-led sections/TA office hours were very or somewhat effective, and this figure was 88% for class time for individual questions, 80% for in-class group work, 75% for peer-led sections, and 68% for online videos designed for the class. Perceptions were less positive for professor office hours (54% believed they were at least somewhat effective and 41% said they had never used them). Regarding assessment methods, the most positively regarded ones were in-class quizzes and online quizzes, with 91% and 82% reporting they were at least somewhat effective, respectively. Around three quarters of respondents regarded exams, the online homework system, and written assignments as at least somewhat effective.

Table 11

Relative Frequencies of FG Students' Perceptions of Pedagogy (n = 65)

	I haven't used this	Very ineffective	Somewhat ineffective	Somewhat effective	Very effective
Online videos	5%	9%	18%	46%	22%
In-class group work	0%	3%	17%	41%	39%
Individual work in class	2%	3%	8%	41%	47%
TA-led sections/TA office hours	2%	5%	5%	33%	56%
Peer-led sections	3%	6%	15%	36%	39%
In-class quizzes	0%	3%	6%	47%	44%
Online	2%	5%	12%	40%	42%
Exams	0%	6%	15%	35%	43%
Written assignments	0%	9%	17%	44%	30%
Online homework system	2%	3%	17%	39%	39%
Professor office hours / Math Lab	41%	2%	3%	21%	33%

Qualitative findings. In the interviews, I asked students to identify the teaching and assessment strategies that they found to be the most and least helpful for their learning.

Teaching strategies. The only teaching strategy that was overwhelmingly viewed as positive by the interview participants were the smaller TA- and peer-led sections. Many interview participants felt that these smaller sections were the most helpful course component for their learning. José claimed, “I think the smaller discussions were the bread and the butter of everyone's week. If you didn't know anything, by you going there you would at least have a chance to do okay on a test.” Alexis felt that the smaller sections, as well as office hours, were the most helpful because they were more individualized to what each student was struggling with at the moment: “The most helpful for me are the Tuesday small group sections and the office hours because that's when I can ask all my questions that I have. They usually help us with anything that we need help on.” While not all interview participants went to office hours (TA or professor), those who did found them to be helpful for the same reason in that they were an opportunity to receive more personalized help.

Interview participants had mixed feelings about the group work component. Laura and the other students at her table tended to grow tired of working through the problems and would turn to talking about non-course-related topics midway through the class session. On the other hand, Devin appreciated the opportunity to work through problems with others:

> It's just nice to be able to work in a setting where there's just a lot of people available because a lot of times you can listen to a lecture or watch a video and you think that you [get it] but it's not necessarily [until] practicing that you understand that oh, I don't know this.

Hanh also appreciated the opportunity for collaborative learning: "[You] have a better understanding because you are looking at it from someone else's perspective as well as your own."

Isaac tended to lecture for much of the time before putting up problems for students to work through in groups or as individuals. Interview participants who were in Isaac's class overwhelmingly felt that this was ineffective. According to Nour,

> [Isaac] lectures on his little board that projects everywhere in the room and he copies his notes and he just reads his annotated edits on his notes so it's not very friendly. He doesn't explain it very easily … He's not writing any explanations down, there's nothing I can take a picture of and take home with me to look at later.

Nour was puzzled about why there was so much lecturing in a flipped (or hybrid, as she called it) course: "If it's a reverse hybrid class and if all the homework is done in class and all the studying is done at home, then why is there that really awkward lecture?" Caitlin offered an idea on how the lecture could be more effective:

> I feel it would be more efficient if midway through his lecture [he said], "here's the concept, here's how we do it, let's work on this for 5 minutes. What kind of problems can arise from this, okay let's go on to the next part." Build it up.

Most of the participants in Isaac's section were not disapproving of lectures in general, but rather the way that Isaac lectured.

Several participants in both Dan and Isaac's classes felt that the larger sections, whether they involved lecturing, group, or individual work, were generally ineffective. Maria said,

> I feel that we don't need to have three days of [the larger class] just because sometimes we're not even learning anything … I think two days is enough and maybe add more time with the TAs or peer instructors.

José felt similarly: “Outside of the large class you seriously got more information than inside the class.”

Participants were also mixed as to whether they found the online videos to be helpful. Nour appreciated the videos, partially for accessibility reasons:

> I think the online videos are nice because they are transcribed to a 'T' as somebody who has a lot of issues watching videos without transcriptions. I can have the video and then the transcript that has all the equations written down so I can follow on with that very well. I do like the videos, especially like I said if Isaac spends the entire class talking to himself and I don't really get it or I'm zoned out or having a bad day or I don't show up. The videos can very much catch me up to speed.

Maria also appreciated the videos, saying that they “go step-by-step, something that sometimes we don't really do in class.” José, on the other hand, felt that the videos were too vague, and found an alternative online resource:

> The videos were not helpful, the videos were very vague and short. I wish there was more examples of working through it. Me and some students, we started using YouTube’s mathbff videos, it's a girl that works you through different logarithms and different equations and teaches you how to set stuff up.

Caitlin felt that there was too much of a leap between the videos and the problems that students were then expected to do: “[The videos are] just the rudimentary very basic of

2+2=4 and then all of a sudden when you get to the actual material he just throws in some crazy square exponentials and all this sine, cosine." Among the participants who did not believe the videos were effective, they tended to either feel that the recordings did not take them through processes step by step, or they believed that their content was too basic and rudimentary.

Assessment strategies. In terms of assessment, students tended to feel negatively toward the online homework and quizzes. The online homework did not provide any feedback and only told the student if what they had entered was correct or incorrect. Matt explained how this was frustrating for his learning process:

> I think I learn a lot better when we're given a sheet of paper and we can talk through with the problems instead of just entering in the problem and getting it wrong and wondering why what you got is wrong.

Participants had the same criticism of the online quizzes. Laura explained that students did not see value in completing them: "I think the online quizzes are not super helpful. I think people do them to get them done. I don't think anyone really cares about them."

For the other assessment methods, there was no consensus among interview participants as to which components were helpful and which were not. Matt appreciated the written assignments, explaining that through completing them, "It would be like you're teaching this concept to someone else which was very helpful." The students who saw the written assignments negatively tended to struggle to explain why they solved a problem in a certain way. Jake explained, "I know how to solve the problem, I just can't explain the formula or something like that."

The students I interviewed also had mixed feelings about the quizzes and exams. Participants who viewed the quizzes favorably appreciated that they could take them as many times as necessary, and that not all of their grade depended on the exams, which were more high-stakes. These students felt they were able to receive feedback through the quizzes. Hanh remarked, “I prefer to do the in-class quizzes because you can have feedback for what you did wrong and you can ask questions.” However, while some students felt that the quiz system relieved pressure, Caitlin felt differently: “In order to pass the class you have to pass all those [quizzes], so there's that pressure on you.” With exams, participants felt either ambivalent or negatively toward them. Those with negative feelings tended to think that there was too much of a leap between what they did on their own and what was asked of them on the exams. Both Amina and Laura explained feeling that the exams were a “curveball.” Other than the online homework and quiz system, participants expressed a range of attitudes toward the assessment methods. I now turn to my findings related to how pedagogy influenced the classroom climate.

The Influence of Pedagogy on the Classroom Climate

Quantitative findings. Table 12 reports the correlations between perceptions of pedagogy and the classroom climate scales. There were several statistically significant small and moderate correlations. Regarding statistically significant correlations for the teaching strategies variables, there was a small negative correlation between perceptions of the online videos and the discrimination scale and a small positive correlation with the inclusion of diverse backgrounds and professor-student interaction scales. There were positive statistically significant correlations between perceptions of in-class group work and the physical space, TA-student interaction, student-student interaction/cohesion, inclusion of diverse backgrounds, and professor-student interaction scales. There were positive statistically significant correlations between perceptions of class time for individual questions and the participation, physical space, TA-student interaction, student-student interaction/cohesion, inclusion of diverse backgrounds, and professor-student interaction scales. Perceptions of the TA-led discussion sections/TA office hours were positively correlated with the TA-student interaction scale. Perceptions of peer-led discussion sessions were positively correlated with the inclusion of diverse backgrounds scale. Finally, there were positive correlations between perceptions of professor office hours/math lab and the physical space, student-student interaction/cohesion, and professor-student interaction scales.

Table 12

Pearson Product-moment Correlations between Classroom Climate Scales and Perceived Effectiveness of Pedagogy for FG Students (n = 65)

	Discrim.	Partic.	Physical	TA-stud	Stud-stud	Diverse back.	Prof-stud
Online videos designed for this class	-0.25*	0.06	-0.02	0.07	0	0.35**	0.33**
In-class group work	0.1	0.21	0.37**	0.37**	0.41***	0.4**	0.45***
Class time for individual questions	0.12	0.36**	0.38**	0.46***	0.4***	0.27*	0.37**
Tuesday small group discussion sections / TA office hours	0.18	0.16	0.17	0.42***	0.11	0.09	0.21
Thursday PAL sessions	0.03	0.06	0.19	0.1	0.07	0.26*	0.22
In-class quizzes	0.07	0.25*	0.11	0.14	0.11	0.2	0.31*
Online quizzes	0	0.07	0.01	0.1	0.11	0.29*	0.33**
Exams	0.24	0.24	0.06	0.05	-0.02	0.27*	0.31*
Written assignments	0.05	0.18	0.06	0.27*	0.08	0.18	0.02
Online homework system	0.1	0.3*	0.15	0.18	0.18	0.37**	0.48***
Professor office hours / Math Lab	0.18	0.19	0.52***	0.26	0.36*	0.23	0.43**

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

Regarding correlations between the perceptions of assessment techniques variables and classroom climate scales, perceptions of in-class quizzes had positive statistically significant correlations with participation and professor-student interaction. Perceptions of online quizzes and exams were both positively correlated with inclusion of diverse backgrounds and professor-student interaction. Perceptions of written assignments were correlated with the TA-student interaction scale. Perceptions of the online homework system were correlated with the participation, inclusion of diverse backgrounds, and professor-student interaction variables.

These correlations mean that FG respondents who appreciated the course's teaching and assessment strategies tended to also appreciate or enjoy the factors that influence classroom climate. There was an especially strong link between positive views of group work and class time for individual questions and positive views of the factors, suggesting that students' time during the large class sessions was more strongly linked to their climate perceptions than their time attending the TA and peer-led sections, attending office hours, and watching the online videos.

Qualitative findings. In my qualitative analysis, several themes emerged related to how pedagogy negatively affected the classroom climate. Those themes are: a lack of structure and organization, communication, problem solving guidance, and facilitation around group work; and a negative effect of lecturing. Conversely, interview participants discussed ways in which the smaller TA- and peer-led sections improved the climate. At the end of this section I discuss a tension that was discussed by the professors and student participants regarding whose responsibility it was to ensure student success in the course. This tension calls into question how much emphasis should be placed on pedagogy and decisions made by the professors versus the individual responsibility that college students need to take for their learning.

Lack of structure and organization. Twelve of the thirteen interview participants discussed how the course lacked a clear structure and organization; by contributing to the atmosphere of collective confusion and frustration, this was one of the main ways in which pedagogy affected the climate. There was a lack of cohesion between the different course components (e.g., larger sections, TA-led sections, online videos, etc.), what content they were covering, and how they were covering it. According to Maria,

> [There is confusion] especially on the lectures because we're talking about something that sometimes wasn't even on the videos, or Dan wants you to learn a format that wasn't on his videos at the same time when most of the time the videos are what he tells you to go look at to know for the next lecture. So we get confused on that and on the test sometimes there's things that weren't ever discussed so we're confused on that … On Tuesdays when our TA is solving something, one problem fills up the whole board and we're like, “we didn't learn this during lectures.”

One phrase from Maria, which was echoed by Laura, seemed to sum up the lack of structure and the resulting confusion: “The class is very all over the place.”

Interview participants struggled to see the connections between the different concepts they were expected to learn. According to Hanh, “[The course] is not cohesive I suppose, it seems very random what we're learning. I don't know how necessarily it all flows together.” Hanh talked about how this was antithetical to the course’s goal of conceptual learning:

> It seems kind of counter-intuitive because if the purpose of the class is to be able to make connections and to make some kind of cohesion between all the concepts that we're learning, how can you do that when … the way that [the concepts are] being taught is not connected?

When I asked Alexis whether she was able to see connections between the different topics, she responded, “It doesn't really link, it's just like two different topics completely.”

The class seemed to move on to new topics before addressing students’ difficulties with the previous ones. In the second interview with Dan at the end of the semester, he acknowledged that he had misestimated students’ abilities with certain concepts, which led to some discontinuity with the way that content was covered:

> I just misestimated where the students were. That I thought question number 2 was a really, really easy question and it turned out that it was not. So once I started figuring that out I could backtrack and [say] “okay, we're not going to get to both sides of this worksheet. We really are struggling just to answer the second question and that we need to spend our time there” … it took me a while to figure that out. So I think students are going to show some frustration with some of those things that need to get redesigned.

There was a lack of cohesion and continuity between course components as well as between concepts, which led to a sense of uncertainty and frustration among students.

Interview participants were preoccupied with knowing what was on the upcoming test, and were frustrated when this was unclear. As mentioned in chapter four, the instructors would often introduce content that would not be covered on an upcoming exam, but rather a subsequent one. Caitlin described the anxiety this caused and expressed a desire for a more streamlined format:

> Just the whole setup of the class is weird. You're learning stuff for the test that's next week and by the time you get to the test that's for that week, you're supposed to remember what you did last week for that. I'd rather have prep for this quiz for this week, take the quiz at the end of the week, okay next week we're starting a brand new test that Friday instead of having to think back, okay, what did we do a week ago? I really don't know anymore.

The lack of structure and clarity seemed to aggravate students' unease about their grades.

Assessment-related apprehension was fueled by a sense that there was always an exam or quiz coming up. Laura felt that she was not able to focus on anything that was not going to be on the upcoming test: "I'm not going to be able to learn something new when I'm trying to study for a test that the new subject is not going to be covered." Nour also described anxiety around feeling unprepared for an exam: "The exam I have today, I'm not ready to take it. The entire class has spent the entire week being like 'we don't get this, this is not snowballing, this is jumping to a whole different league.'" Despite putting in the work, Hafsa also felt unprepared due to a lack of organization around the content:

> Sometimes I find myself watching all the videos online and doing all the practice examples in class, I'm doing all the practice problems posted from the book online but yet when I get to the exam I'm just like, "I don't remember doing this sort of problem or this sort of strategy. It's not familiar to me."

Laura offered an idea for how the exams could be structured in a way that would reduce student anxiety: "Maybe retaking the exams or [submitting] corrections, what you did wrong and getting the right answer and turn those in for a couple more points. I think I would like something like that."

Isaac recognized that students tended to be strategic learners who were focused on passing the exam above everything else. He believed that test anxiety started at earlier levels of education:

> I've been seeing this for years. I know how much this is coming out of the way things are done in secondary education. That you have to pass those darn standardized tests. So everything is focused on how you do particular problems and … because of that I feel that the people who want to see examples done, they don't want to see general examples done of the material, they want to see you do problems that are going to be on the exam so that I can pass the exam and I can get my points.

The professors and interview participants acknowledged that students were preoccupied with their grades and their performance on the exams in particular. Another contributor to an atmosphere of disjuncture and frustration was a lack of communication on the part of the instructors.

Lack of communication. Undergirding the negative aspects of the classroom climate was a lack of communication. For instance, there was not a clear schedule of when different topics would be covered and assessed that was laid out ahead of time. Hanh described her frustration with this:

> I prefer when things are very structured, having a calendar of all the things we're going to be working on, when we're working on them, not just every week "oh, I'll send you an email, this is what we're working on in class." Having a structure

> when we're doing the quizzes and what's going to be on the quizzes. A very clear format in a syllabus of exactly what is going to be on there and what we're learning.

Instead of the schedule being presented at the beginning of the semester, students received a weekly email from Dan (which was also posted on the course website) about what the quiz or exam would cover that week, what videos they should watch, what homework they should do, and what would be covered through the in-class activities. As an example, in week 11 of the course, the Friday exam covered topics 32-34 (graphing polynomials, graphing rational expressions, and solving rational inequalities). However, students were asked to review the videos for topics 35-37 (the logarithm function, properties of logarithms, and examples using the properties of logarithms) because that was what was covered in class on the Monday and Wednesday before the exam. In addition, students were encouraged to start working on the homework for topics 38-40 (compounding interest, radioactive decay, and Newton's Law of Cooling). Not only were students being asked to focus on three different sets of topics in the same week, they were not informed of this until the Sunday before the week started. Caitlin expressed frustration with this method of communicating to students: "The class drains me … all these dates and deadlines you just need to magically remember that they give you no reminder for."

The design of the course's website lacked organization. When I asked Jake what he would do to improve the course, he said: "Clarifying and getting the structure built up online and having students know what they are doing." The website's homepage was a long list of topics with a link to each topic's video. However, practice problems were listed in a separate location, as well as the documents that corresponded to the problems that students worked on in class. The written assignments were also listed separately, and the online homework system was hosted through a different platform. This decentralized organization kept students from being able to connect different components that fit under any given topic.

In some cases, participants in Isaac's section perceived that Dan held all of the information and that Isaac was not kept in the loop, causing a communication breakdown. According to Nour,

> The whole concept of there being an instructor who's not present [is problematic] … So if we all collectively don't understand something they can't make room in the curriculum to re-explain it or put a review day in because it's not being communicated to the person who runs the class. So that confusing to me, definitely.

Nour did not understand why Dan seemed to be running the class while Isaac was the instructor of her section:

> Most of our emails don't even come from the professor, they come from the instructor of the class who isn't actually the person who's teaching. So that even itself, I called [Isaac] Dan one time, he was like, "I'm not Dan." I was like "what! What do you mean?" He said "Dan is the instructor for the class." [Then] where the heck is Dan?

The perceived lack of communication between Dan and Isaac contributed to the atmosphere of confusion and frustration for those participants who were in Isaac's section.

There was also faulty communication with respect to students' grades. Some of the students I interviewed were not sure what their grade was. They could see a score when they logged onto the course website, but it was unclear to what grade the score corresponded. Nour commented:

> I don't really know what my grade is right now, to be honest with you. I don't know, I've looked a hundred times, I have no idea how to read it. There's no letter, there's no numbers that I understand … I have no idea where I stand in that class. I could have a D, I could have an A, I have no idea.

Several of the interview participants were also confused about what components would make up their final grade. For instance, some of the interviews occurred after Dan had emailed out the information about "extra material for A students," referring to "level three" of the grading system. However, the participants did not seem to have a clear understanding of what this "extra material" was. Course requirements and expectations were not communicated clearly, and specific deadlines were sent out piecemeal instead of in one document at the beginning of the semester. This lack of communication was one aspect of pedagogy that negatively affected the classroom climate. Students' sense of frustration was also fueled by a perceived lack of guidance.

Lack of guidance through the problem-solving process. There was not only a lack of cohesion between the different course components and concepts, but also a lack of structure in terms of how content was taught. Students felt like something was missing because problems would be introduced in class, but they would never find out definitively what the correct answer was to the problem. Interview participants described this as a loop that had not been closed. Laura explained,

> [Isaac] just kind of shows [the problems] and then we're done. That's it, we don't know, the frustrating part about that is that I don't know if I'm doing it right, so if I get an answer I'll be like great but am I doing this right? So I wish he would almost go over it so that we could all see the step-by-step in how to get the answer, how to get it right.

Hafsa described how she would restructure the group work component:

> I would have an agenda of what we need to do and then how we're going to do it and then actually do it. Then later on wrap it up and review what we did, who understands what, make sure everyone is on the same page or [else] some people will just get left behind.

The students I interviewed seemed to want a step-by-step process to learning new concepts.

Many of the interview participants were sympathetic to the active learning approach, but felt they needed more guidance than what was being given. José remarked,

> The professor, Isaac, when you would tell him, "I don't understand why this class is set up this way" … I would hear people asking him that. And he was very shocked [and said] "Oh, because we're trying to scaffold you by forcing you to work through the information so you can retain it better." But it was really difficult because once again it's hard to figure out anything if you're not even given an equation or set rules to follow. It becomes very difficult for you even to understand how to start.

At the same time, José expressed appreciation for having to "struggle" to solve problems, which he felt happened through taking the quizzes: "You're going through that struggle too of learning that information and putting it all together which was really satisfying when you were doing it on the quizzes."

Interview participants often reported feeling that there was too much of a jump between what was covered by a video or the professor and then what they were expected to do alone or in groups. Nour explained:

> We had a worksheet a couple weeks back that was on rational equations and all this whodaddy stuff and the example that the instructor gave was, here's the base level of how to do it, and [then] the worksheet just takes it and just exponentially makes it harder and you're just supposed to make the jump of knowledge and make a couple of assumptions to finish it … we all sat and stared at each other [at the table]. We were like we're not getting anywhere with this. [The TA] would come and explain once, we'd get that and we'd jump to the next [problem] and then we wouldn't get it again.

Caitlin explained feeling intimidated by this leap:

> There is no stepping stone. [Isaac is] just like, "here's the basic principles, now try doing it like 10 times harder on steroids," and it's very intimidating and "oh, what do you mean there's all these exceptions to this rule that you didn't mention to us?"

The perception that the work became exponentially more difficult when they were asked to work alone or in groups seemed to erode the trust that students had in the instructors.

In the interview at the end of the semester, Dan recognized that they were asking students to make a leap between what they covered and what was on the exam, and felt that this process was important for developing students' problem-solving abilities:

> In my class, you [the student] think it's all about uniformity and that I have to, I'm not teaching you unless the course is only about being a machine to crank out answers to certain types of problems and it's unfair if I ask you a question that you haven't practiced exactly many times before coming into the test. At the other end, the message is just the opposite. So what do employers want? Employers want, think creatively, think critically, solve problems, communicate. None of which the students think is fair.

Dan felt that students automatically reacted negatively when they found content to be difficult:

> I think students are equating unfair with difficult. "If it's hard for me it's not fair to ask me to do it." I think next time around I'll be much more clear from the beginning that every student in this class will encounter material that they find difficult.

There was a clear tension around how much structure and baseline information to provide to students so that they felt supported but also had to learn for themselves. The lack of guidance that students perceived extended to expectations around group work.

Lack of facilitation around group work. The course was structured in a way that seemed to expect that tables would become collaborative and well-functioning groups with minimal facilitation on the part of the instructors. As described above, Dan did sometimes encourage students to explain concepts to each other or to talk to each other during group work time. However, there were no group work guidelines or expectations that were shared with students. Because most of the participation grade was based on what occurred in the smaller sections, students were also not held accountable for how much they contributed to group work processes.

While some tables were tight-knit, other tables lacked interaction and cohesiveness. A lack of facilitation and communication of expectations related to group work meant that the less cohesive groups were not “nudged” toward becoming more collaborative. Hanh described how one’s experience in the course depended on their table or group: “If you're with a good group things will go well, if you're not with a good group, not everyone is engaged, it won't be as positive of an experience.” Nour had observed, “There are groups of tables where everybody is by themselves. Everybody does their own thing … there's not a sense of community. There's no group there it's just a group of individuals.”

As discussed in the section above on student-student interaction, for students who ended up at a tight-knit table, this greatly improved their overall subjective experience of the course. Interestingly, for some interview participants, they believed the shared confusion was what led to the tight-knit bonds they felt with the students at their table. Laura said, “We really bond over not understanding topics … I think it's like struggling together brought us closer.” When I asked José what he thought made his table so tight-knit, he responded:

> Confusion and a single goal of passing the class. Every day we would go in, there would always be the joke of “hey, … what's the one thing we're going to get out of how things develop today?” That kind of joking and that atmosphere, the common understanding [that] no one actually knew what we were doing.

Through these comments, Laura and José demonstrated how a negative aspect of the climate (collective sense of confusion and frustration) made it easier for tight-knit bonds to form among students, which improved the climate.

Because there was no sorting of students into groups based on their abilities, some students ended up at a table where everyone was learning the content for the first time, which could aggravate confusion and frustration. According to Amina, “If your group doesn't necessarily know how to do anything, it's kind of hard to actually learn anything.” José put this more starkly: “If you had a table where no one understood anything, then you guys were like dead in the water for that day.” Laura felt fortunate to be at a table where some students were more advanced: “I have some really smart people at my table which is super nice because they know how to explain it a little bit easier in a personal sense.” The dynamics of any particular table seemed largely to come down to chance.

During the observations when I did minute-by-minute tracking, I noticed that there was also uneven attention paid to the tables by the instructors and TAs. For example, one day in Dan’s section, one table received 3 minutes of attention, another table received 21 minutes, and another received 40 minutes. One day in one of Isaac’s sections, there were two tables that received no attention from a TA or professor, compared with another table that received 19 minutes. I did not detect any gender or racial patterns in terms of which students and tables tended to receive more instructor attention. Part of this disparity was likely due to the existence of tables where students appeared to be able to help each other. There were also tables where the majority of students were not focusing on the math problems and were discussing out-of-class topics; these tables tended to be overlooked by instructors. Alexis explained:

> Other tables, they leave early or they just don't pay attention and they're on their phones and stuff like that. So [the instructors] don't really, if they see you doing that they'll look at you but they're like, “well I'm not going to bother with them because they're clearly not even trying to do it.”

When I interviewed Isaac, he explained that he did not want to intervene at those tables in order to get them back on track, remarking that “I didn't want to have some kind of a policing system.”

On the other hand, some of the uneven patterns of attention came down to personal relationships. For instance, while José was very appreciative of the help he received from TAs through the smaller sections and office hours, he felt that his table did not receive much attention from the TAs during the larger section:

> The first day of instruction, the TAs don't necessarily know anyone … those first tables that were able to call them and build almost a teacher-student group relationship early on in the course, they kind of got the first dibs, in a sense, where the TA would naturally gravitate towards them, maybe not voluntarily but more of a normalized function of the class. Because I didn't, I noticed that we didn't have very many TAs that would come and talk to our group.

If students ended up at a table that did not form an early relationship with a TA, or that gave off an appearance of disengagement, they may have been at a disadvantage when it came to receiving help from the professor and TAs.

In the student interviews, I asked participants whether they thought that assigned groups would be better than students choosing their own groups through where they sat on the first day of class. Participants were mixed in their responses. Some thought it would improve the course experience. José thought that assigned groups would benefit students who tended to be shy:

> It would help those students that feel like, it doesn't even matter necessarily just about race or cultural identity, it matters that some people are too shy or introverted to want to talk to other people and feel a little intimidated by larger groups or things like that, and that can sometimes cause them a lot of stress. And if they're stressed and they feel awkward, then they're not necessarily going to want to come to class. But by randomly generating a roster and seating chart I think that will kind of work to the advantage of the students having to get to know each other.

Caitlin felt that it would facilitate communication between students: “if you come in knowing what to expect, it forces you guys to talk to each other more right away and get that awkward communication phase out of the way.” José recommended randomly assigning students based on a pre-course assessment, so that “it's not like one super group where all these people have seen this material and they're super awesome … and then other groups were like, they’re completely lost.”

Other participants were not in favor of assigned groups. Laura felt that predetermined groups may lead to a heightened discomfort level: “I think [students would] want to sit by someone that they're comfortable with because I'm not super comfortable asking for help off of someone that I'm not friendly with.” Alexis had a similar attitude:

> I sit by people who I feel like are either going to help me a lot or I can become friends with, so talk to about stuff. So that would be the only drawback to

> assigned seats. It's like the teachers are controlling who you're by and with that sometimes students don't really identify with those types of people.

The instructors' lack of facilitation of the course's group work component meant that while some students enjoyed positive table dynamics, others were more isolated at their tables.

Negative effect of lecturing. In Isaac's class, participants felt that his lecturing was not only ineffective, but that it also negatively affected the climate. Nour described how lecturing fueled a disengaged atmosphere:

> It's very easy to have your laptop open and because he's so quiet, you could tune him out and spend 50 minutes on Amazon and look for socks. I've done that before. He doesn't ever check in, he doesn't ask questions, he doesn't really catch the attention of anybody. He just goes and talks to his pen that he's writing with.

Caitlin had a similar perception:

> It's just a very strange experience really because [Isaac] just talks for probably 30 minutes, just rambling on about these random things, and I'm not sure if it's just, you know how those teachers in high school whose voice just puts you to sleep.

Ying talked about how the lecturing also contributed to confusion and frustration:

> If you lecture for too long, like maybe 30 minutes out of the hour, then I feel sometimes you'll get students thinking "oh my gosh, why is he talking so much," they'll be in that mood and they'll be like "I don't really understand."

Some of the participants who had Isaac talked about how he would go off on tangents during his lectures, often about the history of math, which caused an especially negative reaction. Amina explained, "Sometimes he'll go off on a tangent, the history [of math] and who started it and by the time you get to group work nobody knows what they're doing. It's a whole 50 minutes kind of wasted." For the students in Isaac's sections, his lecturing compounded the frustration and disengagement that were caused by a lack of guidance, communication, structure, and organization. These negative experiences were partially ameliorated by the smaller TA- and peer-led sections.

Smaller sections improved the climate. Many of the interview participants felt that the small TA-led sections on Tuesdays and peer-led sessions on Thursdays were when they were able to make sense of the material. According to Alexis, "The only structure I feel is in the discussions." Nour described what a typical Tuesday section was like:

> On Tuesdays when [the TA] was like, "What questions do you have?" Everybody would open their mouth and be like "What's going on? What was yesterday, I didn't understand a word [the professor] said?" And Tuesdays is a time for us to learn it for the first time.

Jake believed that these smaller sections were opportunities for receiving more guidance, as well as a more structured approach to covering content:

> I feel like since the Monday, Wednesday and Friday classes we spend most of the time just working on your own and sometimes you don't even know what you're doing exactly because they just throw a worksheet in front of you and you try to figure it out yourself. So the Tuesdays and Thursdays I tend to find that it's where you learn how to do things their way, the right way … they actually take the time to go through step-by-step.

For Amina, the Thursday peer-led session helped to alleviate the anxiety she felt around not knowing what would be on the upcoming exam:

> I feel [the Thursday section is] when everything really comes together and [the peer tutor] narrows exactly what's going to be on the quiz the following day or the exam … there's practice problems and what he thinks is going to be on the quiz and they're usually kind of spot on.

Interview participants seemed to associate these smaller sections with a sense of relief that the content and expectations were being clarified for them.

In addition to a greater sense of clarity, participants also described these sections as having a more comfortable, less intimidating atmosphere. Laura commented, “The Tuesday, Thursday sessions are very helpful because you're comfortable and you can ask questions.” Ying expressed a similar sentiment: “the TA and the [peer] session is a lot more helpful to me because it's a smaller setting. I feel it's in a way more comfortable to ask because you guys see each other a lot.” Matt echoed Laura and Ying, saying that “I feel like it's more open, friendlier.”

Another contrast with the larger sections was that the smaller ones were often characterized as having high levels of energy and student engagement. According to Alexis:

> In the lecture, students are not as engaged as they are in the discussions from my point of view. Most of the time [in the lecture] we just listen to Isaac and then we do independent work so there is not really that time for questions in those lectures. When there's discussion [sections], that's when we can ask all the questions that we have.

The smaller TA- and peer-led sections alleviated both the sense of confusion and the lack of engagement that permeated the course.

Tensions around professor responsibility vs. student responsibility. In both the student and professor interviews, there was a tension between how much responsibility the students needed to take on to succeed in the course versus how much was the responsibility of the instructors. Whereas in the sections above, students saw a lack of guidance as a failing of the instructors that negatively affected their experiences and learning, Laura saw the course as an opportunity to learn how to take on individual responsibility:

> [The course is] structured so differently that a lot of it is on you and on your time, I think it's a good independent course teaching those kinds of lessons of how to manage your time and get everything done and schedule it, that you're getting everything done outside of class. So it's a lot of work that is on you which I think is nice because it's preparing you for the future or preparing you for other college courses.

Hanh also appreciated the responsibility for learning that was put on the students: "I think it's cool that we are also based in this kind of format where we kind of have to learn ourselves."

Some interview participants expressed a view that students needed to take on responsibility for their learning. Devin remarked:

> I don't believe in, "oh it's the teachers' fault if I don't do well," I don't believe in that … part of me thinks that maybe it's rare to have a legitimately bad class or a bad teacher because people are always going to learn stuff they want to learn.

Matt also tended to place the burden of responsibility on the student:
“It's everyone paying for school, they don't have to be here if they don't want to be.” In a similar vein, Caitlin did not believe that the instructional staff had a responsibility to help students who were clearly disengaged: “It's not like [the instructors] don't care, but they're only going to care about the students that want to care, which is kind of the purpose of college in these general education courses.”

The interviews with Isaac and Dan also touched on the question of responsibility. Dan spoke about the need for students to take on more responsibility, which can be difficult for first-year students:

> Your first semester in college, and life is different and you have to take on the responsibility yourself, and just be able to take on personal responsibility to get the job done, is much more their responsibility than the teacher's responsibility now. And that's a struggle area.

Dan acknowledged that the expectation could cause tension with students: “[The students’] expectation of a math course is that somebody else tells them how to do math, and I don't do that for them.”

Isaac spoke at length about student motivation. He believed that there were some students who were intrinsically motivated: “You're motivated because you have some, either emotional or whatever you want to call it, but you have some sort of internal investment, some desire to find out what's next, find out where this goes.” During the second interview, Isaac argued that those students would have succeeded regardless of the teaching approach: “The people that did the best in the class will probably be the people who would have done well anyway." On the other hand, for students who lacked motivation, Isaac felt there was little that could be done to get them to succeed:

> I don't really know what to say to people to make them care. It's the motivational aspect is something that has to come from more than just our mouths because they'll just look and say, oh well, that old man up there is just rambling on and he's telling me why I should care about this. The thing is people have to find out for themselves.

Isaac believed that students were unmotivated because they lacked a clear purpose for pursuing higher education. He argued, "There's no method of education that works for a person who doesn't know what they want to be."

Both Dan and Isaac seemed to think that at least some of the students in the course did not want to take on the level of responsibility required of them. Many of the students I interviewed talked about students needing to take on more responsibility for their learning. Yet, almost all of the participants also felt that the professors should have done more to clarify and communicate the course structure and expectations and guide and facilitate learning. For both the professor and student interview participants, the exact point where responsibility shifted from the instructor to the student was ambiguous.

Mixed Methods Meta-inferences

The next two pages present the meta-inferences for the research questions explored in this chapter. The quantitative and qualitative findings about how pedagogy influenced the classroom climate were complementary. While the survey data revealed correlations between students' perceptions of pedagogy and the factors that influence the classroom climate, the qualitative data demonstrated specific ways in which pedagogy shaped the climate.

Table 13

Mixed Methods Meta-inferences for Research Questions 2a and 2b

Research question	Meta-inference
2a. How does the course pedagogy align with traditional pedagogy, active learning, and/or inclusive pedagogy?	Qualitative only: • The course pedagogy was most closely aligned with the active learning paradigm, although there were aspects of all three paradigms. • While Isaac's espoused theory of learning and view on the role of the professor were aligned with the active learning paradigm, in practice his actions were often more aligned with the traditional pedagogy paradigm. • Dan believed that an important part of his role was to validate students, which is an aspect of inclusive pedagogy. • While the course content and assessment methods did not fit under just one paradigm, they were most closely aligned with the traditional pedagogy paradigm.

2b. How does pedagogy influence the classroom climate?	*Complementary:* For this question, the quantitative and qualitative strands came to separate but complementary conclusions: • With the survey data, there were several positive, statistically significant correlations between students' perceptions of teaching and assessment strategies that were utilized and the classroom climate scales. Teaching strategies had more statistically significant correlations with the climate scales than assessment strategies. In-class group work and class time for individual questions had the most statistically significant correlations, suggesting they had a closer association with climate perceptions than the other pedagogical strategies in use. • The qualitative analysis revealed that pedagogy contributed to a sense of collective confusion and frustration through a lack of structure and organization, communication, and guidance. • In Isaac's sections, his lecturing contributed to an atmosphere of frustration and disengagement. • A lack of facilitation around group work led to differentiated experiences regarding student-student interaction. Some interview participants had tightknit and collaborative relationships with the students at their table, but other students lacked interaction and strong relationships. • The qualitative data revealed that the smaller TA- and peer-led sections improved the climate through providing more structure and guidance. The smaller sections also tended to provide a more comfortable environment and be more interactive. • In the professor and student interviews, there was tension around the extent to which student learning and the classroom climate were the responsibility of the professor versus the responsibility of the students.

Chapter Six: The Influence of the Course on FG Students' Academic Plans

This chapter responds to the research question:

RQ3: How do first-generation (FG) students' experiences in the course influence their intentions to take additional mathematics courses and persist in STEM?

I first present quantitative evidence that explored FG survey respondents' academic plans. I then summarize what interview participants shared with me about how the course experience had influenced (or not influenced) their plans. I end the chapter by presenting mixed methods meta-inferences.

Quantitative Findings

Table 14 reports the results of questions about the influence of FG respondents' experiences in the course on their intention to major in a STEM field and their intention to take additional math courses. Regarding the intention to pursue STEM, 12% of FG respondents said they had never planned to major in STEM and 48% said that the course had no influence on their plans. Of the FG respondents, 20% said that it had made them much less or slightly less likely to major in a STEM field and 20% said it had made them much more or slightly more likely to major in a STEM field. With respect to taking additional math courses, 8% of FG respondents said they had never planned to take additional courses and 45% said it had no influence. Twenty-one percent said it had made them much less or slightly less likely to take additional courses and 16% said it had made them much or slightly more likely.

Table 14

Impact of Course Experience on Future STEM and Math Intentions Among FG Students (n = 65)

To what extent, if any, has your experience in this course influenced your intention to major in a science, technology, engineering, and mathematics (STEM) field?	
I have never planned to pursue a major in a STEM field	8 (12%)
It has made me much less likely to major in a STEM field	4 (6%)
It has made me slightly less likely to major in a STEM field	9 (14%)
It has not had any influence	31 (48%)
It has made me slightly more likely to major in a STEM field	9 (14%)
It has made me much more likely to major in a STEM field	4 (6%)
To what extent, if any, has your experience in this course influenced your intention to take additional math courses?	
I have never planned to take additional math courses	5 (8%)
It has made me much less likely to major in a STEM field	6 (9%)
It has made me slightly less likely to major in a STEM field	8 (12%)
It has not had any influence	29 (45%)
It has made me slightly more likely to major in a STEM field	7 (11%)
It has made me much more likely to major in a STEM field	10 (15%)

I also analyzed respondents' intended major at the beginning of the semester and whether their intended major had changed, for both CG and FG students. Fifty-nine percent of FG respondents were classified as STEM throughout, meaning that they were at least considering pursuing a STEM major at both the beginning of the semester and at the time of taking the survey; in comparison, 54% of CG students were classified as STEM throughout. Twenty-six percent of FG respondents were classified as non-STEM throughout (including those who remained undecided), compared to 39% of CG respondents. Finally, 15% of FG respondents had either left STEM or were considering leaving STEM at the time of the survey, compared to 7% of CG students (see table 15).

Table 15

CG and FG Respondents' STEM Status During Study

	CG (n = 96)	FG (n = 66)
STEM throughout	52 (54%)	39 (59%)
Non-STEM throughout	37 (39%)	17 (26%)
Left STEM or considering leaving STEM	7 (7%)	10 (15%)

Next, I compared the FG STEM throughout respondents ("STEM stayers") with those who had left or were considering leaving STEM ("STEM leavers") on the questions about the impact of the course on their intentions to pursue STEM and math. Among the 10 FG STEM leavers, 60% said the course had made them much less or slightly less likely to pursue STEM, compared with 13% of the STEM stayers. Twenty percent of the leavers said the course had no influence on their STEM persistence intentions, compared with 54% of the stayers. None of the leavers said the course had made them more likely to pursue STEM, compared with 29% of stayers. Fifty percent of the leavers said the course had made them much less or slightly less likely to take additional math courses, compared with 13% of STEM stayers. Twenty percent of leavers said the course had had no influence on their plans to take additional math courses, compared with 46% of stayers. Ten percent of the leavers said the course made them more likely to take additional math courses, compared with 38% of stayers (see table 16).

Table 16

Impact of Course on FG STEM Leavers (n = 10) and Stayers (n = 39)

To what extent, if any, has your experience in this course influenced your intention to major in a science, technology, engineering, and mathematics (STEM) field?

	Left or considering leaving STEM	Stayed in STEM
I have never planned to pursue a major in a STEM field	1 (10%)	2 (5%)
It has made me much less likely to major in a STEM field	2 (20%)	1 (3%)
It has made me slightly less likely to major in a STEM field	4 (40%)	4 (10%)
It has not had any influence	2 (20%)	21 (54%)
It has made me slightly more likely to major in a STEM field	--	8 (21%)
It has made me much more likely to major in a STEM field	--	3 (8%)
NA	1 (10%)	--

To what extent, if any, has your experience in this course influenced your intention to take additional math courses?

	Left or considering leaving STEM	Stayed in STEM
I have never planned to take additional math courses	1 (10%)	1 (3%)
It has made me much less likely to take additional math courses	3 (30%)	1 (3%)
It has made me slightly less likely to take additional math courses	2 (20%)	4 (10%)
It has not had any influence	2 (20%)	18 (46%)
It has made me slightly more likely to take additional math courses	1 (10%)	6 (15%)
It has made me much more likely to take additional math courses	--	9 (23%)
No response	1 (10%)	--

I then looked at some characteristics of the STEM FG leavers and stayers. Eight of the ten leavers were in Isaac's class (80%), compared with 54% of the stayers. Eighty percent of the leavers had non-dominant gender identities (women, agender/non-binary, or gender queer/gender non-conforming), compared with 67% of the stayers. Fifty-seven percent of leavers were classified as underrepresented racial and/or ethnic minoritized

(URM), compared with 66% of stayers. However, it should be noted that 20% of the leavers indicated “something else” or “prefer not to answer” as their race; the percentage of White students among both the leavers and stayers was roughly even (30% and 28%, respectively). Thirty percent of leavers were eligible for a Pell grant compared with 67% of stayers. The two groups were roughly even when it came to eligibility for the institution’s need-based scholarship (40% and 44%, respectively) and whether they had taken out student loans (50% and 51%, respectively). Table 17 summarizes the demographic information for the leavers and stayers.

Table 17

Distribution of Demographic Indicators for FG STEM Stayers and Leavers

		Leavers (*n* = 10)	Stayers (*n* = 39)
Professor			
	Professor 1(Dan)	2 (20%)	18 (46%)
	Professor 2 (Isaac)	8 (80%)	21 (54%)
Gender			
	Agender/non-binary	1 (10%)	--
	Gender queer/gender non-conforming	1 (10%)	--
	Man	2 (20%)	13 (33%)
	Woman	6 (60%)	26 (67%)
Race/ethnicity			
	Asian – non-URM	--	1 (3%)
	Asian – URM	2 (20%)	11 (28%)
	Black/African American	1 (10%)	8 (21%)
	Latinx/Hispanic	1 (10%)	4 (10%)
	Mixed race	1 (10%)	1 (3%)
	Native American	--	--
	White	3 (30%)	11 (28%)
	Something else	1 (10%)	3 (8%)
	Prefer not to answer	1 (10%)	--
URM/non-URM			
	URM	4 (57%)	23 (66%)
Pell grant eligibility			
	Eligible to receive Pell grant	3 (30%)	26 (67%)
Institution’s need-based scholarship eligibility	Eligible to receive institution’s need-based scholarship	4 (40%)	17 (44%)
Student loans status			
	Has taken out student loans	5 (50%)	20 (51%)

Finally, I examined differences between leavers and stayers with regard to the classroom climate scales. Table 18 reports the mean value for each group on each scale, the difference between the two means, and the corresponding effect size. For all seven scales, the stayers scored higher than the leavers. For the participation and professor-student interaction scales, there were large effect sizes for the mean difference between the two groups (*d* = .88 and .77, respectively). For physical space and discrimination, the effect sizes were moderate (*d* = .68 and .61, respectively). For student-student interaction and cohesion, TA-student interaction, and inclusion of diverse backgrounds, there were small effect sizes for the mean difference between the two groups (*d* = .48, .34, and .32, respectively).

Table 18

Mean Response on Classroom Climate Scales for FG Stayers (n = 10) and Leavers (n = 39)

Scale	Mean (SD) for stayers	Mean (SD) for leavers	Difference in means	*d*
Discrimination	3.23 (.58)	2.88 (.53)	0.35	0.61
Inclusion of diverse backgrounds	2.26 (.73)	2.03 (.75)	0.23	0.32
Participation	2.91 (.70)	2.27 (.87)	0.64	0.88
Physical space	3.06 (.64)	2.6 (.83)	0.46	0.68
Professor-student interaction	2.66 (.72)	2.07 (.96)	0.59	0.77
Student-student int./cohesion	2.97 (.61)	2.66 (.77)	0.31	0.48
TA-student interaction	3.26 (.58)	3.02 (1.1)	0.24	0.34

I performed t-tests to test the statistical significance of these differences. Because I was performing seven t-tests, I made a Bonferroni adjustment, setting the alpha level to .007. None of the differences were statistically significant. Given the moderate and large effect sizes, it is likely that a larger sample size would have yielded statistically significant differences. For example, according to a power analysis, in order to have a 90% chance of detecting an effect size of .88 with an alpha level of .007, I would have needed a sample size of 86 (43 in each group). To detect an effect size of .4, I would have needed a sample size of 400 (200 in each group). Because there were only 10 respondents in the "leavers" category, the lack of statistical significance is not surprising.

Qualitative Findings

Out of the interview participants, one student believed that the course had had a negative effect on their STEM persistence plans, three believed there was a positive effect, and nine said there was no impact. Caitlin was the participant who said there was a negative effect on her academic plans. She explained:

> [The course] definitely influenced [my plans] because I was originally going to go into a health-based major. It definitely influenced that because I was like, if I switch it I don't have to go up and take calculus … it's definitely had some influence on what I like and don't like. It's definitely had some impact.

While Caitlin did not attribute this negative effect to any specific aspect of the course, there were many factors that contributed to her negative experience. Caitlin appreciated the TAs and sat at a collaborative table, but felt highly frustrated with the course in terms of its lack of structure and guidance. She held negative views of Isaac, proclaiming that he did not care about students and that he failed to provide a "driving force" for the class. She also believed that being first-generation made it harder to pick up on "little tips" that helped other students in the course.

Devin noted a positive effect of the course on his intention to major in computer science:

> In a way I took this class really to see can I vibe with these topics … it was really just to see, can I like this, can I even do this. And I would answer yes to both of those questions. So it has helped me.

When I asked Devin at the beginning of the interview how the course was going, he said it was going well because he appreciated the focus on conceptual learning: "I personally like [the class] because the focus is a lot on understanding the concepts and understanding the logic behind the math and I feel that that's just key for doing well in math." Devin enjoyed the course despite noting the disengaged climate and the lack of motivation among many of his peers.

Matt was considering pursuing math as a major as a result of the course:

> I think [the class has] made me entertain the idea of more going on the road of a mathematic goal major maybe. Because I've never before this chapter learning about graphs, graphing, rational functions and polynomials, I've never known about this so I just think it's cool. And [Isaac] was telling us how you can apply it in real-life with, I want to say CDs and something and the bumps on CDs and how you can angle them or something with this same concept to produce different sounds and all that. So I thought that was interesting so it kind of opened my eyes to a lot of stuff you can do with math.

Matt also received encouragement from the TAs:

> I've also talked to the TAs too and I kind of gotten their perspective on what can I do with a major in this. And one of them I've talked to said he loves it and he's taking a math class based on just proving certain theories which I thought was really cool and exciting.

Matt very clearly appreciated the relationships he had formed with the other students at his table, explaining that "if I didn't have that, it wouldn't be one of my more favorite classes." Jake was the third participant who felt that the course had made him more likely to take additional math courses.

Matt, Devin, and Jake echoed the other participants in some of the criticisms of the course, especially around the larger sections being less effective. However, their experiences were not overwhelmingly negative. The tables where they sat were collaborative and they found the TAs to be very helpful. All three have positive associations with math. Jake described himself as a "numbers person," Matt talked about how he had always liked math, and Devin mentioned that much of the material was repeat for him.

Of the students who said there was no impact, some, such as Nour and Maria, said there was no impact because they did not have to go much further in math for their major, and felt they would be able to complete their remaining math courses. Amina still planned to pursue the same major, although she wanted to skip the next math class and go straight on to Calculus 1 in order to avoid a similar course format: "I feel like pre-calc 2 is the same kind of setup as this one, so I might just end up skipping to calc 1." While the course did not alter José's plans, he also said that he would avoid courses with a similar pedagogical approach in the future:

> I've decided now that I'm going to ask a lot of questions as to how is the class set up and things like that before I take one. Just so that I don't repeat the mistake I did of not asking a lot of questions beforehand. I thought [the course] was going to be a regular lecture-based class.

While the interview participants tended to have more negative than positive views of their experiences in the course, they varied in terms of the extent to which those experiences affected their intentions to persist in STEM.

Mixed Methods Meta-inferences

The table on the following page provides meta-inferences for the question about how students' experiences in the course influenced their math and STEM persistence intentions. For this research question, the quantitative and qualitative findings were largely convergent.

Table 19

Mixed Methods Meta-inferences for Research Question 3

Research question	Meta-inference
3. How do FG students' experiences in the course influence their intentions to take additional mathematics courses and persist in STEM?	*Convergent:* • Nearly half of survey respondents said the course had no impact on their intention to take additional math and STEM courses. The remaining respondents were split in terms of whether the course made them less or more likely to take additional math and STEM courses. Among the interview participants, one student believed that the course had a negative effect on their STEM persistence plans, three believed there was a positive effect, and nine said there was no impact. • The FG survey respondents who were considering STEM at the beginning of the semester but then were considering or decided to leave STEM scored lower on all of the classroom climate scales compared to the STEM stayers. These differences were largest for the participation, professor-student interaction, physical space, and discrimination scales. The interview participant who reported a negative effect of the course on her persistence intentions was highly frustrated with the course; her experience was representative of many of the negative climate themes that emerged in the qualitative analysis. The three students who reported a positive effect, who were all White men, had criticisms of the course but reported an overall positive experience. They all sat at collaborative tables, found the TAs to be helpful, and had positive associations with math.

Chapter Seven: Discussion, Implications, and Conclusion

In this chapter, I discuss how the findings of my study align with and extend the literature on classroom climate and pedagogy in introductory STEM courses. I first explore the connections between pedagogy and classroom climate and provide some implications for my conceptual framework based on my findings. Next, I discuss my findings in the context of the three teaching and learning paradigms. I also contextualize my findings on the influence of the course on students' persistence intentions within the STEM education literature. I then provide the implications of my study for practice, institutional leadership, and research. Finally, I discuss the limitations of my study and give some concluding thoughts.

Discussion

The connections between classroom climate and pedagogy. In this section, I tie my findings to the literature on how pedagogy influences the classroom climate.

Confusion, frustration, and disengagement: negative reactions to pedagogy. Regarding the overall climate of the course, the interview participants tended to describe a classroom characterized by disengagement and collective confusion and frustration. The confusion and frustration caused students to disengage, and the disengagement in turn led to more confusion. At least among the FG students I interviewed, these aspects of the climate did not seem to be experienced differently by students with multiple marginalized identities (e.g., FG women, FG students of color). The literature has explored student disengagement and expressions of frustration in the classroom in three ways: as classroom incivilities, as signs of resistance to pedagogy, and as signs of low student motivation (Ambrose et al., 2010; Boice, 1996; Borrego et al., 2018). In all three cases, student frustration and disengagement are the result of negative reactions to the teaching and learning strategies being utilized.

The specific aspects of pedagogy that were causing these negative reactions, which will be discussed in subsequent sections, were: a lack of structure, organization, and communication; a lack of problem-solving guidance and facilitation around group work; and a test-based assessment system. In Isaac's sections, students were also reacting negatively to lecturing and a lack of instructor immediacy. In addition, many of the students I interviewed had not taken courses before that used a flipped classroom model or that were taught in an active learning classroom. While the participants did not say so explicitly, it is possible that this lack of previous exposure contributed to their negative reactions.

Many of the student behaviors I observed, such as leaving early, being on their phones, and sighing loudly, can be characterized as classroom incivilities (Boice, 1996). According to Feldmann (2001), "Classroom incivility is any action that interferes with a harmonious and cooperative learning atmosphere in the classroom" (p. 137). Boice's (1996) study of introductory courses at a large, public research university drew attention to this issue. Boice found that about half of the courses were characterized by "chronic, disheartening patterns" (p. 479) of classroom incivility. In these courses, in which students expressed annoyance and demoralization, professors tended to be less aware of classroom incivilities than students were. Boice explained that "with persistent CI [classroom incivility], students grew more and more uninvolved, oppositional, combative" (p. 480). The author believed that the main driver of high levels of classroom incivility was a lack of instructor immediacy (i.e., warmth, approachability).

Bingham, Carlson, Dwyer, and Prisbell (2009) studied the link between classroom incivility (using the term *student misbehaviors*) and classroom climate, focusing specifically on students' sense of connectiveness with other students. The authors found that:

> Students' perceptions that the students in their class engage in *inconsiderate* misbehaviors such as passive disruptions (e.g., coming to class unprepared), leave-taking disruptions (e.g., making book bag sounds), time-taking disruptions (e.g., arriving late for class), side-conversation disruptions (e.g., whispering to another student during lecture), and inattentive disruptions (e.g., ignoring or not turning in assignments) are inversely related to student perceptions of classroom connectedness. (p. 49)

These five types of disruptions (passive, leave-taking, time-taking, side-conversation, and inattentive) were all present in the pre-calculus class. Although some of the interview participants in my study believed that the collective expressions of confusion and frustration led to a greater sense of cohesion among students, Bingham et al.'s findings suggest that these negative expressions can harm the sense of connectedness among students in a course.

Students' frustration and disengagement can also be understood as forms of resistance to the course pedagogy (Borrego et al., 2018; Seidel & Tanner, 2013). Some of the student behaviors, such as being on their phones instead of participating in group work, were forms of passive resistance. Other actions, such as talking over the professor, are examples of active resistance (Seidel & Tanner, 2013). Kearney, Plax, Hays, and Ivey (1991) studied students' self-reported reasons for their resistance in the classroom.

Common reasons included a lack of clarity about expectations and content, the professor straying from the subject, and boring lectures. There is an extensive body of literature on student resistance to active learning in higher education (e.g., Borrego et al., 2018; Ellis, 2015; Finelli et al., 2018; Seidel & Tanner, 2013). Often, students do not resist the active learning methodology itself but rather the way in which it is implemented by the instructor (Seidel & Tanner, 2013). Indeed, most of the interview participants were not opposed to a flipped classroom format per se; instead, they were reacting negatively to a sense of disjuncture and the instructors' lack of clarity. In my conceptual framework, quality of implementation should be seen as a factor that mediates the influence of pedagogy on the classroom climate.

In addition to resisting pedagogy, student disengagement can be a sign of low motivation. Students lose motivation when they do not see the value of what they are doing or do not believe they can be successful. Appearing disengaged can be a sign of work-avoidant goals, reflecting a desire to finish the task as quickly and with as little effort as possible. Strategies for motivating students include connecting course material to students' lives and future goals; providing authentic, real-world tasks that are challenging but attainable; communicating clear expectations; and providing constructive feedback (Ambrose et al., 2010). In the pre-calculus course, these elements were largely missing.

The three aspects discussed in this section are not mutually exclusive but rather build on each other. When students react negatively to pedagogy, they engage in resistance, which can take the form of classroom incivilities. Dissatisfaction with pedagogy lowers students' motivation levels, causing them to disengage. Dan and Isaac tended to ignore these negative reactions. The instructors did not seem to alter their pedagogical approach, nor did they address the students' incivilities. Indeed, student resistance in the classroom is often met with resistance on the part of the instructor (Ropers-Huilman, 1999; Sidelinger, Bolen, Frisby, & McMullen, 2012). My findings demonstrated several ways in which the actions of the two professors affected the classroom climate.

Role of the professors in shaping the climate. FG students in Dan's section perceived their interactions with the professor differently than students in Isaac's sections. Students in Dan's class picked up on small cues that demonstrated that he cared about their success; as such, he played a validating role (Rendón, 1994). These cues included him asking what their name was or asking them to show him how they had approached a problem instead of simply giving them the answer. Study participants who were in Isaac's sections felt less positively about their interactions with him, and some of the interview participants described him as aloof and unapproachable. Given the importance of students perceiving the instructor as approachable and caring (Gasiewski et al., 2012), this put students in Dan's section at an advantage. Efforts to learn students' names are especially impactful and likely contributed to this difference, as Isaac did not make this attempt (Tanner, 2011).

Dan conveyed a higher level of instructor immediacy, which is the use of behaviors that "effectively decreases the social distance between [the instructor] and their students" (Seidel & Tanner, 2013, p. 591). Such behavior includes smiling, looking students in the eye, and moving around the classroom. Instructor immediacy is associated with positive student outcomes such as higher motivation and learning (Seidel & Tanner, 2013). The instructor's demeanor sets the tone for the course, and acting aloof can send students a message that the course is not a safe environment to ask questions or make mistakes, or that it is acceptable to disengage or carry out classroom incivilities (Boice, 1996; Borrego et al., 2018). Given the importance of these subtle behaviors, my conceptual framework should explicitly consider them as a component of one's teaching strategies that can influence the classroom climate.

This study produced some evidence that students' experiences with the professors varied by race and ethnicity. A regression analysis found that Latinx and mixed race survey respondents, on average, scored lower on the professor-student interaction and inclusion of diverse background scales. The inclusion of diverse backgrounds scale included items about the professor's sharing of their own backgrounds and experiences. As such, the lower scores on these two scales suggest that Latinx and mixed race students had more negative perceptions of the instructors and were also less likely to agree that the professors shared personal information about themselves. Because the regression analysis controlled for which professor the respondents had, it appears that these dynamics existed for both Isaac and Dan. The finding that there were some differences by race and ethnicity in students' perceptions of the professor aligns with other studies that have found students of color to view their interactions with White professors less positively (Hurtado, Cuellar, & Guillermo-Wann, 2011). It is possible that because both Dan and Isaac were White, it was more difficult for Latinx and mixed race students to relate to them or view them as approachable (Espinosa, 2011; Harper, 2013; Holmes, 2013; Hurtado, Eagan, et al., 2011; Rendón, 1994).

In the series of regressions that used the climate scales as dependent variables and student demographics as independent ones, the R-squared for the professor-student interaction and inclusion of diverse backgrounds scales was large, suggesting that students' experiences of these factors may vary based on their multiple social identities. Among the FG survey respondents, STEM leavers scored substantially lower on the professor-student interaction scale compared to STEM stayers. While this does not imply causation, it suggests that interactions with the professors could have played a role in whether students wanted to continue to pursue STEM or not, and that this dynamic may have disproportionately harmed minoritized students. Taken together, the findings of this study are aligned with others in that student interactions with faculty play a large role in shaping their overall experiences, and that these interactions are not experienced evenly across different student groups (Cantú, 2012; Fries-Britt et al., 2010; A. Johnson, 2007; Rendón Linares & Muñoz, 2011). In reforming introductory STEM courses, one priority should be to increase the extent to which underrepresented students believe that the professor takes a personal interest in them and cares about their success. In the pre-calculus course, the teaching assistants also played an important role.

Role of the teaching assistants in shaping the climate. Although the survey results demonstrated a range of student perceptions of their interactions with the TAs, the interview participants universally appreciated the teaching assistants. In the regression analysis that predicted perceptions of TA-student interactions using student demographic variables, the R-squared was lower than most of the other scales, suggesting that students generally did not have different experiences with the TAs based on their identities. Interview participants believed that the TAs tried hard, cared about students succeeding in the course, and were relatable and approachable. These qualities in the TAs take on heightened importance in courses where the instructor lacks immediacy (Seymour & Hewitt, 1997).

Some of the literature has highlighted the positive role that TAs can play (Hsu, Murphy, & Treisman, 2008; Philipp, Tretter, & Rich, 2016). Mervis (2010) described a reformed introductory chemistry course in which the TAs acted as “Sherpas … guiding students up the mountain” (p. 306). A study that surveyed students in gateway science courses at a large research university found that students who felt that their TAs created a warm climate in the lab were more likely to plan on staying in STEM (O’Neal, Wright, Cook, Perorazio, & Purkiss, 2007). Undergraduate TAs can serve as role models, may be eager to provide a better educational experience than they had, and also tend to be more relatable than the professor because they more recently were in the students’ position (Hsu et al., 2008; Philipp et al., 2016). Undergraduate and graduate TAs are important classroom actors that can validate students and provide a sense of belonging. While interview participants did not speak to this, it is possible that the gender and racial diversity of the TAs helped marginalized students feel a greater sense of belonging in the course (Schinske et al., 2016).

Despite positive findings, the reliance on TAs in large introductory STEM courses is often referenced, either implicitly or explicitly, as negative. For instance, Hurtado et al. (2011) discussed the “overabundance of courses taught by unqualified teaching assistants” (p. 572). In Benbow and Vivyan’s (2016) study of introductory computer science courses, students complained about overcrowded TA sessions. While the inclusion of TAs with teaching roles in introductory courses is not a cure-all, TAs should be seen as potential assets who are capable of improving the classroom climate for underrepresented students.

Lack of structure, organization, and communication. Most of the FG students I interviewed were deeply frustrated by the course's lack of structure, organization, and communication. It is possible that the interview participants, as first-generation students, were more affected by these dynamics because they were not as prepared for a course that required them to navigate confusion and ambiguity (Soria & Stebleton, 2012; Strayhorn, 2012). FG students often lack the social and cultural capital necessary to identify academic support resources because they have not been socialized to do so (Martin et al., 2014). The comparison between CG and FG survey respondents on the classroom climate scales suggests that FG students had a more negative experience in the course, which could have been due to difficulties they experienced coping with the lack of structure. Whereas most of the interview participants did not seem to think their first-generation status affected their experiences in the class, both José and Caitlin did recognize that as FG students, they were less prepared to seek out the resources they needed to be successful.

Some have argued that in order to be inclusive, a course must be highly structured so that students who are less comfortable with or knowledgeable about navigating university classes (e.g., going to office hours, emailing the professor) have clarity on what is expected of them (Supiano, 2018). According to Penner (2018), "An inclusive class is a structured class … putting the effort into creating structure for your students is a significant act of 'academic care'" (pp. A268-69). Clear structure and communication should be established at the beginning of the term through the course syllabus, which should lay out learning objectives for each class session (Penner, 2018). The pre-calculus syllabus lacked this level of organization.

Several studies have found that incorporating more structure into a course leads to improved student learning and persistence (Crimmins & Midkiff, 2017; Freeman, Haak, & Wenderoth, 2011; Pascarella et al., 2008). Eddy and Hogan (2014) compared two introductory biology courses. One was taught using a traditional, low-structure approach that used high-stakes exams and lecturing. The other was similar, but incorporated a moderate amount of structure by providing clear instructions for what students needed to do before, during, and after each class; using assessment mechanisms that made students accountable for doing out-of-class work; and incorporating carefully facilitated in-class collaborative group work. While performance in the more structured course was higher for all student demographic groups, it was disproportionately higher for Black and first-generation students. The authors also found that students viewed the climate of the moderately structured class more positively. Regarding my conceptual framework, a course's level of structure, organization, and communication should be considered as a fourth aspect of pedagogy that influences the classroom climate. A strong overall structure and communication system should be accompanied by guidance for students in day-to-day course activities.

Lack of guidance through the problem-solving process. The FG students I interviewed spoke about feeling lost and confused when working on problems in class. Students were presented with problems to work on but would never find out if they had correctly solved them, leaving them feeling frustrated. They also felt like they were given the problems without first having the level of knowledge they needed to be able to work towards a solution.

Going through a worksheet of problems is a loosely structured activity; the lack of structure at the activity level likely contributed to students' negative reactions to pedagogy, and may have also hindered their conceptual learning (Theobald, Eddy, Grunspan, Wiggins, & Crowe, 2017). Theobald et al. (2017) compared a loosely structured activity (students going through a worksheet in groups) with a highly structured jigsaw activity. During the jigsaw activity, each student was first given one of the three sections of the worksheet to work on individually, then discussed it with other students who had been given the same section, and finally met with students who had worked on the other two sections of the worksheet. In this version, the worksheet included guiding prompts about participation and turn taking. Students in the jigsaw version reported feeling more positively about group dynamics and demonstrated more gains in their conceptual knowledge.

Premo, Cavagnetto, and Davis (2018) compared undergraduate laboratory classrooms that used jigsaw activities with classes that used unstructured collaborative activities. The authors found that students in the jigsaw classes spent more time discussing problems and concepts with each other and were more supportive of their peers. Having a clear structure to active learning activities can provide students with a sense of what is expected of them, and is also likely to signal to them that the professor has thought through their approach.

Scaffolding is another strategy for mitigating student resistance to active learning by offering more support when an activity is new, and gradually decreasing support and encouraging more student autonomy as students grow more accustomed to the activity (Borrego et al., 2018). In the case of the pre-calculus course, the instructors may have wanted to model or guide students through an approach to solving problems in groups at the beginning of the term. As students grow accustomed to group work, the instructors can take a more hands-off approach and place more responsibility on students. Providing FG students with a high degree of guidance for active learning activities at the beginning of the term can help them build social and cultural capital that will assist them in navigating future active learning classes (Dika & D'Amico, 2016). In addition to scaffolding, communicating to students the intention behind classroom activities (e.g., saying to students that some struggling with concepts is important for learning) will also likely mitigate resistance (Borrego et al., 2018).

Lack of facilitation around group work and varied experiences interacting with other students. Whereas some students I interviewed reported having collaborative groups and forming tight-knit bonds with the students at their table, other interview participants lacked interaction with their group members. Given the importance of peer relationships for persistence in STEM, the fact that some students lacked collaboration is troubling (Fries-Britt et al., 2010; Harper, 2013; Seymour & Hewitt, 1997). The statistically significant correlations between FG students' perceptions of group work and many of the classroom climate scales provide some evidence of the importance of this component for students' affective experiences of the class.

In general, group work is thought to improve the classroom climate through encouraging interdependence and a sense of community, which may be especially beneficial for FG students (Ciani, Summers, Easter, & Sheldon, 2008; S. L. Eddy &

Hogan, 2014). However, group work needs to be well structured in order to achieve these benefits. Theobald et al. (2017) described high functioning groups as ones "in which teammates collaborate, participate equitably, and disagree productively" (p. 2). Unfortunately, groups are often dysfunctional, which can be due to a lack of preparation for working in groups among students, a lack of training on how to structure and facilitate groups on the part of the professor, or group tasks that are poorly structured (Theobald et al., 2017).

Because group work activities lacked structure in the pre-calculus class, active and equitable participation among group members was not achieved (Theobald et al., 2017). The literature offers various strategies that instructors can use to add structure to collaborative learning. Including students' contributions to group work in their grade encourages interaction, and peer assessment can hold students accountable to their groups (Hodges, 2018). Other ways to make collaborative learning more structured include sharing guidelines for group work with specific prompts and assigning each student a unique role (Tanner, 2013; Theobald et al., 2017). These strategies can increase equity and comfort for all students in the group (Theobald et al., 2017). It is likely that the unstructured nature of group work in the pre-calculus class decreased students' motivation and contributed to the disengaged climate (Premo, Cavagnetto, & Davis, 2018).

Several studies have addressed the question of whether the instructor should assign teams or whether students should select their own groups. When students are asked to form their own groups, they tend to sort themselves by demographic characteristics such as race and gender (Freeman, Theobald, Crowe, & Wenderoth, 2017). It is important for students to feel comfortable in their groups so that they do not disengage from group activities (Cooper & Brownell, 2016). One challenge in assigning teams is to avoid having students feel isolated or marginalized (e.g., a Black student at a table with all White students) (Tanner, 2013). Cooper and Brownell (2016) found that in the context of a biology classroom, it was important for lesbian, gay, bisexual, transgender, queer, intersex, and asexual (LGBTQIA) students to be able to choose who they worked with in order to feel comfortable with group work.

Ciani et al. (2008) compared sections of an undergraduate psychology course where the instructor assigned groups with sections in which students chose their own groups, and found that students reported a greater sense of community when they were able to choose their own groups. While not assigning groups risks that groups would be uneven in terms of previous exposure to course content, Harlow, Harrison, and Meyertholen (2016) found no difference in team effectiveness between mixed ability groups and equal ability groups in the context of an introductory physics class.

Allowing students to choose their own groups, however, is not without its tradeoffs. For instance, having groups that are all White or all students of color may lead to a negative racial climate and hinder cross-racial interactions (Hurtado, Milem, Clayton-Pederson, & Allen, 1998; Strayhorn & Johnson, 2014). When students select their own groups, a sense of exclusivity around certain groups may emerge, as was the case with the tables in the pre-calculus class that were perceived to be where the "popular kids" sat. The question of assigning groups in college classes is a nuanced issue. Assessment is another complex aspect of pedagogy that influences the classroom climate.

Assessment. As is often the case, while the pre-calculus course activities had been substantially redesigned, a large percentage of students' grades was still based on a traditional test-based approach (Shepard, 2000). Many of the interview participants tended to fixate on how they were assessed, which is consistent with the literature suggesting that students prioritize assessment over other course components (Gibbs et al., 2004). The exams caused a great deal of anxiety in many of the students I interviewed, and it was difficult for them to focus on course activities that were not directly related to an upcoming exam. The feeling of being unprepared for tests and not knowing what was on the upcoming test contributed to the overall atmosphere of confusion and frustration. This aligns with the literature that has found that a test-based approach to assessment can cause students anxiety, produce a competitive classroom climate, and harm students' sense of self-worth (Gibbs et al., 2004; Seymour & Hewitt, 1997). These dynamics can disproportionately affect students with marginalized identities whose past educational experiences make them more likely to doubt that they belong and can be successful in STEM (Rust, 2002).

It seemed that there was a sense of entrenchment in terms of the instructors' attitudes toward exams. While Isaac recognized that test anxiety was an issue for students, he still seemed to believe that tests were an appropriate form of assessment. According to Dan, the department likely would have discouraged a move away from exams. If it is not possible to eliminate tests, there are ways to reduce the anxiety they cause in students, including giving students the opportunity to submit corrections, as Laura suggested during her interview. In describing an introductory biology course taught in an active learning classroom, Langley and Guzey (2014) described how the instructor, through having students do a post-exam analysis, saw the exams as a learning tool.

Students often lacked feedback on their work. This focus on summative, rather than formative, assessment is also aligned with the traditional paradigm. Some forms of assessment, such as the exams and online homework and quizzes, were not designed in a way that allowed for feedback. For other assessment components, such as the written assignments and in-person quizzes, there was an opportunity for feedback, but a feedback mechanism was not built into the process. For example, students who waited until the last minute to take the quizzes did not have time to work through areas of confusion with a TA or instructor. The lack of feedback not only limited student learning, but also likely contributed to the disengaged classroom climate (Gasiewski et al., 2012). Lecturing was another aspect that caused disengagement.

Lecturing. Interview participants who were in Isaac's sections expressed negative attitudes about his lecturing. The influence of lecturing on the classroom climate seemed to align with other studies that have found that it often leads to a disengaged and impersonal climate (Barker & Garvin-Doxas, 2004; Gasiewski et al., 2012). Most of the interview participants were not opposed to all lecturing, but were rather dissatisfied with Isaac's approach to lecturing, characterized by long periods of him talking, often while looking down, without asking if students had questions. Seymour and Hewitt (1997) called this approach "silent teaching" (p. 154), which can be especially harmful for the climate. Lecturing that incorporates some interactive elements likely creates a warmer atmosphere than silent teaching (Hurtado, Eagan, et al., 2011). Gasiewski et al.'s (2012) study of introductory STEM courses found that some lectures could be quite engaging:

> Even when lecture was the primary vehicle for conveying course content, the professor's attitude, knowledge base, enthusiasm for the subject, and ability to explain the content clearly were all important characteristics that influenced students' level of engagement. These qualitative findings suggest that the lecture itself may not be the problem, but the style of lecture combined with the professor's own engagement profoundly impact students' engagement. (p. 247)

Even when classes take place in active learning spaces, they can still reflect traditional forms of pedagogy that cause students to disengage (Brooks & Solheim, 2014; Lester et al., 2016).

Participation and comfort in the active learning classrooms. There is some evidence of patterns in terms of which students were more likely to participate and feel comfortable in the physical classroom environment. In the regression analysis, White and non-URM Asian FG respondents scored higher on the participation and physical space scales, on average. In the comparison of FG and CG students, FG students scored lower on both of the scales. In observing the class, I perceived that men, and especially white men, seemed to feel more comfortable participating, taking up physical space, and being visible (e.g., leaving early or arriving late, sighing loudly). This is consistent with other studies that have shown that men are more likely to participate in class (Sarah L. Eddy, Brownell, & Wenderoth, 2014; Garvin-Doxas & Barker, 2004).

Taken in total, it seems that students with marginalized identities were more likely to feel uncomfortable in the classroom and less likely to participate. This may be indicative of prior educational experiences that told them they did not belong in a math classroom (Ochoa & Pineda, 2008). Among the FG survey respondents, the STEM leavers scored lower on the participation and physical space scales compared to the stayers, suggesting that it is important to pay attention to these issues. Active learning classrooms are often discussed in the literature as encouraging a warmer climate compared to traditional lecture halls (Park & Choi, 2014). However, it is important to note that even in these redesigned spaces, students with more privileged identities may still feel more comfortable in them. Just as an active learning classroom does not guarantee the use of active learning pedagogy, it also does not guarantee a more equitable climate. The impersonal and neutral manner in which the course content was presented may have also affected marginalized students' experiences in the course.

Ignoring issues of identity and discrimination. Issues of inequity, discrimination, and students' multiple identities were largely ignored by the instructors and their pedagogical approach. There was no incorporation of the societal implications of the content students were learning, the history of racism and sexism in the field of mathematics, or the contributions of people with underrepresented identities to the field. There was also not a recognition or incorporation of students' identities and backgrounds. This decontextualization mirrors a tendency to falsely frame the STEM subjects as neutral and objective, despite being historically rooted in Western European cultural practices (A. Johnson, 2007; le Roux, 2016). When these issues are ignored, students may default to associating those who succeed in math and science with White, upper-class men, a common stereotype that is pervasive in our culture. This in turn makes it difficult for students with marginalized identities to feel a sense of belonging, connect to the course material, and believe that they can be successful (A. Johnson, 2007; Schinske et al., 2016).

While Isaac and Dan acknowledged that there were inequities in math education during their interviews, they were reluctant to name and discuss specific forms of oppression such as racism and sexism. This tendency is common in STEM and reflective of a colorblind perspective (A. Johnson, 2007; McCoy, Winkle-Wagner, & Luedke, 2015). Colorblind ideology is “rooted in the perception that people should not notice racial difference, nor judge people based on their skin color because doing so actually invites divisiveness and tension” (Alemán & Gaytán, 2017). The absence of recognition of the ways in which math has excluded certain groups may have made it more likely that students saw their struggles as individual ones instead of structural (Seymour & Hewitt, 1997).

While student identities were not rejected in the class, they were also not affirmed (A. Johnson et al., 2011; Tierney, 2000). DeSurra and Church (1994) described a classroom climate continuum that ranged from explicitly marginalizing and implicitly marginalizing to implicitly centering and explicitly centering. By ignoring students’ identities and backgrounds, under this framework one could argue that the classroom climate was implicitly marginalizing. However, the FG students I interviewed, many who were women and students of color, described the course as welcoming to all students and devoid of discriminatory behavior. The interview participants also did not report any feelings of identity-based isolation (e.g., being the only woman of color or the only immigrant student) or being too visible (Davis et al., 2004).

The students with whom I spoke did not hold expectations that social issues would be incorporated into the class. Many of the interview participants talked about math as a subject without a social context, which led them to believe that identity was irrelevant in the course. This attitude, which seemed to be shared by the instructors, is consistent with the tendency to associate inclusive pedagogy with subjects such as ethnic studies and women's studies (Armstrong, 2011). According to Armstrong, a common misconception is that "if a course's content is not in direct conversation with issues having to do with difference and social justice, then that course's classroom is not a place where issues of inclusivity can be addressed or fostered" (p. 53).

These attitudes expressed by the students are also reflective of colorblind ideology. For students with both dominant and non-dominant identities who were educated in the United States, they have been socialized to buy into ideologies of meritocracy and colorblindness, seeing inequities as individual issues instead of systemic ones (Alemán & Gaytán, 2017; Eliason & Turalba, 2019). When I asked students about whether they thought discrimination was present or if underrepresented students may have had a different experience in the course, participants with both dominant and non-dominant gender and racial identities tended to talk about the issues in surface level terms (e.g., everyone was treated the same, no one was ignored, everyone had the opportunity to speak). This framing is also consistent with colorblindness, which "focuses on the surface, on the bare fact of racial classification, rather than looking down into the nature of social practices" (Haney López, 2006). This theme is similar to Eliason and Turalba's (2019) finding that third-year health education students tended to not see a connection between their comfort level participating in class and larger structural dynamics. The authors argued that the students "had not yet developed a worldview related to social structural determinants in regards to their own experiences in the classroom, and the majority fell back on individual level or classroom situation explanations for their lack of participation” (p. 1274).

While inclusive pedagogy argues that any class should weave in diverse representations, the FG students I interviewed did not seem bothered by the course’s decontextualized nature, and some even talked about appreciating the avoidance of social issues. Indeed, students with marginalized identities may appreciate opportunities to be anonymous in a classroom setting (Cooper & Brownell, 2016). In Johnson’s (2007) study, “Two American Indian women both majored in science partly because of the presumed absence of the ethnic” (p. 819). In addition, it is possible that underrepresented students felt welcomed because the course was relatively diverse for the institution (58% of students in the course were White compared with 68% of undergraduate students at the university), and students tend to be more aware of their minoritized status when they feel substantially outnumbered (Seymour & Hewitt, 1997; Vivyan, 2016).

There was some quantitative evidence that contradicted the interview participants’ beliefs that marginalized students did not have different experiences in the course. There is moderate evidence that first-generation survey respondents felt less positively about four of the factors that influence the classroom climate (discrimination, participation, physical space, and student-student interaction/cohesion). Among the FG survey respondents, White and non-URM Asian students felt more positively about participating in class and Latinx and mixed race students felt less positively about professor-student interaction and the inclusion of diverse backgrounds. Since FG students who were planning to leave STEM scored lower on the discrimination scale than FG students who intended to stay, it is possible that perceptions of discrimination in the classroom knowingly or unknowingly influenced decisions to leave. However, it is not possible to make arguments of causation based on my analysis.

These findings from the survey data are consistent with a large body of research that has found differential course experiences by race, ethnicity, and generation status (Booker, 2007; Collier & Morgan, 2008; Holmes, 2013; A. Johnson et al., 2011). The decontextualized approach maintained the status quo in terms of the students' and professors' views of math as devoid of a social context (Tuitt, 2016). It remains an open question as to whether this discouraged FG students from persisting in STEM or harmed their ability to see themselves as being successful in science and math. Additionally, it is possible that students who wished to see their identities reflected in course content avoided the pre-calculus class and STEM altogether because of the perception of STEM as being separate from societal issues (Eliason & Turalba, 2019). Another area of ambiguity was the tension between professor and student responsibility.

Professor and student responsibility. As discussed in the findings, a tension that emerged from analyzing the professor and student interview data was around how much responsibility the professors and students needed to assume for creating a positive climate and ensuring student learning. Both Dan and Isaac seemed to feel that students had not assumed a sufficient level of responsibility. While many of the students I interviewed believed it was important for students to shoulder a high level of responsibility, they also felt that the instructors had not done enough to create an environment in which students could be successful and enjoy the course.

The teaching and learning literature has explored the topic of professor and student responsibility. The inclusive pedagogy paradigm calls for there to be shared power and responsibility between the students and professor (Tuitt, 2003). Power sharing implies that students have an influence over what happens in the course, including policies and assessment. When students feel that their input was heard, they may be more motivated to take on additional responsibility (Weimer, 2002).

While student ownership over their learning can increase their motivation, expecting students to take on a high level of responsibility and autonomy may harm those who are less prepared to seek out resources by attending office hours or emailing the instructors, for example (Supiano, 2018). An attitude that students need to take on a high degree of responsibility may harm the classroom climate. For instance, Gasiewski et al. (2012) found that in the introductory courses where professors believed it was primarily the students' responsibility to succeed in the class, students were significantly less engaged. Improved communication of expectations for students and explanation of why certain strategies are being used would likely lead to students taking on more responsibility (Finelli et al., 2018). A scaffolded approach in which students take on increasingly more responsibility as the term progresses may be ideal for balancing a goal of equity with a goal of student autonomy (Borrego et al., 2018). I now turn to a discussion on how my findings advance understandings of the three teaching and learning paradigms.

Connecting the findings to the teaching and learning paradigms.

Aligning pedagogy with the teaching and learning paradigms. Dan's pedagogical strategies most closely aligned with the active learning paradigm, although he used aspects of all three paradigms. Some of Isaac's approaches were aligned with active learning, whereas others were more aligned with traditional pedagogy. This finding points to a reality that in practice, one's pedagogy will rarely only fall under one teaching and learning approach or paradigm (Campbell, Cabrera, Ostrow Michel, & Patel, 2017). For instance, this course mirrored a tendency to use active learning teaching strategies while maintaining a more traditional approach to assessment (Shepard, 2000). And while Dan did not explicitly seek to use inclusive pedagogy, his focus on validating students falls under the inclusive pedagogy umbrella (Hurtado et al., 2012; Rendón, 1994; Tuitt, 2003).

Another finding from my study is that espoused teaching and learning approaches and philosophies were sometimes contradicted by those in practice. While Isaac had come to see lecturing as ineffective, he still resorted to its use. When professors work to reform their teaching and learning approach, their old educational theories and frameworks do not disappear. Additionally, professors may feel they need to deviate from their "ideal" teaching approach due to perceived barriers such as large class sizes or lack of access to technology (Ferrare & Hora, 2014).

The effect of pedagogy on the climate: Implications for the three paradigms. Notably, the aspects of pedagogy that had the greatest effect on the climate (the lack of communication, structure, and organization) were not specific to any of the three paradigms that were discussed in chapter two. One could argue that under any pedagogical approach, a well-designed structure and clear communication between the instructor and students is important for achieving student engagement and buy-in. Yet, the importance of this dimension of pedagogy should be especially relevant to inclusive pedagogy, as a disorganized course may disproportionately harm FG and other marginalized students who are less prepared to seek out resources that can help them navigate the lack of clarity (Penner, 2018; Supiano, 2018).

The parts of the course that were based on traditional pedagogy seemed to negatively influence the climate, mirroring the findings of other studies (Eagan Jr. & Jaeger, 2008; Holmes, 2013; A. Johnson, 2007; Tobias, 1990). As discussed above, these aspects included exams, other types of assessment that did not allow for feedback, and in Isaac's case, lecturing. Conversely, the validation and sense of instructor immediacy provided by Dan and the TAs, which are aligned with inclusive pedagogy, created a warmer classroom climate.

The group work component reflects a belief in collaborative learning and the professor as facilitator, which are aligned with both active learning and inclusive pedagogy. Group work affected the climate in different ways. For students who enjoyed the interactions with other students at their table, the opportunity to work with others likely improved the climate. The students who lacked interaction with their peers did not benefit in the same way. However, even for students at interactive tables, a lack of facilitation and guidance around group work processes produced confusion and frustration. As such, the negative effects of group work on the climate were not inherent to the approach but were rather due to poor implementation. A more structured approach to group work would have made interaction more even across groups and would have caused less frustration.

Potential for inclusive pedagogy. In chapter two, I argued that inclusive pedagogy is necessary for creating welcoming and equitable climates in STEM gateway courses. My findings point to potential benefits and challenges to using inclusive pedagogies in the context of this pre-calculus course. As discussed earlier, the FG students I interviewed expected a class that taught the prevailing concepts of mathematics without questioning or critiquing them, avoided discussions of students' individual backgrounds and identities as well as broader societal issues, and omitted an exploration of past and present inequities in the field of mathematics. The pre-calculus course met the students' expectations in this regard. These attitudes were likely formed through experiences in K-12 math education that had also decontextualized the subject from its social context. Math is somewhat unique in that students arrive to college having already experienced at least 13 years of education in the subject, so their preconceived notions of what a math classroom is are particularly strong (Lloyd, 2002; O'Leary, Fitzpatrick, & Hallett, 2017).

Given these preconceived notions, students may resist pedagogy that contextualizes math within systems of power and oppression, requires students to take on additional responsibility, and upends the traditional power dynamic between the students and professor (D. Riley & Claris, 2009). The literature provides examples of students resisting inclusive pedagogy. For instance, Alemán and Gaytán (2017) found that students of color whose prior education was characterized by colorblind ideology tended to resist critical race pedagogy. Jett (2013) wrote about using culturally responsive teaching that centered African American experiences in an undergraduate math classroom. On the course evaluation, one student wrote: "Don't focus on race; focus on math" (p. 102). In response, Jett reflected that "some students cannot fathom mathematics and culturally responsive teaching as a marriage, rather they view it as an either/or" (p. 113).

While students may resist activities that represent a radical departure from their previous experiences in math courses, there are some inclusive pedagogy strategies that represent more subtle differences from mainstream approaches. For instance, including content about the contributions of marginalized people to the field can create a greater sense of belonging in a course for students with similar backgrounds (Schinske et al., 2016). As was seen in this study and countless other ones, receiving validation from the instructor that students belong in a course and can be successful is immensely important and not likely to be met with student resistance when it is carried out authentically (Hurtado, Cuellar, et al., 2011; Rendón, 1994; Rendón Linares & Muñoz, 2011).

Dewsbury (2018) argued that "central to inclusiveness is an understanding of self (the instructor) and student" (p. 4). As such, instructors are encouraged to survey students at the beginning of the term about their backgrounds, interests, and goals in order to tie the curriculum to students' identities and aspirations (Jett, 2013). In addition, instructors can share their own backgrounds with students in order to create a more personal connection.

Students' potential resistance to inclusive pedagogy does not mean that it is not worth attempting. Through inclusive pedagogy, students may come to see their struggles in math and STEM more broadly as a result of systemic inequities instead of individual inadequacies; this realization could in turn strengthen their determination to persist (Tuitt, 2003). However, instructors should put careful consideration into how to encourage students to share power and take on more responsibility, as the inclusive pedagogy paradigm encourages (D. Riley & Claris, 2006), as this could discourage FG students who may benefit from a high degree of structure and guidance. Instructors should be prepared for students to react emotionally to discussions of identity, inequity, and oppression; this type of negative reaction may be especially strong for those who welcome the opportunity to be anonymous in a classroom setting (Ochoa & Pineda, 2008; Trees & Jackson, 2007). Instructors would likely benefit from working with their institution's faculty development center on how to approach these issues in the classroom, especially when they are unaccustomed to doing so.

Inclusive pedagogy serves as a helpful framework for centering the experiences of marginalized students and continuously examining power dynamics in the classroom. Ultimately, however, what works for an instructor will be a result of trial and error, as pedagogical change is an iterative process (Addis et al., 2013; Bensimon, 2007). Any one strategy will have varying degrees of success depending on the course's specific context (Dewsbury, 2018; Shuster & Preszler, 2014). The ultimate goal for those teaching gateway STEM courses should be to foster a classroom climate in which underrepresented students feel welcomed and affirmed. The pedagogical strategies that can achieve that goal will look different across the landscape of introductory STEM classes. These efforts are necessary for improving underrepresented student persistence in STEM.

Influence of the course on persistence in math and STEM. My study's quantitative and qualitative findings indicate that for many students, the course did not affect their intentions to take additional math or STEM courses, either positively or negatively. This could partially be because for most students, they did not intent to major in math. None of the FG survey respondents listed math as a major they were considering. Only one of the interview participants said they were considering math. As such, the course may have had a limited impact on how they saw themselves as belonging or not belonging in STEM (Carlone & Johnson, 2007). The gateway courses that were directly linked to the intended major (e.g., introductory chemistry for a student planning to major in chemistry) may have had more of an effect on persistence. In addition, whereas the pre-calculus classroom climate was largely negative, students did not describe it as weed-out or competitive, which are the climate characteristics most associated with student attrition from STEM (Vivyan, 2016).

The survey respondents who said the course had an effect on their STEM persistence intentions were roughly evenly split between whether there was a positive or negative impact. The FG survey respondents who were classified as STEM leavers scored lower than STEM stayers on all of the classroom climate scales. This suggests that a student's subjective experience of the climate could have influenced whether they wanted to take additional math and STEM courses, although it is not possible to conclude this from the data.

Among the interview participants, Caitlin, who had an overwhelmingly negative experience in the course, indicated that the class had made her less likely to pursue a health-based major. Devin, Matt, and Jake, all White men, reported a positive effect of the course on their STEM persistence intentions. As I noted in the findings, they all described positive associations with math. It is possible that their status as White men meant that their previous experiences with math education had been more positive and affirming. Indeed, women and students of color are more likely to have negative associations with mathematics that originate from prior educational experiences (Peters, 2013).

This study makes a unique contribution to the literature on pedagogy and classroom climate by highlighting the nuances of these concepts. Pedagogy is so multi-faceted that it will rarely, if ever, fall under only one approach or paradigm. The way that pedagogy plays out in practice often differs from the instructor's intention. Marginalized students may both benefit from and resist pedagogies that seek to place STEM content within a social context. A classroom climate is sometimes not overwhelmingly positive or negative; whereas students were frustrated and disengaged, the course did not seem to deter most of them from pursuing STEM. The discussion of my findings leads to several implications for practitioners, institutional leaders, and researchers.

Implications

Implications for instructors and faculty development professionals. In this section, I include several teaching and learning strategies and approaches that instructors may want to consider as they work to create a welcoming classroom climate. These recommendations are applicable for diverse contexts but are especially relevant for introductory gateway STEM courses. Faculty development professionals should consider incorporating these themes into their work with faculty if they do not already do so. Most of the strategies discussed here have been found to increase student engagement and motivation (Ambrose et al., 2010). Thus, through the techniques discussed in this section, instructors can encourage students to take agency in their learning by increasing their motivation for learning, while also providing an appropriate level of structure and guidance.

Focus on clear structure and communication. Especially for FG students in their first year of college, having a highly structured course, regardless of other pedagogical decisions, is a way to make it more inclusive. The need for clear communication and structure should be seen as an overarching pedagogical goal that applies to teaching strategies, assessment, and curriculum. For faculty developers, a focus on increasing structure is promising because it is a principle that can be applied to any teaching and learning context (S. L. Eddy & Hogan, 2014). Whereas some instructors may believe that pedagogical contexts in which students have a more active role are inherently less structured, the results of this study suggest that courses using active learning likely need a higher degree of structure so that students who are less prepared for that type of setting are adequately supported.

The course syllabus should lay out deadlines and expectations for students. In addition, it is helpful for the syllabus to reflect a backward design approach where the instructor communicates how course content and assessment methods align with each learning outcome (G. Wiggins & McTighe, 2005). The students should be able to discern between the different themes or topics that are covered but also see how they connect with each other. In order to avoid confusion or a sense of disjuncture, it may also be helpful for the course to be organized by units so that one topic or theme is fully covered before moving to the next one (G. P. Wiggins & McTighe, 2011). The course website (or whatever is used as the main communication mechanism) could be organized by unit so that students can see how different course materials (e.g., readings, videos, assignments) fit together.

Structure is also important within each course activity. Above, I provided the example of the jigsaw activity as a more structured alternative to students going through a worksheet with minimal guidance. The instructor should be mindful throughout of clearly communicating with students. It is important to explain the pedagogical approach being used, the reasons for using it, and what is expected of both the instructor and students (Finelli et al., 2018). For courses that are taught in active learning classrooms, the professor should explain to students the reasons behind their decision to use a non-traditional classroom setting. In discussing the need for structure and guidance, faculty developers can engage with faculty in conversations on how much responsibility can be expected of students versus the amount of responsibility instructors need to assume.

Use a systemic approach to course design. As noted above, the pre-calculus class used elements of all three teaching and learning paradigms. This is not necessarily problematic. For instance, there could be instances in which a lecture is inclusive. Furthermore, the paradigms overlap with each other in several areas. However, courses need to be internally coherent. Biggs (1996) argued that "attempts to enhance teaching need to address the system as a whole, not simply add 'good' components, such as a new curriculum or method" (p. 350). Backward design, described in the previous section, is a useful tool for ensuring that all components of a course are cohesive (G. P. Wiggins & McTighe, 2011). If a course has learning objectives that reflect a high level of understanding but uses a test-based approach to assessment, the instructor should be able to justify how the exams allow students to demonstrate deep understanding of course content (Biggs, 1996). Instructors should regularly audit their courses to ensure that learning assessment and course activities are aligned with the learning objectives (Whetten, 2007). Faculty developers should consider using a systemic approach to their work with instructors instead of focusing on one specific teaching or grading method.

Structure group work. Especially at the beginning of the term in an introductory course, group work should be highly structured. Group work activities can be designed in a way that encourages participation from each member. This can include assigning each student a role, providing group work guidelines, and having group members assess each other on their contributions (Tanner, 2013; Theobald et al., 2017). The instructor can consider scaffolding, in which groups gradually take on an increasing amount of independence and responsibility as the course progresses (Borrego et al., 2018). Professors should carefully consider the benefits and drawbacks of assigning groups versus allowing students to select their own ones before deciding which approach to use. When making this decision, the instructor should consider the demographic makeup of the course. For instance, if the class is relatively homogenous, it may be harmful to prevent marginalized students from selecting their own group.

Team-based learning (TBL) is one example of a highly structured group activity (Parmelee, Michaelsen, Cook, & Hudes, 2012). Students are given materials to review before coming to class. The class session begins with students individually answering a set of multiple-choice questions on the material. Next, students answer the same set of questions as a team, which encourages discussion and consensus building. The instructor then goes over the questions and clarifies any misunderstandings. Finally, the teams of students apply their learning to solving a specific problem that is connected to the topic and that represents an authentic, real-world scenario. Students provide anonymous feedback (both quantitative and qualitative) to their teammates, which encourages accountability (Parmelee et al., 2012).

Provide instructor immediacy. With respect to underrepresented students' sense of belonging in introductory STEM courses, one of the most important efforts a professor can make is to provide validation to students. Much of this is done through displaying high levels of immediacy. Gasiewski et al. (2012) argued:

> Introductory STEM course instructors must think just as carefully and thoroughly about how they interact with and come across to students as they do about the course content and how to assess its mastery, especially when it comes to scaling up STEM achievement and increasing student persistence. (p. 255)

Strategies for increasing immediacy include using eye contact with students, moving around the classroom, using a relaxed body position, and calling students by their names (Considine, Mihalick, Mogi-Hein, Penick-Parks, & Van Auken, 2017). One method for encouraging more personal interactions between the student and professor and among students is to have students put out tent cards with their names on them (Tanner, 2013). In addition to immediacy, communicating high expectations, providing students with authentic feedback, and reaching out to students who appear disengaged are other ways to validate students (Killpack & Melón, 2016; Nelson Laird et al., 2008).

For faculty development professionals, it is important to note that a fixed view of ability may hinder the extent to which a professor can validate students. For instance, Dan's belief that the vast majority of his students were not "A students" may have limited the extent to which he encouraged individuals who were working hard in the class to complete the level 3 materials and earn an A. Canning, Muenks, Green, and Murphy (2019) found that STEM faculty who believed ability was fixed had larger racial achievement gaps and were less effective in motivating students. Faculty development programs should include discussions about the educational benefits of having a growth mindset that does not view ability as fixed (Dweck, 2007).

Include teaching assistants. When they are involved in instructional activities and not merely grading student work, teaching assistants are valuable assets for creating positive classroom climates and effective active learning classroom experiences. TAs, especially undergraduate ones, tend to be viewed as more relatable and approachable than the professor. TAs can be important sources of validation. Given the importance of underrepresented students seeing themselves reflected in their instructors, and the lack of diversity among STEM professors (Espinosa, 2011; Harper, 2013; Holmes, 2013; Hurtado, Eagan, et al., 2011; Rendón, 1994), it is important for TAs to be diverse in terms of gender, race, ethnicity, and other identities. The role played by TAs is especially important at large research universities where it is often difficult for students to access the professor (Soria & Stebleton, 2012).

If lecturing is necessary, make it interactive. While lecturing is not ideal for conceptual learning, there may be times when the professor believes the most effective way to convey material is through a lecture. There are different ways in which one can lecture. Hora and Ferrare (2014), for instance, identified five different types of lectures. Stain et al. (2018) distinguished between a didactic course, in which 80% or more of class time is spent lecturing, and an interactive lecture in which the professor incorporates interactive components, such as group work or clicker questions. In order to maintain student engagement and motivation, professors who lecture should incorporate opportunities for interaction (Trees & Jackson, 2007; R. E. Wilson & Kittleson, 2013).

Incorporate diverse backgrounds. The literature offers several strategies that professors can use to incorporate students' diverse backgrounds and experiences into their course. Schinske et al. (2016) included "scientist spotlight" homework that focused on the work of scientists with marginalized identities as a way to incorporate counterstereotypes into the curriculum of a community college introductory biology course. For each assignment, students read a research article written by the scientist (which was tied to the current unit being studied) and also read about the scientist's background. The authors found that students who participated in the scientist spotlight assignments were more likely to hold non-stereotypical ideas of who a scientist is and were more likely to be interested in pursuing STEM.

The instructor can survey students at the beginning of their term about their background, goals, and reasons for taking the course, and then create course activities that are likely to resonate with students (Jett, 2013). Other strategies include using case studies that touch on societal issues or the ethical implications of what is being studied, or having students reflect on how the topic or field affects their everyday lives (Chamany, 2006; D. Riley, 2003). Another way to affirm diverse backgrounds is to acknowledge to students that the field of mathematics has an exclusionary history and to assert a commitment to making it more equitable (Tanner, 2013). When students can see their identities reflected in the class, they may be more comfortable in the physical environment of the course, be more willing to participate, and feel more positively about their interactions with the professor. However, it is important to incorporate these efforts into the class in a way that does not tokenize students or make the activities seem like add-on tasks that are separate from the central goals of the course.

Focus on assessment. When professors make changes to their pedagogy, assessment should be among the first considerations and should be seen as part of the learning process itself. It is important to provide students with feedback on their learning throughout a course, and assessments may increase student engagement if they are authentic (i.e., a task that students would need to do in the real world). Authentic assessment can also strengthen a student's science identity by making it easier to envision themselves as a future practitioner in the field (Carlone & Johnson, 2007). Feedback is most effective when it is immediate, when the instructor is explicit with students as to its purpose, and when students perceive that they can use it in future work (Price et al., 2011).

In most cases, exams are not ideal because they do not allow for feedback. Educational research has produced extensive research that a testing approach is not effective. Examinations are not an accurate predictor of subsequent performance and achievement later in life (Gibbs et al., 2004, Shepard, 2000). Testing is also likely to create a competitive and threatening environment, which can be especially detrimental to the success of underrepresented students (Rust, 2002). Surveys of U.S. employers have shown that they prefer assessments of real-world applications instead of exams, as well as assessments of high-order skills that require integration and application of learning (Association of American Colleges and Universities, 2008). If professors are required to use exams, they should consider allowing students to submit corrections in order to improve learning and lessen the pressure that students feel (Langley & Guzey, 2014).

Use an iterative reform process. There is no one-size-fits-all model for creating positive, welcoming classroom climates. Professors may want to consider using a scientific teaching approach, which is an iterative strategy in which the instructor makes a change to their teaching, assesses its effectiveness, and then proceeds to make another change (Addis et al., 2013; Dehaan, 2005). When instructors are evaluating the effect of a new teaching strategy, they should watch for signs of student resistance to the method, such as disengagement or frustration, and should examine the classroom climate implications of the strategy in question. Faculty development centers should offer to assist professors in this process.

This process should include an explicit focus on how students with multiple marginalized identities are experiencing the class. Using the concept of interest convergence, French (2019) found that educators committed to advancing social justice through their pedagogy still prioritized their own personal interests over those of their students. For example, a straight, cisgender, woman teacher chose to move on from a student-initiated discussion of sexual orientation and gender identity because she believed that school was not an appropriate place to discuss politically charged topics. The teacher believed she was using justice-oriented teaching by respecting everyone's beliefs on the topic. However, French argued that the teacher was serving her own interests of reinforcing a culture of heteronormativity instead of upholding the interests of marginalized students. Instructors who are committed to using pedagogy to advance equity should be aware that a focus on creating a welcoming classroom for underrepresented students may come at a cost – in terms of comfort, prestige, or power – to the instructor and/or students with dominant identities.

Implications for institutional leaders. This study has implications for individuals who have power over institutional policies and initiatives affecting teaching and learning reform in STEM.

Center reform efforts on equity, not economic competitiveness. In chapter two, I used the concept of interest convergence to explain why there has been so much focus on improving underrepresented student persistence in STEM: to expand the STEM workforce and bring down wages for those working in the STEM fields (Basile & Lopez, 2015). In order to advance social justice, institutional leaders should center reform efforts on improving the lives of students who have historically been excluded from the STEM fields. This framing would shift the discussion away from technocratic, one-size-fits-all solutions and toward a focus on how to bring about structural change that addresses the root causes of inequity (G. M. Anderson et al., 2015; D. M. Riley, 2014).

Engage in dialogue about what inclusive pedagogy looks like at their institution. Institutional leaders should acknowledge that truly inclusive pedagogy will look different depending on the specific context. Questions that can guide dialogue among instructors, faculty developers, and decision makers are: What cultures, backgrounds, and ethnicities are represented by our students? Do the demographics of our teaching staff match the demographics of our students? Which students tend to advance in STEM and which students tend to switch into non-STEM majors or leave the institution? How are STEM gateway courses ignoring or affirming student identities? Discussions of this nature are necessary as institutions work toward creating inclusive classroom climates.

Make issues of race and racism central to pedagogical reform efforts. Critical race theorists remind us that racism is a normal, everyday experience in the United States (Abes, 2016). Education systems often use ideologies of meritocracy and colorblindness to mask racial inequities that are rooted in the country's history of oppression and subordination (Johnson, 2007; Parsons et al., 2011). While the students and instructors in the pre-calculus class did not intend to advance racial inequity, my study produced some quantitative evidence that first-generation students of color had more negative experiences in the class compared to White FG students.

Unfortunately, faculty development in STEM often limits discussions around diversity to learning styles, avoiding less comfortable subjects such as race and racism. Institutional leaders should encourage STEM faculty development programs to engage instructors in exercises where they consider their own privilege and implicit biases and learn about bias reduction strategies (Killpack & Melón, 2016). Leaders should also commit to recruiting STEM faculty of color, given the importance of having diverse faculty for underrepresented students (Espinosa, 2011; Harper, 2013; Holmes, 2013; Eagan, et al., 2011; Rendón, 1994). Finally, especially in courses taught by White professors, there should be an explicit focus on hiring racially and ethnically diverse teaching assistants.

Resist treating active learning (or any teaching approach) as a panacea. As discussed in chapters one and two, the STEM teaching and learning literature often treats active learning as a panacea, suggesting that a large-scale adoption of active learning will eliminate disparities in STEM education outcomes. In the case of the pre-calculus course, pedagogical reforms stemming largely from the active learning paradigm did not create a positive classroom climate, which was largely due to a lack of structure, communication, and guidance. Institutional leaders should remember that active learning can be implemented poorly, leading to unintended outcomes. While I believe that inclusive pedagogy has a greater potential than active learning for bringing about equity in introductory STEM courses, an intent to be inclusive will not always translate to *being* inclusive. A nuanced understanding of pedagogy that focuses on fidelity of implementation, as well as the importance of context, is needed at the level of institutional leadership.

Recognize that active learning classrooms do not ensure the use of active learning. The use of an active learning classroom does not ensure that active learning will occur (Brooks & Solheim, 2014; Lester et al., 2016). In the pre-calculus class, Isaac often lectured for half of the class time, during which students remained passive. If institutional leaders invest in ALCs, they should encourage instructors who use them to participate in faculty development on teaching in these new classroom environments. Decision makers may even consider making this training mandatory for instructors using ALCs, especially if the classrooms are in high demand.

Allow for flexibility with assessment. Especially in the STEM fields, instructors often have departmental expectations of using a test-based approach to assessment (Barnes, Bull, Campbell, & Perry, 2001; Rask, 2010). Given the enormous importance of assessment for shaping student experiences, professors attempting to use active learning or inclusive pedagogy can only achieve so much if they are still required to grade students using exams. Professors who are reforming their teaching approach should be allowed greater flexibility with how they assess their students' learning.

Assess the classroom climate. In addition to regularly assessing the campus climate (Rankin & Reason, 2005), leaders should partner with institutional researchers to assess the classroom climate, especially in courses that are known to serve as gatekeepers for students. This type of analysis should disaggregate the data by different student groups (e.g., gender, race and ethnicity, generation status) in order to examine whether students with marginalized identities are experiencing the climate differently than majority students. Assessment findings can drive discussions with the professors, who may then be more motivated to reform their courses with a goal of creating a welcoming climate for all students.

Invest in training and development of faculty and instructors. Given the complexity of teaching and learning and the iterative nature of pedagogical improvement, professors who are motivated to improve their teaching should be supported by robust faculty development efforts. STEM faculty members who want to move toward inclusive pedagogy but are accustomed to traditional pedagogy or active learning may find this support especially beneficial. The opportunity to receive feedback may help instructors to see points of divergence between their intended pedagogy and actual day-to-day practices. Sustained interactions between faculty developers and instructors are preferable to one-off workshops (Gehrke & Kezar, 2016).

It is essential for leaders to focus on the sustainability of faculty development initiatives. Strategies that leaders can use in this regard include linking faculty development to improved learning outcomes, educating trustees about the importance of faculty development, and communicating findings about the effectiveness of these efforts. The creation of pedagogical expertise in each department should also be a priority. Such experts can serve as mentors for faculty who are beginning a transition to a new pedagogical approach (Honan, Westmoreland, & Tew, 2013).

Departments need to create a culture of classroom observation so that the practice becomes normalized. Department chairs can encourage senior faculty to request that their classes be observed in order to model the behavior for junior professors (Huston & Weaver, 2008). Feedback should be formative and shared through two-way conversations (Donnelly, 2007). It is also important to communicate that when observation is used for professional development, feedback will be confidential and not used for tenure and promotion considerations (Huston & Weaver, 2008).

Implications for research.

Apply a critical lens to the study of pedagogy and the classroom climate. My interview participants used surface level understandings of racism and other forms of oppression to argue that inequity was not present in the classroom. The influence of critical theory on my research approach led me to look beneath the surface, acknowledging that structural inequities are often difficult to see. By disaggregating the data on classroom climate by students' multiple social identities, I found some evidence that students of color and first-generation students had more negative experiences compared to majority students. Through focusing my observations on the ways in which majority students and minoritized students navigated the classroom space, I detected some racial and gendered patterns of interaction that may have made the classroom more comfortable for students with dominant identities. Students, especially those who are just beginning their college-level studies, may not be aware of subtle, power-based classroom dynamics. Researchers can use critical theory, especially CRT and LatCrit, to inform strategies for detecting inequities that exist beneath the surface.

Researchers should consider using an intersectional approach to STEM education studies. While my quantitative strand examined differences in experiences along various dimensions of identity, it was not truly intersectional because it treated identities as separate instead of interrelated. Future studies that use intersectionality as a framework should avoid disaggregating data by singular dimensions of identity and should instead examine the experiences of students with multiple marginalized identities who confront unique barriers to advancing in STEM – for instance, women of color and LGBTQ students of color (Charleston et al., 2014; Museus & Griffin, 2011; Ong, 2005).

Be specific in describing pedagogy. Given the complexities of implementing teaching and learning strategies, it is important that pedagogical research be based on fine-grained analysis that incorporates multiple data points and describes the approach in as much detail as possible. For example, instead of indicating that a course is a lecture class, researchers could differentiate between an interactive lecture and a completely passive lecture (Campbell et al., 2017; Hora & Ferrare, 2014). It is also important to examine each facet of pedagogy (teaching strategies, curriculum, and assessment), as an instructor's teaching strategies may be operating under a different approach or paradigm than their curriculum and assessment methods.

Assess implementation of pedagogy. The disparity I found between espoused and actual pedagogy points to the need for pedagogical research to include measures of fidelity of implementation for the practice being studied (Stains & Vickrey, 2017). Researchers often assume that professors carried out a teaching strategy by following all of the corresponding guidelines. However, since this is not always the case, researchers must include instruments, such as classroom observation, that capture the day-to-day pedagogical practices. Without doing so, they run the risk of erroneously concluding that a certain approach was successful or unsuccessful in reaching its intended outcomes.

Include qualitative measures of classroom climate. In this study, it would have been difficult to uncover the overarching classroom climate themes of confusion, frustration, and disengagement through quantitative measures. These themes were instead discovered through student interviews and classroom observations. Student interviews also allowed me to gain important contextual details about the mechanisms that led to a climate of confusion, frustration, and disengagement. The contributions of the qualitative strand of my study support the argument against studying the classroom climate using only Likert-type survey scales (Sohn, 2016). In this project, a case study approach that allowed for various forms of measurement, including observation, was useful for developing a nuanced and holistic understanding of the climate.

Conduct more research on inclusive pedagogy in math and STEM courses. As mentioned in chapter two, while there are powerful arguments supporting the use of inclusive pedagogy in introductory STEM courses, there is still a lack of research documenting its use in these contexts. Further research is needed that can begin to reveal whether marginalized students benefit from inclusive pedagogy and whether it creates a more welcoming classroom climate in comparison to active learning. It is important for such research to explore the conditions under which students are likely to resist inclusive pedagogy, and which strategies can be used to mitigate student resistance. Potential research questions in this area include: How do marginalized students experience the classroom climate of an introductory STEM course that incorporates inclusive pedagogy? In gateway STEM courses, how do marginalized students buy into or resist inclusive pedagogy? How do instructors of STEM courses experience the integration of inclusive pedagogy?

Explore the effect of classroom climate in major-specific courses vs. non-major-specific courses. As I mentioned earlier in this chapter, one possible reason that the course did not influence the STEM persistence plans of many FG students is that their intended major was not math. Most of the study participants needed to pass the course and eventually pass calculus, but in the service of advancing in a non-math STEM major. Researchers should explore, for example: For students intending to major in biology, does their experience of the classroom climate in their introductory biology course have an outsize influence on their persistence intentions compared to other gateway courses? Future studies that compare the effect of the climate on persistence intentions in major-specific and non-major-specific gateway courses are needed.

Study Limitations

As a person who succeeded in math courses myself, it at times was difficult to truly empathize with those study participants who either entered college with math-related anxieties or struggled in the pre-calculus course. This study did not consider how students' previous experiences and backgrounds affected their course experiences. It is possible that students' math self-efficacy, as well as their K-12 math experiences, affected FG students' experiences in the course (Espinoza, 2013). While the survey sample was representative with regard to some identities, full-time students, women, and

Asian students were overrepresented in the sample, whereas Black/African American, Hispanic/Latinx, and Native American students were underrepresented.

There were several limitations of the study design. Because I interviewed and surveyed students only once, I was not able to capture changes in their perceptions of the climate over time. Interviewing students several months after the course may have produced different or more nuanced findings regarding the influence of the course on their STEM persistence intentions. As I mentioned above, the quantitative analysis was not intersectional because it examined dimensions of identity separately instead of considering the unique experiences of students with multiple marginalized identities. The survey did not ask about students' perceptions of lecturing, as I did not foresee it as being an aspect of pedagogy that was utilized, which limited the quantitative findings that linked perceptions of pedagogy to climate perceptions. Another limitation was that I did not observe the smaller TA- and peer-led sections, which were important for improving students' experiences of the climate. Finally, my focus on just one class limits the generalizability of my findings to other STEM contexts. Despite these limitations, I believe that my study advances our understanding of what is needed to create inclusive climates in introductory STEM courses.

Conclusion

I conducted this study within a context of nationwide efforts to reduce inequitable disparities in STEM postsecondary education outcomes. Large, introductory math and science courses often serve as gatekeepers for underrepresented students who enter college intending to major in a STEM field. The climate of these courses in particular has been criticized for being unwelcoming to students with marginalized identities. In the

STEM higher education literature, I noticed a tendency to treat active learning as a panacea for improving introductory courses. I wondered, however, whether adapting active learning without explicitly focusing on creating an equitable classroom climate could make a meaningful difference in terms of encouraging underrepresented students to persist in STEM. This question led me to study the classroom climate of a gateway math course that was moving away from a traditional pedagogical model and toward active learning.

The literature often portrays the climate of introductory STEM courses as having a competitive, weed-out culture. The climate I found was instead characterized by confusion, frustration, and disengagement, much of which was due to a lack of structure, organization, and communication. One conclusion of my study was that a course must be well structured and clearly communicate expectations in order to be inclusive. Structure and communication are foundations for creating a positive classroom climate and providing a context in which students who lack social and cultural capital can succeed. This principle should be applied regardless of the other teaching and learning strategies being utilized.

It remains to be determined whether inclusive pedagogy is needed to create truly inclusive classroom climates in gateway STEM courses. One aspect of inclusive pedagogy, the important role of the instructor in validating students, was confirmed by this study, which also highlighted the importance of teaching assistants in this regard. Proponents of inclusive pedagogy argue that instructors must acknowledge the historical and current inequities in STEM and recognize and affirm marginalized students' multiple identities. Conversely, the pre-calculus class presented math as decontextualized from its social and historical context, and the multiple identities of FG students were ignored. However, this decontextualization aligned with FG students' expectations, many of whom felt that the course was welcoming *because* they believed identity to be irrelevant in math. Inclusive pedagogy also encourages instructors to share power and responsibility with students. Professors should be cautious, however, as an expectation of shared power in the classroom may harm students who are unprepared to navigate such a context. More research is needed that explores the conditions under which pedagogy creates welcoming and inclusive classroom climates in introductory STEM courses.

References

Abes, E. S. (2016). Situating paradigms in student development theory. *New Directions for Student Services*, (154), 9–16. http://doi.org/10.1002/ss

Addis, E. A., Quardokus, K. M., Bassham, D. C., Becraft, P. W., Boury, N., Coffman, C. R., … Powell-Coffman, J. A. (2013). Implementing pedagogical change in introductory biology courses through the use of faculty learning communities. *Journal of College Science Teaching*, *43*(2), 22–29.

Aldridge, J. M., Fraser, B. J., & Huang, T. I. (1999). Investigating classroom environments in Taiwan and Australia with multiple research methods. *The Journal of Educational Research*, *93*(1), 48–62. http://doi.org/10.2307/27542246

Alemán, S. M., & Gaytán, S. (2017). 'It doesn't speak to me': Understanding student of color resistance to critical race pedagogy. *International Journal of Qualitative Studies in Education*, *30*(2), 128–146. http://doi.org/10.1080/09518398.2016.1242801

Allen, J. M., Muragishi, G. A., Smith, J., Thoman, D. B., & Brown, E. R. (2015). To grab and to hold: Cultivating communal goals to overcome cultural and structural barriers in first generation college students' science interest. *Translational Issues in Psychological Science*, *1*(4), 331–341.

Ambrose, S. A., Bridges, M. W., Dipietro, M., Lovett, M. C., & Norman, M. K. (2010). *How learning works: Seven research-based principles for smart teaching*. San Francisco, CA: Jossey-Bass.

Anderson, E., & Kim, D. American Council on Education. (2006). *Increasing the success of minority students in science and technology.* Washington, D.C.

Anderson, G. M., Barone, R. P., Sun, J. C., & Bowlby, N. (2015). The new stratification: Differentiating opportunity by race and class at community colleges in the United States. In A. Martínez-Alemán, B. Pusser, & E. M. Bensimon (Eds.), *Critical approaches to the study of higher education: A practical introduction* (pp. 257–284). Baltimore, MD: John Hopkins University Press.

Armstrong, M. A. (2011). Small world: Crafting an inclusive classroom (no matter what you teach). *The NEA Higher Education Journal*, 51–61.

Association of American Colleges and Universities. (2008). *Our students' best work: A framework for accountability worthy of our mission.* Washington, D.C.

Barefoot, B. (2004). Higher education's revolving door: Confronting the problem of student drop out in US colleges and universities. *Open Learning*, *19*(1), 9–18. http://doi.org/10.1080/0268051042000177818

Barker, L. J., & Garvin-Doxas, K. (2004). Making visible the behaviors that influence learning environment: A qualitative exploration of computer science classrooms. *Computer Science Education*, *14*(2), 119–145. http://doi.org/10.1080/08993400412331363853

Barnes, L. L. B., Bull, K. S., Campbell, N. J., & Perry, K. M. (2001). Effects of academic discipline and teaching goals in predicting grading beliefs among undergraduate teaching faculty. *Research in Higher Education*, *42*(4), 455–467. http://doi.org/10.1023/A:1011006909774

Barr, D. A., Gonzalez, M. E., & Wanat, S. F. (2008). The leaky pipeline: Factors associated with early decline in interest in premedical studies among underrepresented minority undergraduate students. *Academic Medicine*, *83*(5), 503–511. http://doi.org/10.1097/ACM.0b013e31816bda16

Bartolome, L. I. (1994). Beyond the methods fetish: Toward a humanizing pedagogy. *Harvard Educational Review*, *64*(2), 173–194. http://doi.org/10.17763/haer.64.2.58q5m5744t325730

Basile, V., & Lopez, E. (2015). And still I see no changes: Enduring views of students of color in science and mathematics education policy reports. *Science Education*, *99*(3), 519–548. http://doi.org/10.1002/sce.21156

Bauman, G. L. (2005). Promoting organizational learning in higher education to achieve equity in educational outcomes. *New Directions for Higher Education*, (131), 23–35. http://doi.org/10.1002/he.184

Bell, D. (1988). White superiority in America: Its legal legacy, its economic costs. *Villanova Law Review*, *33*, 767–779. http://doi.org/10.1525/sp.2007.54.1.23.

Benbow, R. J., & Vivyan, E. Wisconsin Center for Education Research. (2016). *Gender and belonging in undergraduate computer science: A comparative case study of student experiences in gateway courses* (WCER Working Paper No. 2016-2).

Benschop, Y., & Doorewaard, H. (1998). Covered by equality: The gender subtext of organizations. *Organization Studies*, *19*(5), 787–805.

Bensimon, E. M. (2004). The diversity scorecard: A learning approach to institutional change. *Change: The Magazine of Higher Learning*, (January/February), 44–52.

Bensimon, E. M. (2005). Closing the achievement gap in higher education: An organizational learning perspective. *New Directions for Higher Education*, (131), 99–111. http://doi.org/10.1002/he.190

Bensimon, E. M. (2007). The underestimated significance of practitioner knowledge in the scholarship on student success. *The Review of Higher Education*, *30*(4), 441–469. http://doi.org/10.1353/rhe.2007.0032

Bergerson, A. A. (2003). Critical race theory and white racism: Is there room for white scholars in fighting racism in education? *International Journal of Qualitative Studies in Education*, *16*(1), 51–63. http://doi.org/10.1080/0951839032000033527

Bernal, D. D. (2002). Critical race theory, Latino critical theory, and critical raced-gendered epistemologies: Recognizing students of color as holders and creators of knowledge. *Qualitative Inquiry*, *8*(1), 105–126. http://doi.org/10.1177/107780040200800107

Biggs, J. (1996). Enhancing teaching through constructive alignment. *Higher education*, *32*(3), 347-364.

Bingham, S. G., Carlson, R. E., Dwyer, K. K., & Prisbell, M. (2009). Student misbehaviors, instructor responses, and connected classroom climate: Implications for the basic course. *Basic Communication Course Annual*, *21*, 30–68.

Bishop, F. L. (2015). Using mixed methods research designs in health psychology: An illustrated discussion from a pragmatist perspective. *British Journal of Health Psychology*, *20*(1), 5–20. http://doi.org/10.1111/bjhp.12122

Bishop, J. L., & Verleger, M. A. (2013, June). *The flipped classroom: A survey of the research.* Paper presented at the ASEE Annual Conference, Atlanta, GA.

Boice, B. (1996). Classroom incivilities. *Research in Higher Education*, *37*(4), 453–486. http://doi.org/10.1007/BF01730110

Booker, K. C. (2007). Perceptions of classroom belongingness among African American college students. *College Student Journal*, *41*(1), 178–186.

Borrego, M., Prince, M., Nguyen, K. A., Tharayil, S., Finelli, C. J., Shekhar, P., & Waters, C. (2018). Strategies to mitigate student resistance to active learning. *International Journal of STEM Education*, *5*(7), 1–16. http://doi.org/10.1186/s40594-018-0102-y

Bourdieu, P. (1986). The forms of capital. In J. Richardson (Ed.), *Handbook of theory and research for the sociology of education* (pp. 241–258). New York, NY: Greenwood Press.

Boyer, E. (1990). *Scholarship reconsidered: Priorities of the professoriate*. Princeton, NJ: Carnegie Foundation for the Advancement of Teaching.

Brandt, C. B. (2008). Discursive geographies in science: Space, identity, and scientific discourse among indigenous women in higher education. *Cultural Studies of Science Education*, *3*(3), 703–730. http://doi.org/10.1007/s11422-007-9075-8

Braxton, J. M. (2008). Toward a scholarship of practice centered on college student retention. *New Directions for Teaching and Learning*, (115), 101–112. http://doi.org/10.1002/tl

Braxton, J. M., Bray, N. J., & Berger, J. B. (2000). Faculty teaching skills and their influence on the college student departure process. *Journal of College Student Development*, *41*(2), 215–226.

Braxton, J. M., Jones, W. A., Hirschy, A. S., & Hartley III, H. V. (2008). The role of active learning in college student persistence. *New Directions for Teaching and Learning*, *115*, 71–83. http://doi.org/10.1002/tl

Bronfenbrenner, U. (1979). *The ecology of human development: Experiments by nature and design*. Harvard University Press.

Brooks, D. C., & Solheim, C. A. (2014). Pedagogy matters, too: The impact of adapting teaching approaches to formal learning environments on student learning. *New Directions for Teaching and Learning*, (137), 53–61. http://doi.org/10.1002/tl

Brown, M. K., Hershok, C., Finelli, C. J., & O'Neal, C. Center for Research on Learning and Teaching. (2009). *Teaching for retention in science, engineering, and math disciplines: A guide for faculty* (CRLT Occasional Paper No. 25).

Brown, T. A. (2006). *Confirmatory factor analysis for applied research*. New York, NY: Guilford Publications.

Buncick, M. C., Betts, P. G., & Horgan, D. D. (2001). Using demonstrations as a contextual road map: Enhancing course continuity and promoting active engagement in introductory college physics. *International Journal of Science Education*, *23*(12), 1237–1255. http://doi.org/10.1080/09500690010025030

Byars-Winston, A. (2014). Toward a framework for multicultural STEM-focused career interventions. *Career Development Quarterly*, *62*(4), 340–357. http://doi.org/10.1002/j.2161-0045.2014.00087.x

Cabrera, A. F., & Nora, A. (1994). College student perceptions of prejudice and discrimination and their feelings of alienation: A construct validation approach. *The Review of Education, Pedagogy, Cultural Studies*, *16*(3–4), 387–409. http://doi.org/10.1080/1071441940160310

Campbell, C. M., Cabrera, A. F., Ostrow Michel, J., & Patel, S. (2017). From comprehensive to singular: A latent class analysis of college teaching practices. *Research in Higher Education*, *58*(6), 581–604. http://doi.org/10.1007/s11162-016-9440-0

Canning, E. A., Muenks, K., Green, D. J., & Murphy, M. C. (2019). STEM faculty who believe ability is fixed have larger racial achievement gaps and inspire less student motivation in their classes. *Science Advances*, *5*(2), 1–7. http://doi.org/10.1126/sciadv.aau4734

Cantú, N. (2012). Getting there cuando no hay camino (when there is no path): Paths to discovery testimonios by Chicanas in STEM. *Equity & Excellence in Education*, *45*(3), 472–487. http://doi.org/10.1080/10665684.2012.698936

Carlone, H. B., & Johnson, A. (2007). Understanding the science experiences of successful women of color: Science identity as an analytic lens. *Journal of Research in Science Teaching*, *44*(8), 1187–1218. http://doi.org/10.1002/tea

Carnevale, A. P., & Strohl, J. Georgetown Public Policy Institute. (2013). *Separate and unequal: How higher education reinforces the intergenerational reproduction of white racial privilege*.

Chamany, K. (2006). Science and social justice: Making the case for case studies. *Journal of College Science Teaching*, *36*(2), 54–60.

Chang, M. J., Eagan, M. K., Lin, M. H., & Hurtado, S. (2011). Considering the impact of racial stigmas and science identity: Persistence among biomedical and behavioral science aspirants. *The Journal of Higher Education*, *82*(5), 564–596. http://doi.org/10.1353/jhe.2011.0030

Charette, R. N. (2013). The STEM crisis is a myth. *IEEE Spectrum*, *50*(9), 44–59. http://doi.org/10.1109/MSPEC.2013.6587189

Charleston, L. J., Adserias, R. P., Lang, N. M., & Jackson, J. F. L. (2014). Intersectionality and STEM: The role of race and gender in the academic pursuits of African American women in STEM. *Journal of Progressive Policy & Practice*, *2*(3), 273–293.

Chen, X., & Soldner, M. National Center for Education Statistics. (2013). *STEM attrition: College students' paths into and out of STEM fields* (NCES No. 2014-001). Washington, D.C.

Cho, S., Crenshaw, K., & McCall, L. (2013). Toward a field of intersectionality studies: Theory, applications, and praxis. *Signs*, *38*(4), 785–810. http://doi.org/10.1086/669608

Ciani, K. D., Summers, J. J., Easter, M. A., & Sheldon, K. M. (2008). Collaborative learning and positive experiences: Does letting students choose their own groups matter? *Educational Psychology*, *28*(6), 627–641. http://doi.org/10.1016/j.ocecoaman.2012.02.008

Colbeck, C. L., Cabrera, A. F., & Terenzini, P. T. (2001). Learning professional confidence: Linking teaching practices, students' self-perceptions, and gender. *Review of Higher Education*, *24*(2), 173–191.

Cole, D. (2008). Constructive criticism: The role of student-faculty interactions on African American and Hispanic students' educational gains. *Journal of College Student Development*, *49*(6), 587–605. http://doi.org/10.1353/csd.0.0040

Collier, P. J., & Morgan, D. L. (2008). "Is that paper really due today?": Differences in first-generation and traditional college students' understandings of faculty expectations. *Higher Education*, *55*(4), 425–446. http://doi.org/10.1007/s10734-007-9065-5

Considine, J. R., Mihalick, J. E., Mogi-Hein, Y. R., Penick-Parks, M. W., & Van Auken, P. M. (2017). How do you achieve inclusive excellence in the classroom? *New Directions for Teaching and Learning*, (151), 171–187. http://doi.org/10.1002/tl

Cooper, K. M., & Brownell, S. E. (2016). Coming out in class: Challenges and benefits of active learning in a biology classroom for LGBTQIA students. *CBE Life Sciences Education*, *15*(3), 1–19. http://doi.org/10.1187/cbe.16-01-0074

Cotton, D. R. E., Stokes, A., & Cotton, P. A. (2010). Using observational methods to research the student experience. *Journal of Geography in Higher Education*, *34*(3), 463–473. http://doi.org/10.1080/03098265.2010.501541

Crenshaw, K. (1988). Race, reform, and retrenchment: Transformation and legitimiation in antidiscrimination law. *German Law Journal*, *12*(1), 247–284. http://doi.org/10.1525/sp.2007.54.1.23.

Crenshaw, K. (1989). Demarginalizing the intersection of race and sex: A black feminist critique of antidiscrimination doctrine. *The University of Chicago Legal Forum*, 139–67.

Crenshaw, K. (1991). Mapping the margins: Intersectionality, identity politics, and violence against women of color. *Stanford Law Review*, *43*(6), 1241–1299.

Creswell, J. W. (2009). The selection of a research design. In *Research design: Qualitative, quantitative, and mixed methods approaches, 3rd Edition* (pp. 3-21). Thousand Oaks, CA: Sage Publications.

Creswell, J. W. (2013). *Research design: Qualitative, quantitative, and mixed methods approaches*. Thousand Oaks, CA: Sage Publications.

Creswell, J. W., & Plano Clark, V. L. (2011). *Designing and conducting mixed methods research* (2nd ed.). Thousand Oaks, CA: Sage Publications.

Crimmins, M. T., & Midkiff, B. (2017). High structure active learning pedagogy for the teaching of organic chemistry: Assessing the impact on academic outcomes. *Journal of Chemical Education*, *94*(4), 429–438. http://doi.org/10.1021/acs.jchemed.6b00663

Crisp, G., Nora, A., & Taggart, A. (2009). Student characteristics, pre-college, college, and environmental factors as predictors of majoring in and earning a STEM degree: An analysis of students attending a Hispanic serving institution. *American Educational Research Journal*, *46*(4), 924–942. http://doi.org/10.3102/0002831209349460

Crotty, M. J. (1998). *The foundations of social research: Meaning and perspective in the research process*. Thousand Oaks, CA: Sage Publications.

Cunningham, J. (2016). Credential disconnection: A Marxist analysis of college graduate underemployment. *Critical Studies in Education*, *57*(2), 224–237. http://doi.org/10.1080/17508487.2015.1053960

Daempfle, P. (2003). An analysis of the high attrition rates among first year college science, math, and engineering majors. *Journal of College Student Retention: Research, Theory and Practice*, *5*(1), 37–52. http://doi.org/10.2190/DWQT-TYA4-T20W-RCWH

Danowitz, M. A., & Tuitt, F. (2011). Enacting inclusivity through engaged pedagogy: A higher education perspective. *Equity & Excellence in Education*, *44*(1), 40–56. http://doi.org/10.1080/10665684.2011.539474

Davis, M., Dias-Bowie, Y., Greenberg, K., Klukken, G., Pollio, H. R., Thomas, S. P., & Thompson, C. L. (2004). "A fly in the buttermilk": Descriptions of university life by successful Black undergraduate students at a predominately White southeastern university. *The Journal of Higher Education*, *75*(4), 420–445. http://doi.org/10.1353/jhe.2004.0018

Dehaan, R. L. (2005). The impending revolution in undergraduate science education. *Journal of Science Education and Technology*, *14*(2), 253–269. http://doi.org/10.1007/s10956-005-4425-3

Delgado, R. (1990). When a story is just a story: Does voice really matter? *Virginia Law Review*, *76*(1), 95–111.

Dellinger, A. B., & Leech, N. L. (2007). Toward a unified validation framework in mixed methods research. *Journal of Mixed Methods Research*, *1*(4), 309–332. http://doi.org/10.1177/1558689807306147

den Brok, P., Fisher, D., Rickards, T., & Bull, E. (2006). Californian science students' perceptions of their classroom learning environments. *Educational Research and Evaluation*, *12*(1), 3–25. http://doi.org/10.1080/13803610500392053

DeSurra , C. , & Church , K. A. (1994). *Unlocking the classroom closet: Privileging the marginalized voices of gay/lesbian college students*. Paper presented at the Annual Meeting of the Speech Communication Association.

Dewsbury, B. M. (2018). Context determines strategies for 'activating' the inclusive classroom. *Journal of Microbiology & Biology Education*, *18*(3), 1–5. http://doi.org/10.1128/jmbe.v18i3.1347

Dika, S. L., & D'Amico, M. M. (2016). Early experiences and integration in the persistence of first-generation college students in STEM and non-STEM majors. *Journal of Research in Science Teaching*, *53*(3), 368–383. http://doi.org/10.1002/tea.21301

Dillman, D. A., Smyth, J. D., & Christian, L. M. (2014). *Internet, phone, mail, and mixed mode surveys: The tailored design method* (4th ed.). Hoboken, NJ: John Wiley & Sons.

Dixson, A. D., & Rousseau, C. K. (2005). And we are still not saved: Critical race theory in education ten years later. *Race Ethnicity and Education*, *8*(1), 7–27. http://doi.org/10.1080/1361332052000340971

Donmoyer, R. (2006). Take my paradigm … please! The legacy of Kuhn's construct in educational research. *International Journal of Qualitative Studies in Education*, *19*(1), 11–34. http://doi.org/10.1080/09518390500450177

Donnelly, R. (2007). Perceived impact of peer observation of teaching in higher education. *International Journal of Teaching and Learning in Higher Education,* *19*(2), 117-129.

Dweck, C. S. (2007). *Mindset: The New Psychology of Success*. New York, NY: Ballantine Books.

Eagan Jr., M. K., & Jaeger, A. J. (2008). Closing the gate: Part-time faculty instruction in gatekeeper courses and first-year persistence. *New Directions for Teaching and Learning*, *115*, 39–53. http://doi.org/10.1002/tl

Eavis, P. (2019, April 5). U.S. adds 196,000 jobs in March, a return to solid growth. *New York Times*.

Eddy, S. L., Brownell, S. E., & Wenderoth, M. P. (2014). Gender gaps in achievement and participation in multiple introductory biology classrooms. *CBE Life Sciences Education*, *13*(3), 478–492. http://doi.org/10.1187/cbe.13-10-0204

Eddy, S. L., & Hogan, K. A. (2014). Getting under the hood: How and for whom does increasing course structure work? *Cell Biology Education*, *13*(3), 453–468. http://doi.org/10.1187/cbe.14-03-0050

Eliason, M. J., & Turalba, R. (2019). Recognizing oppression: College students' perceptions of identity and its impact on class participation. *The Review of Higher Education*, *42*(3), 1257–1281.

Ellis, D. E. (2015). What discourages students from engaging with innovative instructional methods: Creating a barrier framework. *Innovative Higher Education*, *40*(2), 111–125. http://doi.org/10.1007/s10755-014-9304-5

Espinosa, L. L. (2011). Pipelines and pathways: Women of color in undergraduate STEM majors and the college experiences that contribute to persistence. *Harvard Educational Review*, *81*(2), 209–240.

Espinoza, A. (2013). The college experiences of first-generation college Latino students in engineering. *Journal of Latino/a American Studies*, *5*(2), 71–84.

Feldmann, L. J. (2001). Classroom civility is another of our instructor responsibilities. *College Teaching*, *49*(4), 137–140.

Ferrare, J. J., Benbow, R. J., & Vivyan, E. (2014, April). *Constructing classroom culture: A framework for analysis in the context of gateway chemistry courses.* Paper presented at the Annual Meeting of the American Educational Research Association, Philadelphia, PA.

Ferrare, J. J., & Hora, M. T. (2014). Cultural models of teaching and learning in math and science: Exploring the intersections of culture, cognition, and pedagogical situations. *The Journal of Higher Education*, *85*(6), 792–825. http://doi.org/10.1353/jhe.2014.0030

Ferrare, J. J., & Lee, Y. G. Wisconsin Center for Education Research. (2014). *Should we still be talking about leaving? A comparative examination of social inequality in undergraduate patterns of switching majors* (WCER Working Paper No. 2014-5).

Finelli, C. J., Nguyen, K., Demonbrun, M., Borrego, M., Prince, M., Husman, J., … Waters, C. K. (2018). Reducing student resistance to active learning: Strategies for instructors. *Journal of College Science Teaching*, *47*(5), 80–91. http://doi.org/10.1093/molbev/msg067

Fraser, B. J. (2012). Classroom learning environments: Retrospect, context and prospect. In B. J. Fraser, K. Tobin, & C. J. McRobbie (Eds.), *Second International Handbook of Science Education* (pp. 1191–1239). Springer Science & Business Media. http://doi.org/10.1007/978-1-4020-9041-7

Fraser, B., McRobbie, C., & Fisher, D. (1996). *Development, validation and use of personal and class forms of a new classroom environment questionnaire.* Paper presented at the Western Australia Institute for Educational Research Forum.

Freeman, S., Eddy, S. L., McDonough, M., Smith, M. K., Okoroafor, N., Jordt, H., & Wenderoth, M. P. (2014). Active learning increases student performance in science, engineering, and mathematics. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(23), 8410–8415. http://doi.org/10.1073/pnas.1319030111

Freeman, S., Haak, D., & Wenderoth, M. P. (2011). Increased course structure improves performance in introductory biology. *CBE Life Sciences Education*, *10*(2), 175–186. http://doi.org/10.1187/cbe.10-08-0105

Freeman, S., Theobald, R., Crowe, A. J., & Wenderoth, M. P. (2017). Likes attract: Students self-sort in a classroom by gender, demography, and academic characteristics. *Active Learning in Higher Education*, *18*(2), 115–126. http://doi.org/10.1177/1469787417707614

Freire, P. (1973). *Education for critical consciousness*. New York, NY: Seabury.

Freire, P. (2000). *Pedagogy of the oppressed* (30th anniv). New York, NY: Continuum.

French, K. R. (2019). The paradox of teaching for social justice: Interest convergence in early-career educators. *Urban Education*. Advanced online publication. doi: 0042085919850259.

Fries-Britt, S. L., Younger, T. K., & Hall, W. D. (2010). Lessons from high-achieving students of color in physics. *New Directions for Institutional Research*, *148*, 75–83. http://doi.org/10.1002/ir

Friesen, N. (2011). The lecture as a trans-medial pedagogical form: An historical analysis. *Educational Researcher*, *40*(3), 95–102. http://doi.org/10.3102/0013189X11404603

Fyfe, N. R. (1992). Observations on observations. *Journal of Geography in Higher Education*, *16*(2). http://doi.org/10.1080/07351698809533738

Gainen, J. (1995). Barriers to success in quantitative gatekeeper courses. *New Directions for Teaching and Learning*, *1995*(61), 5–14. http://doi.org/10.1002/tl.37219956104

Garcia, G. A., Gasiewski, J. A., & Hurtado, S. (2011, November). *Principles of good practice in introductory STEM courses: Listening to the voices of faculty and students*. Paper presented at the Association for the Study of Higher Education Annual Conference, Charlotte, NC.

Garvin-Doxas, K., & Barker, L. J. (2004). Communication in computer science classrooms: Understanding defensive climates as a means of creating supportive behaviors. *Journal of Educational Resources in Computing*, *4*(1), 1–18. http://doi.org/10.1145/1060071.1060073

Gasiewski, J. A., Eagan, M. K., Garcia, G. A., Hurtado, S., & Chang, M. J. (2012). From gatekeeping to engagement: A multicontextual, mixed method study of student academic engagement in introductory STEM courses. *Research in Higher Education*, *53*(2), 229–261. http://doi.org/10.1007/s11162-011-9247-y

Gehrke, S., & Kezar, A. (2016). STEM reform outcomes through communities of transformation. *Change: The Magazine of Higher Learning*, *48*(1), 30–38. http://doi.org/10.1080/00091383.2016.1121084

Gentile, L., Caudill, L., Fetea, M., Hill, A., Hoke, K., Lawson, B., … Szajda, D. (2012). Challenging disciplinary boundaries in the first year: A new introductory integrated science course for STEM majors. *Journal of College Science Teaching*, *41*(5), 44–51.

Gibbs, G., Simpson, C., James, D., & Fleming, S. (2004). Conditions under which assessment supports students' learning. *Learning and Teaching in Higher Education*, (1), 3–31.

Giddings, L. S., & Grant, B. M. (2009). From rigour to trustworthiness: Validating mixed methods. In S. Andrew & E. J. Halcomb (Eds.), *Mixed Methods Research for Nursing and the Health Sciences* (pp. 119–134). Blackwell Publishing. http://doi.org/10.1002/9781444316490.ch7

Gildersleeve, R. E., Kuntz, A. M., Pasque, P. A., & Carducci, R. (2010). The role of critical inquiry in (re)constructing the public agenda for higher education: Confronting the conservative modernization of the academy. *The Review of Higher Education*, *34*(1), 85–121. http://doi.org/10.1353/rhe.2010.0009

Giroux, H. A. (1988). *Teachers as intellectuals: Toward a critical pedagogy of learning*. South Hadley, MA: Bergin Garvey.

Giroux, H. A. (2006). Challenging neoliberalism's new world order: The promise of critical pedagogy. *Cultural Studies <=> Critical Methodologies*, *6*(1), 21–32. http://doi.org/10.1177/1532708605282810

Gonzalez, R. G., & Morrison, J. (2016). Culture or no culture? A Latino critical research analysis of Latino persistence research. *Journal of Hispanic Higher Education*, *15*(1), 87–108. http://doi.org/10.1177/1538192715579460

Graham, M. J., Frederick, J., Byars-Winston, A., Hunter, A.-B., & Handelsman, J. (2013). Increasing persistence of college students in STEM. *Science*, *341*, 1455–1456. http://doi.org/10.1126/science.1240487

Griffith, A. L. Cornell Higher Education Research Institute. (2010). *Persistence of women and minorities in STEM field majors: Is it the school that matters?*

Guba, E. G., & Lincoln, Y. S. (1998). Competing paradigms in qualitative research. In N. K. Denzin & Y. S. Lincoln (Eds.), *The Landscape of Qualitative Research: Theories and Issues* (pp. 195–220). London: Sage Publications.

Hall, R. M., & Sandler, B. R. (1982). *The classroom climate: A chilly one for women?*

Haney López, I. F. (2006, November 3). Colorblind to the reality of race in America. *The Chronicle of Higher Education*. Retrieved from hhttps://www.chronicle.com/article/Colorblind-to-the-Reality-of/125777931165&site=ehost-live&scope=cite

Hanson, A. R., & Gulish, A. (2016). From college to career: Making sense of the post-millenial job market. *The Georgetown Public Policy Review*, *21*(1), 1–23.

Harackiewicz, J. M., Canning, E. a., Tibbetts, Y., Giffen, C. J., Blair, S. S., Rouse, D. I., & Hyde, J. S. (2014). Closing the social class achievement gap for first-generation students in undergraduate biology. *Journal of Educational Psychology*, *106*(2), 375–389. http://doi.org/10.1037/a0034679

Harackiewicz, J. M., Canning, E. A., Tibbetts, Y., Priniski, S. J., & Hyde, J. S. (2015). Closing achievement gaps with a utility-value intervention: Disentangling race and social class. *Journal of Personality and Social Psychology*, 1–21. http://doi.org/10.1037/pspp0000075

Harlen, W. (2005). Teachers' summative practices and assessment for learning – tensions and synergies. *Curriculum Journal*, *16*(2), 207–223. http://doi.org/10.1080/09585170500136093

Harlow, J. J. B., Harrison, D. M., & Meyertholen, A. (2016). Effective student teams for collaborative learning in an introductory university physics course. *Physical Review Physics Education Research*, *12*(1), 1–11. http://doi.org/10.1103/PhysRevPhysEducRes.12.010138

Harper, S. R. (2010). An anti-deficit achievement framework for research on students of color in STEM. *New Directions for Institutional Research*, (148), 63–74. http://doi.org/10.1002/ir

Harper, S. R. (2013). Am I my brother's teacher? Black undergraduates, racial socialization, and peer pedagogies in predominantly white postsecondary contexts. *Review of Research in Education*, *37*(1), 183–211. http://doi.org/10.3102/0091732X12471300

Haynes, D. M. (2014). Always the exception: Women and women of color scientists in historical perspective. *Peer Review*, *16*(2).

Hazari, Z., Sadler, P. M., & Sonnert, G. (2013). The science identity of college students: Exploring the intersection of gender, race, and ethnicity. *Journal of College Science Teaching*, *42*(5), 82–91.

Helle, L., Tynjälä, P., & Olkinuora, E. (2006). Project-based learning in post-secondary education – theory, practice and rubber sling shots. *Higher Education*, *51*(2), 287–314. http://doi.org/10.1007/s10734-004-6386-5

Hernández, E. (2016). Utilizing critical race theory to examine race/ethnicity, racism, and power in student development theory and research. *Journal of College Student Development*, *57*(2), 168–180. http://doi.org/10.1353/csd.2016.0020

Heyman, J. B. (2016). *Pathways into STEM among low-income, urban immigrant emergent bilingual/multilingual young adults: Opportunity, access, and persistence* (Unpublished doctoral dissertation). Columbia University, New York, NY.

Higher Education Research Institute (2016). *2017 diverse learning environments classroom climate module.* Retrieved from https://www.heri.ucla.edu/PDFs/surveyAdmin/dle/2017/DLE-2017-MODULE-1-Classroom-Climate.pdf

Hirschy, A. S., & Wilson, M. E. (2002). The sociology of the classroom and its influence on student learning. *Peabody Journal of Education*, *77*(3), 85–100.

Hodges, L. C. (2018). Contemporary issues in group learning in undergraduate science classrooms: A perspective from student engagement. *CBE—Life Sciences Education*, *17*(2), 1–10. http://doi.org/10.1187/cbe.17-11-0239

Holmes, K. M. (2013). *The perceived undergraduate classroom experiences of African American women in science, technology, engineering, and mathematics (STEM)* (Unpublished doctoral dissertation). University of Maryland, College Park.

Honan, J. P., Westmoreland, A., & Tew, W. M. (2013). Creating a culture of appreciation for faculty development. *New Directions for Teaching and Learning*, *2013*(133), 33-45.

Hooks, B. (1994). *Teaching to transgress: Education as the practice of freedom*. New York, NY: Routledge.

Hora, M., & Ferrare, J. (2014). Remeasuring postsecondary teaching: How singular categories of instruction obscure the multiple dimensions of classroom practice. *Journal of College Science Teaching*, *43*(3), 36–42. http://doi.org/10.2505/4/jcst14_043_03_36

Howard Hughes Medical Institute. (2014). *HHMI announces $60 million initiative to improve science education for undergraduates.* Retrieved from http://www.hhmi.org/news/hhmi-announces-60-million-initiative-improve-science-education-undergraduates

Howell, D. C. (2013). *Statistical methods for psychology* (8th ed.). Belmont, CA: Wadsworth.

Hsu, E., Murphy, T. J., & Treisman, P. U. (2008). Supporting high minority achievement in introductory collegiate mathematics courses: What we have learned from 30 years of the emerging scholars program. In M. P. Carlson & C. Rassmussen (Eds.), *Making the Connection: Research and Practice in Undergraduate Mathematics Education* (pp. 205–220). Washington, DC: The Mathematical Association of America.

Hurtado, S., Alvarez, C. L., Guillermo-Wann, C., Cuellar, M., & Arellano, L. (2012). A model for diverse learning environments. In J. C. Smart & M. B. Paulsen (Eds.), *Higher Education: Handbook of Theory and Research* (Vol. 27, pp. 41–122). Springer Science & Business Media. http://doi.org/10.1007/978-90-481-8598-6

Hurtado, S., Cabrera, N. L., Lin, M. H., Arellano, L., & Espinosa, L. L. (2009). Diversifying science: Underrepresented student experiences in structured research programs. *Research in Higher Education*, *50*(2), 189–214. http://doi.org/10.1007/slll62-008-9114-7

Hurtado, S., Cuellar, M., & Guillermo-Wann, C. (2011). Quantitative measures of students' sense of validation: Advancing the study of diverse learning environments. *Enrollment Management Journal*, *5*(2), 53–71.

Hurtado, S., Eagan, M. K., Tran, M. C., Newman, C. B., Chang, M. J., & Velasco, P. (2011). "We do science here": Underrepresented students' interactions with faculty in different college contexts. *Journal of Social Issues*, *67*(3), 553–579. http://doi.org/10.1111/j.1540-4560.2011.01714.x

Hurtado, S., Milem, J. F., Clayton-Pederson, A. R., & Allen, W. R. (1998). Enhancing campus climates for racial/ethnic diversity: Educational policy and practice. *The Review of Higher Education*, *21*(3), 279–302.

Huston, T., & Weaver, C. L. (2008). Peer coaching: Professional development for experienced faculty. *Innovative Higher Education, 33*(1), 5-20.

Intemann, K. (2009). Why diversity matters: Understanding and applying the diversity component of the National Science Foundation's broader impacts criterion. *Social Epistemology*, *23*(3–4), 249–266. http://doi.org/10.1080/02691720903364134

Iverson, S. V. (2007). Camouflaging power and privilege: A critical race analysis of university diversity policies. *Educational Administration Quarterly*, *43*(5), 586–611. http://doi.org/10.1177/0013161X07307794

Jehangir, R. R. (2010). Stories as knowledge: Bringing the lived experience of first-generation college students into the academy. *Urban Education*, *45*(4), 533–553. http://doi.org/10.1177/0042085910372352

Jehangir, R. R., Stebleton, M. J., & Deenanath, V. National Resource Center for The First-Year Experience. (2015). *An exploration of intersecting identities of first-generation, low-income students* (Research Reports on College Transitions No. 5).

Jett, C. C. (2013). Culturally responsive collegiate mathematics education: Implications for African American students. *Interdisciplinary Journal of Teaching & Learning*, *3*(2), 102–116. Retrieved from https://acces.bibl.ulaval.ca/login?url=https://search.ebscohost.com/login.aspx?direct=true&db=eue&AN=94849144&lang=fr&site=ehost-live

Johnson, A. (2007). Unintended consequences: How science professors discourage women of color. *Science Education*, *91*(5), 805–821. http://doi.org/10.1002/sce

Johnson, A., Brown, J., Carlone, H., & Cuevas, A. K. (2011). Authoring identity amidst the treacherous terrain of science: A multiracial feminist examination of the journeys of three women of color in science. *Journal of Research in Science Teaching*, *48*(4), 339–366. http://doi.org/10.1002/tea.20411

Johnson, J. R. (2004). Universal instructional design and critical (communication) pedagogy: Strategies for voice, inclusion, and social justice/change. *Equity & Excellence in Education*, *37*(2), 145–153. http://doi.org/10.1080/10665680490453995

Joiner, K. F., Malone, J. A., & Haimes, D. H. (2002). Assessment of classroom environments in reformed calculus education. *Learning Environments Research*, *5*(1991), 51–76. http://doi.org/10.1023/A:1015635122875

Jones, S. R., & Abes, E. S. (2013). *Identity development of college students: Advancing frameworks for multiple dimensions of identity*. San Francisco, CA: Jossey-Bass.

Joseph, G. G. (1987). Foundations of Eurocentrism in mathematics. *Race & Class*, *28*(3), 13–28. http://doi.org/10.1177/030639688702800302

Kearney, P., Plax, T. G., Hays, E. R., & Ivey, M. J. (1991). College teacher misbehaviors: What students don't like about what teachers say and do. *Communication Quarterly*, *39*(4), 309–324. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=eric&AN=ED343191&site=ehost-live

Kerrigan, M. R. (2014). A framework for understanding community colleges' organizational capacity for data use: A convergent parallel mixed methods study. *Journal of Mixed Methods Research*, *8*(4), 341–362. http://doi.org/10.1177/1558689814523518

Kezar, A., Gehrke, S., & Elrod, S. (2015). Implicit theories of change as a barrier to change on college campuses: An examination of STEM reform. *The Review of Higher Education*, *38*(4), 479–506. http://doi.org/10.1353/rhe.2015.0026

Killpack, T. L., & Melón, L. C. (2016). Toward inclusive STEM classrooms: What personal role do faculty play? *CBE Life Sciences Education*, *15*(3), 1–9. http://doi.org/10.1187/cbe.16-01-0020

Kim, C., Tamborini, C. R., & Sakamoto, A. (2015). Field of study in college and lifetime earnings in the United States. *Sociology of Education*, *88*(4), 320–339. http://doi.org/10.1177/0038040715602132

Kim, E., & Hargrove, D. (2013). Deficient or resilient: A critical review of Black male academic success and persistence in higher education. *The Journal of Negro Education*, *82*(3), 300–311. http://doi.org/10.7709/jnegroeducation.82.3.0300

Kincheloe, J. L., & McLaren, P. L. (1998). Rethinking critical theory and qualitative research. In N. K. Denzin & Y. S. Lincoln (Eds.), *The Landscape of Qualitative Research: Theories and Issues*. London: Sage Publications.

Korn, M. (2018, October 26). Some 43% of college grads are underemployed in first job. *The Wall Street Journal*.

Ladson-Billings, G., & Tate IV, W. F. (1995). Toward a critical race theory of education. *Teachers College Record*, *97*(1), 47–68. http://doi.org/10.1080/10282580701850413

Langley, D., & Guzey, S. S. (2014). Conducting an introductory biology course in an active learning classroom: A case study of an experienced faculty member. *New Directions for Teaching and Learning*, (137), 71–76. http://doi.org/10.1002/tl

Lather P. (1986) Issues of validity in openly ideological research: Between a rock and a soft place. *Interchange*, 17(4), 63–84.

le Roux, K. (2016). Re-imagining mathematics and mathematics education for equity and social justice in the changing South African university. *Critical Studies in Teaching & Learning*, *4*(2), 45–67. http://doi.org/10.14426/cristal.v4i2.74

Lerman, S. (2000). The social turn in mathematics education research. In J. Boaler (Ed.), *Multiple perspectives on the teaching and learning of Mathematics* (pp. 19–44). Westport, CT: Greenwood Publishing Group.

Lester, J., Yamanaka, A., & Struthers, B. (2016). Gender microaggressions and learning environments: The role of physical space in teaching pedagogy and communication. *Community College Journal of Research and Practice*, *40*(11).

Levine, L. (2011). Offshoring (or offshore outsourcing) and job loss among U S. workers. Washington, DC: Congressional Research Service.

Lloyd, G. (2002). Mathematics teachers' beliefs and experiences with innovative curriculum materials. In G. C. Leder, E. Pehkonen, & G. Törner (Eds.), *Beliefs: A hidden variable in mathematics education?* (pp. 149–159). Dordrecht, Netherlands: Springer.

Ma, Y., & Savas, G. (2014). Which is more consequential: Fields of study or institutional selectivity? *The Review of Higher Education*, *37*(2), 221–247. http://doi.org/10.1353/rhe.2014.0001

Mangan, K. (2015, May 18). The challenge of the first-generation student. *The Chronicle of Higher Education*. Retrieved from http://www.chronicle.com/article/The-Challenge-of-the/230137

Marchesani, L. S., & Adams, M. (1992). Dynamics of diversity in the teaching-learning process: A faculty development model for analysis and action. *New Directions for Teaching and Learning*, (52), 9–20.

Markman, L. P. (2016). *Exploration of supportive practices in instructional design for undergraduate online developmental pre-algebra/math courses* (Doctoral dissertation). Retrieved from ProQuest.

Martin-Dunlop, C., & Fraser, B. J. (2008). Learning environment and attitudes associated with an innovative science course designed for prospective elementary teachers. *International Journal of Science and Mathematics Education*, *6*(1), 163–190. http://doi.org/10.1007/s10763-007-9070-2

Martin, J. P., Miller, M. K., & Simmons, D. R. (2014). Exploring the theoretical social capital “deficit” of first generation college students: Implications for engineering education. *International Journal of Engineering Education*, *30*(4), 822–836. Retrieved from http://www.scopus.com/inward/record.url?eid=2-s2.0-84906318325&partnerID=tZOtx3y1

Mayberry, M. (1998). Reproductive and resistant pedagogies: The comparative roles of collaborative learning and feminist pedagogy in science education. *Journal of Research in Science Teaching*, *35*(4), 443–459. http://doi.org/10.1002/(SICI)1098-2736(199804)35:4<443::AID-TEA14>3.0.CO;2-A

McCoy, D. L., Winkle-Wagner, R., & Luedke, C. L. (2015). Colorblind mentoring? Exploring white faculty mentoring of students of color. *Journal of Diversity in Higher Education*, *8*(4), 225–242.

McGowen, M. (2006). Who are the students who take precalculus? *Maa Notes*. http://doi.org/10.5948/UPO9781614443025.006

McLaren, P. L. (1998). *Life in schools: An introduction to critical pedagogy in the foundations of education*. Reading, MA: Addison Wesley Longman.

Merriam, S. B. (2015). *Qualitative research: A guide to design and implementation*. San Francisco, CA: Jossey-Bass.

Mervis, J. (2010). Better intro courses seen as key to reducing attrition of STEM majors. *Science*, *330*, 306.

Mitchell, T. D., Donahue, D. M., & Young-Law, C. (2012). Service learning as a pedagogy of whiteness. *Equity & Excellence in Education*, *45*(4), 612–629. http://doi.org/10.1080/10665684.2012.715534

Morales, E. E., & Trotman, F. K. (2010). *A focus on hope: Fifty resilient students speak*. Lanham, MD: University Press of America.

Morgan, D. L. (2007). Paradigms lost and pragmatism regained: Methodological implications of combining qualitative and quantitative methods. *Journal of Mixed Methods Research*, *1*(1), 48–76. http://doi.org/10.1177/2345678906292462

Mulnix, A. B., Vandegrift, E. V. H., & Chaudhury, S. R. (2016). How important is achieving equity in STEM education to you? *Journal of College Science Teaching*, *45*(4), 8–11.

Mumby, D., & Stohl, C. (1991). Power and discourse in organization studies: Absence and the dialectic of control. *Discourse and Society*, *2*(3), 313–332. http://doi.org/0803973233

Muncey, T. (2009). Does mixed methods constitute a change in paradigm? In S. Andrew & E. J. Halcomb (Eds.), *Mixed Methods Research for Nursing and the Health Sciences* (pp. 13–30). Blackwell Publishing. http://doi.org/10.1002/9781444316490.ch2

Museus, S. D. (2011). Generating ethnic minority student success (GEMS): A qualitative analysis of high-performing institutions. *Journal of Diversity in Higher Education*, *4*(3), 147–162. http://doi.org/10.1037/a0028508

Museus, S. D., & Griffin, K. A. (2011). Mapping the margins in higher education: On the promise of intersectionality frameworks in research and discourse. *New Directions for Institutional Research*, *151*, 5–13. http://doi.org/10.1002/ir

Museus, S. D., & Liverman, D. (2010). High-performing institutions and their implications for studying underrepresented minority students in STEM. *New Directions for Institutional Research*, *148*, 17–27. http://doi.org/10.1002/ir

Nash, J. C. (2008). Re-thinking intersectionality. *Feminist Review*, *89*(1), 1–15. http://doi.org/10.1057/fr.2008.4

National Center for Education Statistics. (2016). *The condition of education 2016* (NCES 2016-144). Washington, D.C.

National Science Board. (2015). *Revisiting the STEM workforce: A companion to science and engineering indicators 2014* (NSB No. 2015-10). Arlington, VA.

Nelson Laird, T. F., Chen, D., & Kuh, G. D. (2008). Classroom practices at institutions with higher-than-expected persistence rates: What student engagement data tell us. *New Directions for Teaching and Learning*, (115), 85–99. http://doi.org/10.1002/tl

Nicol, D. J., & Macfarlane-Dick, D. (2006). Formative assessment and self-regulated learning: A model and seven principles of good feedback practice. *Studies in Higher Education*, *31*(2), 199–218. http://doi.org/10.1080/03075070600572090

O'Leary, K., Fitzpatrick, C. L., & Hallett, D. (2017). Math anxiety is related to some, but not all, experiences with math. *Frontiers in Psychology*, *8*, 1–14. http://doi.org/10.3389/fpsyg.2017.02067

O'Neal, C., Wright, M., Cook, C., Perorazio, T., & Purkiss, J. (2007). The impact of teaching assistants on student retention in the sciences: Lessons for TA training. *Journal of College Science Teaching*, *36*(5), 24–30.

Ochoa, G. L., & Pineda, D. (2008). Deconstructing power, privilege, and silence in the classroom. *Radical History Review*, *Fall*(102), 45–62. http://doi.org/10.1215/01636545-2008-012

Ong, M. (2005). Body projects of young women of color in physics: Intersections of gender, race, and science. *Social Problems*, *52*(4), 593–617. http://doi.org/10.1525/sp.2005.52.4.593

Park, E. L., & Choi, B. K. (2014). Transformation of classroom spaces: Traditional versus active learning classroom in colleges. *Higher Education*, *68*(5), 749–771. http://doi.org/10.1007/s10734-014-9742-0

Parmelee, D., & Hudes, P. (2012). Team-based learning: A relevant strategy in health professionals' education. *Medical Teacher*, *34*, 411–3. http://doi.org/10.3109/0142159X.2012.643267

Parmelee, D., Michaelsen, L. K., Cook, S., & Hudes, P. D. (2012). Team-based learning: A practical guide: AMEE guide no. 65. *Medical Teacher*, *34*(5), e275-e287.

Parsons, E. R. C., Rhodes, B., & Brown, C. (2011). Unpacking the CRT in negotiating white science. *Cultural Studies of Science Education*, *6*(4), 951–960. http://doi.org/10.1007/s11422-011-9349-z

Pascarella, E. T., Seifert, T. A., & Whitt, E. J. (2008). Effective instruction and college student persistence: Some new evidence. *New Directions for Teaching and Learning*, *115*, 55–70. http://doi.org/10.1002/tl

Patton, L. D., Harper, S. R., & Harris, J. (2015). Using critical race theory to (re)interpret widely studied topics related to students in US higher education. In A. M. Martínez Alemán, B. Pusser, & E. M. Bensimon (Eds.), *Critical approaches to the study of higher education: A practical introduction* (pp. 193–219). Baltimore, MD: John Hopkins University Press.

Patton, M. Q. (2014). *Qualitative research and evaluation methods: Integrating theory and practice* (4th ed.). Thousand Oaks, CA: Sage Publications.

PayScale. (n.d.). Majors That Pay You Back. Retrieved January 6, 2016, from http://www.payscale.com/college-salary-report-2014/majors-that-pay-you-back

Pell Institute for the Study of Opportunity in Higher Education. (2016). *Indicators of higher education equity in the United States: 2016 historical trend report*.

Penner, M. R. (2018). Building an inclusive classroom. *The Journal of Undergraduate Neuroscience Education*, *16*(3), 268–272.

Peralta, C., Caspary, M., & Boothe, D. (2013). Success factors impacting Latina/o persistence in higher education leading to STEM opportunities. *Cultural Studies of Science Education*, *8*, 905–918. http://doi.org/10.1007/s11422-013-9520-9

Perna, L., Lundy-Wagner, V., Drezner, N. D., Gasman, M., Yoon, S., Bose, E., & Gary, S. (2009). The contribution of HBCUs to the preparation of African American women for STEM careers: A case study. *Research in Higher Education*, *50*(1), 1–23. http://doi.org/10.1007/s11162-008-9110-y

Peters, M. L. (2013). Examining the relationships among classroom climate, self-efficacy, and achievement in undergraduate mathematics: A multi-level analysis. *International Journal of Science and Mathematics Education*, *11*(2), 459–480. http://doi.org/10.1007/s10763-012-9347-y

Philipp, S. B., Tretter, T. R., & Rich, C. V. (2016). Development of undergraduate teaching assistants as effective instructors in STEM courses. *Journal of College Science Teaching*, *45*(3), 74–82.

Pillow, W. S. (2003). Confession, catharsis, or cure? Rethinking the uses of reflexivity as methodological power in qualitative research. *International Journal of Qualitative Studies in Education*, *16*(2), 175–196. http://doi.org/10.1080/0951839032000060635

Pluye, P., & Hong, Q. N. (2014). Combining the power of stories and the power of numbers: Mixed methods research and mixed studies reviews. *Annual Review of Public Health*, *35*(1), 29–45. http://doi.org/10.1146/annurev-publhealth-032013-182440

Premo, J., Cavagnetto, A., & Davis, W. B. (2018). Promoting collaborative classrooms: The impacts of interdependent cooperative learning on undergraduate interactions and achievement. *CBE—Life Sciences Education*, *17*(ar32), 1–16. http://doi.org/10.1187/cbe.17-08-0176

President's Council of Advisors on Science and Technology. (2012). *Engage to excel: Producing one million additional college graduates with degrees in science, technology, engineering, and mathematics*.

Price, M., Carroll, J., O'Donovan, B., & Rust, C. (2011). If I was going there I wouldn't start from here: A critical commentary on current assessment practice. *Assessment & Evaluation in Higher Education*, *36*(4), 479–492. doi:10.1080/02602930903512883

Prince, M. (2004). Does active learning work ? A review of the research. *Journal of Engineering Education*, (July), 223–231.

Rankin, S. R., & Reason, R. D. (2005). Differing perceptions: How students of color and white students perceive campus climate for underrepresented groups. *Journal of College Student Development*, *46*(1), 43–61. http://doi.org/10.1353/csd.2005.0008

Rask, K. (2010). Attrition in STEM fields at a liberal arts college: The importance of grades and pre-collegiate preferences. *Economics of Education Review*, *29*(6), 892–900. http://doi.org/10.1016/j.econedurev.2010.06.013

Rendón, L. L. (1994). Validating culturally diverse students: Toward a new model of learning and student development. *Innovative Higher Education*, *19*(1).

Rendón, L. L., Jalomo, R. E., & Nora, A. (2000). Theoretical considerations in the study of minority student retention in higher education. In J. M. Braxton (Ed.), *Reworking the student departure puzzle* (pp. 127–156). Nashville, TN: Vanderbilt University Press.

Rendón Linares, L. I., & Muñoz, S. M. (2011). Revisiting validation theory: Theoretical foundations, applications, and extension. *Enrollment Management Journal*, *5*(2), 12–33. http://doi.org/10.1300/J050v03n02_08

Riegle-Crumb, C., King, B., & Irizarry, Y. (2019). Does STEM stand out? Examining racial/ethnic gaps in persistence across postsecondary fields. *Educational Researcher*. Advance online publication. doi: 0013189X19831006.

Riley, D. (2003). Pedagogies of liberation in an engineering thermodynamics class. *American Society For Engineering Education Annual Conference & Exposition*. Retrieved from http://www.cirtl.net/node/5514

Riley, D., & Claris, L. (2006). Power/knowledge : Using Foucault to promote critical understandings of content and pedagogy in engineering thermodynamics. Chicago, IL.

Riley, D., & Claris, L. (2009). From persistence to resistance: Pedagogies of liberation for inclusive science and engineering. *International Journal of Gender, Science and Technology*, *1*(1), 37–60. Retrieved from http://genderandset.open.ac.uk/index.php/genderandset/article/viewArticle/25

Riley, D. M. (2003). Employing liberative pedagogies in engineering education. *Journal of Women and Minorities in Science and Engineering*, *9*(2), 137–158. http://doi.org/10.1615/JWomenMinorScienEng.v9.i2.20

Riley, D. M. (2014). What's wrong with evidence? Epistemological roots and pedagogical implications of "evidence-based practice" in STEM education. *ASEE Annual Conference & Exposition*. Retrieved from http://www.asee.org/public/conferences/32/papers/9995/view

Rogers, M., Keller, L. D., Crouse, A., & Price, M. F. (2015). Implementing comprehensive reform of introductory physics at a primarily undergraduate institution: A longitudinal case study. *Journal of College Science Teaching*, *44*(3), 82–90.

Ropers-Huilman, B. (1999). Scholarship on the other side: Power and caring in feminist education. *NWSA Journal*, *11*(1), 1–13.

Rovai, A. P. (2002). Development of an instrument to measure classroom community. *Internet and Higher Education*, *5*(3), 197–211. http://doi.org/10.1016/S1096-7516(02)00102-1

Russell, M. L., & Atwater, M. M. (2005). Traveling the road to success: A discourse on persistence throughout the science pipeline with African American students at a predominantly White institution. *Journal of Research in Science Teaching*, *42*(6), 691–715. http://doi.org/10.1002/tea.20068

Rust, C. (2002). The impact of assessment on student learning: How can the research literature practically help to inform the development of departmental assessment strategies and learner-centred assessment practices? *Active Learning in Higher Education*, *3*(2), 145–158. http://doi.org/10.1177/1469787402003002004

Saha, S., Guiton, G., Wimmers, P. F., & Wilkerson, L. (2008). Student body racial and ethnic composition and diversity-related outcomes in US medical schools. *JAMA*, *300*(10), 1135. http://doi.org/10.1001/jama.300.10.1135

Saha, S., & Shipman, S. A. (2008). Race-neutral versus race-conscious workforce policy to improve access to care. *Health Affairs*, *27*(1), 234–245. http://doi.org/10.1377/hlthaff.27.1.234

Saldaña, J. (2016). *The coding manual for qualitative researchers*. Thousand Oaks, CA: Sage Publications.

Sandelowski, M. (2000). Focus on research methods: Combining qualitative and quantitative sampling, data collection, and analysis techniques in mixed methods studies. *Research in Nursing & Health*, *23*, 246–255. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.472.7825&rep=rep1&type=pdf

Schinske, J. N., Perkins, H., Snyder, A., & Wyer, M. (2016). Scientist spotlight homework assignments shift students' stereotypes of scientists and enhance science identity in a diverse introductory science class. *CBE Life Sciences Education*, *15*(3), 1–18. http://doi.org/10.1187/cbe.16-01-0002

Seidel, S. B., & Tanner, K. D. (2013). "What if students revolt?" - Considering student resistance: Origins, options, and opportunities for investigation. *CBE Life Sciences Education*, *12*(4), 586–595. http://doi.org/10.1187/cbe-13-09-0190

Seymour, E., & Hewitt, N. M. (1997). *Talking about leaving: Why undergraduates leave the sciences*. Boulder, CO: Westview Press.

Shapiro, D., Dundar, A., Huie, F., Wakhungu, P.K., Bhimdiwala, A. & Wilson, S. E. National Student Clearinghouse Research Center. (2018). *Completing college: A national view of student completion rates – fall 2012 cohort* (Signature Report No. 16). Herndon, VA.

Shaw, E. J., & Barbuti, S. (2010). Patterns of persistence in intended college major with a focus on STEM majors. *NACADA Journal*, *30*(2), 19–34.

Shepard, L. (2000). The role of assessment in a learning culture. *Educational Researcher*, *29*(7), 4–14.

Shuster, M. I., & Preszler, R. (2014). Introductory biology course reform: A tale of two courses . *International Journal for the Scholarship of Teaching and Learning*, *8*(2). Retrieved from http://digitalcommons.georgiasouthern.edu/ij-sotl/vol8/iss2/5

Sidelinger, R. J., Bolen, D. M., Frisby, B. N., & McMullen, A. L. (2012). Instructor compliance to student requests: An examination of student-to-student connectedness as power in the classroom. *Communication Education*, *61*(3), 290–308. http://doi.org/10.1080/03634523.2012.666557

Snyder, T. D., de Brey, C., & Dillow, S. A. National Center for Education Statistics. (2016). *Digest of education statistics 2014* (NCES No. 2016-006). Washington, D.C.

Sohn, B. K. (2016). *The student experience of other students* (Doctoral dissertation). Retrieved from Trace: Tennessee Research and Creative Exchange.

Sommeiller, E., & Price, M. Economic Policy Institute. (2018). *The new gilded age: Income inequality in the U.S. by state, metropolitan area, and county.* Washington, D.C.

Sonnert, G., & Sadler, P. M. (2014). The impact of taking a college pre-calculus course on students' college calculus performance. *International Journal of Mathematical Education in Science and Technology*, *45*(8), 1188–1207.

Soria, K. M., & Gorny, L. S. (2012). *Defining first-generation students by degrees.* Paper presented at the AIR Forum, New Orleans, LA.

Soria, K. M., & Stebleton, M. J. (2012). First-generation students' academic engagement and retention. *Teaching in Higher Education*, *17*(6), 673–685. http://doi.org/10.1080/13562517.2012.666735

Sosnowski, N. H. (2002). *Women of color staking a claim for cyber domain: Unpacking the racial/ gender gap in science, mathematics, engineering and technology (SMET)* (Doctoral dissertation). Retrieved from ProQuest Information and Learning Company.

Stage, F. K. (2007). Answering critical questions using quantitative data. *New Directions for Institutional Research*, (133), 1–16. http://doi.org/10.1002/ir

Stains, M., Harshman, J., Barker, M. K., Chasteen, S. V., Cole, R., DeChenne-Peters, S. E., … Young, A. M. (2018). Anatomy of STEM teaching in North American universities. *Science*, *359*(6383), 1468–1470.

Stains, M., & Vickrey, T. (2017). Fidelity of implementation: An overlooked yet critical construct to establish effectiveness of evidence-based instructional practices. *CBE Life Sciences Education*, *16*(1), 1–11. http://doi.org/10.1187/cbe.16-03-0113

Stebleton, M. J., & Aleixo, M. B. (2016). Black African immigrant college students' perceptions of belonging at a predominately White institution. *Journal of The First-Year Experience & Students in Transition*, *28*(1), 89–107.

Stephens, N. M., Fryberg, S. A., Markus, H. R., Johnson, C. S., & Covarrubias, R. (2012). Unseen disadvantage: How American universities' focus on independence undermines the academic performance of first-generation college students. *Journal of Personality and Social Psychology*, *102*(6), 1178–1197. http://doi.org/10.1037/a0027143

Stokstad, E. (2001). Reintroducing the intro course. *Science*, *293*(August), 1608–1610. http://doi.org/10.1126/science.293.5535.1608

Stone, C., Trisi, D., Sherman, A., & Horton, E. Center on Budget and Policy Priorities. (2015). *A guide to statistics on historical trends in income inequality.*

Strange, C. C., & Banning, J. H. (2001). *Educating by design: Creating campus learning environments that work*. San Francisco, CA: Jossey-Bass.

Strayhorn, T. L. (2012). *College students' sense of belonging: A key to educational success for all students*. Routledge.

Strayhorn, T. L., & Johnson, R. M. (2014). Why are all the White students sitting together in college? Impact of Brown V. Board of Education on cross-racial interactions among Blacks and Whites. *The Journal of Negro Education*, *83*(3), 385–399. http://doi.org/10.7709/jnegroeducation.83.3.0385

Strayhorn, T. L., Long III, L. L., Kitchen, J. A., Williams, M. S., & Stentz, M. (2013, June). *Academic and social barriers to Black and Latino male collegians' success in engineering and related STEM fields.* Paper presented at the ASEE Annual Conference, Atlanta, GA.

Sue, D. W., Capodilupo, C. M., Torino, G. C., Bucceri, J. M., B Holder, A. M., Nadal, K. L., & Esquilin, M. (2007). Racial microaggressions in everyday life: Implications for clinical practice. *American Psychologist*, *62*(4), 271–286. http://doi.org/10.1037/0003-066X.62.4.271

Sue, D. W., Torino, G. C., Capodilupo, C. M., Rivera, D. P., & Lin, A. I. (2009). How white faculty perceive and react to difficult dialogues on race: Implications for education and training. *The Counseling Psychologist*, *37*(8), 1090–1115. http://doi.org/10.1177/0011000009340443

Sunstein, B. S., & Chiseri-Strater, E. (2011). *Fieldworking: Reading and writing research*. Macmillan.

Supiano, B. (2018, May 6). Traditional teaching may deepen inequality. Can a different approach fix it? *The Chronicle of Higher Education*.

Swaminathan, R., & Alfred, M. V. (2001). Strangers in the mirror: Immigrant students in the higher education classroom. *Adult Learning*, *12/13*(4/1), 29–32.

Swan, A. K. (2012). Female students' experiences with project-based work in introductory engineering classes at two- and four-year institutions. *Journal of Women and Minorities in Science and Engineering*, *18*(4), 337–357. http://doi.org/10.1615/JWomenMinorScienEng.2013004350

Sykes, G. (1990). Learning to teach with cases. *Journal of Policy Analysis and Management*, *9*(2), 297–302.

Tanner, K. D. (2011). Moving theory into practice: A reflection on teaching a large, introductory biology course for majors. *CBE Life Sciences Education*, *10*(2), 113–122. http://doi.org/10.1187/cbe.11-03-0029

Tanner, K. D. (2013). Structure matters: Twenty-one teaching strategies to promote student engagement and cultivate classroom equity. *CBE Life Sciences Education*, *12*(3), 322–331. http://doi.org/10.1187/cbe.13-06-0115

Tashakkori, A., & Teddlie, C. (2008). Quality of inferences in mixed methods research: Calling for an integrative framework. In M. M. Bergman (Ed.), *Advances in Mixed Methods Research* (pp. 1–8). London, UK: Sage Publications. http://doi.org/10.4135/9780857024329

Tate, E. D., & Linn, M. C. (2005). How does identity shape the experiences of women of color engineering students? *Journal of Science Education and Technology*, *14*(5–6), 483–493. http://doi.org/10.1007/s10956-005-0223-1

Theobald, E. J., Eddy, S. L., Grunspan, D. Z., Wiggins, B. L., & Crowe, A. J. (2017). Student perception of group dynamics predicts individual performance: Comfort and equity matter. *PLoS ONE*, *12*(7), 1–16. http://doi.org/10.1371/journal.pone.0181336

Tierney, W. G. (2000). Power, identity, and the dilemma of college student departure. In J. M. Braxton (Ed.), *Reworking the student departure puzzle* (pp. 213–234). Nashville, TN: Vanderbilt University Press.

Tierney, W. G. (2013). Life history and identity. *Review of Higher Education*, *36*(2), 255–282. http://doi.org/10.1353/rhe.2013.0006

Tinto, V. (1975). Dropouts from higher education: A theoretical synthesis of recent literature. *A Review of Educational Research*, *45*, 89–125.

Tinto, V. (2012). Enhancing student success: Taking the classroom success seriously. *The International Journal of the First Year in Higher Education*, *3*(1), 1–8. http://doi.org/10.5204/intjfyhe.v3i1.119

Tobias, S. (1990). *They're not dumb, they're different: Stalking the second tier*. Tuscon, AZ: Research Corporation.

Toma, J. D. (2011). Approaching rigor in applied qualitative research. In C. F. Conrad & R. C. Serlin (Eds.), *The SAGE handbook for research in education* (pp. 263–280). Thousand Oaks, CA: Sage Publications.

Toutkoushian, R. K., Stollberg, R. S., & Slaton, K. A. (2015). *Talking 'bout my generation: Defining "first-generation students" in higher education research.* Paper presented at the Association for the Study of Higher Education Annual Conference, Denver, CO.

Trees, A. R., & Jackson, M. H. (2007). The learning environment in clicker classrooms: Student processes of learning and involvement in large university-level courses using student response systems. *Learning, Media and Technology*, *32*(1), 21–40. http://doi.org/10.1080/17439880601141179

Trenor, J. M. (2009). Phenomenological inquiry of the major choice processes of an overlooked demographic. *Proceedings of The Research in Engineering Education Symposium*, 1–6.

Tsui, L. (2007). Effective strategies to increase diversity in STEM fields: A review of the research literature. *The Journal of Negro Education*, *76*(4), 555–581.

Tsukada, H., & Perreault, A. (2016). Complicating how classroom climate works: Advancing the framework. *Transformative Dialogues: Teaching & Learning Journal*, *9*(2), 1–18. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=eue&AN=119642464&site=eds-live

Tuitt, F. (2003). Afterword: Realizing a more inclusive pedagogy. In A. Howell & F. Tuitt (Eds.), *Race and higher education: Rethinking pedagogy in diverse college classrooms* (pp. 243–268). Cambridge, MA: Harvard Educational Review.

Tuitt, F. (2016). Inclusive pedagogy 2.0: Implications for race, equity, and higher education in a global context. In F. Tuitt, C. Haynes, & S. Stewart (Eds.), *Race, equity, and the learning environment: The global relevance of critical and inclusive pedagogies in higher education* (pp. 205–221). Sterling, VA: Stylus Publishing.

Twigg, C. A. The National Center for Public Policy and Higher Education. (2005a). *Course redesign improves learning and reduces cost.*

Twigg, C. A. The National Center for Academic Transformation. (2005b). *Increasing success for underserved students: Redesigning introductory courses.*

U.S. Department of Education. (2014). *Web tables: Profile of undergraduate students: 2011-2012* (NCES No. 2015-167).

U.S. Department of Education. (2015). *Science, technology, engineering and math: Education for global leadership*. Retrieved from http://www.ed.gov/stem

U.S. Immigration and Customs Enforcement. (2012). *STEM-designated degree program list.* Retrieved from https://www.ice.gov/sites/default/files/documents/Document/2014/stem-list.pdf

Vahala, M. E., & Winston, R. B. (1994). College classroom environments: Disciplinary and institutional-type differences and effects on academic achievement in introductory courses. *Innovative Higher Education*, *19*(2), 99–122. http://doi.org/10.1007/BF01191592

Valero, P. (2008). Discourses of power in mathematics education research: Concepts and possibilities for action. *PNA*, *2*(2), 43–60.

Van Dinther, M., Dochy, F., & Segers, M. (2011). Factors affecting students' self-efficacy in higher education. *Educational Research Review*, *6*(2), 95–108. http://doi.org/10.1016/j.edurev.2010.10.003

Verdin, D., & Godwin, A. (2015). *First in the family: A comparison of first-generation and non-first-generation engineering college students*. Paper presented at the IEEE Annual Conference.

Vivyan, E. (2016). *Classroom culture clash: Exploring classroom culture and persistence for undergraduate students in introductory science, technology, engineering, and mathematics courses at two public universities* (Unpublished doctoral dissertation). University of Wisconsin, Madison, WI.

Volkwein, J. F., & Cabrera, A. F. (1998). *Student measures associated with favorable classroom experiences.* Paper presented at the Annual Forum of the Association for Institutional Research, Minneapolis, MN.

Walker, J. D., Cotner, S. H., Baepler, P. M., & Decker, M. D. (2008). A delicate balance: Integrating active learning into a large lecture course. *CBE-Life Sciences Education*, *7*, 361–367. http://doi.org/10.1187/cbe.08

Watkins, J., & Mazur, E. (2013). Retaining students in science, technology, engineering, and mathematics (STEM) majors. *Journal of College Science Teaching*, *42*(5), 36–41. http://doi.org/10.2505/4/jcst13_042_05_36

Weimer, M. (2002). *Learner-centered instruction*. San Francisco, CA: Jossey-Bass.

Whalen, D. F., & Shelley, M. C. (2010). Academic success for STEM and non-STEM majors. *Journal of STEM Education*, *11*(1), 45–60. Retrieved from http://search.proquest.com.ezproxy.library.yorku.ca/docview/851225217?accountid=15182

Whetten, D. A. (2007). Principles of effective course design: What I wish I had known about learning-centered teaching 30 years ago. *Journal of management education*, *31*(3), 339-357.

Wieman, C. (2014). Stop lecturing me. *Scientific American*, *311*(2), 70–71. http://doi.org/10.1038/scientificamerican0814-70

Wiggins, G., & McTighe, J. (2005). *Understanding by design*. Alexandria, VA: Association for Supervision and Curriculum Development.

Wiggins, G. P., & McTighe, J. (2011). *The understanding by design guide to creating high-quality units*. Alexandria, VA: Association for Supervision and Curriculum Development.

Wilson, R. (1997, February 7). "Reform calculus" has been a disaster, critics charge. *The Chronicle of Higher Education*. Retrieved from http://www.chronicle.com/article/Reform-Calculus-Has-Been-a/77411

Wilson, R. E., & Kittleson, J. (2013). Science as a classed and gendered endeavor: Persistence of two white female first-generation college students within an undergraduate science context. *Journal of Research in Science Teaching*, *50*(7), 802–825. http://doi.org/10.1002/tea.21087

Wolfe, J. (2000). Gender, ethnicity, and classroom discourse: Communication patterns of Hispanic and White students in networked classrooms. *Written Communication*, *17*(4), 491–519. http://doi.org/0803973233

Worthley, M. (2013). *A mixed methods explanatory study of the failure/drop rate for freshman STEM calculus students* (Doctoral dissertation). Retrieved from ProQuest.

Wright, M. C., McKay, T., Hershock, C., Miller, K., & Tritz, J. (2014). Better than expected: Using learning analytics to promote student success in gateway science. *Change: The Magazine of Higher Learning*, *46*(1), 28–34. http://doi.org/10.1080/00091383.2014.867209

Yin, R. K. (2014). *Case study research: Design and methods* (5th ed.). Thousand Oaks, CA: Sage Publications.

Yorke, M. (2003). Formative assessment in higher education: Moves towards theory and the enhancement of pedagogic practice. *Higher Education*, *45*, 477–501.

Yoshikawa, H., Weisner, T. S., Kalil, A., & Way, N. (2013). Mixing qualitative and quantitative research in developmental science: Uses and methodological choices. *Qualitative Psychology*, *1*(S), 3–18. http://doi.org/10.1037/2326-3598.1.S.3

Yosso, T. J. (2005). Whose culture has capital? A critical race theory discussion of community cultural wealth. *Race Ethnicity and Education*, *8*(1), 69–91. http://doi.org/10.1080/1361332052000341006

Yu, C. (2002). *Evaluating cutoff criteria of model fit indices for latent variable models with binary and continuous outcomes* (Unpublished doctoral dissertation). University of California, Los Angeles, CA.

Appendix A: Summary of the Three Teaching and Learning Paradigms in STEM

<table>
<tr><th></th><th>Traditional pedagogy</th><th>Active learning</th><th>Inclusive pedagogy</th></tr>
<tr><td>Supporting/background literature</td><td>Hermeneutics</td><td>Cognitive science; scientific teaching literature</td><td>Critical theory, critical pedagogy, and related pedagogies including feminist pedagogy, transformative learning, and culturally relevant pedagogy</td></tr>
<tr><td>Underlying theory of learning</td><td>Knowledge is static and objective; knowledge can be transferred from one person to another</td><td>Knowledge is socially constructed</td><td>Knowledge is socially constructed and mediated by cultural, historical, and institutional contexts</td></tr>
<tr><td rowspan="3">Goal</td><td colspan="2">Student learning of a discipline’s prevailing concepts and ideas; reproduce the dominant discourses of STEM</td><td>Question and criticize science and the relationship between science systems and power and oppression; transform the STEM fields</td></tr>
<tr><td>Rote memorization of content</td><td colspan="2">Improve students’ conceptual understanding; persistence</td></tr>
<tr><td colspan="2">Prepare students for future professions</td><td>Prepare students for future professions while also criticizing industries that harm marginalized communities</td></tr>
<tr><td>Issues of racism, sexism, classism, and other forms of oppression</td><td>Not addressed</td><td>Achievement gaps are recognized – way to address them is to use active learning</td><td>Explicitly recognizes and challenges racism, sexism, and other forms of discrimination; highlights power imbalances in STEM education</td></tr>
<tr><td rowspan="2">Teaching activities: Role of professor</td><td>Transmits knowledge to students</td><td colspan="2">Facilitator of learning</td></tr>
<tr><td colspan="2"></td><td>Plays a validating role for students; uses an ethic of care</td></tr>
</table>

	Traditional pedagogy	Active learning	Inclusive pedagogy
Teaching activities: Role of students	Passively receive knowledge	Students are actively engaged in the learning process	
			Students share responsibility for learning with the professor. Power is shared between the professor and students in the class
Content	Content is decontextualized from its real-world application	Encourages real-world application of content and material that is relevant to students, although does not question for whom the content is relevant	Content should be linked to students' life experiences – especially for underrepresented students. Content should also be linked to how students might use it in the future. Strong emphasis on praxis.
Assessment	Test-based; summative	Stresses formative assessment and authentic assessment	

Appendix B: Student Consent Form

Title of Research Study: Students' Experiences in a Redesigned Gateway STEM Course

Researcher: Kate K. Diamond

Supported By: This research is supported by the University of Minnesota Mixed Methods Interdisciplinary Graduate Group.

Why am I being asked to take part in this research study?
We are asking you to take part in this research study because you are a student in sections 1, 2, or 3 of [math class] during the Fall 2017 semester.

What should I know about a research study?

- Someone will explain this research study to you.
- Whether or not you take part is up to you.
- You can choose not to take part.
- You can agree to take part and later change your mind.
- Your decision will not be held against you.
- You can ask all the questions you want before you decide.

Who can I talk to?
For questions about research appointments, the research study, research results, or other concerns, call the study team at:

Researcher Name: Kate K. Diamond Phone Number: 617-913-9905 Email Address: koehl220@umn.edu	Study Staff (if applicable): Phone Number: Email Address:

This research has been reviewed and approved by an Institutional Review Board (IRB) within the Human Research Protections Program (HRPP). To share feedback privately with the HRPP about your research experience, call the Research Participants' Advocate Line at 612-625-1650 or go to www.irb.umn.edu/report.html. You are encouraged to contact the HRPP if:

- Your questions, concerns, or complaints are not being answered by the research team.
- You cannot reach the research team.
- You want to talk to someone besides the research team.
- You have questions about your rights as a research participant.
- You want to get information or provide input about this research.

Why is this research being done?
The purpose of this research is to better understand student experiences in a gateway math course. The study responds to a national urgency to improve student success in the science, technology, engineering, and mathematics (STEM) fields, especially for underrepresented students. The outcomes of this research will inform efforts to better meet the needs of students in gateway math courses.

How long will the research last?
We expect that you will be in this research study for four months: September through December, 2017.

How many people will be studied?
We expect about 250 people here will be in this research study.

What happens if I say "Yes, I want to be in this research"?
There are two phases of the study, both are optional.

Phase 1: If you agree to participate, you will be asked to complete a short survey. The survey will be administered in class toward the middle of the semester, and should take about 15 minutes. The survey will also be posted online if you prefer to fill it out online. The survey will ask you questions about your experiences in the course. For example, it may ask you whether you agree or disagree with the statement, "The physical environment of this course supports my learning."

Phase 2: If you agree to participate, the researcher will contact you at a later time to set up a 60 to 90-minute interview. Interviews will occur toward the end of the semester and will take place in a private meeting room on the University of Minnesota campus. If you participate in an interview, the researcher will request your permission to audio record it. Interview participants will receive a $25 gift card in recognition of their time. The interviews will also explore your experiences in this course. For example, the researcher may ask you, "How has your experience in this course gone so far?"

What happens if I do not want to be in this research?
You can leave the research at any time and it will not be held against you.

What happens if I say "Yes", but I change my mind later?
You can leave the research at any time and it will not be held against you.

Is there any way being in this study could be bad for me?
The study has minimal risks which include possible invasion of privacy and loss or breach in confidentiality. Students will be asked to share potentially sensitive

information about their emotions, attitudes, and experiences surrounding their experiences in the course.

What happens to the information collected for the research?
Efforts will be made to limit the use and disclosure of your personal information, including research study and medical records, to people who have a need to review this information. We cannot promise complete secrecy. Organizations that may inspect and copy your information include the IRB and other representatives of this institution.

Will I have a chance to provide feedback after the study is over?
After the study, you might be asked to complete a survey about your experience as a research participant. You do not have to complete the survey if you do not want to. If you do choose to complete the survey, your responses will be anonymous.
If you are not asked to complete a survey after the study is over, but you would like to share feedback, please contact the study team or the Human Research Protection Program (HRPP). See the "Who Can I Talk To?" section of this form for study team and HRPP contact information.

Optional Elements:
The following research activities are optional, meaning that you do not have to agree to them in order to participate in the research study. Please indicate your willingness to participate in these optional activities by placing your initials next to each activity.

I agree	**I disagree**	
______	_______	The researcher may audio or video record me to aid with data analysis. The researcher will not share these recordings with anyone outside of the immediate study team.

Signature Block for Capable Adult
Your signature documents your permission to take part in this research.

____ ____________________
Signature of participant Date

____
Printed name of participant

____ ____________________
Signature of person obtaining consent Date

____
Printed name of person obtaining consent

Appendix C: Student Survey

Welcome to the survey

I will first ask you about your experience in this course. At the end, I will ask questions about your background to help me understand how experiences vary based on personal characteristics. Finally, there is space for any comments you would like to add about these or other issues.

Section 1. Information about your experiences *in this class*

To what extent do you agree or disagree with the following statements about your experiences **in this class?**

	Strongly disagree	Somewhat disagree	Somewhat agree	Strongly agree
1. I make friends among other students	○	○	○	○
2. I cooperate with other students when doing assigned work	○	○	○	○
3. I feel comfortable sharing my own perspectives in class	○	○	○	○
4. Some students tend to dominate class discussions	○	○	○	○
5. I have been singled out in class because of my identity (such as race/ethnicity, gender, sexual orientation, disability status, religious affiliation, etc.)	○	○	○	○
6. I feel that this course is like a family	○	○	○	○
7. The professor encourages students from diverse backgrounds to work together	○	○	○	○
	Strongly disagree	Somewhat disagree	Somewhat agree	Strongly agree
8. I feel there is a general atmosphere of prejudice	○	○	○	○
9. I feel connected to others	○	○	○	○
10. The professor shares their own experiences	○	○	○	○
11. Multiple cultures are represented in this course	○	○	○	○
12. Where I sit in the classroom affects my experience in the class	○	○	○	○
13. I am treated differently than other students because of my identity (such as race/ethnicity, gender, sexual orientation, disability status, religious affiliation, etc.)	○	○	○	○
14. I work well with other students in this class	○	○	○	○

To what extent do you agree or disagree with the following statements about your experiences **in this class?**

	Strongly disagree	Somewhat disagree	Somewhat agree	Strongly agree
15. I know other students in this class	○	○	○	○
16. When I work in groups, we work as a team	○	○	○	○
17. People in this course doubt my ability	○	○	○	○
18. I feel that students in this course care about each other	○	○	○	○
19. Multiple perspectives are represented in this course	○	○	○	○
20. I feel isolated in this course	○	○	○	○
21. The physical layout of the classroom makes it easy to interact with the instructor	○	○	○	○
	Strongly disagree	Somewhat disagree	Somewhat agree	Strongly agree
22. The professor shares their own background in class	○	○	○	○
23. The classroom space provides a pleasant environment to be in	○	○	○	○
24. I am friendly to other students	○	○	○	○
25. I work with other students on assignments	○	○	○	○
26. I feel comfortable sharing my own experiences in class	○	○	○	○
27. I help other students who are having trouble with their work	○	○	○	○
28. I learn from other students	○	○	○	○
	Strongly disagree	Somewhat disagree	Somewhat agree	Strongly agree
29. People in this course are surprised when I know the right answer	○	○	○	○
30. I do not feel a spirit of community	○	○	○	○
31. The professor values individual differences in the classroom	○	○	○	○
32. The physical layout of the classroom makes it easy to interact with other students	○	○	○	○
33. Other students in this class are my friends	○	○	○	○
34. I avoid participating in this class	○	○	○	○
35. Microaggressions occur in this class	○	○	○	○

To what extent do you agree or disagree with the following statements about your experiences **in this class?**

	Strongly disagree	Somewhat disagree	Somewhat agree	Strongly agree
36. I feel I have to work harder than other students to be perceived as a good student	○	○	○	○
37. I trust others in this course	○	○	○	○
38. I see a real-world connection to what we study	○	○	○	○
39. I work with other students	○	○	○	○
40. I feel that I can rely on others in this course	○	○	○	○
41. What I'm learning will be useful for my future aspirations	○	○	○	○
42. Students in this class like me	○	○	○	○
	Strongly disagree	Somewhat disagree	Somewhat agree	Strongly agree
43. I don't feel comfortable contributing to class discussions	○	○	○	○
44. I feel that members of this course depend on me	○	○	○	○
45. My personal interests have been integrated into the curriculum	○	○	○	○
46. I get help from other students	○	○	○	○
47. Students tend to participate at the same rate	○	○	○	○
48. I feel uncertain about others in this course	○	○	○	○
49. I cooperate with other students on class activities	○	○	○	○
	Strongly disagree	Somewhat disagree	Somewhat agree	Strongly agree
50. I feel confident that others will support me	○	○	○	○
51. I feel that I belong in this course	○	○	○	○
52. I feel physically comfortable in this class	○	○	○	○
53. Students work with me to achieve class goals	○	○	○	○
54. People don't listen to me	○	○	○	○
55. The physical environment of this course supports my learning	○	○	○	○
56. There are other students like me in this class	○	○	○	○

Section 2. Your interactions with the professor and TAs *in this class*

To what extent do you agree or disagree with the following statements about your interactions with the professor **in this class?**

	Strongly disagree	Somewhat disagree	Somewhat agree	Strongly agree
57. The professor takes a personal interest in me	○	○	○	○
58. The professor tries very hard to help me	○	○	○	○
59. The professor cares about my feelings	○	○	○	○
60. The professor helps me when I have trouble with my work	○	○	○	○
61. The professor talks with me	○	○	○	○
62. The professor is interested in my problems	○	○	○	○
63. The professor comes to my table to talk with me	○	○	○	○
64. The professor's questions help me understand my work	○	○	○	○

To what extent do you agree or disagree with the following statements about your interactions with the TAs **in this class?** (including undergraduate learning assistants)

	Strongly disagree	Somewhat disagree	Somewhat agree	Strongly agree
65. The TAs takes a personal interest in me	○	○	○	○
66. The TAs try very hard to help me	○	○	○	○
67. The TAs care about my feelings	○	○	○	○
68. The TAs help me when I have trouble with my work	○	○	○	○
69. The TAs talk with me	○	○	○	○
70. The TAs are interested in my problems	○	○	○	○
71. The TAs come to my table to talk with me	○	○	○	○
72. The TAs' questions help me understand my work	○	○	○	○

Section 3. Your perceptions of pedagogy *in this class*

In this course, how effective or ineffective are the following teaching and learning strategies for helping you learn?					
	Very ineffective	Somewhat ineffective	Somewhat effective	Very effective	I haven't used this
73. Online videos designed for this course	○	○	○	○	○
74. In-class group work	○	○	○	○	○
75. Class time for individual questions	○	○	○	○	○
76. Tuesday small group discussion sections / TA office hours	○	○	○	○	○
77. Thursday PAL sessions	○	○	○	○	○
	Very ineffective	Somewhat ineffective	Somewhat effective	Very effective	I haven't used this
78. In-class quizzes	○	○	○	○	○
79. Online quizzes	○	○	○	○	○
80. Exams	○	○	○	○	○
81. Written assignments	○	○	○	○	○
82. Online homework system	○	○	○	○	○
83. Professor office hours / Math Lab in Vincent Hall	○	○	○	○	○

Section 4. Your academic and professional plans

84. Did you take this course with the intention of taking additional math courses?
- ○ No
- ○ Yes

85. What major(s) were you planning to pursue **at the beginning of this semester**?

____

86. At the **beginning of the semester**, how certain or uncertain were you that you would complete the major(s) you listed above?

- Very uncertain
- Somewhat uncertain
- Somewhat certain
- Very certain

87. **At this point**, has your intended major(s) changed from the one(s) you listed above?

- No → **Go to question #88**
- I am now considering other majors
- Yes, my intended major(s) have changed

87a. Please list the additional major(s) you are considering: ____

88. For the major(s) you are most likely to complete at this time, are additional math courses (e.g., trigonometry, calculus) required?

- No → **Go to question #89**
- I don't know → **Go to question #89**
- Yes

88a. Is this course a prerequisite for those additional math courses?

- Yes
- No

89. To what extent, if any, has your experience in this course influenced your intention to major in a science, technology, engineering, and mathematics (STEM) field?

- It has made me much less likely to major in a STEM field
- It has made me slightly less likely to major in a STEM field
- It has not had any influence
- It has made me slightly more likely to major in a STEM field
- It has made me much more likely to major in a STEM field

- I have never planned to pursue a major in a STEM field

90. To what extent, if any, has your experience in this course influenced your intention to take additional math courses?

- It has made me much less likely to take additional math courses
- It has made me slightly less likely to take additional math courses
- It has not had any influence
- It has made me slightly more likely to take additional math courses
- It has made me much more likely to take additional math courses

- I have never planned to take additional math courses

91. How important or unimportant is getting good math grades in college for your future?
   - Not at all important
   - Not very important
   - Somewhat important
   - Very important

92. Do you consider yourself a pre-med student?
   - No
   - Medical school is one option I'm considering
   - Yes

Section 5. Information about you

I appreciate your answers to the previous questions. To help me understand how students from different backgrounds experience this course, I would appreciate some information about you.

93. In what year were you born?

____

94. What is your current student status?
   - Part-time
   - Full-time

95. Do either or both of your parents have a four-year undergraduate degree?
   - No
   - Yes

96. What is your gender identity?
   - Man
   - Woman
   - Transmasculine/Trans man
   - Transfeminine/Trans woman
   - Gender queer/Gender non-conforming
   - Agender/Non-binary
   - Prefer not to answer
   - Different identity (please state)
     ____

97. Do you identify with any of the following ethnicities? (check all that apply)
   - ☐ Cambodian
   - ☐ Hispanic or Latino
   - ☐ Hmong
   - ☐ Laotian
   - ☐ Karen
   - ☐ Somali
   - ☐ Vietnamese
   - ☐ None of the above
   - ☐ Prefer not to answer

98. What is your racial identity? (check all that apply)
- ☐ American Indian or Alaskan Native
- ☐ Asian
- ☐ Black or African American
- ☐ Native Hawaiian or other Pacific Islander
- ☐ White (includes Middle Eastern)
- ☐ Prefer not to answer
- ☐ Something else (please state)

  ____

99. Do you need a visa to attend this institution?
- ○ No
- ○ Yes

100. Are you a transfer student?
- ○ No → **Go to question #101**
- ○ Yes

  100a. How long were you at your prior institution(s)?
  - ○ Less than 1 year
  - ○ 1 to 1.99 years
  - ○ 2 to 2.99 years
  - ○ 3+ years

101. How many semesters have you been at the University of Minnesota?
- ○ This is my 1st or 2nd semester at the U of M
- ○ This is my 3rd or 4th semester at the U of M
- ○ This is my 5th or 6th semester at the U of M
- ○ This is my 7th+ semester at the U of M

102. Are you eligible to receive a Pell grant?
- ○ No
- ○ Yes
- ○ I don't know

103. Are you eligible to receive the University of Minnesota Promise Scholarship?
- ○ No
- ○ Yes
- ○ I don't know

104. Have you taken out student loans?
- ○ No
- ○ Yes

105. Surveys tend to ask respondents to indicate various identities and characteristics from a list, as you just did in this section – however, these questions don't always capture the parts of identity that are most meaningful to people. **What are two to three words you would use to describe yourself?**

106. Are you interested in participating in a one-hour interview about this course? If so, please write your email below. **Students who complete an interview will receive a $25 Amazon gift card.**

____

Email address

107. Thank you for completing this survey. If there is anything else you would like to share with me about your experience in this class, please write it below.

Appendix D: Classroom Climate Survey Items

***Final items that were retained through the confirmatory factor analysis are marked with an asterisk.

Scale: Strongly disagree, somewhat disagree, somewhat agree, strongly agree

- Interaction
  a. Student-student interaction (Note: Through the CFA process, this scale was combined with the student feelings of isolation or being too visible scale to create a student-student interaction and cohesion scale)
     i. WIHIC student cohesiveness scale
        - I make friends among other students in this class
        - I know other students in this class
        - I am friendly to other students in this class
        - Other students in this class are my friends
        - I work well with other students in this class
        - I help other students in this class who are having trouble with their work
        - Students in this class like me
        - I get help from other students in this class*
     ii. WIHIC cooperation scale[1]
        - I cooperate with other students when doing assigned work
        - When I work in groups in this class, we work as a team
        - I work with other students on assignments in this class
        - I learn from other students in this class*
        - I work with other students in this class
        - I cooperate with other students on class activities*
        - Students work with me to achieve class goals*
  b. Professor-student interaction – including interactions with TAs
     i. WIHIC teacher support scale
        - The professor takes a personal interest in me*
        - The professor tries very hard to help me*
        - The professor cares about my feelings
        - The professor helps me when I have trouble with my work *
        - The professor talks with me*
        - The professor is interested in my problems
        - The professor comes to my table to talk with me
        - The professor's questions help me understand my work*

[1] 1 item taken out of WIHIC cooperation scale – about sharing books and materials with students – deemed irrelevant for this context

ii. Same items repeated for TAs (including undergraduate assistants)
- The TAs take a personal interest in me*
- The TAs try very hard to help me*
- The TAs care about my feelings
- The TAs help me when I have trouble with my work*
- The TAs talk with me*
- The TAs are interested in my problems*
- The TAs come to my table to talk with me*
- The TAs' questions help me understand my work*

c. Participation

i. DLE classroom climate module[2]
- I feel comfortable sharing my own perspectives in class*
- I feel comfortable sharing my own experiences in class*
- I don't feel comfortable contributing to class discussions*

ii. Created by author
- Some students tend to dominate class discussions
- I avoid participating in this class
- Students tend to participate at the same rate in this class

- Climate for diversity

a. Discrimination

i. DLE classroom climate module
- I have been singled out in class because of my identity (such as race/ethnicity, gender, sexual orientation, disability status, religious affiliation, etc.)
- I feel I have to work harder than other students to be perceived as a good student*

ii. PPD (modified)
- I feel there is a general atmosphere of prejudice in this class*
- I am treated differently than other students because of my identity (such as race/ethnicity, gender, sexual orientation, disability status, religious affiliation, etc.)*

iii. Created by author
- People in this course doubt my ability
- People in this course are surprised when I know the right answer*
- People in this course don't listen to me
- Microaggressions occur in this class*

b. Student feelings of isolation or being too visible (Note: Through the CFA process, this scale was combined with student-student interaction to create a student-student interaction and cohesion scale)

[2] The first two items were originally 1 item on the survey – I split them into two items per Dillman et al.'s (2014) item writing guidelines

i. CCS
- I feel connected to others in this course
- I feel that students in this course care about each other*
- I do not feel a spirit of community
- I feel that this course is like a family
- I feel isolated in this course
- I trust others in this course*
- I feel that I can rely on others in this course*
- I feel that members of this course depend on me
- I feel uncertain about others in this course
- I feel confident that others will support me*

ii. Created by author
- There are other students like me in this class
- I feel that I belong in this course

c. Inclusion of diverse backgrounds

i. DLE classroom climate module (modified)[3]
- The professor shares their own experiences in class*
- The professor shares their own background in class*
- The professor values individual differences in the classroom
- The professor encourages students from diverse backgrounds to work together

ii. Created by author
- Multiple cultures are represented in this course
- Multiple perspectives are represented in this course*
- I see a real-world connection to what we study in this class
- What I'm learning in this class will be useful for my future aspirations
- My personal interests have been integrated into the curriculum of this class*

- Physical space

a. Created by author
- Where I sit in the classroom affects my experience in the class
- The classroom space provides a pleasant environment to be in
- The physical layout of the classroom makes it easy to interact with other students*
- The physical layout of the classroom makes it easy to interact with the instructor
- I feel physically comfortable in this class*
- The physical environment of this course supports my learning*

---

[3] The first two items were originally 1 item on the survey – I split them into two items per Dillman et al.'s (2014) item writing guidelines

Appendix E: Student Interview Protocol

Introduction

1. I'd like to start by knowing a bit more about you. Where are you from, what year are you in, and what are you currently planning on studying?
2. What is your current living situation?
3. How has your experience been so far at the [university]?

Overall course experience and academic plans

4. Now I'd like to move to your experiences in the math class. Why are you taking it?
5. How has the course gone for you so far?
6. What were you planning on studying at the beginning of the semester? Has that changed at all?
    a. Why have your plans changed?
    b. Has this course had any impact on what you plan to study going forward? How so?
7. Do you plan to take additional math courses after this? Why or why not?

Classroom climate

8. Each course takes on a general atmosphere. For example, students may sense that a course has an overall tone of competition, student indifference, or high student energy. What are some words you would use to describe the general atmosphere of this course?
9. We all have several different identities, and some of them are more significant to us than others. For example, some of the identities that resonate with me are being a woman, white, Minnesotan, doctoral student, and an introvert. How would you describe yourself in terms of the identities that may resonate with you?
    a. Do you feel that this course is a welcoming space to those identities? Why or why not?
    b. Overall, how do you think sense of belonging in this class might be different for students with marginalized identities (for example, students of color or low-income students), if at all?
10. The next question is about interactions with other students in the course. How did you end up sitting at the table where you sit?
11. How would you describe your interactions with students in the course?
    a. Do you see any pattern in terms of how students interact with each other related to gender, race, or other aspects of identity?
    b. Can you describe how you and the members at your table work on problems?
    c. Do the students at your table know things about you and your background?
12. How would you describe your interactions with the professor?

    a. Does the professor know things about you and your background?
    b. Do you think the professor believes that you can be successful in this course?
    c. Do you feel that he cares about students succeeding in the course? Why or why not?
13. How would you describe your interactions with the teaching assistants?
    a. Do the TAs know things about you and your background?
    b. Do you think the TAs believe that you can be successful in this course?
    c. Do you feel that the TAs care about students succeeding in the course? Why or why not?
14. Do you tend to participate in this class?
    a. Sometimes courses are pretty even in terms of all students contributing to class discussions, and other times certain students tend to dominate class discussions. How would you describe the patterns of student participation in this course?
    b. What, if anything, has kept you from participating more?
    c. Do you feel comfortable disagreeing with other students?
15. If you have questions about course content, who might you seek out for assistance? Why?
16. How does this class relate to your interests and future goals, if at all?
17. How do you think being a first-generation student informs your experiences in this course?
18. [for students of color] How has the experience been of being a student of color in a class of mainly white students?
19. As you know, this course is taught in an active learning classroom. How does the physical layout of the course affect your experiences?

Teaching and learning

20. I’d like to know more about your experiences with the way the course is taught. I’ve made a list of the different teaching and learning strategies used in the course, including how students are graded. What strategies do you find are most helpful for your learning? Why?
    d. What strategies do you find the least helpful? Why?
21. Do you find the group work you do in class to be helpful for your learning?
    e. Why or why not?
    f. How could group work be changed to make it more helpful?
22. What would you change about the way the course is taught?

Misc.

23. Is there anything else you would like to share with me about anything we’ve discussed today?

Appendix F: Professor Interview Protocols

Interview 1 for both professors

Section 1: Professor background and teaching philosophy

- Can you tell me about your background and how you ended up in your current position?
- How would you describe your overall approach to teaching?
  - How do you think students learn?
  - What do you think the role of the professor should be in the learning process?

Section 2: The pre-calculus course

- Can you tell me more about the pre-calculus course? What is different now compared to how it used to be?
  - Why was it redesigned?
- What would you say are the main teaching and learning strategies used in this course?
  - For each strategy: can you tell me more about why you use that strategy?
  - Tell me more about how you developed the content for the course.
  - How many students do extra material? What do you think the main reason is that students do extra material?
- Why do you teach the course in an active learning classroom?
- How do you select the TAs?
- What is new this year?
- How closely will he and Greg collaborate?
- What are the main challenges for you in this course?
- For those students who don't do well in the course – do you have a sense of why they don't do well?

Section 3: equity

- In the past, have you noticed any patterns in terms of which students tend to succeed and which tend to struggle in this course?
- In this country, at the college level, certain students are less likely to persist in math compared to other students. Why do you think that is?
  - Do you think that math education is structured in a way that benefits certain students over others?

Section 4: classroom climate

- What words would you hope students would use to describe their experiences in this course?
- Every course takes on a general atmosphere. For example, students might describe a course as competitive or informal. How do you hope that students would describe the general atmosphere of this course?
  - What have you done to create that atmosphere?

- Do you think every student experiences the course in the same way?
- Is there anything else you'd like to add?

Interview 2: Dan

How course went

- How do you feel the course went this semester?
- What are the lessons you took in terms of what went well and what could be improved?
- What surprised you about the course this semester?
- In the first interview you talked about wanting to create a cooperative and collaborative course atmosphere. Do you think that was achieved?
    - Would you say some tables were more collaborative than others? Why is that?
- How do you think you would change the course in the future?
- Do you sense that any students have struggled in the course this semester? Why did they struggle?

Teaching philosophy

- What would you say the purpose is of the quizzes?
- What would you say the purpose is of the exams?
- Do you think it matters to students whether or not they perceive that you believe they can be successful in the course?
    - Why or why not?
    - What do you do to send them those messages?

Interview 2: Isaac

How course went

1. How do you feel the course went this semester?
2. How were the 2 sections you taught different from each other?
3. What are the lessons you took in terms of what went well and what could be improved?
4. What surprised you about the course this semester?
5. In the first interview you talked about wanting to create an informal and collaborative environment, where students feel free to show their work in front of others.. Do you think that was achieved?
    - Would you say some tables were more collaborative than others? Why is that?
6. How do you think you would change the course in the future?
7. Do you sense that any students have struggled in the course this semester? Why did they struggle?

Math education

8. In this country, at the college level, certain students are less likely to persist in math compared to other students. Why do you think that is?

- Do you think that math education is structured in a way that benefits certain students over others?

Teaching philosophy

9. If students behaved perfectly, would active learning have an advantage over lecturing?
10. Do you think it matters to students whether or not they perceive that you believe they can be successful in the course?
    - Why or why not?
    - What do you do to send them those messages?

Appendix G: Professor Consent Form

Title of Research Study: Students' Experiences in a Redesigned Gateway STEM Course

Researcher: Kate K. Diamond

Supported By: This research is supported by the University of Minnesota Mixed Methods Interdisciplinary Graduate Group.

Why am I being asked to take part in this research study?
We are asking you to take part in this research study because you are the instructor of sections 1, 2, or 3 of [math class] during the Fall 2017 semester.

What should I know about a research study?

- Someone will explain this research study to you.
- Whether or not you take part is up to you.
- You can choose not to take part.
- You can agree to take part and later change your mind.
- Your decision will not be held against you.
- You can ask all the questions you want before you decide.

Who can I talk to?
For questions about research appointments, the research study, research results, or other concerns, call the study team at:

Researcher Name: Kate K. Diamond Phone Number: 617-913-9905 Email Address: koehl220@umn.edu	Study Staff (if applicable): Phone Number: Email Address:

This research has been reviewed and approved by an Institutional Review Board (IRB) within the Human Research Protections Program (HRPP). To share feedback privately with the HRPP about your research experience, call the Research Participants' Advocate Line at 612-625-1650 or go to www.irb.umn.edu/report.html. You are encouraged to contact the HRPP if:

- Your questions, concerns, or complaints are not being answered by the research team.
- You cannot reach the research team.
- You want to talk to someone besides the research team.
- You have questions about your rights as a research participant.
- You want to get information or provide input about this research.

Why is this research being done?
The purpose of this research is to better understand student experiences in a gateway math course. The study responds to a national urgency to improve student success in the science, technology, engineering, and mathematics (STEM) fields, especially for underrepresented students. The outcomes of this research will inform efforts to better meet the needs of students in gateway math courses.

How long will the research last?
We expect that you will be in this research study for four months: September through December, 2017.

How many people will be studied?
We expect about 250 people here will be in this research study.

What happens if I say "Yes, I want to be in this research"?
You will be interviewed three times during the semester. Each interview will last between 60 and 90 minutes, and will take place in a private meeting room on the University of Minnesota campus. The researcher will request your permission to audio record each interview. The interviews will explore your experiences teaching this course. For example, the researcher may ask you, "Can you describe the teaching and learning strategies you use in this course?"

What happens if I do not want to be in this research?
You can leave the research at any time and it will not be held against you.

What happens if I say "Yes", but I change my mind later?
You can leave the research at any time and it will not be held against you.

Is there any way being in this study could be bad for me?
The study has minimal risks which include possible invasion of privacy and loss or breach in confidentiality. You may be asked to share potentially sensitive information about your emotions, attitudes, and experiences surrounding your experiences in the course.

What happens to the information collected for the research?
Efforts will be made to limit the use and disclosure of your personal information, including research study and medical records, to people who have a need to review this information. We cannot promise complete secrecy. Organizations that may inspect and copy your information include the IRB and other representatives of this institution.

Will I have a chance to provide feedback after the study is over?
After the study, you might be asked to complete a survey about your experience as a research participant. You do not have to complete the survey if you do not

want to. If you do choose to complete the survey, your responses will be anonymous.

If you are not asked to complete a survey after the study is over, but you would like to share feedback, please contact the study team or the Human Research Protection Program (HRPP). See the "Who Can I Talk To?" section of this form for study team and HRPP contact information.

Optional Elements:

The following research activities are optional, meaning that you do not have to agree to them in order to participate in the research study. Please indicate your willingness to participate in these optional activities by placing your initials next to each activity.

I agree	I disagree	
______	_______	The researcher may audio or video record me to aid with data analysis. The researcher will not share these recordings with anyone outside of the immediate study team.

Signature Block for Capable Adult

Your signature documents your permission to take part in this research.

____ ___________________
Signature of participant Date

____
Printed name of participant

____ ___________________
Signature of person obtaining consent Date

____
Printed name of person obtaining consent

Appendix H: R Code

```
################################FACTOR ANALYSIS#######################

###Scale 1: Professor-student interaction

rm(list=ls())
setwd("/Users/Kate/Dropbox/School/Dissertation/ACTUAL
STUDY!!!/Survey/survey data")
data <- read.csv("data_final.csv", na.strings="")
library(psych)
library(car)
library(lavaan)
library(dplyr)


#######################################################################
###########Step 1: look at alphas, see if should drop any items########
#######################################################################

##select all classroom climate items
data1 <- select(data, Q3_1:Q8_8)
###Get the variables from character to numeric, then recode reverse-
coded items, then convert
#from numberic to ordinal for correct analysis in lavaan
#convert to numeric
levels <- c("Strongly disagree","Somewhat disagree","Somewhat
agree","Strongly agree")
data1[] <-  lapply(data1, factor, levels=levels)
data1[] <- lapply(data1, as.numeric)
#recode reverse-coded variables
data1$Q5_8 <- ifelse(data1$Q5_8 == 4,1,ifelse(data1$Q5_8 ==
3,2,ifelse(data1$Q5_8 == 2,3,ifelse(data1$Q5_8 == 1,4,NA))))
data1$Q3_4 <- ifelse(data1$Q3_4 == 4,1,ifelse(data1$Q3_4 ==
3,2,ifelse(data1$Q3_4 == 2,3,ifelse(data1$Q3_4 == 1,4,NA))))
data1$Q4_20 <- ifelse(data1$Q4_20 == 4,1,ifelse(data1$Q4_20 ==
3,2,ifelse(data1$Q4_20 == 2,3,ifelse(data1$Q4_20 == 1,4,NA))))
data1$Q3_5 <- ifelse(data1$Q3_5 == 4,1,ifelse(data1$Q3_5 ==
3,2,ifelse(data1$Q3_5 == 2,3,ifelse(data1$Q3_5 == 1,4,NA))))
data1$Q5_1 <- ifelse(data1$Q5_1 == 4,1,ifelse(data1$Q5_1 ==
3,2,ifelse(data1$Q5_1 == 2,3,ifelse(data1$Q5_1 == 1,4,NA))))
data1$Q3_8 <- ifelse(data1$Q3_8 == 4,1,ifelse(data1$Q3_8 ==
3,2,ifelse(data1$Q3_8 == 2,3,ifelse(data1$Q3_8 == 1,4,NA))))
data1$Q3_13 <- ifelse(data1$Q3_13 == 4,1,ifelse(data1$Q3_13 ==
3,2,ifelse(data1$Q3_13 == 2,3,ifelse(data1$Q3_13 == 1,4,NA))))
data1$Q4_3 <- ifelse(data1$Q4_3 == 4,1,ifelse(data1$Q4_3 ==
3,2,ifelse(data1$Q4_3 == 2,3,ifelse(data1$Q4_3 == 1,4,NA))))
data1$Q4_15 <- ifelse(data1$Q4_15 == 4,1,ifelse(data1$Q4_15 ==
3,2,ifelse(data1$Q4_15 == 2,3,ifelse(data1$Q4_15 == 1,4,NA))))
data1$Q5_19 <- ifelse(data1$Q5_19 == 4,1,ifelse(data1$Q5_19 ==
3,2,ifelse(data1$Q5_19 == 2,3,ifelse(data1$Q5_19 == 1,4,NA))))
data1$Q4_21 <- ifelse(data1$Q4_21 == 4,1,ifelse(data1$Q4_21 ==
3,2,ifelse(data1$Q4_21 == 2,3,ifelse(data1$Q4_21 == 1,4,NA))))
data1$Q4_16 <- ifelse(data1$Q4_16 == 4,1,ifelse(data1$Q4_16 ==
3,2,ifelse(data1$Q4_16 == 2,3,ifelse(data1$Q4_16 == 1,4,NA))))
```

```
data1$Q4_6 <- ifelse(data1$Q4_6 == 4,1,ifelse(data1$Q4_6 ==
3,2,ifelse(data1$Q4_6 == 2,3,ifelse(data1$Q4_6 == 1,4,NA))))
data1$Q5_13 <- ifelse(data1$Q5_13 == 4,1,ifelse(data1$Q5_13 ==
3,2,ifelse(data1$Q5_13 == 2,3,ifelse(data1$Q5_13 == 1,4,NA))))
data1$Q3_12 <- ifelse(data1$Q3_12 == 4,1,ifelse(data1$Q3_12 ==
3,2,ifelse(data1$Q3_12 == 2,3,ifelse(data1$Q3_12 == 1,4,NA))))

######7. Teacher-student interaction
#Q7_1: The professor takes a personal interest in me
#Q7_2: The professor tries very hard to help me
#Q7_3: The professor cares about my feelings
#Q7_4: The professor helps me when I have trouble with my work
#Q7_5: The professor talks with me
#Q7_6: The professor is interested in my problems
#Q7_7: The professor comes to my table to talk with me
#Q7_8: The professor's questions help me understand my work

TSint <- select(data1, Q7_1,Q7_2,Q7_3,Q7_4,Q7_5,Q7_6,Q7_7,Q7_8)


# THE FOLLOWING FIVE LINES PRODUCE THE FREQUENCY
# TABLE FOR EACH VARIABLE FOR INSPECTION
for(i in 1:length(names(TSint))){
  print(names(TSint)[i], quote = F)
  print(table(TSint[, i]))
  print(" ", quote = F)
}

# THE FOLLOWING SIX LINES PRODUCE THE CROSSTABULATION FOR
# EVERY PAIR OF VARIABLES FOR INSPECTION
for(r in 1:(length(names(TSint)) - 1)){
  for(c in (r + 1):length(names(TSint))){
    print(paste(names(TSint)[r], ":", names(TSint)[c]))
    print(table(TSint[, r], TSint[, c]))
    print(" ", quote = F)
  }
}

#Q7_3: 1
#Q7_4: 1
#Q7_5: 1
#Q7_7: 1
#Q7_8: 1

#Q7_1: 4
#Q7_2: 4
#Q7_3: 4
#Q7_4: 4
#Q7_5: 4
#Q7_6: 4
#Q7_7: 4
#Q7_8: 4

###Convert 4s to 3s
names(TSint)[c(1:8)]
for(i in c(1:8)){
```

```
  TSint[, i] = ifelse(TSint[, i] == 4, 3, TSint[, i])
}

###Convert 1s to 2s
names(TSint)[c(3:5,7:8)]
for(i in c(3:5,7:8)){
  TSint[, i] = ifelse(TSint[, i] == 1, 2, TSint[, i])
}

# THE FOLLOWING SIX LINES PRODUCE THE CROSSTABULATION FOR
# EVERY PAIR OF VARIABLES FOR INSPECTION
for(r in 1:(length(names(TSint)) - 1)){
  for(c in (r + 1):length(names(TSint))){
    print(paste(names(TSint)[r], ":", names(TSint)[c]))
    print(table(TSint[, r], TSint[, c]))
    print(" ", quote = F)
  }
}

TS.poly = polychoric(TSint)
alpha(TS.poly$rho)
#alpha = .95

TSint[] <- lapply(TSint, ordered)

TSint.model <- ' TSint =~ Q7_1 + Q7_2 + Q7_3 + Q7_4 + Q7_5 + Q7_6 +
Q7_7 + Q7_8 '
TSint.fit1 <- cfa(TSint.model, std.lv = TRUE, estimator = "WLSMV",
mimic = "Mplus", data=TSint)
summary(TSint.fit1, fit.measures=TRUE, rsquare=TRUE)
fitMeasures(TSint.fit1, "srmr")
#CFI = .99, TLI = .99, RMSEA = .072 [0.033, 0.109], WRMR = .729, SRMR =
.057
##T. A. Brown (2006) suggested the following criteria for these
indices:
#(1) SRMR [standardized root mean square residual] values are close to
.08 or below;
#(2) RMSEA [root mean square error of approximation] values are close
to .06 or below;
#(3) CFI [comparative fit index] and TLI [Tucker-Lewis Index] values
are close to .95 or greater.  (p. 87)
#Also: WRMR should be <1

resid.TSint = residuals(TSint.fit1, type = "cor")
min(resid.TSint$cor)
max(resid.TSint$cor)

resid.cor.matrix = round(resid.TSint$cor, 3)
resid.cor.matrix[!lower.tri(resid.cor.matrix)] = 0

# IDENTIFY THE RESIDUAL CORRELATIONS WITH
# ABSOLUTE VALUE GREATER THEN 0.10
theRows = NULL
theCols = NULL
theCorrs = NULL
for(r in 1:(nrow(resid.cor.matrix))){
```

```
  for(c in 1:(nrow(resid.cor.matrix))){
    if(abs(resid.cor.matrix[r, c]) > 0.1){
      theRows = c(theRows, rownames(resid.cor.matrix)[r])
      theCols = c(theCols, colnames(resid.cor.matrix)[c])
      theCorrs = c(theCorrs, round(resid.cor.matrix[r, c], 3))
    }
  }
}

# PRINT OUT VARIABLE PAIRS FOR THE EXTREME RESIDUAL CORRELATIONS
bad.corrs = cbind(theRows, theCols, theCorrs)
bad.corrs[1, 3]
substr(bad.corrs[1, 3], 1, 1)
bad.corrs[1, 3] = paste(" ", bad.corrs[1, 3], sep = "")

for(i in 1:nrow(bad.corrs)){
  if(substr(bad.corrs[i, 3], 1, 1) == "0"){
    bad.corrs[i, 3] = paste(" ", bad.corrs[i, 3], sep = "")
  }
}
print(bad.corrs, quote = F)

#Q7_3: 3
#Q7_4: 2
#Q7_5: 2
#Q7_6: 1
#Q7_7: 2

##Q7_7 has low r-squared - take out
TSint.model1 <- ' TSint =~ Q7_1 + Q7_2 + Q7_3 + Q7_4 + Q7_5 + Q7_6 +
Q7_8 '
TSint.fit2 <- cfa(TSint.model1, std.lv = TRUE, estimator = "WLSMV",
mimic = "Mplus", data=TSint)
summary(TSint.fit2, fit.measures=TRUE, rsquare=TRUE)
fitMeasures(TSint.fit2, "srmr")
#CFI = .99, TLI = .99, RMSEA = .066 [0.004, 0.111], WRMR = .665, SRMR =
.046

resid.TSint = residuals(TSint.fit2, type = "cor")
min(resid.TSint$cor)
max(resid.TSint$cor)

resid.cor.matrix = round(resid.TSint$cor, 3)
resid.cor.matrix[!lower.tri(resid.cor.matrix)] = 0

# IDENTIFY THE RESIDUAL CORRELATIONS WITH
# ABSOLUTE VALUE GREATER THEN 0.10
theRows = NULL
theCols = NULL
theCorrs = NULL
for(r in 1:(nrow(resid.cor.matrix))){
  for(c in 1:(nrow(resid.cor.matrix))){
    if(abs(resid.cor.matrix[r, c]) > 0.1){
      theRows = c(theRows, rownames(resid.cor.matrix)[r])
      theCols = c(theCols, colnames(resid.cor.matrix)[c])
      theCorrs = c(theCorrs, round(resid.cor.matrix[r, c], 3))
```

```
    }
  }
}

# PRINT OUT VARIABLE PAIRS FOR THE EXTREME RESIDUAL CORRELATIONS
bad.corrs = cbind(theRows, theCols, theCorrs)
bad.corrs[1, 3]
substr(bad.corrs[1, 3], 1, 1)
bad.corrs[1, 3] = paste(" ", bad.corrs[1, 3], sep = "")

for(i in 1:nrow(bad.corrs)){
  if(substr(bad.corrs[i, 3], 1, 1) == "0"){
    bad.corrs[i, 3] = paste(" ", bad.corrs[i, 3], sep = "")
  }
}
print(bad.corrs, quote = F)

#take out Q7_3
TSint.model2 <- ' TSint =~ Q7_1 + Q7_2 + Q7_4 + Q7_5 + Q7_6 + Q7_8 '
TSint.fit3 <- cfa(TSint.model2, std.lv = TRUE, estimator = "WLSMV",
mimic = "Mplus", data=TSint)
summary(TSint.fit3, fit.measures=TRUE, rsquare=TRUE)
fitMeasures(TSint.fit3, "srmr")
#CFI = .99, TLI = .99, RMSEA = .039 [0.000, 0.102], WRMR = .487, SRMR =
.032

resid.TSint = residuals(TSint.fit3, type = "cor")
min(resid.TSint$cor)
max(resid.TSint$cor)

resid.cor.matrix = round(resid.TSint$cor, 3)
resid.cor.matrix[!lower.tri(resid.cor.matrix)] = 0

# IDENTIFY THE RESIDUAL CORRELATIONS WITH
# ABSOLUTE VALUE GREATER THEN 0.10
theRows = NULL
theCols = NULL
theCorrs = NULL
for(r in 1:(nrow(resid.cor.matrix))){
  for(c in 1:(nrow(resid.cor.matrix))){
    if(abs(resid.cor.matrix[r, c]) > 0.1){
      theRows = c(theRows, rownames(resid.cor.matrix)[r])
      theCols = c(theCols, colnames(resid.cor.matrix)[c])
      theCorrs = c(theCorrs, round(resid.cor.matrix[r, c], 3))
    }
  }
}

# PRINT OUT VARIABLE PAIRS FOR THE EXTREME RESIDUAL CORRELATIONS
bad.corrs = cbind(theRows, theCols, theCorrs)
bad.corrs[1, 3]
substr(bad.corrs[1, 3], 1, 1)
bad.corrs[1, 3] = paste(" ", bad.corrs[1, 3], sep = "")

for(i in 1:nrow(bad.corrs)){
  if(substr(bad.corrs[i, 3], 1, 1) == "0"){
```

```
    bad.corrs[i, 3] = paste(" ", bad.corrs[i, 3], sep = "")
  }
}
print(bad.corrs, quote = F)

#Take out 7_6
TSint.model3 <- ' TSint =~ Q7_1 + Q7_2 + Q7_4 + Q7_5 + Q7_8 '
TSint.fit4 <- cfa(TSint.model3, std.lv = TRUE, estimator = "WLSMV",
mimic = "Mplus", data=TSint)
summary(TSint.fit4, fit.measures=TRUE, rsquare=TRUE)
fitMeasures(TSint.fit4, "srmr")
#CFI = 1.0, TLI = 1.0, RMSEA = .017 [0.000, 0.113], WRMR = .389, SRMR =
.023
resid.TSint = residuals(TSint.fit4, type = "cor")
min(resid.TSint$cor)
max(resid.TSint$cor)

TSint[] <- lapply(TSint, as.numeric)
TSint <- select(TSint, Q7_1,Q7_2,Q7_4,Q7_5,Q7_8)
TSint.poly = polychoric(TSint)
alpha(TSint.poly$rho)
#alpha = .95

TSint_final <- rowMeans(TSint)
describe(TSint_final)
hist(TSint_final,breaks=20)
qqPlot(TSint_final)

######FINAL ITEMS######
#Q7_1: The professor takes a personal interest in me
#Q7_2: The professor tries very hard to help me
#Q7_4: The professor helps me when I have trouble with my work
#Q7_5: The professor talks with me
#Q7_8: The professor’s questions help me understand my work

###Scale 2: TA-student interaction
##########################
###########Step 1: look at alphas, see if should drop any
itmes###########
#######################################################################
#####

TASint <- select(data1, Q8_1,Q8_2,Q8_3,Q8_4,Q8_5,Q8_6,Q8_7,Q8_8)

# THE FOLLOWING FIVE LINES PRODUCE THE FREQUENCY
# TABLE FOR EACH VARIABLE FOR INSPECTION
for(i in 1:length(names(TASint))){
  print(names(TASint)[i], quote = F)
  print(table(TASint[, i]))
  print(" ", quote = F)
}

#Q8_2, 8_3, 8_4, 8_5, 8_6, and 8_7 have low frequencies for 1 - convert
1s to 2s
names(TASint)[c(2:7)]
for(i in c(2:7)){
```

```
  TASint[, i] = ifelse(TASint[, i] == 1, 2, TASint[, i])
}

# THE FOLLOWING SIX LINES PRODUCE THE CROSSTABULATION FOR
# EVERY PAIR OF VARIABLES FOR INSPECTION
for(r in 1:(length(names(TASint)) - 1)){
  for(c in (r + 1):length(names(TASint))){
    print(paste(names(TASint)[r], ":", names(TASint)[c]))
    print(table(TASint[, r], TASint[, c]))
    print(" ", quote = F)
  }
}

#Q8_6 - 4
#Q8_5 - 4
#Q8_8 - 4
#Q8_5 - 4
#Q8_3 - 4
#Q8_2 - 4
#Q8_1 - 4

###Convert 4s to 3s
names(TASint)[c(1:3,5:6,8)]
for(i in c(1:3,5:6,8)){
  TASint[, i] = ifelse(TASint[, i] == 4, 3, TASint[, i])
}

# THE FOLLOWING SIX LINES PRODUCE THE CROSSTABULATION FOR
# EVERY PAIR OF VARIABLES FOR INSPECTION
for(r in 1:(length(names(TASint)) - 1)){
  for(c in (r + 1):length(names(TASint))){
    print(paste(names(TASint)[r], ":", names(TASint)[c]))
    print(table(TASint[, r], TASint[, c]))
    print(" ", quote = F)
  }
}
#Q8_8 - 3 - maybe?? - no - wouldn't make sense
#Q8_4 - 4 - also doesn't seem to make sense to collapse

table(TASint$Q8_8)
table(TASint$Q8_4)

TASint.poly = polychoric(TASint)
alpha(TASint.poly$rho)
#alpha = .95

TASint[] <- lapply(TASint, ordered)

TASint.model <- ' TASint =~ Q8_1 + Q8_2 + Q8_3 + Q8_4 + Q8_5 + Q8_6 +
Q8_7 + Q8_8 '
TASint.fit1 <- cfa(TASint.model, std.lv = TRUE, estimator = "WLSMV",
mimic = "Mplus", data=TASint)
summary(TASint.fit1, fit.measures=TRUE, rsquare=TRUE)
fitMeasures(TASint.fit1, "srmr")
#CFI = .98, TLI = .98, RMSEA = .069 [0.028, 0.106], WRMR = .736, SRMR =
.054
```

```
##T. A. Brown (2006) suggested the following criteria for these
indices:
#(1) SRMR [standardized root mean square residual] values are close to
.08 or below;
#(2) RMSEA [root mean square error of approximation] values are close
to .06 or below;
#(3) CFI [comparative fit index] and TLI [Tucker-Lewis Index] values
are close to .95 or greater.  (p. 87)
#Also: WRMR should be <1

resid.TASint = residuals(TASint.fit1, type = "cor")
min(resid.TASint$cor)
max(resid.TASint$cor)

resid.cor.matrix = round(resid.TASint$cor, 3)
resid.cor.matrix[!lower.tri(resid.cor.matrix)] = 0

# IDENTIFY THE RESIDUAL CORRELATIONS WITH
# ABSOLUTE VALUE GREATER THEN 0.10
theRows = NULL
theCols = NULL
theCorrs = NULL
for(r in 1:(nrow(resid.cor.matrix))){
  for(c in 1:(nrow(resid.cor.matrix))){
    if(abs(resid.cor.matrix[r, c]) > 0.1){
      theRows = c(theRows, rownames(resid.cor.matrix)[r])
      theCols = c(theCols, colnames(resid.cor.matrix)[c])
      theCorrs = c(theCorrs, round(resid.cor.matrix[r, c], 3))
    }
  }
}

# PRINT OUT VARIABLE PAIRS FOR THE EXTREME RESIDUAL CORRELATIONS
bad.corrs = cbind(theRows, theCols, theCorrs)
bad.corrs[1, 3]
substr(bad.corrs[1, 3], 1, 1)
bad.corrs[1, 3] = paste(" ", bad.corrs[1, 3], sep = "")

for(i in 1:nrow(bad.corrs)){
  if(substr(bad.corrs[i, 3], 1, 1) == "0"){
    bad.corrs[i, 3] = paste(" ", bad.corrs[i, 3], sep = "")
  }
}
print(bad.corrs, quote = F)

#Q8_4 - 1
#Q8_6 - 3
#Q8_7 - 1
#Q8_8 - 1
#Q8_3 - 3
#Q8_2 - 1

###Take out 8_6
TASint.model1 <- ' TASint =~ Q8_1 + Q8_2 + Q8_3 + Q8_4 + Q8_5 + Q8_7 +
Q8_8 '
```

```
TASint.fit2 <- cfa(TASint.model1, std.lv = TRUE, estimator = "WLSMV",
mimic = "Mplus", data=TASint)
summary(TASint.fit2, fit.measures=TRUE, rsquare=TRUE)
fitMeasures(TASint.fit2, "srmr")
#CFI = .98, TLI = .98, RMSEA = .069 [0.028, 0.106], WRMR = .736, SRMR =
.054

####Had negative variances - try taking out 8_3 instead
TASint.model1 <- ' TASint =~ Q8_1 + Q8_2 + Q8_4 + Q8_5 + Q8_6 + Q8_7 +
Q8_8 '
TASint.fit2 <- cfa(TASint.model1, std.lv = TRUE, estimator = "WLSMV",
mimic = "Mplus", data=TASint)
summary(TASint.fit2, fit.measures=TRUE, rsquare=TRUE)
fitMeasures(TASint.fit2, "srmr")
#CFI = .99, TLI = .99, RMSEA = .022 [0.00, 0.082], WRMR = .524, SRMR =
.039


resid.TASint = residuals(TASint.fit2, type = "cor")
min(resid.TASint$cor)
max(resid.TASint$cor)

###No resids over .1

TASint[] <- lapply(TASint, as.numeric)
TASint <- select(TASint, Q8_1,Q8_2,Q8_4,Q8_5,Q8_6,Q8_7,Q8_8)
TASint.poly = polychoric(TASint)
alpha(TASint.poly$rho)
#alpha = .94

TASint_final <- rowMeans(TASint)
describe(TASint_final)
hist(TASint_final,breaks=20)
qqPlot(TASint_final)


##final items:
#Q8_1: The TAs take a personal interest in me
#Q8_2: The TAs try very hard to help me
#Q8_4: The TAs help me when I have trouble with my work
#Q8_5: The TAs talk with me
#Q8_6: The TAs are interested in my problems
#Q8_7: The TAs come to my table to talk with me
#Q8_8: The TAs' questions help me understand my work


###Scale 3: Student-student interaction/cohesion

######################################################################
#####
##########Step 1: look at alphas, see if should drop any
itmes############
######################################################################
#####
```

```
names(data1)

#Isol_SSint <- data.frame(data1$Q3_9, data1$Q3_14, data1$Q4_4,
data1$Q4_11, data1$Q4_14,
#                         data1$Q4_19, data1$Q5_2, data1$Q5_4,
data1$Q5_5, data1$Q5_11,
#                         data1$Q5_14, data1$Q5_15, data1$Q5_18)

# DIFFERENT WAY TO GET THE SUBSET OF VARIABLES FOR THE DATA FRAME
# THIS METHOD RETAINS THE ORIGINAL VARIABLE NAMES
Isol_SSint <- select(data1, Q3_9, Q3_14, Q4_4, Q4_11, Q4_14, Q4_19,
Q5_2, Q5_4, Q5_5, Q5_11, Q5_14, Q5_15, Q5_18)
Isol_SSint <- na.omit(Isol_SSint)
str(Isol_SSint)

# THE FOLLOWING FIVE LINES PRODUCE THE FREQUENCY
# TABLE FOR EACH VARIABLE FOR INSPECTION
for(i in 1:length(names(Isol_SSint))){
  print(names(Isol_SSint)[i], quote = F)
  print(table(Isol_SSint[, i]))
  print(" ", quote = F)
}

# ALL OF THE VARIABLES HAVE VERY LOW FREQUENCIES FOR THE
# 1 RATING CATEGORY. THIS LEADS TO OVER 200 CELLS WITH
# 0 FREQUENCIES IN THE CROSSTABLULATIONS FOR PAIRS OF
# VARIABLES.
# THE FOLLOWING THREE LINES COMBINES THE 1 AND 2 RATINGS
# INTO THE 2 RATING CATEGORY.
for(i in 1:length(names(Isol_SSint))){
  Isol_SSint[, i] = ifelse(Isol_SSint[, i] == 1, 2, Isol_SSint[, i])
}

# THE FOLLOWING SIX LINES PRODUCE THE CROSSTABULATION FOR
# EVERY PAIR OF VARIABLES FOR INSPECTION
for(r in 1:(length(names(Isol_SSint)) - 1)){
  for(c in (r + 1):length(names(Isol_SSint))){
    print(paste(names(Isol_SSint)[r], ":", names(Isol_SSint)[c]))
    print(table(Isol_SSint[, r], Isol_SSint[, c]))
    print(" ", quote = F)
  }
}

# THERE ARE STILL 45 CELLS WITH 0 FREQUENCIES ACROSS THE
# CROSSTABLULATION TABLES. INSPECTION OF THE CROSSTABULATION
# TABLES SHOWS THAT THE 0 FREQUENCY CELLS CAN BE ELIMINATED
# BY COMBINING RATINGS OF 3 AND 4 INTO THE 3 RATING CATEGORY.
# FOR 11 OF THE VARIABLES. THE FOLLOWING FOUR LINES PERFOM
# THAT OPERATION FOR THE 11 VARIABLES.
names(Isol_SSint)[c(1:3, 6:13)]
for(i in c(1:3, 6:13)){
  Isol_SSint[, i] = ifelse(Isol_SSint[, i] == 4, 3, Isol_SSint[, i])
}

# THE FOLLOWING FIVE LINES PRODUCE THE FREQUENCY
# TABLE FOR EACH VARIABLE FOR INSPECTION
```

```
for(i in 1:length(names(Isol_SSint))){
  print(names(Isol_SSint)[i], quote = F)
  print(table(Isol_SSint[, i]))
  print(" ", quote = F)
}

# THE FOLLOWING SIX LINES PRODUCE THE CROSSTABULATION FOR
# EVERY PAIR OF VARIABLES FOR INSPECTION
for(r in 1:(length(names(Isol_SSint)) - 1)){
  for(c in (r + 1):length(names(Isol_SSint))){
    print(paste(names(Isol_SSint)[r], ":", names(Isol_SSint)[c]))
    print(table(Isol_SSint[, r], Isol_SSint[, c]))
    print(" ", quote = F)
  }
}

Isol.poly = polychoric(Isol_SSint)
alpha(Isol.poly$rho)
#alpha = .9

#######################################################################
#####
###############################Step 2: do
CFA###############################
#######################################################################
#####

###################CFA##################
#convert from numeric to ordinal - in doing this, it is not necessary
to write ordered = ... in the lavaan code
#data1[] <- lapply(data1, ordered)

library(lavaan)
#Isol_SSint.model <- ' Isol_SSint =~ Q4_19+Q3_14+Q5_11+Q4_11+
#
Q4_14+Q5_4+Q5_14+Q5_18+Q3_9+Q4_4+Q5_2+Q5_5+Q5_15 '

#Isol_SSint.fit1 <- cfa(Isol_SSint.model, std.lv = TRUE, estimator =
"WLSMV", mimic = "Mplus", data=data1)

# THE FOLLOWING LINES USE THE Isol_SSint DATA FRAME
# TO PERFORM THE CFA WITH WITH RECODED DATA
Isol_SSint[] <- lapply(Isol_SSint, ordered)

Isol_SSint.model <- ' Isol.SSint =~ Q4_19 + Q3_14 + Q5_11 + Q4_11 +
                         Q4_14 + Q5_4 + Q5_14 + Q5_18 + Q3_9 + Q4_4 +
                         Q5_2 + Q5_5 + Q5_15 '
Isol_SSint.fit1 <- cfa(Isol_SSint.model, std.lv = TRUE, estimator =
"WLSMV", mimic = "Mplus", data=Isol_SSint)
warnings()
summary(Isol_SSint.fit1, fit.measures=TRUE, rsquare=TRUE)
fitMeasures(Isol_SSint.fit1, "srmr")
#CFI = .996, TLI = .995, RMSEA = .020 [0.000, 0.052], WRMR = .666, SRMR
= .070
##T. A. Brown (2006) suggested the following criteria for these
indices:
```

```
#(1) SRMR [standardized root mean square residual] values are close to
.08 or below;
#(2) RMSEA [root mean square error of approximation] values are close
to .06 or below;
#(3) CFI [comparative fit index] and TLI [Tucker-Lewis Index] values
are close to .95 or greater.  (p. 87)
#Also: WRMR should be <1
# ALL OF THE FIT INDICES MEET THE STATED CRITERIA

resid.Isol_SSint = residuals(Isol_SSint.fit1, type = "cor")
min(resid.Isol_SSint$cor)
max(resid.Isol_SSint$cor)

resid.cor.matrix = round(resid.Isol_SSint$cor, 3)
resid.cor.matrix[!lower.tri(resid.cor.matrix)] = 0

# IDENTIFY THE RESIDUAL CORRELATIONS WITH
# ABSOLUTE VALUE GREATER THEN 0.10
theRows = NULL
theCols = NULL
theCorrs = NULL
for(r in 1:(nrow(resid.cor.matrix))){
  for(c in 1:(nrow(resid.cor.matrix))){
    if(abs(resid.cor.matrix[r, c]) > 0.1){
      theRows = c(theRows, rownames(resid.cor.matrix)[r])
      theCols = c(theCols, colnames(resid.cor.matrix)[c])
      theCorrs = c(theCorrs, round(resid.cor.matrix[r, c], 3))
    }
  }
}

# PRINT OUT VARIABLE PAIRS FOR THE EXTREME RESIDUAL CORRELATIONS
bad.corrs = cbind(theRows, theCols, theCorrs)
bad.corrs[1, 3]
substr(bad.corrs[1, 3], 1, 1)
bad.corrs[1, 3] = paste(" ", bad.corrs[1, 3], sep = "")

for(i in 1:nrow(bad.corrs)){
  if(substr(bad.corrs[i, 3], 1, 1) == "0"){
    bad.corrs[i, 3] = paste(" ", bad.corrs[i, 3], sep = "")
  }
}
print(bad.corrs, quote = F)

# 4_11 is involved in 5 extremes, 3_9, 4_4 & 5_15 in 4 resids over .1
# Try taking out only 4_11 first
Isol_SSint.model4 <- ' Isol_SSint =~ Q4_19 + Q3_14 + Q5_11 +
                         Q4_14 + Q5_4 + Q5_14 + Q5_18 + Q3_9 + Q4_4 +
                         Q5_2 + Q5_5 + Q5_15 '

Isol_SSint.fit5 <- cfa(Isol_SSint.model4, std.lv = TRUE, estimator =
"WLSMV", mimic = "Mplus", data=Isol_SSint)
summary(Isol_SSint.fit5, fit.measures=TRUE, rsquare=TRUE)
fitMeasures(Isol_SSint.fit5, "srmr")
#CFI = 1, TLI = 1.012, RMSEA = 0 [0.000, 0.033], WRMR = .546, SRMR =
.060
```

```
resid.Isol_SSint = residuals(Isol_SSint.fit5, type = "cor")
min(resid.Isol_SSint$cor)
max(resid.Isol_SSint$cor)

resid.cor.matrix = round(resid.Isol_SSint$cor, 3)
resid.cor.matrix[!lower.tri(resid.cor.matrix)] = 0

# IDENTIFY THE RESIDUAL CORRELATIONS WITH
# ABSOLUTE VALUE GREATER THEN 0.10
theRows = NULL
theCols = NULL
theCorrs = NULL
for(r in 1:(nrow(resid.cor.matrix))){
  for(c in 1:(nrow(resid.cor.matrix))){
    if(abs(resid.cor.matrix[r, c]) > 0.1){
      theRows = c(theRows, rownames(resid.cor.matrix)[r])
      theCols = c(theCols, colnames(resid.cor.matrix)[c])
      theCorrs = c(theCorrs, round(resid.cor.matrix[r, c], 3))
    }
  }
}

# PRINT OUT VARIABLE PAIRS FOR THE EXTREME RESIDUAL CORRELATIONS
bad.corrs = cbind(theRows, theCols, theCorrs)
bad.corrs[1, 3]
substr(bad.corrs[1, 3], 1, 1)
bad.corrs[1, 3] = paste(" ", bad.corrs[1, 3], sep = "")

for(i in 1:nrow(bad.corrs)){
  if(substr(bad.corrs[i, 3], 1, 1) == "0"){
    bad.corrs[i, 3] = paste(" ", bad.corrs[i, 3], sep = "")
  }
}
print(bad.corrs, quote = F)

### 4_4 & 4_19 are both involved in 4 extreme correlation residuals.
# They both are involved with the same 3 variables.
# But 4_19 is also involved in 5_15, which is involved in 3 extreme
residuals.
# Take out only 4_19
Isol_SSint.model5 <- ' Isol_SSint =~ Q3_14 + Q5_11 +
                         Q4_14 + Q5_4 + Q5_14 + Q5_18 + Q3_9 + Q4_4 +
                         Q5_2 + Q5_5 + Q5_15 '

Isol_SSint.fit6 <- cfa(Isol_SSint.model5, std.lv = TRUE, estimator =
"WLSMV", mimic = "Mplus", data=Isol_SSint)
summary(Isol_SSint.fit6, fit.measures=TRUE, rsquare=TRUE)
fitMeasures(Isol_SSint.fit6, "srmr")
#CFI = 1, TLI = 1.011, RMSEA = 0 [0.000, 0.036], WRMR = .528, SRMR =
.056

resid.Isol_SSint = residuals(Isol_SSint.fit6, type = "cor")
min(resid.Isol_SSint$cor)
max(resid.Isol_SSint$cor)
```

```
resid.cor.matrix = round(resid.Isol_SSint$cor, 3)
resid.cor.matrix[!lower.tri(resid.cor.matrix)] = 0

# IDENTIFY THE RESIDUAL CORRELATIONS WITH
# ABSOLUTE VALUE GREATER THEN 0.10
theRows = NULL
theCols = NULL
theCorrs = NULL
for(r in 1:(nrow(resid.cor.matrix))){
  for(c in 1:(nrow(resid.cor.matrix))){
    if(abs(resid.cor.matrix[r, c]) > 0.1){
      theRows = c(theRows, rownames(resid.cor.matrix)[r])
      theCols = c(theCols, colnames(resid.cor.matrix)[c])
      theCorrs = c(theCorrs, round(resid.cor.matrix[r, c], 3))
    }
  }
}

# PRINT OUT VARIABLE PAIRS FOR THE EXTREME RESIDUAL CORRELATIONS
bad.corrs = cbind(theRows, theCols, theCorrs)
bad.corrs[1, 3]
substr(bad.corrs[1, 3], 1, 1)
bad.corrs[1, 3] = paste(" ", bad.corrs[1, 3], sep = "")

for(i in 1:nrow(bad.corrs)){
  if(substr(bad.corrs[i, 3], 1, 1) == "0"){
    bad.corrs[i, 3] = paste(" ", bad.corrs[i, 3], sep = "")
  }
}
print(bad.corrs, quote = F)

### Several variables are involved in 2 extreme correlation residuals
# 5_4 is involved in the two most extreme residuals
# Try taking out only 5_4
Isol_SSint.model6 <- ' Isol_SSint =~ Q3_14 + Q5_11 +
                        Q4_14 + Q5_14 + Q5_18 + Q3_9 + Q4_4 +
                        Q5_2 + Q5_5 + Q5_15 '

Isol_SSint.fit7 <- cfa(Isol_SSint.model6, std.lv = TRUE, estimator =
"WLSMV", mimic = "Mplus", data=Isol_SSint)
summary(Isol_SSint.fit7, fit.measures=TRUE, rsquare=TRUE)
fitMeasures(Isol_SSint.fit7, "srmr")
#CFI = 1, TLI = 1, RMSEA = 0 [0.000, 0.037], WRMR = .500, SRMR = .054

resid.Isol_SSint = residuals(Isol_SSint.fit7, type = "cor")
min(resid.Isol_SSint$cor)
max(resid.Isol_SSint$cor)

resid.cor.matrix = round(resid.Isol_SSint$cor, 3)
resid.cor.matrix[!lower.tri(resid.cor.matrix)] = 0

# IDENTIFY THE RESIDUAL CORRELATIONS WITH
# ABSOLUTE VALUE GREATER THEN 0.10
theRows = NULL
theCols = NULL
theCorrs = NULL
```

```
for(r in 1:(nrow(resid.cor.matrix))){
  for(c in 1:(nrow(resid.cor.matrix))){
    if(abs(resid.cor.matrix[r, c]) > 0.1){
      theRows = c(theRows, rownames(resid.cor.matrix)[r])
      theCols = c(theCols, colnames(resid.cor.matrix)[c])
      theCorrs = c(theCorrs, round(resid.cor.matrix[r, c], 3))
    }
  }
}

# PRINT OUT VARIABLE PAIRS FOR THE EXTREME RESIDUAL CORRELATIONS
bad.corrs = cbind(theRows, theCols, theCorrs)
bad.corrs[1, 3]
substr(bad.corrs[1, 3], 1, 1)
bad.corrs[1, 3] = paste(" ", bad.corrs[1, 3], sep = "")

for(i in 1:nrow(bad.corrs)){
  if(substr(bad.corrs[i, 3], 1, 1) == "0"){
    bad.corrs[i, 3] = paste(" ", bad.corrs[i, 3], sep = "")
  }
}
print(bad.corrs, quote = F)

# 3_14 is involved in 2 of the largest residuals
# Remove 3_14
Isol_SSint.model7 <- ' Isol_SSint =~ Q5_11 +
                         Q4_14 + Q5_14 + Q5_18 + Q3_9 + Q4_4 +
                         Q5_2 + Q5_5 + Q5_15 '

Isol_SSint.fit8 <- cfa(Isol_SSint.model7, std.lv = TRUE, estimator =
"WLSMV", mimic = "Mplus", data=Isol_SSint)
summary(Isol_SSint.fit8, fit.measures=TRUE, rsquare=TRUE)
fitMeasures(Isol_SSint.fit8, "srmr")
#CFI = 1, TLI = 1.014, RMSEA = 0 [0.000, 0.039], WRMR = .488, SRMR =
.050
resid.Isol_SSint = residuals(Isol_SSint.fit8, type = "cor")
min(resid.Isol_SSint$cor)
max(resid.Isol_SSint$cor)

resid.cor.matrix = round(resid.Isol_SSint$cor, 3)
resid.cor.matrix[!lower.tri(resid.cor.matrix)] = 0

# IDENTIFY THE RESIDUAL CORRELATIONS WITH
# ABSOLUTE VALUE GREATER THEN 0.10
theRows = NULL
theCols = NULL
theCorrs = NULL
for(r in 1:(nrow(resid.cor.matrix))){
  for(c in 1:(nrow(resid.cor.matrix))){
    if(abs(resid.cor.matrix[r, c]) > 0.1){
      theRows = c(theRows, rownames(resid.cor.matrix)[r])
      theCols = c(theCols, colnames(resid.cor.matrix)[c])
      theCorrs = c(theCorrs, round(resid.cor.matrix[r, c], 3))
    }
  }
}
```

```
# PRINT OUT VARIABLE PAIRS FOR THE EXTREME RESIDUAL CORRELATIONS
bad.corrs = cbind(theRows, theCols, theCorrs)
bad.corrs[1, 3]
substr(bad.corrs[1, 3], 1, 1)
bad.corrs[1, 3] = paste(" ", bad.corrs[1, 3], sep = "")

for(i in 1:nrow(bad.corrs)){
  if(substr(bad.corrs[i, 3], 1, 1) == "0"){
    bad.corrs[i, 3] = paste(" ", bad.corrs[i, 3], sep = "")
  }
}
print(bad.corrs, quote = F)

# Only 2 extreme residuals and 3_9, 5_11 is the largest.
# 4 variables remain for SSint, 5 variables remain for ISOL.
# Remove 3_9 (from ISOL scale)
Isol_SSint.model8 <- ' Isol_SSint =~ Q5_11 +
                         Q4_14 + Q5_14 + Q5_18 + Q4_4 +
                         Q5_2 + Q5_5 + Q5_15 '

Isol_SSint.fit9 <- cfa(Isol_SSint.model8, std.lv = TRUE, estimator =
"WLSMV", mimic = "Mplus", data=Isol_SSint)
summary(Isol_SSint.fit9, fit.measures=TRUE, rsquare=TRUE)
fitMeasures(Isol_SSint.fit9, "srmr")
#CFI = 1, TLI = 1.015, RMSEA = 0 [0.000, 0.043], WRMR = .463, SRMR =
.046

resid.Isol_SSint = residuals(Isol_SSint.fit9, type = "cor")
min(resid.Isol_SSint$cor)
max(resid.Isol_SSint$cor)

# ABSOLUTE VALUE OF ALL CORRELATION RESIDUALS ARE < 0.1

# 4 ITEMS FROM SSINT: Q4_14, Q5_11, Q5_14, Q5_18
# 4 ITEMS FROM ISOL: Q4_4, Q5_2, Q5_5, Q5_15

# SSint <-
data.frame(data1$Q4_19,data1$Q3_14,data1$Q5_11,data1$Q4_11,data1$Q4_14,
data1$Q5_4,data1$Q5_14,data1$Q5_18)
# Isol <-
data.frame(data1$Q3_9,data1$Q4_4,data1$Q5_2,data1$Q5_5,data1$Q5_15)
Isol_SSint <- select(data1, Q3_9, Q3_14, Q4_4, Q4_11, Q4_14, Q4_19,
Q5_2, Q5_4, Q5_5, Q5_11, Q5_14, Q5_15, Q5_18)
Isol_SSint <- na.omit(Isol_SSint)
str(Isol_SSint)

for(i in 1:length(names(Isol_SSint))){
  Isol_SSint[, i] = ifelse(Isol_SSint[, i] == 1, 2, Isol_SSint[, i])
}

for(i in c(1:3, 6:13)){
  Isol_SSint[, i] = ifelse(Isol_SSint[, i] == 4, 3, Isol_SSint[, i])
}
```

```
IsolSSintFinal = select(Isol_SSint, Q4_4, Q4_14, Q5_2, Q5_5, Q5_11,
Q5_14,
                        Q5_15, Q5_18)
str(IsolSSintFinal)

Isol.poly = polychoric(IsolSSintFinal)
alpha(Isol.poly$rho)
#alpha = .81

# THE FOLLOWING FIVE LINES PRODUCE THE FREQUENCY
# TABLE FOR EACH VARIABLE FOR INSPECTION
for(i in 1:length(names(IsolSSintFinal))){
  print(names(IsolSSintFinal)[i], quote = F)
  print(table(IsolSSintFinal[, i]))
  print(" ", quote = F)
}

IsolSSintFinal$Isol_SSInt = rowMeans(IsolSSintFinal)
describe(IsolSSintFinal$Isol_SSInt)
library(BHH2)
dotPlot(IsolSSintFinal$Isol_SSInt)

###Scale 4: Participation

PP <- select(data1, Q3_3,Q4_12,Q5_8,Q3_4,Q4_20,Q5_12)
PP <- na.omit(PP)

# THE FOLLOWING FIVE LINES PRODUCE THE FREQUENCY
# TABLE FOR EACH VARIABLE FOR INSPECTION
for(i in 1:length(names(PP))){
  print(names(PP)[i], quote = F)
  print(table(PP[, i]))
  print(" ", quote = F)
}
######4 of the variables have low frequencies for the 1 value - convert
1s to 2s
names(PP)
names(PP)[c(1:3, 5)]
for(i in c(1:3, 5)){
  PP[, i] = ifelse(PP[, i] == 1, 2, PP[, i])
}

# THE FOLLOWING SIX LINES PRODUCE THE CROSSTABULATION FOR
# EVERY PAIR OF VARIABLES FOR INSPECTION
for(r in 1:(length(names(PP)) - 1)){
  for(c in (r + 1):length(names(PP))){
    print(paste(names(PP)[r], ":", names(PP)[c]))
    print(table(PP[, r], PP[, c]))
    print(" ", quote = F)
  }
}
#Q3_4 - 4
#Q5_8 - 4
#Q4_12 - 4
names(PP)
names(PP)[c(2:4)]
```

```
for(i in c(2:4)){
  PP[, i] = ifelse(PP[, i] == 4, 3, PP[, i])
}
# THE FOLLOWING FIVE LINES PRODUCE THE FREQUENCY
# TABLE FOR EACH VARIABLE FOR INSPECTION
for(i in 1:length(names(PP))){
  print(names(PP)[i], quote = F)
  print(table(PP[, i]))
  print(" ", quote = F)
}
# THE FOLLOWING SIX LINES PRODUCE THE CROSSTABULATION FOR
# EVERY PAIR OF VARIABLES FOR INSPECTION
for(r in 1:(length(names(PP)) - 1)){
  for(c in (r + 1):length(names(PP))){
    print(paste(names(PP)[r], ":", names(PP)[c]))
    print(table(PP[, r], PP[, c]))
    print(" ", quote = F)
  }
}


PP.poly = polychoric(PP)
alpha(PP.poly$rho)
#alpha = .73

#######DROP Q3_4, 5_12 - LOW CORRELATIONS
PP <- select(PP, Q3_3,Q4_12,Q5_8,Q4_20)
PP.poly = polychoric(PP)
alpha(PP.poly$rho)
#alpha = .85

PP[] <- lapply(PP, ordered)

PP.model <- ' PP =~ Q3_3 + Q4_12 + Q5_8 + Q4_20 '
PP.fit1 <- cfa(PP.model, std.lv = TRUE, estimator = "WLSMV", mimic =
"Mplus", data=PP)
summary(PP.fit1, fit.measures=TRUE, rsquare=TRUE)
fitMeasures(PP.fit1, "srmr")
#CFI = .99, TLI = .98, RMSEA = .077 [0.000, 0.189], WRMR = .478, SRMR =
.037
##T. A. Brown (2006) suggested the following criteria for these
indices:
#(1) SRMR [standardized root mean square residual] values are close to
.08 or below;
#(2) RMSEA [root mean square error of approximation] values are close
to .06 or below;
#(3) CFI [comparative fit index] and TLI [Tucker-Lewis Index] values
are close to .95 or greater.  (p. 87)
#Also: WRMR should be <1

resid.PP = residuals(PP.fit1, type = "cor")
min(resid.PP$cor)
max(resid.PP$cor)

####no correlations above |.1|
###Try dropping 4_20 - lowest r-square and factor loading
```

```
PP.model1 <- ' PP =~ Q3_3 + Q4_12 + Q5_8 '
PP.fit2 <- cfa(PP.model1, std.lv = TRUE, estimator = "WLSMV", mimic =
"Mplus", data=PP)
summary(PP.fit2, fit.measures=TRUE, rsquare=TRUE)
fitMeasures(PP.fit2, "srmr")

#CFI = 1.0, TLI = 1.0, RMSEA = .00 [0.00, 0.00], WRMR = .00, SRMR = .00

#######Fit measures are all good

PP <- select(PP, Q3_3, Q4_12, Q5_8)
PP[] <- lapply(PP, as.numeric)
PP_final <- rowMeans(PP)
describe(PP_final)
hist(PP_final,breaks=20)
qqPlot(PP_final)

###Scale 5: Discrimination

Descrim <- select(data1,Q3_5,Q5_1,Q3_8,Q3_13,Q4_3,Q4_15,Q5_19,Q4_21)
Descrim <- na.omit(Descrim)

# THE FOLLOWING FIVE LINES PRODUCE THE FREQUENCY
# TABLE FOR EACH VARIABLE FOR INSPECTION
for(i in 1:length(names(Descrim))){
  print(names(Descrim)[i], quote = F)
  print(table(Descrim[, i]))
  print(" ", quote = F)
}

##all variables have low frequencies for 1 - convert 1s to 2s
for(i in 1:length(names(Descrim))){
  Descrim[, i] = ifelse(Descrim[, i] == 1, 2, Descrim[, i])
}

# THE FOLLOWING SIX LINES PRODUCE THE CROSSTABULATION FOR
# EVERY PAIR OF VARIABLES FOR INSPECTION
for(r in 1:(length(names(Descrim)) - 1)){
  for(c in (r + 1):length(names(Descrim))){
    print(paste(names(Descrim)[r], ":", names(Descrim)[c]))
    print(table(Descrim[, r], Descrim[, c]))
    print(" ", quote = F)
  }
}

#Q4_15 - 4
#Q3_13 - 2
#Q5_1 - 4 or Q5_19 - 2
#Q3_5 - 2 or Q3_8 - 4

###For Q4_15, 5_1, and 3_8 - convert 4s to 3s; for Q3_13 - convert 2 to
3 (CHECK WITH BOB TO SEE IF OK)
table(Descrim$Q3_13)

names(Descrim)
```

```
names(Descrim)[c(2:3,6)]
for(i in c(2:3,6)){
  Descrim[, i] = ifelse(Descrim[, i] == 4, 3, Descrim[, i])
}
names(Descrim)[c(4)]
for(i in c(4)){
  Descrim[, i] = ifelse(Descrim[, i] == 2, 3, Descrim[, i])
}

# THE FOLLOWING SIX LINES PRODUCE THE CROSSTABULATION FOR
# EVERY PAIR OF VARIABLES FOR INSPECTION
for(r in 1:(length(names(Descrim)) - 1)){
  for(c in (r + 1):length(names(Descrim))){
    print(paste(names(Descrim)[r], ":", names(Descrim)[c]))
    print(table(Descrim[, r], Descrim[, c]))
    print(" ", quote = F)
  }
}
###No empty cells
Descrim.poly = polychoric(Descrim)
alpha(Descrim.poly$rho)
#alpha = .88

Descrim[] <- lapply(Descrim, ordered)

Descrim.model <- ' Descrim =~ Q3_5 + Q5_1 + Q3_8 + Q3_13 + Q4_3 + Q4_15
+ Q5_19 + Q4_21 '
Descrim.fit1 <- cfa(Descrim.model, std.lv = TRUE, estimator = "WLSMV",
mimic = "Mplus", data=Descrim)
summary(Descrim.fit1, fit.measures=TRUE, rsquare=TRUE)
fitMeasures(Descrim.fit1, "srmr")
#CFI = .94, TLI = .92, RMSEA = .105 [0.073, 0.139], WRMR = 1.068, SRMR
= .101
##T. A. Brown (2006) suggested the following criteria for these
indices:
#(1) SRMR [standardized root mean square residual] values are close to
.08 or below;
#(2) RMSEA [root mean square error of approximation] values are close
to .06 or below;
#(3) CFI [comparative fit index] and TLI [Tucker-Lewis Index] values
are close to .95 or greater.  (p. 87)
#Also: WRMR should be <1

resid.Descrim = residuals(Descrim.fit1, type = "cor")
min(resid.Descrim$cor)
max(resid.Descrim$cor)

resid.cor.matrix = round(resid.Descrim$cor, 3)
resid.cor.matrix[!lower.tri(resid.cor.matrix)] = 0

# IDENTIFY THE RESIDUAL CORRELATIONS WITH
# ABSOLUTE VALUE GREATER THEN 0.10
theRows = NULL
theCols = NULL
theCorrs = NULL
for(r in 1:(nrow(resid.cor.matrix))){
```

```
  for(c in 1:(nrow(resid.cor.matrix))){
    if(abs(resid.cor.matrix[r, c]) > 0.1){
      theRows = c(theRows, rownames(resid.cor.matrix)[r])
      theCols = c(theCols, colnames(resid.cor.matrix)[c])
      theCorrs = c(theCorrs, round(resid.cor.matrix[r, c], 3))
    }
  }
}

# PRINT OUT VARIABLE PAIRS FOR THE EXTREME RESIDUAL CORRELATIONS
bad.corrs = cbind(theRows, theCols, theCorrs)
bad.corrs[1, 3]
substr(bad.corrs[1, 3], 1, 1)
bad.corrs[1, 3] = paste(" ", bad.corrs[1, 3], sep = "")

for(i in 1:nrow(bad.corrs)){
  if(substr(bad.corrs[i, 3], 1, 1) == "0"){
    bad.corrs[i, 3] = paste(" ", bad.corrs[i, 3], sep = "")
  }
}
print(bad.corrs, quote = F)

#3_8 - 4
#4_3 - 6
#4_15 - 4
#5_19 - 4
#3_5 - 4
#5_1 - 3
#3_13 - 3

####4_3 associated with 6 extreme correlations - take out
Descrim.model1 <- ' Descrim =~ Q3_5 + Q5_1 + Q3_8 + Q3_13 + Q4_15 +
Q5_19 + Q4_21 '
Descrim.fit2 <- cfa(Descrim.model1, std.lv = TRUE, estimator = "WLSMV",
mimic = "Mplus", data=Descrim)
summary(Descrim.fit2, fit.measures=TRUE, rsquare=TRUE)
fitMeasures(Descrim.fit2, "srmr")
#CFI = .97, TLI = .96, RMSEA = .069 [0.016, 0.113], WRMR = .737, SRMR =
.071

resid.Descrim = residuals(Descrim.fit2, type = "cor")
min(resid.Descrim$cor)
max(resid.Descrim$cor)

resid.cor.matrix = round(resid.Descrim$cor, 3)
resid.cor.matrix[!lower.tri(resid.cor.matrix)] = 0

# IDENTIFY THE RESIDUAL CORRELATIONS WITH
# ABSOLUTE VALUE GREATER THEN 0.10
theRows = NULL
theCols = NULL
theCorrs = NULL
for(r in 1:(nrow(resid.cor.matrix))){
  for(c in 1:(nrow(resid.cor.matrix))){
    if(abs(resid.cor.matrix[r, c]) > 0.1){
      theRows = c(theRows, rownames(resid.cor.matrix)[r])
```

```
      theCols = c(theCols, colnames(resid.cor.matrix)[c])
      theCorrs = c(theCorrs, round(resid.cor.matrix[r, c], 3))
    }
  }
}

# PRINT OUT VARIABLE PAIRS FOR THE EXTREME RESIDUAL CORRELATIONS
bad.corrs = cbind(theRows, theCols, theCorrs)
bad.corrs[1, 3]
substr(bad.corrs[1, 3], 1, 1)
bad.corrs[1, 3] = paste(" ", bad.corrs[1, 3], sep = "")

for(i in 1:nrow(bad.corrs)){
  if(substr(bad.corrs[i, 3], 1, 1) == "0"){
    bad.corrs[i, 3] = paste(" ", bad.corrs[i, 3], sep = "")
  }
}
print(bad.corrs, quote = F)

#3_8 - 2
#4_15 - 2
#5_19 - 3
#4_21 - 1
#5_1 - 2
#3_5 - 2

###Take out 5_19
Descrim.model2 <- ' Descrim =~ Q3_5 + Q5_1 + Q3_8 + Q3_13 + Q4_15 +
Q4_21 '
Descrim.fit3 <- cfa(Descrim.model2, std.lv = TRUE, estimator = "WLSMV",
mimic = "Mplus", data=Descrim)
summary(Descrim.fit3, fit.measures=TRUE, rsquare=TRUE)
fitMeasures(Descrim.fit3, "srmr")
#CFI = 1.0, TLI = 1.0, RMSEA = .00 [0.00, 0.088], WRMR = .486, SRMR =
.055

resid.Descrim = residuals(Descrim.fit3, type = "cor")
min(resid.Descrim$cor)
max(resid.Descrim$cor)

resid.cor.matrix = round(resid.Descrim$cor, 3)
resid.cor.matrix[!lower.tri(resid.cor.matrix)] = 0

# IDENTIFY THE RESIDUAL CORRELATIONS WITH
# ABSOLUTE VALUE GREATER THEN 0.10
theRows = NULL
theCols = NULL
theCorrs = NULL
for(r in 1:(nrow(resid.cor.matrix))){
  for(c in 1:(nrow(resid.cor.matrix))){
    if(abs(resid.cor.matrix[r, c]) > 0.1){
      theRows = c(theRows, rownames(resid.cor.matrix)[r])
      theCols = c(theCols, colnames(resid.cor.matrix)[c])
      theCorrs = c(theCorrs, round(resid.cor.matrix[r, c], 3))
    }
  }
```

```
}

# PRINT OUT VARIABLE PAIRS FOR THE EXTREME RESIDUAL CORRELATIONS
bad.corrs = cbind(theRows, theCols, theCorrs)
bad.corrs[1, 3]
substr(bad.corrs[1, 3], 1, 1)
bad.corrs[1, 3] = paste(" ", bad.corrs[1, 3], sep = "")

for(i in 1:nrow(bad.corrs)){
  if(substr(bad.corrs[i, 3], 1, 1) == "0"){
    bad.corrs[i, 3] = paste(" ", bad.corrs[i, 3], sep = "")
  }
}
print(bad.corrs, quote = F)

##Take out 4_15
Descrim.model3 <- ' Descrim =~ Q3_5 + Q5_1 + Q3_8 + Q3_13 + Q4_21 '
Descrim.fit4 <- cfa(Descrim.model3, std.lv = TRUE, estimator = "WLSMV",
mimic = "Mplus", data=Descrim)
summary(Descrim.fit4, fit.measures=TRUE, rsquare=TRUE)
fitMeasures(Descrim.fit4, "srmr")
#CFI = 1.0, TLI = 1.0, RMSEA = .00 [0.00, 0.088], WRMR = .486, SRMR =
.055

resid.Descrim = residuals(Descrim.fit4, type = "cor")
min(resid.Descrim$cor)
max(resid.Descrim$cor)

resid.cor.matrix = round(resid.Descrim$cor, 3)
resid.cor.matrix[!lower.tri(resid.cor.matrix)] = 0

# IDENTIFY THE RESIDUAL CORRELATIONS WITH
# ABSOLUTE VALUE GREATER THEN 0.10
theRows = NULL
theCols = NULL
theCorrs = NULL
for(r in 1:(nrow(resid.cor.matrix))){
  for(c in 1:(nrow(resid.cor.matrix))){
    if(abs(resid.cor.matrix[r, c]) > 0.1){
      theRows = c(theRows, rownames(resid.cor.matrix)[r])
      theCols = c(theCols, colnames(resid.cor.matrix)[c])
      theCorrs = c(theCorrs, round(resid.cor.matrix[r, c], 3))
    }
  }
}

# PRINT OUT VARIABLE PAIRS FOR THE EXTREME RESIDUAL CORRELATIONS
bad.corrs = cbind(theRows, theCols, theCorrs)
bad.corrs[1, 3]
substr(bad.corrs[1, 3], 1, 1)
bad.corrs[1, 3] = paste(" ", bad.corrs[1, 3], sep = "")

for(i in 1:nrow(bad.corrs)){
  if(substr(bad.corrs[i, 3], 1, 1) == "0"){
    bad.corrs[i, 3] = paste(" ", bad.corrs[i, 3], sep = "")
  }
```

```
}
print(bad.corrs, quote = F)

###Try taking out 3_5 instead
##Take out 4_15
Descrim.model4 <- ' Descrim =~ Q5_1 + Q3_8 + Q3_13 + Q4_21 + Q4_15 '
Descrim.fit5 <- cfa(Descrim.model4, std.lv = TRUE, estimator = "WLSMV",
mimic = "Mplus", data=Descrim)
summary(Descrim.fit5, fit.measures=TRUE, rsquare=TRUE)
fitMeasures(Descrim.fit5, "srmr")
#CFI = 1.0, TLI = 1.0, RMSEA = .00 [0.00, 0.075], WRMR = .301, SRMR =
.032

resid.Descrim = residuals(Descrim.fit5, type = "cor")
min(resid.Descrim$cor)
max(resid.Descrim$cor)

#######No resids over .1

Descrim[] <- lapply(Descrim, as.numeric)
Descrim <- select(Descrim, Q5_1, Q3_8, Q3_13, Q4_21, Q4_15)
Descrim.poly = polychoric(Descrim)
alpha(Descrim.poly$rho)
#alpha = .82

######3. Microaggressions, stereotypes, and other forms of
discrimination
###3a. DLE classroom climate module
#Q5_1: I feel I have to work harder than other students to be perceived
as a good student
###3b. PPD (modified)
#Q3_8: I feel there is a general atmosphere of prejudice in this class
#Q3_13: I am treated differently than other students because of my
identity (such as race/ethnicity, gender, sexual orientation,
disability status, religious affiliation, etc.)
###3c. Created by author
#Q4_15: People in this course are surprised when I know the right
answer
#Q4_21: Microaggressions occur in this class

###Scale 6: Inclusion of diverse backgrounds

#######################################################################
#####
###########Step 1: look at alphas, see if should drop any
itmes############
#######################################################################
#####

######5. Inclusion of diverse backgrounds
###5a. DLE classroom climate module (modified)
#Q3_10: The professor shares their own experiences in class
#Q4_8: The professor shares their own background in class
#Q4_17: The professor values individual differences in the classroom
#Q3_7: The professor encourages students from diverse backgrounds to
work together
```

```
###5b. Created by author
#Q3_11: Multiple cultures are represented in this course
#Q4_5: Multiple perspectives are represented in this course
#Q5_3: I see a real-world connection to what we study in this class
#Q5_6: What I'm learning in this class will be useful for my future
aspirations
#Q5_10: My personal interests have been integrated into the curriculum
of this class

Diverse_back <- select(data1,
Q3_10,Q4_8,Q4_17,Q3_7,Q3_11,Q4_5,Q5_3,Q5_6,Q5_10)

# THE FOLLOWING FIVE LINES PRODUCE THE FREQUENCY
# TABLE FOR EACH VARIABLE FOR INSPECTION
for(i in 1:length(names(Diverse_back))){
  print(names(Diverse_back)[i], quote = F)
  print(table(Diverse_back[, i]))
  print(" ", quote = F)
}

# THE FOLLOWING SIX LINES PRODUCE THE CROSSTABULATION FOR
# EVERY PAIR OF VARIABLES FOR INSPECTION
for(r in 1:(length(names(Diverse_back)) - 1)){
  for(c in (r + 1):length(names(Diverse_back))){
    print(paste(names(Diverse_back)[r], ":", names(Diverse_back)[c]))
    print(table(Diverse_back[, r], Diverse_back[, c]))
    print(" ", quote = F)
  }
}


#Need to take out 4s: Q3_7, Q3_10, Q3_11, Q4_5, Q4_8, Q4_17, Q5_3,
Q5_6, Q5_10

###Convert 4s to 3s
names(Diverse_back)
names(Diverse_back)[c(1:9)]
for(i in c(1:9)){
  Diverse_back[, i] = ifelse(Diverse_back[, i] == 4, 3, Diverse_back[,
i])
}

#Need to take out 1s: Q3_10, Q3_11, Q4_5, Q4_17

###Convert 1s to 2s
names(Diverse_back)[c(1,3,5:6)]
for(i in c(1,3,5:6)){
  Diverse_back[, i] = ifelse(Diverse_back[, i] == 1, 2, Diverse_back[,
i])
}

# THE FOLLOWING SIX LINES PRODUCE THE CROSSTABULATION FOR
# EVERY PAIR OF VARIABLES FOR INSPECTION
for(r in 1:(length(names(Diverse_back)) - 1)){
  for(c in (r + 1):length(names(Diverse_back))){
    print(paste(names(Diverse_back)[r], ":", names(Diverse_back)[c]))
```

```
    print(table(Diverse_back[, r], Diverse_back[, c]))
    print(" ", quote = F)
  }
}

TS.poly = polychoric(Diverse_back)
alpha(TS.poly$rho)
#alpha = .86

###Alpha would go up if take out 5_6 - take out
Diverse_back[] <- lapply(Diverse_back, ordered)

Diverse_back.model <- ' Diverse_back =~ Q3_7 + Q3_10 + Q3_11 + Q4_5 +
Q4_8 + Q4_17 + Q5_3 + Q5_10 '
Diverse_back.fit1 <- cfa(Diverse_back.model, std.lv = TRUE, estimator =
"WLSMV", mimic = "Mplus", data=Diverse_back)
summary(Diverse_back.fit1, fit.measures=TRUE, rsquare=TRUE)
fitMeasures(Diverse_back.fit1, "srmr")
#CFI = .92, TLI = .89, RMSEA = .12 [0.089, 0.153], WRMR = 1.12, SRMR =
.105
##T. A. Brown (2006) suggested the following criteria for these
indices:
#(1) SRMR [standardized root mean square residual] values are close to
.08 or below;
#(2) RMSEA [root mean square error of approximation] values are close
to .06 or below;
#(3) CFI [comparative fit index] and TLI [Tucker-Lewis Index] values
are close to .95 or greater.  (p. 87)
#Also: WRMR should be <1

resid.Diverse_back = residuals(Diverse_back.fit1, type = "cor")
min(resid.Diverse_back$cor)
max(resid.Diverse_back$cor)

resid.cor.matrix = round(resid.Diverse_back$cor, 3)
resid.cor.matrix[!lower.tri(resid.cor.matrix)] = 0

# IDENTIFY THE RESIDUAL CORRELATIONS WITH
# ABSOLUTE VALUE GREATER THEN 0.10
theRows = NULL
theCols = NULL
theCorrs = NULL
for(r in 1:(nrow(resid.cor.matrix))){
  for(c in 1:(nrow(resid.cor.matrix))){
    if(abs(resid.cor.matrix[r, c]) > 0.1){
      theRows = c(theRows, rownames(resid.cor.matrix)[r])
      theCols = c(theCols, colnames(resid.cor.matrix)[c])
      theCorrs = c(theCorrs, round(resid.cor.matrix[r, c], 3))
    }
  }
}

# PRINT OUT VARIABLE PAIRS FOR THE EXTREME RESIDUAL CORRELATIONS
bad.corrs = cbind(theRows, theCols, theCorrs)
bad.corrs[1, 3]
substr(bad.corrs[1, 3], 1, 1)
```

```
bad.corrs[1, 3] = paste(" ", bad.corrs[1, 3], sep = "")

for(i in 1:nrow(bad.corrs)){
  if(substr(bad.corrs[i, 3], 1, 1) == "0"){
    bad.corrs[i, 3] = paste(" ", bad.corrs[i, 3], sep = "")
  }
}
print(bad.corrs, quote = F)

#Take out 4_17 - lots of high correlations, pretty low r-square and
loading

Diverse_back.model1 <- ' Diverse_back =~ Q3_7 + Q3_10 + Q3_11 + Q4_5 +
Q4_8 + Q5_3 + Q5_10 '
Diverse_back.fit2 <- cfa(Diverse_back.model1, std.lv = TRUE, estimator
= "WLSMV", mimic = "Mplus", data=Diverse_back)
summary(Diverse_back.fit2, fit.measures=TRUE, rsquare=TRUE)
fitMeasures(Diverse_back.fit2, "srmr")

resid.Diverse_back = residuals(Diverse_back.fit2, type = "cor")
min(resid.Diverse_back$cor)
max(resid.Diverse_back$cor)

resid.cor.matrix = round(resid.Diverse_back$cor, 3)
resid.cor.matrix[!lower.tri(resid.cor.matrix)] = 0

# IDENTIFY THE RESIDUAL CORRELATIONS WITH
# ABSOLUTE VALUE GREATER THEN 0.10
theRows = NULL
theCols = NULL
theCorrs = NULL
for(r in 1:(nrow(resid.cor.matrix))){
  for(c in 1:(nrow(resid.cor.matrix))){
    if(abs(resid.cor.matrix[r, c]) > 0.1){
      theRows = c(theRows, rownames(resid.cor.matrix)[r])
      theCols = c(theCols, colnames(resid.cor.matrix)[c])
      theCorrs = c(theCorrs, round(resid.cor.matrix[r, c], 3))
    }
  }
}

# PRINT OUT VARIABLE PAIRS FOR THE EXTREME RESIDUAL CORRELATIONS
bad.corrs = cbind(theRows, theCols, theCorrs)
bad.corrs[1, 3]
substr(bad.corrs[1, 3], 1, 1)
bad.corrs[1, 3] = paste(" ", bad.corrs[1, 3], sep = "")

for(i in 1:nrow(bad.corrs)){
  if(substr(bad.corrs[i, 3], 1, 1) == "0"){
    bad.corrs[i, 3] = paste(" ", bad.corrs[i, 3], sep = "")
  }
}
print(bad.corrs, quote = F)
#3_10: 3
#3_11: 5
#4_5: 2
```

```
#4_8: 1
#5_3: 3

##Take out 5_3
Diverse_back.model2 <- ' Diverse_back =~ Q3_7 + Q3_10 + Q3_11 + Q4_5 +
Q4_8 + Q5_10 '
Diverse_back.fit3 <- cfa(Diverse_back.model2, std.lv = TRUE, estimator
= "WLSMV", mimic = "Mplus", data=Diverse_back)
summary(Diverse_back.fit3, fit.measures=TRUE, rsquare=TRUE)
fitMeasures(Diverse_back.fit3, "srmr")

resid.Diverse_back = residuals(Diverse_back.fit3, type = "cor")
min(resid.Diverse_back$cor)
max(resid.Diverse_back$cor)

resid.cor.matrix = round(resid.Diverse_back$cor, 3)
resid.cor.matrix[!lower.tri(resid.cor.matrix)] = 0

# IDENTIFY THE RESIDUAL CORRELATIONS WITH
# ABSOLUTE VALUE GREATER THEN 0.10
theRows = NULL
theCols = NULL
theCorrs = NULL
for(r in 1:(nrow(resid.cor.matrix))){
  for(c in 1:(nrow(resid.cor.matrix))){
    if(abs(resid.cor.matrix[r, c]) > 0.1){
      theRows = c(theRows, rownames(resid.cor.matrix)[r])
      theCols = c(theCols, colnames(resid.cor.matrix)[c])
      theCorrs = c(theCorrs, round(resid.cor.matrix[r, c], 3))
    }
  }
}

# PRINT OUT VARIABLE PAIRS FOR THE EXTREME RESIDUAL CORRELATIONS
bad.corrs = cbind(theRows, theCols, theCorrs)
bad.corrs[1, 3]
substr(bad.corrs[1, 3], 1, 1)
bad.corrs[1, 3] = paste(" ", bad.corrs[1, 3], sep = "")

for(i in 1:nrow(bad.corrs)){
  if(substr(bad.corrs[i, 3], 1, 1) == "0"){
    bad.corrs[i, 3] = paste(" ", bad.corrs[i, 3], sep = "")
  }
}
print(bad.corrs, quote = F)

##Take out 3_7

Diverse_back.model3 <- ' Diverse_back =~ Q3_10 + Q3_11 + Q4_5 + Q4_8 +
Q5_10 '
Diverse_back.fit4 <- cfa(Diverse_back.model3, std.lv = TRUE, estimator
= "WLSMV", mimic = "Mplus", data=Diverse_back)
summary(Diverse_back.fit4, fit.measures=TRUE, rsquare=TRUE)
fitMeasures(Diverse_back.fit4, "srmr")

resid.Diverse_back = residuals(Diverse_back.fit4, type = "cor")
```

```
min(resid.Diverse_back$cor)
max(resid.Diverse_back$cor)

resid.cor.matrix = round(resid.Diverse_back$cor, 3)
resid.cor.matrix[!lower.tri(resid.cor.matrix)] = 0

# IDENTIFY THE RESIDUAL CORRELATIONS WITH
# ABSOLUTE VALUE GREATER THEN 0.10
theRows = NULL
theCols = NULL
theCorrs = NULL
for(r in 1:(nrow(resid.cor.matrix))){
  for(c in 1:(nrow(resid.cor.matrix))){
    if(abs(resid.cor.matrix[r, c]) > 0.1){
      theRows = c(theRows, rownames(resid.cor.matrix)[r])
      theCols = c(theCols, colnames(resid.cor.matrix)[c])
      theCorrs = c(theCorrs, round(resid.cor.matrix[r, c], 3))
    }
  }
}

# PRINT OUT VARIABLE PAIRS FOR THE EXTREME RESIDUAL CORRELATIONS
bad.corrs = cbind(theRows, theCols, theCorrs)
bad.corrs[1, 3]
substr(bad.corrs[1, 3], 1, 1)
bad.corrs[1, 3] = paste(" ", bad.corrs[1, 3], sep = "")

for(i in 1:nrow(bad.corrs)){
  if(substr(bad.corrs[i, 3], 1, 1) == "0"){
    bad.corrs[i, 3] = paste(" ", bad.corrs[i, 3], sep = "")
  }
}
print(bad.corrs, quote = F)


##Take out 3_11

Diverse_back.model4 <- ' Diverse_back =~ Q3_10 + Q4_5 + Q4_8 + Q5_10 '
Diverse_back.fit5 <- cfa(Diverse_back.model4, std.lv = TRUE, estimator
= "WLSMV", mimic = "Mplus", data=Diverse_back)
summary(Diverse_back.fit5, fit.measures=TRUE, rsquare=TRUE)
fitMeasures(Diverse_back.fit5, "srmr")
#CFI = .99, TLI = .99, RMSEA = .026  [0.00, 0.16], WRMR = .307, SRMR =
.027

resid.Diverse_back = residuals(Diverse_back.fit5, type = "cor")
min(resid.Diverse_back$cor)
max(resid.Diverse_back$cor)

Diverse_back[] <- lapply(Diverse_back, as.numeric)
Diverse_back <- select(Diverse_back, Q3_10, Q4_5, Q4_8, Q5_10)
Diverse_back.poly = polychoric(Diverse_back)
alpha(Diverse_back.poly$rho)
#alpha = .84

Diverse_back_final <- rowMeans(Diverse_back)
```

```
describe(Diverse_back_final)
hist(Diverse_back_final,breaks=20)
qqPlot(Diverse_back_final)

####Final items####
######5. Inclusion of diverse backgrounds
###5a. DLE classroom climate module (modified)
#Q3_10: The professor shares their own experiences in class
#Q4_8: The professor shares their own background in class
###5b. Created by author
#Q4_5: Multiple perspectives are represented in this course
#Q5_10: My personal interests have been integrated into the curriculum
of this class

###Scale 7: Physical space

#########Look at alphas
Physical <- select(data1, Q3_12,Q4_9,Q4_18,Q4_7,Q5_17,Q5_20)

# THE FOLLOWING FIVE LINES PRODUCE THE FREQUENCY
# TABLE FOR EACH VARIABLE FOR INSPECTION
for(i in 1:length(names(Physical))){
  print(names(Physical)[i], quote = F)
  print(table(Physical[, i]))
  print(" ", quote = F)
}

# THE FOLLOWING SIX LINES PRODUCE THE CROSSTABULATION FOR
# EVERY PAIR OF VARIABLES FOR INSPECTION
for(r in 1:(length(names(Physical)) - 1)){
  for(c in (r + 1):length(names(Physical))){
    print(paste(names(Physical)[r], ":", names(Physical)[c]))
    print(table(Physical[, r], Physical[, c]))
    print(" ", quote = F)
  }
}

###for 4 variables - convert 1s to 2s
names(Physical)[c(2:3,5:6)]
for(i in c(2:3,5:6)){
  Physical[, i] = ifelse(Physical[, i] == 1, 2, Physical[, i])
}
# THE FOLLOWING FIVE LINES PRODUCE THE FREQUENCY
# TABLE FOR EACH VARIABLE FOR INSPECTION
for(i in 1:length(names(Physical))){
  print(names(Physical)[i], quote = F)
  print(table(Physical[, i]))
  print(" ", quote = F)
}
# THE FOLLOWING SIX LINES PRODUCE THE CROSSTABULATION FOR
# EVERY PAIR OF VARIABLES FOR INSPECTION
for(r in 1:(length(names(Physical)) - 1)){
  for(c in (r + 1):length(names(Physical))){
    print(paste(names(Physical)[r], ":", names(Physical)[c]))
    print(table(Physical[, r], Physical[, c]))
    print(" ", quote = F)
```

```
  }
}
#5_20 - 4
#4_7 - 4
#4_9 - 4
#####For 3 variables above - convert 4s to 3s
names(Physical)
names(Physical)[c(2,4,6)]
for(i in c(2,4,6)){
  Physical[, i] = ifelse(Physical[, i] == 4, 3, Physical[, i])
}
# THE FOLLOWING FIVE LINES PRODUCE THE FREQUENCY
# TABLE FOR EACH VARIABLE FOR INSPECTION
for(i in 1:length(names(Physical))){
  print(names(Physical)[i], quote = F)
  print(table(Physical[, i]))
  print(" ", quote = F)
}
# THE FOLLOWING SIX LINES PRODUCE THE CROSSTABULATION FOR
# EVERY PAIR OF VARIABLES FOR INSPECTION
for(r in 1:(length(names(Physical)) - 1)){
  for(c in (r + 1):length(names(Physical))){
    print(paste(names(Physical)[r], ":", names(Physical)[c]))
    print(table(Physical[, r], Physical[, c]))
    print(" ", quote = F)
  }
}

Physical.poly = polychoric(Physical)
alpha(Physical.poly$rho)
#alpha = .76

######Drop 3_12 - low correlation
Physical <- select(Physical, Q4_9,Q4_18,Q4_7,Q5_17,Q5_20)
Physical.poly = polychoric(Physical)
alpha(Physical.poly$rho)
#alpha = .78
str(Physical)
Physical[] <- lapply(Physical, ordered)

Physical.model <- ' Physical =~ Q4_9 + Q4_18 + Q4_7 + Q5_17 + Q5_20 '
Physical.fit1 <- cfa(Physical.model, std.lv = TRUE, estimator =
"WLSMV", mimic = "Mplus", data=Physical)
summary(Physical.fit1, fit.measures=TRUE, rsquare=TRUE)
fitMeasures(Physical.fit1, "srmr")
#CFI = .89, TLI = .79, RMSEA = .124 [0.064, 0.189], WRMR = .783, SRMR =
.083
##T. A. Brown (2006) suggested the following criteria for these
indices:
#(1) SRMR [standardized root mean square residual] values are close to
.08 or below;
#(2) RMSEA [root mean square error of approximation] values are close
to .06 or below;
#(3) CFI [comparative fit index] and TLI [Tucker-Lewis Index] values
are close to .95 or greater.  (p. 87)
#Also: WRMR should be <1
```

```
####Drop 4_7 - lowest R-square and loading
Physical.model1 <- ' Physical =~ Q4_9 + Q4_18 + Q5_17 + Q5_20 '
Physical.fit2 <- cfa(Physical.model1, std.lv = TRUE, estimator =
"WLSMV", mimic = "Mplus", data=Physical)
summary(Physical.fit2, fit.measures=TRUE, rsquare=TRUE)
fitMeasures(Physical.fit2, "srmr")
#CFI = .99, TLI = .98, RMSEA = .038 [0.000, 0.165], WRMR = .359, SRMR =
.04
####fit indices are all good

resid.Physical = residuals(Physical.fit2, type = "cor")
min(resid.Physical$cor)
max(resid.Physical$cor)

resid.cor.matrix = round(resid.Physical$cor, 3)
resid.cor.matrix[!lower.tri(resid.cor.matrix)] = 0
resid.cor.matrix

###Drop 4_9 - lowest r-square, has cor over .1
Physical.model2 <- ' Physical =~ Q4_18 + Q5_17 + Q5_20 '
Physical.fit3 <- cfa(Physical.model2, std.lv = TRUE, estimator =
"WLSMV", mimic = "Mplus", data=Physical)
summary(Physical.fit3, fit.measures=TRUE, rsquare=TRUE)
fitMeasures(Physical.fit3, "srmr")
#CFI = 1.0, TLI = 1.0, RMSEA = .00, WRMR = .00, SRMR = 0
####fit indices are all good

resid.Physical = residuals(Physical.fit3, type = "cor")
min(resid.Physical$cor)
max(resid.Physical$cor)

#####No correlations over |.1|

Physical <- select(Physical, Q4_18,Q5_17,Q5_20)
Physical[] <- lapply(Physical, as.numeric)
Physical.poly = polychoric(Physical)
alpha(Physical.poly$rho)
#alpha = .77

Physical_final <- rowMeans(Physical)
describe(Physical_final)
hist(Physical_final,breaks=20)
qqPlot(Physical_final)

#########NOTE: also tried doing this but focusing on the residual
correlations instead of
##starting by looking at the r-square and loadings - ended up with the
same 3 items

################################RQ1A###################################

#################For each scale - collapse values according to how I
collapsed them when doing CFAs#########
#######And then create scale variable####################
```

```
####Descrim
Descrim <- select(data1,Q3_5,Q5_1,Q3_8,Q3_13,Q4_3,Q4_15,Q5_19,Q4_21)
for(i in 1:length(names(Descrim))){
  Descrim[, i] = ifelse(Descrim[, i] == 1, 2, Descrim[, i])
}
for(i in c(2:3,6)){
  Descrim[, i] = ifelse(Descrim[, i] == 4, 3, Descrim[, i])
}
for(i in c(4)){
  Descrim[, i] = ifelse(Descrim[, i] == 2, 3, Descrim[, i])
}
Descrim <- select(Descrim, Q5_1, Q3_8, Q3_13, Q4_21, Q4_15)
data$Descrim_final <- rowMeans(Descrim)


#####PP
PP <- select(data1, Q3_3,Q4_12,Q5_8,Q3_4,Q4_20,Q5_12)
for(i in c(1:3, 5)){
  PP[, i] = ifelse(PP[, i] == 1, 2, PP[, i])
}
for(i in c(2:4)){
  PP[, i] = ifelse(PP[, i] == 4, 3, PP[, i])
}
PP <- select(PP, Q3_3, Q4_12, Q5_8)
data$PP_final <- rowMeans(PP)

#####Physical
Physical <- select(data1, Q3_12,Q4_9,Q4_18,Q4_7,Q5_17,Q5_20)
for(i in c(2:3,5:6)){
  Physical[, i] = ifelse(Physical[, i] == 1, 2, Physical[, i])
}
for(i in c(2,4,6)){
  Physical[, i] = ifelse(Physical[, i] == 4, 3, Physical[, i])
}
Physical <- select(Physical, Q4_18,Q5_17,Q5_20)
data$Physical_final <- rowMeans(Physical)

########TASint
TASint <- select(data1, Q8_1,Q8_2,Q8_3,Q8_4,Q8_5,Q8_6,Q8_7,Q8_8)
for(i in c(2:7)){
  TASint[, i] = ifelse(TASint[, i] == 1, 2, TASint[, i])
}
for(i in c(1:3,5:6,8)){
  TASint[, i] = ifelse(TASint[, i] == 4, 3, TASint[, i])
}
TASint <- select(TASint, Q8_1,Q8_2,Q8_4,Q8_5,Q8_6,Q8_7,Q8_8)
data$TASint_final <- rowMeans(TASint)

######ISOL_SSint
Isol_SSint <- select(data1, Q3_9, Q3_14, Q4_4, Q4_11, Q4_14, Q4_19,
Q5_2, Q5_4, Q5_5, Q5_11, Q5_14, Q5_15, Q5_18)
for(i in 1:length(names(Isol_SSint))){
  Isol_SSint[, i] = ifelse(Isol_SSint[, i] == 1, 2, Isol_SSint[, i])
}
for(i in c(1:3, 6:13)){
  Isol_SSint[, i] = ifelse(Isol_SSint[, i] == 4, 3, Isol_SSint[, i])
```

```
}
Isol_SSint <- select(Isol_SSint, Q4_4, Q4_14, Q5_2, Q5_5, Q5_11, Q5_14,
                        Q5_15, Q5_18)
data$Isol_SSint_final <- rowMeans(Isol_SSint)

########TSint_Diverse
TSint_Diverse <- select(data1, Q3_10, Q4_8, Q4_5, Q5_10, Q7_2, Q7_3,
Q7_4, Q7_5, Q7_8)
for(i in c(1:8)){
  TSint_Diverse[, i] = ifelse(TSint_Diverse[, i] == 4, 3,
TSint_Diverse[, i])
}
for(i in c(3, 6:9)){
  TSint_Diverse[, i] = ifelse(TSint_Diverse[, i] == 1, 2,
TSint_Diverse[, i])
}
TSint_Diverse$Q4_8 = ifelse(TSint_Diverse$Q4_8 == 3, 2,
TSint_Diverse$Q4_8)
TSint_Diverse <-  select(TSint_Diverse, Q4_5, Q5_10, Q7_2, Q7_4, Q7_5,
Q7_8)
data$TSint_Diverse_final <- rowMeans(TSint_Diverse)

##########Look at correlations between scales
data_cors <- select(data, Isol_SSint_final, PP_final, Physical_final,
Descrim_final,
                    TSint_Diverse_final, TASint_final)
data_cors <- na.omit(data_cors)
cor(data_cors)


#########Check assumptions for MANOVA
###Normality of each scale (for FG and non-FG students) and homog. of
variance
data$FG <- ifelse(data$Q33 == "No",1,ifelse(data$Q33 == "Yes",0,NA))
data$FG <- as.factor(data$FG)
data_FG <- subset(data, FG == 1)

boxplot(data_FG$Isol_SSint_final, data_FG$PP_final,
data_FG$Physical_final, data_FG$Descrim_final,
        data_FG$TSint_Diverse_final, data_FG$TASint_final)

##Descrim
describe(data$Descrim_final[data$FG == 1])
hist(data$Descrim_final[data$FG == 1], breaks=20)
qqPlot(data$Descrim_final[data$FG == 1])
plot(density(na.omit(data$Descrim_final[data$FG == 1])))

describe(data$Descrim_final[data$FG == 0])
hist(data$Descrim_final[data$FG == 0], breaks=20)
qqPlot(data$Descrim_final[data$FG == 0])
plot(density(na.omit(data$Descrim_final[data$FG == 0])))

leveneTest(data$Descrim_final,data$FG)
var(data$Descrim_final[data$FG == 1], na.rm = T)/
  var(data$Descrim_final[data$FG == 0], na.rm = T)
```

```
###BOB: SKEW AND KURTOSIS NUMBERS ARE OK AND HOMOGENEITY OF VARIANCE
NOT VIOLATED,
#BUT PLOTS LOOK OFF - NEED TO DO TRANSFORMATION?

##PP
describe(data$PP_final[data$FG == 1])
hist(data$PP_final[data$FG == 1], breaks=20)
qqPlot(data$PP_final[data$FG == 1])
plot(density(na.omit(data$PP_final[data$FG == 1])))

describe(data$PP_final[data$FG == 0])
hist(data$PP_final[data$FG == 0], breaks=20)
qqPlot(data$PP_final[data$FG == 0])
plot(density(na.omit(data$PP_final[data$FG == 0])))

leveneTest(data$PP_final,data$FG)
var(data$PP_final[data$FG == 1], na.rm = T)/
  var(data$PP_final[data$FG == 0], na.rm = T)

###BOB: SKEW AND KURTOSIS NUMBERS ARE OK AND HOMOGENEITY OF VARIANCE
NOT VIOLATED,
#BUT PLOTS LOOK OFF - NEED TO DO TRANSFORMATION?

##Physical
describe(data$Physical_final[data$FG == 1])
hist(data$Physical_final[data$FG == 1], breaks=20)
qqPlot(data$Physical_final[data$FG == 1])
plot(density(na.omit(data$Physical_final[data$FG == 1])))

describe(data$Physical_final[data$FG == 0])
hist(data$Physical_final[data$FG == 0], breaks=20)
qqPlot(data$Physical_final[data$FG == 0])
plot(density(na.omit(data$Physical_final[data$FG == 0])))

leveneTest(data$Physical_final,data$FG)
var(data$Physical_final[data$FG == 1], na.rm = T)/
  var(data$Physical_final[data$FG == 0], na.rm = T)

###BOB: SKEW AND KURTOSIS NUMBERS ARE OK AND HOMOGENEITY OF VARIANCE
NOT VIOLATED,
#BUT PLOTS FOR FG=0 LOOK OFF - NEED TO DO TRANSFORMATION?

##TASint
describe(data$TASint_final[data$FG == 1])
hist(data$TASint_final[data$FG == 1], breaks=20)
qqPlot(data$TASint_final[data$FG == 1])
plot(density(na.omit(data$TASint_final[data$FG == 1])))

describe(data$TASint_final[data$FG == 0])
hist(data$TASint_final[data$FG == 0], breaks=20)
qqPlot(data$TASint_final[data$FG == 0])
plot(density(na.omit(data$TASint_final[data$FG == 0])))

leveneTest(data$TASint_final,data$FG)
var(data$TASint_final[data$FG == 1], na.rm = T)/
  var(data$TASint_final[data$FG == 0], na.rm = T)
```

```
##Conclusion: substantial skew - need to transform

##Isol_SSint
describe(data$Isol_SSint_final[data$FG == 1])
hist(data$Isol_SSint_final[data$FG == 1], breaks=20)
qqPlot(data$Isol_SSint_final[data$FG == 1])
plot(density(na.omit(data$Isol_SSint_final[data$FG == 1])))

describe(data$Isol_SSint_final[data$FG == 0])
hist(data$Isol_SSint_final[data$FG == 0], breaks=20)
qqPlot(data$Isol_SSint_final[data$FG == 0])
plot(density(na.omit(data$Isol_SSint_final[data$FG == 0])))

leveneTest(data$Isol_SSint_final,data$FG)
var(data$Isol_SSint_final[data$FG == 1], na.rm = T)/
  var(data$Isol_SSint_final[data$FG == 0], na.rm = T)

##Conclusion: substantial skew - need to transform

##TSint_Diverse
describe(data$TSint_Diverse_final[data$FG == 1])
hist(data$TSint_Diverse_final[data$FG == 1], breaks=20)
qqPlot(data$TSint_Diverse_final[data$FG == 1])
plot(density(na.omit(data$TSint_Diverse_final[data$FG == 1])))

describe(data$TSint_Diverse_final[data$FG == 0])
hist(data$TSint_Diverse_final[data$FG == 0], breaks=20)
qqPlot(data$TSint_Diverse_final[data$FG == 0])
plot(density(na.omit(data$TSint_Diverse_final[data$FG == 0])))

leveneTest(data$TSint_Diverse_final,data$FG)
var(data$TSint_Diverse_final[data$FG == 1], na.rm = T)/
  var(data$TSint_Diverse_final[data$FG == 0], na.rm = T)

##Conclusion: there doesn't appear to be extreme violations

############Transformations for TASint and Isol_SSint

####TASint
table(data$TASint_final)
data$TASint_final_reflect <- 4.28571428571429 - data$TASint_final
table(data$TASint_final_reflect)
###now subtract .99 to put lowest value close to 0
data$TASint_final_reflect <- data$TASint_final_reflect - .99

data$TASint_final_transf <- sqrt(data$TASint_final_reflect)
par(mfrow = c(1,1))
describe(data$TASint_final_transf[data$FG == 1])
hist(data$TASint_final_transf[data$FG == 1], breaks=20)
qqPlot(data$TASint_final_transf[data$FG == 1])
plot(density(na.omit(data$TASint_final_transf[data$FG == 1])))

describe(data$TASint_final_transf[data$FG == 0])
hist(data$TASint_final_transf[data$FG == 0], breaks=20)
qqPlot(data$TASint_final_transf[data$FG == 0])
plot(density(na.omit(data$TASint_final_transf[data$FG == 0])))
```

```
leveneTest(data$TASint_final_transf,data$FG)
var(data$TASint_final_transf[data$FG == 1], na.rm = T)/
  var(data$TASint_final_transf[data$FG == 0], na.rm = T)

###BOB: WOULD YOU SAY THAT NOW THERE ARE NOT EXTREME VIOLATIONS OF
NORMALITY?

####Isol_SSint
table(data$Isol_SSint_final)
data$Isol_SSint_final_reflect <- 4.125 - data$Isol_SSint_final
table(data$Isol_SSint_final_reflect)
###now subtract .99 to put lowest value close to 0
data$Isol_SSint_final_reflect <- data$Isol_SSint_final_reflect - .99

data$Isol_SSint_final_transf <- sqrt(data$Isol_SSint_final_reflect)

describe(data$Isol_SSint_final_transf[data$FG == 1])
hist(data$Isol_SSint_final_transf[data$FG == 1], breaks=20)
qqPlot(data$Isol_SSint_final_transf[data$FG == 1])
plot(density(na.omit(data$Isol_SSint_final_transf[data$FG == 1])))

describe(data$Isol_SSint_final_transf[data$FG == 0])
hist(data$Isol_SSint_final_transf[data$FG == 0], breaks=20)
qqPlot(data$Isol_SSint_final_transf[data$FG == 0])
plot(density(na.omit(data$Isol_SSint_final_transf[data$FG == 0])))

leveneTest(data$Isol_SSint_final_transf,data$FG)
var(data$Isol_SSint_final_transf[data$FG == 1], na.rm = T)/
  var(data$Isol_SSint_final_transf[data$FG == 0], na.rm = T)

###BOB: WOULD YOU SAY THAT NOW THERE ARE NOT EXTREME VIOLATIONS OF
NORMALITY?

#######################################################################
##
#      Oct 4 2018 update - separate TSint and Diverse_back variables
#
#######################################################################
##

###Diverse_back
Diverse_back <- select(data1,
Q3_10,Q4_8,Q4_17,Q3_7,Q3_11,Q4_5,Q5_3,Q5_6,Q5_10)
for(i in c(1:9)){
  Diverse_back[, i] = ifelse(Diverse_back[, i] == 4, 3, Diverse_back[,
i])
}
for(i in c(1,3,5:6)){
  Diverse_back[, i] = ifelse(Diverse_back[, i] == 1, 2, Diverse_back[,
i])
}
Diverse_back <- select(Diverse_back, Q3_10, Q4_5, Q4_8, Q5_10)
data$Diverse_back_final <- rowMeans(Diverse_back)

###TSint
```

```
TSint <- select(data1, Q7_1,Q7_2,Q7_3,Q7_4,Q7_5,Q7_6,Q7_7,Q7_8)
for(i in c(1:8)){
  TSint[, i] = ifelse(TSint[, i] == 4, 3, TSint[, i])
}
for(i in c(3:5,7:8)){
  TSint[, i] = ifelse(TSint[, i] == 1, 2, TSint[, i])
}
TSint <- select(TSint, Q7_1,Q7_2,Q7_4,Q7_5,Q7_8)
data$TSint_final <- rowMeans(TSint)

##########Look at correlations between scales
data_cors <- select(data, Isol_SSint_final, PP_final, Physical_final,
Descrim_final,
                    TSint_final, Diverse_back_final, TASint_final)
data_cors <- na.omit(data_cors)
cor(data_cors)

################################RQ1B###################################

###########################################################
#       2. Check normality and homog. of variance         #
#                    for each scale                       #
###########################################################

#########Check assumptions for MANOVA
###Normality of each scale (for FG and non-FG students) and homog. of
variance
data$FG <- ifelse(data$Q33 == "No",1,ifelse(data$Q33 == "Yes",0,NA))
data$FG <- as.factor(data$FG)
table(data$FG)

##Descrim
par(mfrow = c(2,2))
describe(data$Descrim_final[data$FG == 1])
hist(data$Descrim_final[data$FG == 1], breaks=20)
qqPlot(data$Descrim_final[data$FG == 1])
plot(density(na.omit(data$Descrim_final[data$FG == 1]), bw = 0.15))
boxplot(na.omit(data$Descrim_final[data$FG == 1]), horizontal = T)

par(mfrow = c(2,2))
describe(data$Descrim_final[data$FG == 0])
hist(data$Descrim_final[data$FG == 0], breaks=20)
qqPlot(data$Descrim_final[data$FG == 0])
plot(density(na.omit(data$Descrim_final[data$FG == 0])))
boxplot(na.omit(data$Descrim_final[data$FG == 0]), horizontal = T)

leveneTest(data$Descrim_final,data$FG)
var(data$Descrim_final[data$FG == 1], na.rm = T)/
  var(data$Descrim_final[data$FG == 0], na.rm = T)

###No extreme violation of homog. of variance; skew is under |1|; skew
#is in same direction for both groups; no extreme outliers --> don't
need to
#worry about non-normality

##PP
```

```
par(mfrow = c(2,2))
describe(data$PP_final[data$FG == 1])
hist(data$PP_final[data$FG == 1], breaks=20)
qqPlot(data$PP_final[data$FG == 1])
plot(density(na.omit(data$PP_final[data$FG == 1]), bw = 0.15))
boxplot(na.omit(data$PP_final[data$FG == 1]), horizontal = T)

par(mfrow = c(2,2))
describe(data$PP_final[data$FG == 0])
hist(data$PP_final[data$FG == 0], breaks=20)
qqPlot(data$PP_final[data$FG == 0])
plot(density(na.omit(data$PP_final[data$FG == 0]), bw = 0.15))
boxplot(na.omit(data$PP_final[data$FG == 0]), horizontal = T)

leveneTest(data$PP_final,data$FG)
var(data$PP_final[data$FG == 1], na.rm = T)/
  var(data$PP_final[data$FG == 0], na.rm = T)

###No extreme violation of homog. of variance; skew is under |1|; skew
#is in same direction for both groups; no extreme outliers --> don't
need to
#worry about non-normality

##Physical
par(mfrow = c(2,2))
describe(data$Physical_final[data$FG == 1])
hist(data$Physical_final[data$FG == 1], breaks=20)
qqPlot(data$Physical_final[data$FG == 1])
plot(density(na.omit(data$Physical_final[data$FG == 1])))
boxplot(na.omit(data$Physical_final[data$FG == 1]), horizontal = T)

par(mfrow = c(2,2))
describe(data$Physical_final[data$FG == 0])
hist(data$Physical_final[data$FG == 0], breaks=20)
qqPlot(data$Physical_final[data$FG == 0])
plot(density(na.omit(data$Physical_final[data$FG == 0]), bw = 0.15))
boxplot(na.omit(data$Physical_final[data$FG == 0]), horizontal = T)

leveneTest(data$Physical_final,data$FG)
var(data$Physical_final[data$FG == 1], na.rm = T)/
  var(data$Physical_final[data$FG == 0], na.rm = T)

###No extreme violation of homog. of variance; skew is under |1|; skew
#is in same direction for both groups; no extreme outliers --> don't
need to
#worry about non-normality

##TASint
par(mfrow = c(2,2))
describe(data$TASint_final[data$FG == 1])
hist(data$TASint_final[data$FG == 1], breaks=20)
qqPlot(data$TASint_final[data$FG == 1])
plot(density(na.omit(data$TASint_final[data$FG == 1])))
boxplot(na.omit(data$TASint_final[data$FG == 1]), horizontal = T)

par(mfrow = c(2,2))
```

```
describe(data$TASint_final[data$FG == 0])
hist(data$TASint_final[data$FG == 0], breaks=20)
qqPlot(data$TASint_final[data$FG == 0])
plot(density(na.omit(data$TASint_final[data$FG == 0])))
boxplot(na.omit(data$TASint_final[data$FG == 0]), horizontal = T)

leveneTest(data$TASint_final,data$FG)
var(data$TASint_final[data$FG == 1], na.rm = T)/
  var(data$TASint_final[data$FG == 0], na.rm = T)
###No extreme violation of homog. of variance; skew is over but close
to |1|; skew
#is in same direction for both groups; no extreme outliers --> don't
need to
#worry about non-normality BUT MIGHT BE WORTH TRYING TO TRANSFORM IF
HAVING ISSUES WITH
#MULTIVARIATE OUTLIERS

##Isol_SSint
par(mfrow = c(2,2))
describe(data$Isol_SSint_final[data$FG == 1])
hist(data$Isol_SSint_final[data$FG == 1], breaks=20)
qqPlot(data$Isol_SSint_final[data$FG == 1])
plot(density(na.omit(data$Isol_SSint_final[data$FG == 1])))
boxplot(na.omit(data$Isol_SSint_final[data$FG == 1]), horizontal = T)

par(mfrow = c(2,2))
describe(data$Isol_SSint_final[data$FG == 0])
hist(data$Isol_SSint_final[data$FG == 0], breaks=20)
qqPlot(data$Isol_SSint_final[data$FG == 0])
plot(density(na.omit(data$Isol_SSint_final[data$FG == 0])))
boxplot(na.omit(data$Isol_SSint_final[data$FG == 0]), horizontal = T)

leveneTest(data$Isol_SSint_final,data$FG)
var(data$Isol_SSint_final[data$FG == 1], na.rm = T)/
  var(data$Isol_SSint_final[data$FG == 0], na.rm = T)

###No extreme violation of homog. of variance; skew is over but close
to |1|; skew
#is in same direction for both groups; no extreme outliers --> don't
need to
#worry about non-normality BUT MIGHT BE WORTH TRYING TO TRANSFORM IF
HAVING ISSUES WITH
#MULTIVARIATE OUTLIERS

##TSint
par(mfrow = c(2,2))
describe(data$TSint_final[data$FG == 1])
hist(data$TSint_final[data$FG == 1], breaks=20)
qqPlot(data$TSint_final[data$FG == 1])
plot(density(na.omit(data$TSint_final[data$FG == 1])))
boxplot(na.omit(data$TSint_final[data$FG == 1]), horizontal = T)

par(mfrow = c(2,2))
describe(data$TSint_final[data$FG == 0])
hist(data$TSint_final[data$FG == 0], breaks=20)
qqPlot(data$TSint_final[data$FG == 0])
```

```
plot(density(na.omit(data$TSint_final[data$FG == 0])))
boxplot(na.omit(data$TSint_final[data$FG == 0]), horizontal = T)

leveneTest(data$TSint_final,data$FG)
var(data$TSint_final[data$FG == 1], na.rm = T)/
  var(data$TSint_final[data$FG == 0], na.rm = T)

###No extreme violation of homog. of variance; skew is under |1|; skew
#is in same direction for both groups; no extreme outliers --> don't
need to
#worry about non-normality

##Diverse_back

par(mfrow = c(2,2))
describe(data$Diverse_back_final[data$FG == 1])
hist(data$Diverse_back_final[data$FG == 1], breaks=20)
qqPlot(data$Diverse_back_final[data$FG == 1])
plot(density(na.omit(data$Diverse_back_final[data$FG == 1])))
boxplot(na.omit(data$Diverse_back_final[data$FG == 1]), horizontal = T)

par(mfrow = c(2,2))
describe(data$Diverse_back_final[data$FG == 0])
hist(data$Diverse_back_final[data$FG == 0], breaks=20)
qqPlot(data$Diverse_back_final[data$FG == 0])
plot(density(na.omit(data$Diverse_back_final[data$FG == 0])))
boxplot(na.omit(data$Diverse_back_final[data$FG == 0]), horizontal = T)

leveneTest(data$Diverse_back_final,data$FG)
var(data$Diverse_back_final[data$FG == 1], na.rm = T)/
  var(data$Diverse_back_final[data$FG == 0], na.rm = T)

###No extreme violation of homog. of variance; skew is under |1|; no
extreme outliers --> don't need to
#worry about non-normality

###########################################################
#       3. Transformations for TASint and Isol_SSint      #
###########################################################

####TASint
table(data$TASint_final)
data$TASint_final_reflect <- 4.28571428571429 - data$TASint_final
table(data$TASint_final_reflect)
###now subtract .99 to put lowest value close to 0
data$TASint_final_reflect <- data$TASint_final_reflect - .99
##then take the square root
data$TASint_final_transf <- sqrt(data$TASint_final_reflect)
describe(data$TASint_final_transf)

par(mfrow = c(2,2))
describe(data$TASint_final_transf[data$FG == 1])
hist(data$TASint_final_transf[data$FG == 1], breaks=20)
qqPlot(data$TASint_final_transf[data$FG == 1])
plot(density(na.omit(data$TASint_final_transf[data$FG == 1])))
```

```
boxplot(na.omit(data$TASint_final_transf[data$FG == 1]), horizontal =
T)

par(mfrow = c(2,2))
describe(data$TASint_final_transf[data$FG == 0])
hist(data$TASint_final_transf[data$FG == 0], breaks=20)
qqPlot(data$TASint_final_transf[data$FG == 0])
plot(density(na.omit(data$TASint_final_transf[data$FG == 0])))
boxplot(na.omit(data$TASint_final_transf[data$FG == 0]), horizontal =
T)

leveneTest(data$TASint_final_transf,data$FG)
var(data$TASint_final_transf[data$FG == 0], na.rm = T)/
  var(data$TASint_final_transf[data$FG == 1], na.rm = T)

###THERE IS NO LONGER AN EXTREME VIOLATION OF THE NORMALITY ASSUMPTION

####Isol_SSint
table(data$Isol_SSint_final)
data$Isol_SSint_final_reflect <- 4.125 - data$Isol_SSint_final
table(data$Isol_SSint_final_reflect)
###now subtract .99 to put lowest value close to 0
data$Isol_SSint_final_reflect <- data$Isol_SSint_final_reflect - .99
##then take the square root
data$Isol_SSint_final_transf <- sqrt(data$Isol_SSint_final_reflect)
describe(data$Isol_SSint_final_transf)

par(mfrow = c(2,2))
describe(data$Isol_SSint_final_transf[data$FG == 1])
hist(data$Isol_SSint_final_transf[data$FG == 1], breaks=20)
qqPlot(data$Isol_SSint_final_transf[data$FG == 1])
plot(density(na.omit(data$Isol_SSint_final_transf[data$FG == 1])))
boxplot(na.omit(data$Isol_SSint_final_transf[data$FG == 1]), horizontal
= T)

par(mfrow = c(2,2))
describe(data$Isol_SSint_final_transf[data$FG == 0])
hist(data$Isol_SSint_final_transf[data$FG == 0], breaks=20)
qqPlot(data$Isol_SSint_final_transf[data$FG == 0])
plot(density(na.omit(data$Isol_SSint_final_transf[data$FG == 0])))
boxplot(na.omit(data$Isol_SSint_final_transf[data$FG == 0]), horizontal
= T)

leveneTest(data$Isol_SSint_final_transf,data$FG)
var(data$Isol_SSint_final_transf[data$FG == 1], na.rm = T)/
  var(data$Isol_SSint_final_transf[data$FG == 0], na.rm = T)

###THERE IS NO LONGER AN EXTREME VIOLATION OF THE NORMALITY ASSUMPTION

###########################################################
#       4. Check for multivariate outliers                #
###########################################################

#######start with untrasformed variables######
library(MVN)
```

```
# IDENTIFY POTENTIAL MULTIVARIATE OUTLIERS FOR THE FG GROUP

data_FG <- subset(data, FG == 1)
names(data_FG)

data_FG_vars <- select(data_FG, Descrim_final:TSint_final)
data_FG_vars <- na.omit(data_FG_vars)
par(mfrow = c(1,1))
FG.original.count = NULL
FG.original.outliers = NULL
for(i in 1:100){
  mv.outliers = mvOutlier(data_FG_vars)
  #count = sum(mv.outliers$outlier[, 2] > qchisq(0.001, 8, lower.tail =
F))
  count = sum(mv.outliers$outlier[, 1] > qchisq(0.001, 8, lower.tail =
F))
  out = mv.outliers$outlier[1:count, ]
  FG.original.count = c(FG.original.count, count)
  #FG.original.outliers = c(FG.original.outliers,
as.numeric(levels(out$Observation))[out$Observation])
  FG.original.outliers = c(FG.original.outliers,
as.numeric(rownames(out)))
}

table(FG.original.count)
table(FG.original.outliers)

##Rows that are outliers over 50 times: 31, 40, 105, 151, 152

# IDENTIFY POTENTIAL MULTIVARIATE OUTLIERS FOR THE NON-FG GROUP
data_notFG <- subset(data, FG == 0)

# NONE OF THE VARIABLES ARE TRANSFORMED
data_notFG_vars <- select(data_notFG, Descrim_final:TSint_final)
data_notFG_vars <- na.omit(data_notFG_vars)
names(data_notFG_vars)

NFG.original.count = NULL
NFG.original.outliers = NULL

for(i in 1:100){
  mv.outliers = mvOutlier(data_notFG_vars)
  #count = sum(mv.outliers$outlier[, 2] > qchisq(0.001, 8, lower.tail =
F))
  count = sum(mv.outliers$outlier[, 1] > qchisq(0.001, 8, lower.tail =
F))
  out = mv.outliers$outlier[1:count, ]
  NFG.original.count = c(NFG.original.count, count)
  #FG.original.outliers = c(FG.original.outliers,
as.numeric(levels(out$Observation))[out$Observation])
  NFG.original.outliers = c(NFG.original.outliers,
as.numeric(rownames(out)))
}

table(NFG.original.count)
table(NFG.original.outliers)
```

```
####Rows that are outliers more than 50 times: 39, 42, 55, 149, 157

############Check for multivariate outliers when TASint and Isol_SSint
are transformed
data_FG <- subset(data, FG == 1)
names(data_FG)

data_FG_vars <- select(data_FG,
Descrim_final:Physical_final,Diverse_back_final:TSint_final,
                       Isol_SSint_final_transf, TASint_final_transf)
data_FG_vars <- na.omit(data_FG_vars)
names(data_FG_vars)

FG.transf.count = NULL
FG.transf.outliers = NULL
for(i in 1:100){
  mv.outliers = mvOutlier(data_FG_vars)
  #count = sum(mv.outliers$outlier[, 2] > qchisq(0.001, 8, lower.tail =
F))
  count = sum(mv.outliers$outlier[, 1] > qchisq(0.001, 8, lower.tail =
F))
  out = mv.outliers$outlier[1:count, ]
  FG.transf.count = c(FG.transf.count, count)
  #FG.transf.outliers = c(FG.transf.outliers,
as.numeric(levels(out$Observation))[out$Observation])
  FG.transf.outliers = c(FG.transf.outliers, as.numeric(rownames(out)))
}

table(FG.transf.count)
table(FG.transf.outliers)

####Row that is outlier over 50 times: 135

# IDENTIFY POTENTIAL MULTIVARIATE OUTLIERS FOR THE NON-FG GROUP
data_notFG <- subset(data, FG == 0)

data_notFG_vars <- select(data_notFG,
Descrim_final:Physical_final,Diverse_back_final:TSint_final,
                          Isol_SSint_final_transf, TASint_final_transf)
data_notFG_vars <- na.omit(data_notFG_vars)
names(data_notFG_vars)

NFG.transf.count = NULL
NFG.transf.outliers = NULL

for(i in 1:100){
  mv.outliers = mvOutlier(data_notFG_vars)
  #count = sum(mv.outliers$outlier[, 2] > qchisq(0.001, 8, lower.tail =
F))
  count = sum(mv.outliers$outlier[, 1] > qchisq(0.001, 8, lower.tail =
F))
  out = mv.outliers$outlier[1:count, ]
  NFG.transf.count = c(NFG.transf.count, count)
  #FG.transf.outliers = c(FG.transf.outliers,
as.numeric(levels(out$Observation))[out$Observation])
```

```
  NFG.transf.outliers = c(NFG.transf.outliers,
as.numeric(rownames(out)))
}

table(NFG.transf.count)
table(NFG.transf.outliers)

#####Row that is outlier over 50 times: 90, 157

###########USING THE TRANSFORMED VARIABLES REDUCES THE NUMBER
######OF MV OUTLIERS

###########################################################
#                   5. Run MANOVA                          #
###########################################################

####First do MANOVAs with transformed variables
########no rows removed

fit <- manova(cbind(Descrim_final, PP_final,
Physical_final,TSint_final, Diverse_back_final,
                    Isol_SSint_final_transf, TASint_final_transf) ~ FG,
data = data)
summary(fit) #p=.156
summary.aov(fit)

#######Remove MV outliers (135 and 90 an 157)
names(data)
data_vars <- select(data,
c(Descrim_final:Physical_final,TSint_final,Diverse_back_final,
                            Isol_SSint_final_transf,
TASint_final_transf, FG))
nrow(data_vars)
head(data_vars)
remove = c("90","135","157")
data_vars = data_vars[!rownames(data_vars) %in% remove, ]
nrow(data_vars)

fit <- manova(cbind(Descrim_final, PP_final,
Physical_final,TSint_final,Diverse_back_final,
                    Isol_SSint_final_transf, TASint_final_transf) ~ FG,
data = data_vars)
summary(fit) #p=.14
summary.aov(fit)

###MANOVA with only 4 SS variables
fita <- manova(cbind(Descrim_final, PP_final, Physical_final,
                    Isol_SSint_final_transf) ~ FG, data = data_vars)
summary(fita) #p=.02

# CORRELATIONS AMONG 6 VARIABLES
data_vars <- na.omit(data_vars)
names(data_vars)
cor.mat <- data_vars[, 1:7]
cor(cor.mat)
```

```
#########TRY MANOVA WITH ALL VARIABLES UNTRANSFORMED

# RUN MANOVA WITHOUT ANY CASES EXCLUDED
names(data)
fit <- manova(cbind(Isol_SSint_final, PP_final, Physical_final,
Descrim_final,
                    TSint_final, Diverse_back_final, TASint_final) ~
FG, data = data)
summary(fit) #p=.17
summary.aov(fit)

#########TRy excluding variables that are MV outliers more than 50
times
table(FG.original.outliers)
table(NFG.original.outliers)
names(data)
data_vars <- select(data, c(Descrim_final:FG))
nrow(data_vars)
head(data_vars)
remove = c("31","40","105","151","152","39","42","55","149","157")
data_vars = data_vars[!rownames(data_vars) %in% remove, ]
nrow(data_vars)

fit <- manova(cbind(Isol_SSint_final, PP_final, Physical_final,
Descrim_final,
                    TSint_final, Diverse_back_final, TASint_final) ~
FG, data = data_vars)
summary(fit) #p=.32
summary.aov(fit)

# CORRELATIONS AMONG 6 VARIABLES
data_vars <- na.omit(data_vars)
cor.mat <- data_vars[, 1:7]
cor(cor.mat)

############################################################
#      6. try running 2 separate MANOVAs                   #
############################################################

##Use the 2 transformed variables with the 3 MV outliers removed
data_vars <- select(data,
c(Descrim_final:Physical_final,TSint_final,Diverse_back_final,
                            Isol_SSint_final_transf,
TASint_final_transf, FG))
nrow(data_vars)
head(data_vars)
remove = c("90","135","157")
data_vars = data_vars[!rownames(data_vars) %in% remove, ]
nrow(data_vars)

# CORRELATIONS AMONG 7 VARIABLES
data_vars <- na.omit(data_vars)
names(data_vars)
cor.mat <- data_vars[, 1:7]
cor(cor.mat)
```

```
#Combine Isol_SSint, TSint, and TASint in 1 MANOVA
#Combine Descrim, PP, Physical, and Diverse_back in 2nd MANOVA
#Most of the correlations fall between |.3| and |.6|

data_vars <- select(data,
c(Descrim_final:Physical_final,TSint_final,Diverse_back_final,
                            Isol_SSint_final_transf,
TASint_final_transf, FG))
remove = c("90","135","157")
data_vars = data_vars[!rownames(data_vars) %in% remove, ]

fit1 <- manova(cbind(Isol_SSint_final_transf,
                     TSint_final, TASint_final_transf) ~ FG, data =
data_vars)
summary(fit1) #p = .08
summary.aov(fit1)

fit2 <- manova(cbind(PP_final, Physical_final, Descrim_final,
Diverse_back_final) ~ FG, data = data_vars)
summary(fit2) #p = .08
summary.aov(fit2)

###########################################################
#      7. try removing univariate outliers first         #
###########################################################

##Use the 2 transformed variables
####I used this approach to ID outliers:

boxplot.stats(data$Isol_SSint_final_transf)$out #no outliers
boxplot.stats(data$TASint_final_transf)$out #no outliers
boxplot.stats(data$TSint_final)$out #no outliers
boxplot.stats(data$Diverse_back_final)$out #no outliers
boxplot.stats(data$Descrim_final)$out
boxplot.stats(data$Physical_final)$out
boxplot.stats(data$PP_final)$out #no outliers

data_out_removed <- filter(data, Descrim_final > 2.4 & Physical_final >
2.4)
dim(data)
dim(data_out_removed)

###Now check for MV outliers
data_FG <- subset(data_out_removed, FG == 1)
names(data_FG)

data_FG_vars <- select(data_FG,
Descrim_final:Physical_final,TSint_final,Diverse_back_final,
                       Isol_SSint_final_transf, TASint_final_transf)
data_FG_vars <- na.omit(data_FG_vars)
names(data_FG_vars)

FG.transf.count = NULL
FG.transf.outliers = NULL
for(i in 1:100){
  mv.outliers = mvOutlier(data_FG_vars)
```

```
  #count = sum(mv.outliers$outlier[, 2] > qchisq(0.001, 8, lower.tail =
F))
  count = sum(mv.outliers$outlier[, 1] > qchisq(0.001, 8, lower.tail =
F))
  out = mv.outliers$outlier[1:count, ]
  FG.transf.count = c(FG.transf.count, count)
  #FG.transf.outliers = c(FG.transf.outliers,
as.numeric(levels(out$Observation))[out$Observation])
  FG.transf.outliers = c(FG.transf.outliers, as.numeric(rownames(out)))
}

table(FG.transf.count)
table(FG.transf.outliers)

####Rows that are outliers over 50 times: 2, 119

# IDENTIFY POTENTIAL MULTIVARIATE OUTLIERS FOR THE NON-FG GROUP
data_notFG <- subset(data_out_removed, FG == 0)

data_notFG_vars <- select(data_notFG,
Descrim_final:Physical_final,TSint_final,Diverse_back_final,
                          Isol_SSint_final_transf, TASint_final_transf)
data_notFG_vars <- na.omit(data_notFG_vars)
names(data_notFG_vars)

NFG.transf.count = NULL
NFG.transf.outliers = NULL

for(i in 1:100){
  mv.outliers = mvOutlier(data_notFG_vars)
  #count = sum(mv.outliers$outlier[, 2] > qchisq(0.001, 8, lower.tail =
F))
  count = sum(mv.outliers$outlier[, 1] > qchisq(0.001, 8, lower.tail =
F))
  out = mv.outliers$outlier[1:count, ]
  NFG.transf.count = c(NFG.transf.count, count)
  #FG.transf.outliers = c(FG.transf.outliers,
as.numeric(levels(out$Observation))[out$Observation])
  NFG.transf.outliers = c(NFG.transf.outliers,
as.numeric(rownames(out)))
}

table(NFG.transf.count)
table(NFG.transf.outliers)

#####Row that is outlier over 50 times: 80, 136

####First do MANOVAs with transformed variables
########no MV outliers removed
fit <- manova(cbind(Descrim_final, PP_final,
Physical_final,TSint_final,Diverse_back_final,
                    Isol_SSint_final_transf, TASint_final_transf) ~ FG,
data = data_out_removed)
summary(fit) #p=.51
summary.aov(fit)
```

```
#######Remove MV outliers (80,136,2,119)
names(data)
data_vars <- select(data_out_removed,
c(Descrim_final:Physical_final,TSint_final,Diverse_back_final,
                                       Isol_SSint_final_transf,
TASint_final_transf, FG))
nrow(data_vars)
head(data_vars)
remove = c("80","119","136","2")
data_vars = data_vars[!rownames(data_vars) %in% remove, ]
nrow(data_vars)

fit <- manova(cbind(Descrim_final, PP_final,
Physical_final,TSint_final,Diverse_back_final,
                    Isol_SSint_final_transf, TASint_final_transf) ~ FG,
data = data_vars)
summary(fit) #p=.52
summary.aov(fit)

##############################################################
#8. do table with original climate scales comparing FG and CG#
##############################################################

rm(list=ls())
setwd("/Users/Kate/Dropbox/School/Dissertation/ACTUAL
STUDY!!!/Survey/survey data")
data <- read.csv("data_final.csv", na.strings="")
library(psych)
library(car)
library(dplyr)

##select all classroom climate items
data1 <- select(data, Q3_1:Q8_8)
###Get the variables from character to numeric, then recode reverse-
coded items, then convert
#from numberic to ordinal for correct analysis in lavaan
#convert to numeric
levels <- c("Strongly disagree","Somewhat disagree","Somewhat
agree","Strongly agree")
data1[] <-  lapply(data1, factor, levels=levels)
data1[] <- lapply(data1, as.numeric)
#recode reverse-coded variables
data1$Q5_8 <- ifelse(data1$Q5_8 == 4,1,ifelse(data1$Q5_8 ==
3,2,ifelse(data1$Q5_8 == 2,3,ifelse(data1$Q5_8 == 1,4,NA))))
data1$Q3_4 <- ifelse(data1$Q3_4 == 4,1,ifelse(data1$Q3_4 ==
3,2,ifelse(data1$Q3_4 == 2,3,ifelse(data1$Q3_4 == 1,4,NA))))
data1$Q4_20 <- ifelse(data1$Q4_20 == 4,1,ifelse(data1$Q4_20 ==
3,2,ifelse(data1$Q4_20 == 2,3,ifelse(data1$Q4_20 == 1,4,NA))))
data1$Q3_5 <- ifelse(data1$Q3_5 == 4,1,ifelse(data1$Q3_5 ==
3,2,ifelse(data1$Q3_5 == 2,3,ifelse(data1$Q3_5 == 1,4,NA))))
data1$Q5_1 <- ifelse(data1$Q5_1 == 4,1,ifelse(data1$Q5_1 ==
3,2,ifelse(data1$Q5_1 == 2,3,ifelse(data1$Q5_1 == 1,4,NA))))
data1$Q3_8 <- ifelse(data1$Q3_8 == 4,1,ifelse(data1$Q3_8 ==
3,2,ifelse(data1$Q3_8 == 2,3,ifelse(data1$Q3_8 == 1,4,NA))))
data1$Q3_13 <- ifelse(data1$Q3_13 == 4,1,ifelse(data1$Q3_13 ==
3,2,ifelse(data1$Q3_13 == 2,3,ifelse(data1$Q3_13 == 1,4,NA))))
```

```
data1$Q4_3 <- ifelse(data1$Q4_3 == 4,1,ifelse(data1$Q4_3 ==
3,2,ifelse(data1$Q4_3 == 2,3,ifelse(data1$Q4_3 == 1,4,NA))))
data1$Q4_15 <- ifelse(data1$Q4_15 == 4,1,ifelse(data1$Q4_15 ==
3,2,ifelse(data1$Q4_15 == 2,3,ifelse(data1$Q4_15 == 1,4,NA))))
data1$Q5_19 <- ifelse(data1$Q5_19 == 4,1,ifelse(data1$Q5_19 ==
3,2,ifelse(data1$Q5_19 == 2,3,ifelse(data1$Q5_19 == 1,4,NA))))
data1$Q4_21 <- ifelse(data1$Q4_21 == 4,1,ifelse(data1$Q4_21 ==
3,2,ifelse(data1$Q4_21 == 2,3,ifelse(data1$Q4_21 == 1,4,NA))))
data1$Q4_16 <- ifelse(data1$Q4_16 == 4,1,ifelse(data1$Q4_16 ==
3,2,ifelse(data1$Q4_16 == 2,3,ifelse(data1$Q4_16 == 1,4,NA))))
data1$Q4_6 <- ifelse(data1$Q4_6 == 4,1,ifelse(data1$Q4_6 ==
3,2,ifelse(data1$Q4_6 == 2,3,ifelse(data1$Q4_6 == 1,4,NA))))
data1$Q5_13 <- ifelse(data1$Q5_13 == 4,1,ifelse(data1$Q5_13 ==
3,2,ifelse(data1$Q5_13 == 2,3,ifelse(data1$Q5_13 == 1,4,NA))))
data1$Q3_12 <- ifelse(data1$Q3_12 == 4,1,ifelse(data1$Q3_12 ==
3,2,ifelse(data1$Q3_12 == 2,3,ifelse(data1$Q3_12 == 1,4,NA))))

####Descrim
Descrim <- select(data1,Q3_5,Q5_1,Q3_8,Q3_13,Q4_3,Q4_15,Q5_19,Q4_21)
Descrim <- select(Descrim, Q5_1, Q3_8, Q3_13, Q4_21, Q4_15)
data$Descrim_final <- rowMeans(Descrim)


#####PP
PP <- select(data1, Q3_3,Q4_12,Q5_8,Q3_4,Q4_20,Q5_12)
PP <- select(PP, Q3_3, Q4_12, Q5_8)
data$PP_final <- rowMeans(PP)

#####Physical
Physical <- select(data1, Q3_12,Q4_9,Q4_18,Q4_7,Q5_17,Q5_20)
Physical <- select(Physical, Q4_18,Q5_17,Q5_20)
data$Physical_final <- rowMeans(Physical)

########TASint
TASint <- select(data1, Q8_1,Q8_2,Q8_3,Q8_4,Q8_5,Q8_6,Q8_7,Q8_8)
TASint <- select(TASint, Q8_1,Q8_2,Q8_4,Q8_5,Q8_6,Q8_7,Q8_8)
data$TASint_final <- rowMeans(TASint)

######ISOL_SSint
Isol_SSint <- select(data1, Q3_9, Q3_14, Q4_4, Q4_11, Q4_14, Q4_19,
Q5_2, Q5_4, Q5_5, Q5_11, Q5_14, Q5_15, Q5_18)
Isol_SSint <- select(Isol_SSint, Q4_4, Q4_14, Q5_2, Q5_5, Q5_11, Q5_14,
                     Q5_15, Q5_18)
data$Isol_SSint_final <- rowMeans(Isol_SSint)

###Diverse_back
Diverse_back <- select(data1,
Q3_10,Q4_8,Q4_17,Q3_7,Q3_11,Q4_5,Q5_3,Q5_6,Q5_10)
Diverse_back <- select(Diverse_back, Q3_10, Q4_5, Q4_8, Q5_10)
data$Diverse_back_final <- rowMeans(Diverse_back)

###TSint
TSint <- select(data1, Q7_1,Q7_2,Q7_3,Q7_4,Q7_5,Q7_6,Q7_7,Q7_8)
TSint <- select(TSint, Q7_1,Q7_2,Q7_4,Q7_5,Q7_8)
data$TSint_final <- rowMeans(TSint)
```

```
data$FG <- ifelse(data$Q33 == "No",1,ifelse(data$Q33 == "Yes",0,NA))
data$FG <- as.factor(data$FG)
table(data$FG)
data_FG <- subset(data, FG == 1)
data_CG <- subset(data, FG == 0)

########Check normality, homog. of variance first

##Descrim
par(mfrow = c(2,2))
require(psych)
describe(data$Descrim_final[data$FG == 1])
hist(data$Descrim_final[data$FG == 1], breaks=20)
qqPlot(data$Descrim_final[data$FG == 1])
plot(density(na.omit(data$Descrim_final[data$FG == 1]), bw = 0.15))
boxplot(na.omit(data$Descrim_final[data$FG == 1]), horizontal = T)


par(mfrow = c(2,2))
describe(data$Descrim_final[data$FG == 0])
hist(data$Descrim_final[data$FG == 0], breaks=20)
qqPlot(data$Descrim_final[data$FG == 0])
plot(density(na.omit(data$Descrim_final[data$FG == 0])))
boxplot(na.omit(data$Descrim_final[data$FG == 0]), horizontal = T)

leveneTest(data$Descrim_final,data$FG)
var(data$Descrim_final[data$FG == 1], na.rm = T)/
  var(data$Descrim_final[data$FG == 0], na.rm = T)

###No extreme violation of homog. of variance; skew
#is in same direction for both groups; no extreme outliers --> don't
need to
#worry about non-normality

##PP
par(mfrow = c(2,2))
describe(data$PP_final[data$FG == 1])
hist(data$PP_final[data$FG == 1], breaks=20)
qqPlot(data$PP_final[data$FG == 1])
plot(density(na.omit(data$PP_final[data$FG == 1]), bw = 0.15))
boxplot(na.omit(data$PP_final[data$FG == 1]), horizontal = T)

par(mfrow = c(2,2))
describe(data$PP_final[data$FG == 0])
hist(data$PP_final[data$FG == 0], breaks=20)
qqPlot(data$PP_final[data$FG == 0])
plot(density(na.omit(data$PP_final[data$FG == 0]), bw = 0.15))
boxplot(na.omit(data$PP_final[data$FG == 0]), horizontal = T)

leveneTest(data$PP_final,data$FG)
var(data$PP_final[data$FG == 1], na.rm = T)/
  var(data$PP_final[data$FG == 0], na.rm = T)

###No extreme violation of homog. of variance; skew is under |1|; skew
#is in same direction for both groups; no extreme outliers --> don't
need to
```

```
#worry about non-normality

##Physical
par(mfrow = c(2,2))
describe(data$Physical_final[data$FG == 1])
hist(data$Physical_final[data$FG == 1], breaks=20)
qqPlot(data$Physical_final[data$FG == 1])
plot(density(na.omit(data$Physical_final[data$FG == 1])))
boxplot(na.omit(data$Physical_final[data$FG == 1]), horizontal = T)

par(mfrow = c(2,2))
describe(data$Physical_final[data$FG == 0])
hist(data$Physical_final[data$FG == 0], breaks=20)
qqPlot(data$Physical_final[data$FG == 0])
plot(density(na.omit(data$Physical_final[data$FG == 0]), bw = 0.15))
boxplot(na.omit(data$Physical_final[data$FG == 0]), horizontal = T)

leveneTest(data$Physical_final,data$FG)
var(data$Physical_final[data$FG == 1], na.rm = T)/
  var(data$Physical_final[data$FG == 0], na.rm = T)

###No extreme violation of homog. of variance; skew is under |1|; skew
#is in same direction for both groups; no extreme outliers --> don't
need to
#worry about non-normality

##TASint
par(mfrow = c(2,2))
describe(data$TASint_final[data$FG == 1])
hist(data$TASint_final[data$FG == 1], breaks=20)
qqPlot(data$TASint_final[data$FG == 1])
plot(density(na.omit(data$TASint_final[data$FG == 1])))
boxplot(na.omit(data$TASint_final[data$FG == 1]), horizontal = T)

par(mfrow = c(2,2))
describe(data$TASint_final[data$FG == 0])
hist(data$TASint_final[data$FG == 0], breaks=20)
qqPlot(data$TASint_final[data$FG == 0])
plot(density(na.omit(data$TASint_final[data$FG == 0])))
boxplot(na.omit(data$TASint_final[data$FG == 0]), horizontal = T)

leveneTest(data$TASint_final,data$FG)
var(data$TASint_final[data$FG == 1], na.rm = T)/
  var(data$TASint_final[data$FG == 0], na.rm = T)
###No extreme violation of homog. of variance; skew is under |1|; skew
#is in same direction for both groups; no extreme outliers --> don't
need to
#worry about non-normality

##Isol_SSint
par(mfrow = c(2,2))
describe(data$Isol_SSint_final[data$FG == 1])
hist(data$Isol_SSint_final[data$FG == 1], breaks=20)
qqPlot(data$Isol_SSint_final[data$FG == 1])
plot(density(na.omit(data$Isol_SSint_final[data$FG == 1])))
boxplot(na.omit(data$Isol_SSint_final[data$FG == 1]), horizontal = T)
```

```
par(mfrow = c(2,2))
describe(data$Isol_SSint_final[data$FG == 0])
hist(data$Isol_SSint_final[data$FG == 0], breaks=20)
qqPlot(data$Isol_SSint_final[data$FG == 0])
plot(density(na.omit(data$Isol_SSint_final[data$FG == 0])))
boxplot(na.omit(data$Isol_SSint_final[data$FG == 0]), horizontal = T)

leveneTest(data$Isol_SSint_final,data$FG)
var(data$Isol_SSint_final[data$FG == 1], na.rm = T)/
  var(data$Isol_SSint_final[data$FG == 0], na.rm = T)

###No extreme violation of homog. of variance; skew is under |1|; no
extreme outliers --> don't need to
#worry about non-normality

##TSint
par(mfrow = c(2,2))
describe(data$TSint_final[data$FG == 1])
hist(data$TSint_final[data$FG == 1], breaks=20)
qqPlot(data$TSint_final[data$FG == 1])
plot(density(na.omit(data$TSint_final[data$FG == 1])))
boxplot(na.omit(data$TSint_final[data$FG == 1]), horizontal = T)

par(mfrow = c(2,2))
describe(data$TSint_final[data$FG == 0])
hist(data$TSint_final[data$FG == 0], breaks=20)
qqPlot(data$TSint_final[data$FG == 0])
plot(density(na.omit(data$TSint_final[data$FG == 0])))
boxplot(na.omit(data$TSint_final[data$FG == 0]), horizontal = T)

leveneTest(data$TSint_final,data$FG)
var(data$TSint_final[data$FG == 1], na.rm = T)/
  var(data$TSint_final[data$FG == 0], na.rm = T)

###No extreme violation of homog. of variance; skew is under |1|; skew
#is in same direction for both groups; no extreme outliers --> don't
need to
#worry about non-normality

##Diverse_back

par(mfrow = c(2,2))
describe(data$Diverse_back_final[data$FG == 1])
hist(data$Diverse_back_final[data$FG == 1], breaks=20)
qqPlot(data$Diverse_back_final[data$FG == 1])
plot(density(na.omit(data$Diverse_back_final[data$FG == 1])))
boxplot(na.omit(data$Diverse_back_final[data$FG == 1]), horizontal = T)

par(mfrow = c(2,2))
describe(data$Diverse_back_final[data$FG == 0])
hist(data$Diverse_back_final[data$FG == 0], breaks=20)
qqPlot(data$Diverse_back_final[data$FG == 0])
plot(density(na.omit(data$Diverse_back_final[data$FG == 0])))
boxplot(na.omit(data$Diverse_back_final[data$FG == 0]), horizontal = T)
```

```
leveneTest(data$Diverse_back_final,data$FG)
var(data$Diverse_back_final[data$FG == 1], na.rm = T)/
  var(data$Diverse_back_final[data$FG == 0], na.rm = T)

###No extreme violation of homog. of variance; skew is under |1|; skew
is in same direction;
#no extreme outliers --> don't need to worry about non-normality


###Trying to figure out how to do cohen's d effect sizes
library(lsr)
cohensD(data_CG$Descrim_final,data_FG$Descrim_final)
##Note: confirmed this works by entering data here too:
https://www.socscistatistics.com/effectsize/Default3.aspx
cohensD(data_CG$PP_final,data_FG$PP_final)
cohensD(data_CG$Physical_final,data_FG$Physical_final)
cohensD(data_CG$TASint_final,data_FG$TASint_final)
cohensD(data_CG$Isol_SSint_final,data_FG$Isol_SSint_final)
cohensD(data_CG$Diverse_back_final,data_FG$Diverse_back_final)
cohensD(data_CG$TSint_final,data_FG$TSint_final)

################################RQ1C####################################
#######################################################
#       2. Create demographic variables              #
#######################################################

########section
data$section <- ifelse(data$Q42 == "Section 10 (meets MTW 8:00-
8:50AM)","Prof_1",
                       ifelse(data$Q42 == "Section 20 (meets MTW 12:20-
1:10PM)" |
                                data$Q42 == "Section 30 (meets MTW
3:35-4:25PM)", "Prof_2", NA))

table(data$section)

#gender
data$gender <- data$Q26
table(data$gender)
data$gender_bin <- ifelse(data$gender == "Man","Man",ifelse(data$gender
== "Woman",

"Woman",NA))
table(data$gender_bin)
#Pell
data$Pell <- ifelse(data$Q34 == "Yes","Pell-eligible",ifelse(data$Q34
== "I don't know" | data$Q34 == "No","Not eligible or doesn't
know",NA))
table(data$Pell)
data$Pell_num <- ifelse(data$Q34 == "Yes",1,ifelse(data$Q34 == "I don't
know" | data$Q34 == "No",0,NA))
table(data$Pell_num)
#Promise
data$Promise <- ifelse(data$Q35 == "Yes","Promise-
eligible",ifelse(data$Q35 == "I don't know" | data$Q35 == "No","Not
eligible or doesn't know",NA))
```

```
table(data$Q35)
table(data$Promise)
data$Promise_num <- ifelse(data$Q35 == "Yes",1,ifelse(data$Q35 == "I
don't know" | data$Q35 == "No",0,NA))
####Student loans
table(data$Q36)
data$Loans <- ifelse(data$Q36 == "Yes","Has loans",ifelse(data$Q36 ==
"No","No loans",NA))
table(data$Loans)
data$Loans <- factor(data$Loans) %>%
  relevel(ref = "No loans")
data$Loans_num <- ifelse(data$Q36 == "Yes",1,ifelse(data$Q36 ==
"No",0,NA))

###composite measure of financial hardship
data$fin_hard <- data$Pell_num + data$Promise_num + data$Loans_num
table(data$fin_hard)
#####recode race variable#####
data$Eth_Somali <- ifelse(grepl("Somali",data$Q27,fixed=TRUE),1,0)
data$Eth_Viet <- ifelse(grepl("Vietnamese",data$Q27,fixed=TRUE),1,0)
data$Eth_Lat <- ifelse(grepl("Hispanic or
Latino",data$Q27,fixed=TRUE),1,0)
data$Eth_Hmong <- ifelse(grepl("Hmong",data$Q27,fixed=TRUE),1,0)
data$Eth_Laot <- ifelse(grepl("Laotian",data$Q27,fixed=TRUE),1,0)
sum(data$Eth_Lat)

data$Race_White <- ifelse(grepl("White (includes Middle
Eastern)",data$Q28,fixed=TRUE),1,0)
data$Race_Black <- ifelse(grepl("Black or African
American",data$Q28,fixed=TRUE),1,0)
data$Race_Asian <- ifelse(grepl("Asian",data$Q28,fixed=TRUE),1,0)
data$Race_AmInd <- ifelse(grepl("American Indian or Alaskan
Native",data$Q28,fixed=TRUE),1,0)
data$Race_PacIs <- ifelse(grepl("Native Hawaiian or other Pacific
Islander",data$Q28,fixed=TRUE),1,0)
sum(grepl("Native Hawaiian or other Pacific
Islander",data$Q28,fixed=TRUE))
data$Race_Else <- ifelse(grepl("Something else (please
state)",data$Q28,fixed=TRUE),1,0)
data$Race_NoAnswer <- ifelse(grepl("Prefer not to
answer",data$Q28,fixed=TRUE),1,0)

race <-
data.frame(data$Eth_Lat,data$Race_White,data$Race_Black,data$Race_Asian
,data$Race_AmInd,
                   data$Race_PacIs)
head(race)
row.count <- rowSums(race, na.rm=T)
data$race <- NA
data$race[which(data$Eth_Viet == 1 | data$Eth_Hmong == 1 |
data$Eth_Laot == 1)] <- "Asian_URM"

data$race[which(data$Eth_Lat == 1 & data$Race_White == 1)] <-
"Latino/Hispanic"
data$race
data$race[row.count > 1 & is.na(data$race)] <- "Mixed race"
```

```
data$race[row.count == 1 & data$Race_White == 1] <- "White"
data$race[row.count == 1 & data$Race_Black == 1] <- "Black/African
American"
data$race[row.count == 1 & data$Eth_Lat == 1] <- "Latino/Hispanic"
data$race[row.count == 1 & data$Race_Asian == 1 & is.na(data$race)] <-
"Asian_nonURM"
data$race[row.count == 1 & data$Race_AmInd == 1] <- "Native American"
data$race[row.count == 1 & data$Race_PacIs == 1] <- "Pacific Islander"
data$race[row.count == 1 & data$Race_Else == 1] <- "Something else"
data$race[row.count == 1 & data$Race_NoAnswer == 1] <- "Prefer not to
answer"

data$URM <- ifelse(data$race == "Black/African American" | data$race ==
"Latino/Hispanic" | data$race == "Asian_URM" |
                     data$race == "Native American", "URM",
ifelse(data$race == "White" | data$race == "Asian_nonURM", "non-URM",
NA))
table(data$URM)
table(data$race)

###########For regressions - recode race variable so that categories
are collapsed
########Create subset of data with only FG students#######
data$FG <- ifelse(data$Q33 == "No",1,ifelse(data$Q33 == "Yes",0,NA))
data$FG <- as.factor(data$FG)
data_FG <- subset(data, FG == 1)

data_FG$race_recode <- ifelse(data_FG$race ==
"Asian_nonURM","Asian_nonURM",
                              ifelse(data_FG$race ==
"Asian_URM","Asian_URM",
                                     ifelse(data_FG$race ==
"Black/African American", "Black/African American",
                                            ifelse(data_FG$race ==
"Latino/Hispanic","Latino/Hispanic",
                                                   ifelse(data_FG$race
== "Mixed race","Mixed race",

ifelse(data_FG$race == "White","White",NA))))))
table(data_FG$race)
table(data_FG$race_recode)

boxplot(TSint_final ~ race_recode, data=data_FG)
data_FG1 <- subset(data_FG, !is.na(TSint_final) & !is.na(race) &
!is.na(section) & !is.na(gender) & !is.na(Pell))

data_FG1 %>%
  group_by(race_recode) %>%
  summarise(mean=mean(TSint_final)) %>%
  arrange(mean)

boxplot(TASint_final ~ race_recode, data=data_FG)
data_FG1 %>%
  group_by(race_recode) %>%
  summarise(mean=mean(TASint_final)) %>%
  arrange(mean)
```

```
boxplot(Isol_SSint_final ~ race_recode, data=data_FG)
data_FG2 <- subset(data_FG1, !is.na(Isol_SSint_final))
data_FG2 %>%
  group_by(race_recode) %>%
  summarise(mean=mean(Isol_SSint_final)) %>%
  arrange(mean)

boxplot(PP_final ~ race_recode, data=data_FG)
data_FG1 %>%
  group_by(race_recode) %>%
  summarise(mean=mean(PP_final)) %>%
  arrange(mean)

boxplot(Descrim_final ~ race_recode, data=data_FG)
data_FG2 <- subset(data_FG1, !is.na(Descrim_final))

data_FG2 %>%
  group_by(race_recode) %>%
  summarise(mean=mean(Descrim_final)) %>%
  arrange(mean)

boxplot(Physical_final ~ race_recode, data=data_FG)
data_FG1 %>%
  group_by(race_recode) %>%
  summarise(mean=mean(Physical_final)) %>%
  arrange(mean)

data_FG$White_Asian <- ifelse(data_FG$race == "White" | data_FG$race ==
"Asian_nonURM","White/non-URM_Asian",
                              ifelse(!is.na(data_FG$race), "non-
White/non-URM_Asian", NA))
data_FG$Latino_mixed <- ifelse(data_FG$race == "Latino/Hispanic" |
data_FG$race == "Mixed race","Latino/mixed race",
                               ifelse(!is.na(data_FG$race), "non-
Latino/mixed race", NA))
data_FG$Black_AsianURM <- ifelse(data_FG$race == "Black/African
American" | data_FG$race == "Asian_URM","Black/Asian_URM",
                                 ifelse(!is.na(data_FG$race), "non-
Black/Asian_URM", NA))
table(data_FG$White_Asian)
table(data_FG$Latino_mixed)
table(data_FG$Black_AsianURM)
data_FG$White_Asian <- factor(data_FG$White_Asian) %>%
  relevel(ref = "non-White/non-URM_Asian")
data_FG$Latino_mixed <- factor(data_FG$Latino_mixed) %>%
  relevel(ref = "non-Latino/mixed race")
data_FG$Black_AsianURM <- factor(data_FG$Black_AsianURM) %>%
  relevel(ref = "non-Black/Asian_URM")

#######################################################
#       3. Look at correlations among variables       #
#######################################################
```

```
data_cors <- select(data_FG, Descrim_final:TSint_final, White_Asian,
Latino_mixed, Black_AsianURM, section, gender_bin, Pell, Promise,
Loans, fin_hard)
data_cors <- na.omit(data_cors)
data_cors$White_Asian <- as.numeric(data_cors$White_Asian)
data_cors$Latino_mixed <- as.numeric(data_cors$Latino_mixed)
data_cors$Black_AsianURM <- as.numeric(data_cors$Black_AsianURM)
data_cors$Loans <- as.numeric(data_cors$Loans)
data_cors$section <- ifelse(data_cors$section == "Prof_1",1,
                            ifelse(data_cors$section == "Prof_2",2,NA))
data_cors$gender_bin <- ifelse(data_cors$gender_bin == "Man",1,
                               ifelse(data_cors$gender_bin ==
"Woman",2,NA))
data_cors$Pell <- ifelse(data_cors$Pell == "Not eligible or doesn't
know",1,
                         ifelse(data_cors$Pell == "Pell-
eligible",2,NA))
data_cors$Promise <- ifelse(data_cors$Promise == "Not eligible or
doesn't know",1,
                            ifelse(data_cors$Promise == "Promise-
eligible",2,NA))
str(data_cors)
options(scipen=999)
round(cor(data_cors),2)

###Correlation matrix along with p-values
library(Hmisc)
rcorr(as.matrix(data_cors))

###Take out some of the financial variables
data_cors0 <- select(data_cors, Descrim_final:gender_bin,fin_hard)
round(cor(data_cors0),2)
rcorr(as.matrix(data_cors0))
head(data_cors)

#######################################################
#       4. Regressions - including all variables      #
#######################################################

########################################
#####Regression - TSint#########
########################################

data_FG1 <- subset(data_FG, !is.na(TSint_final) & !is.na(race) &
!is.na(section) & !is.na(gender_bin) & !is.na(fin_hard))

regmod1 <- lm(TSint_final ~ White_Asian + Latino_mixed + Black_AsianURM
+ section + gender_bin + fin_hard, data=data_FG1)
summary(regmod1)

####Check assumptions
##VIF
vif(regmod1)

length(regmod1$fitted.values)
length(data_FG1$TSint_final)
```

```
par(mfrow=c(1,1))
plot(regmod1$fitted.values,data_FG1$TSint_final)
reg.line=lm(data_FG1$TSint_final~regmod1$fitted.values)
abline(reg.line$coef)
lines(lowess(data_FG1$TSint_final~regmod1$fitted.values), lwd=2,
col="red")
fit.mod = lm(data_FG1$TSint_final~regmod1$fitted.values)
confband = as.data.frame(predict(fit.mod, interval="confidence"))
confband$fitted.values=regmod1$fitted.values
confband=arrange(confband, fitted.values)
lines(cbind(confband$fitted.values, confband$lwr), col="blue",
      lwd=2,lty="dashed")
lines(cbind(confband$fitted.values, confband$upr), col="blue",
      lwd=2,lty="dashed")

##check residuals
plotResiduals = function(mod){
  library(dplyr)
  if(length(labels(mod)) > 1){
    the.title = NULL
    for(i in 1:(length(labels(mod)) - 1)){
      the.title = paste(the.title,labels(mod)[i], "+")
    }
    the.title = paste(the.title,
                      labels(mod)[length(labels(mod))])
  } else{
    the.title = labels(mod)
  }
  plot(mod$fitted.values,mod$residuals, main = the.title)
  abline(h=0)
  lines(lowess(mod$residuals~mod$fitted.values), lwd=2, col="red")
  #create a 95% confidence band
  resid.mod = lm(mod$residuals~mod$fitted.values)
  confband = as.data.frame(predict(resid.mod,
                                   interval="confidence"))
  confband$fitted.values= mod$fitted.values
  confband=arrange(confband, fitted.values)
  lines(cbind(confband$fitted.values, confband$lwr), col="blue",
        lwd=2,lty="dashed")
  lines(cbind(confband$fitted.values, confband$upr), col="blue",
        lwd=2,lty="dashed")
} #end of plotResiduals()

plotResiduals(regmod1)

##normality of residuals
hist(regmod1$residuals)
plot(density(regmod1$residuals))
qqPlot(regmod1$residuals)
##homogeneity of variance
plot(regmod1$fitted.values,regmod1$residuals)
abline(h=0)
#########Levene's test
cutIncrement = 0.01
minN = 20
theMax = minN
```

```
theN = 0
cutValue = min(regmod1$fitted.values)
cutoffs = NULL
while(cutValue < max(regmod1$fitted.values)){
  while(theN < theMax & cutValue < max(regmod1$fitted.values)){
    cutValue = cutValue + cutIncrement
    theN = sum(regmod1$fitted.values <= cutValue)}
  cutoffs = c(cutoffs, cutValue)
  theMax = theN + minN
}
cutoffs
min(regmod1$fitted.values)
max(regmod1$fitted.values)
#ADD A GROUPING VARIABLE BASED ON
#THE FITTED CUTOFF VALUES TO regmod1

regmod1$resid.group = 0
for(i in 1:nrow(data_FG1)){
  for(n in length(cutoffs):1){
    if(regmod1$fitted.values[i] <= cutoffs[n]){
      regmod1$resid.group[i] = round(cutoffs[n], 2)
    }
  }
}
table(regmod1$resid.group)
regmod1$resid.group = ifelse(regmod1$resid.group ==
                              2.91, 2.62, regmod1$resid.group)
table(regmod1$resid.group)
leveneTest(regmod1$residuals, regmod1$resid.group)
####p-values is greater than .05 which is good
VARIANCE = tapply(regmod1$residuals, regmod1$resid.group, var)
max(VARIANCE)/min(VARIANCE)
#####this is under 4 which is good

################################
#######Regression - SSint#######
################################
regmod2 <- lm(Isol_SSint_final_transf ~ White_Asian + Latino_mixed +
Black_AsianURM + section + gender_bin + fin_hard, data=data_FG1)
summary(regmod2)

####Check assumptions
##VIF
vif(regmod2)

data_FG2 <- subset(data_FG1, !is.na(Isol_SSint_final_transf))
length(regmod2$fitted.values)
plot(regmod2$fitted.values,data_FG2$Isol_SSint_final_transf)
reg.line=lm(data_FG2$Isol_SSint_final_transf~regmod2$fitted.values)
abline(reg.line$coef)
lines(lowess(data_FG2$Isol_SSint_final_transf~regmod2$fitted.values),
lwd=2, col="red")
fit.mod = lm(data_FG2$Isol_SSint_final_transf~regmod2$fitted.values)
confband = as.data.frame(predict(fit.mod, interval="confidence"))
confband$fitted.values=regmod2$fitted.values
library(dplyr)
```

```
confband=arrange(confband, fitted.values)
lines(cbind(confband$fitted.values, confband$lwr), col="blue",
      lwd=2,lty="dashed")
lines(cbind(confband$fitted.values, confband$upr), col="blue",
      lwd=2,lty="dashed")

##check residuals
plotResiduals(regmod2)

##normality of residuals
hist(regmod2$residuals)
plot(density(regmod2$residuals))
qqPlot(regmod2$residuals)
##homogeneity of variance
plot(regmod2$fitted.values,regmod2$residuals)
abline(h=0)
#########Levene's test
cutIncrement = 0.01
minN = 20
theMax = minN
theN = 0
cutValue = min(regmod2$fitted.values)
cutoffs = NULL
while(cutValue < max(regmod2$fitted.values)){
  while(theN < theMax & cutValue < max(regmod2$fitted.values)){
    cutValue = cutValue + cutIncrement
    theN = sum(regmod2$fitted.values <= cutValue)}
  cutoffs = c(cutoffs, cutValue)
  theMax = theN + minN
}
cutoffs
min(regmod2$fitted.values)
max(regmod2$fitted.values)
#ADD A GROUPING VARIABLE BASED ON
#THE FITTED CUTOFF VALUES TO regmod2

regmod2$resid.group = 0
for(i in 1:nrow(data_FG2)){
  for(n in length(cutoffs):1){
    if(regmod2$fitted.values[i] <= cutoffs[n]){
      regmod2$resid.group[i] = round(cutoffs[n], 2)
    }
  }
}
table(regmod2$resid.group)
regmod2$resid.group = ifelse(regmod2$resid.group ==
                               .77, .55, regmod2$resid.group)
table(regmod2$resid.group)
library(car)
leveneTest(regmod2$residuals, regmod2$resid.group)
####p-values is greater than .05 which is good
VARIANCE = tapply(regmod2$residuals, regmod2$resid.group, var)
max(VARIANCE)/min(VARIANCE)
#####this is under 4 which is good

################################
```

```
#####Regression - Descrim#######
################################

regmod3 <- lm(Descrim_final ~ White_Asian + Latino_mixed +
Black_AsianURM + section + gender_bin + fin_hard, data=data_FG1)
summary(regmod3)

####Check assumptions
##VIF
vif(regmod3)

length(regmod3$fitted.values)
data_FG2 <- subset(data_FG1, !is.na(Descrim_final))
plot(regmod3$fitted.values,data_FG2$Descrim_final)
reg.line=lm(data_FG2$Descrim_final~regmod3$fitted.values)
abline(reg.line$coef)
lines(lowess(data_FG2$Descrim_final~regmod3$fitted.values), lwd=2,
col="red")
fit.mod = lm(data_FG2$Descrim_final~regmod3$fitted.values)
confband = as.data.frame(predict(fit.mod, interval="confidence"))
confband$fitted.values=regmod3$fitted.values
confband=arrange(confband, fitted.values)
lines(cbind(confband$fitted.values, confband$lwr), col="blue",
      lwd=2,lty="dashed")
lines(cbind(confband$fitted.values, confband$upr), col="blue",
      lwd=2,lty="dashed")

##check residuals
plotResiduals(regmod3)

##normality of residuals
hist(regmod3$residuals)
plot(density(regmod3$residuals))
qqPlot(regmod3$residuals)
##homogeneity of variance
plot(regmod3$fitted.values,regmod3$residuals)
abline(h=0)
#########Levene's test
cutIncrement = 0.01
minN = 20
theMax = minN
theN = 0
cutValue = min(regmod3$fitted.values)
cutoffs = NULL
while(cutValue < max(regmod3$fitted.values)){
  while(theN < theMax & cutValue < max(regmod3$fitted.values)){
    cutValue = cutValue + cutIncrement
    theN = sum(regmod3$fitted.values <= cutValue)}
  cutoffs = c(cutoffs, cutValue)
  theMax = theN + minN
}
cutoffs
min(regmod3$fitted.values)
max(regmod3$fitted.values)
#ADD A GROUPING VARIABLE BASED ON
#THE FITTED CUTOFF VALUES TO regmod3
```

```
regmod3$resid.group = 0
for(i in 1:nrow(data_FG2)){
  for(n in length(cutoffs):1){
    if(regmod3$fitted.values[i] <= cutoffs[n]){
      regmod3$resid.group[i] = round(cutoffs[n], 2)
    }
  }
}
table(regmod3$resid.group)
regmod3$resid.group = ifelse(regmod3$resid.group ==
                               3.28, 3.12, regmod3$resid.group)
table(regmod3$resid.group)
leveneTest(regmod3$residuals, regmod3$resid.group)
####p-values is LESS THAN .05 WHICH IS BAD
VARIANCE = tapply(regmod3$residuals, regmod3$resid.group, var)
max(VARIANCE)/min(VARIANCE)
#####this is under 4 which is good

################################
##Regression - Physical#########
################################
regmod4 <- lm(Physical_final ~ White_Asian + Latino_mixed +
Black_AsianURM + section + gender_bin + fin_hard, data=data_FG1)
summary(regmod4)

####Check assumptions
##VIF
vif(regmod4)

length(regmod4$fitted.values)
plot(regmod4$fitted.values,data_FG1$Physical_final)
reg.line=lm(data_FG1$Physical_final~regmod4$fitted.values)
abline(reg.line$coef)
lines(lowess(data_FG1$Physical_final~regmod4$fitted.values), lwd=2,
col="red")
fit.mod = lm(data_FG1$Physical_final~regmod4$fitted.values)
confband = as.data.frame(predict(fit.mod, interval="confidence"))
confband$fitted.values=regmod4$fitted.values

confband=arrange(confband, fitted.values)
lines(cbind(confband$fitted.values, confband$lwr), col="blue",
      lwd=2,lty="dashed")
lines(cbind(confband$fitted.values, confband$upr), col="blue",
      lwd=2,lty="dashed")

##check residuals
plotResiduals(regmod4)

##normality of residuals
hist(regmod4$residuals)
plot(density(regmod4$residuals))
qqPlot(regmod4$residuals)
##homogeneity of variance
plot(regmod4$fitted.values,regmod4$residuals)
abline(h=0)
```

```
#########Levene's test
cutIncrement = 0.01
minN = 20
theMax = minN
theN = 0
cutValue = min(regmod4$fitted.values)
cutoffs = NULL
while(cutValue < max(regmod4$fitted.values)){
  while(theN < theMax & cutValue < max(regmod4$fitted.values)){
    cutValue = cutValue + cutIncrement
    theN = sum(regmod4$fitted.values <= cutValue)}
  cutoffs = c(cutoffs, cutValue)
  theMax = theN + minN
}
cutoffs
min(regmod4$fitted.values)
max(regmod4$fitted.values)
#ADD A GROUPING VARIABLE BASED ON
#THE FITTED CUTOFF VALUES TO regmod4

regmod4$resid.group = 0
for(i in 1:nrow(data_FG1)){
  for(n in length(cutoffs):1){
    if(regmod4$fitted.values[i] <= cutoffs[n]){
      regmod4$resid.group[i] = round(cutoffs[n], 2)
    }
  }
}
table(regmod4$resid.group)
regmod4$resid.group = ifelse(regmod4$resid.group ==
                               3.33, 3.13, regmod4$resid.group)
table(regmod4$resid.group)

leveneTest(regmod4$residuals, regmod4$resid.group)
####p-values is greater than .05 which is good
VARIANCE = tapply(regmod4$residuals, regmod4$resid.group, var)
max(VARIANCE)/min(VARIANCE)
#####this is under 4 which is good

################################
#########Regression - PP########
################################
regmod5 <- lm(PP_final ~ White_Asian + Latino_mixed + Black_AsianURM +
section + gender_bin + fin_hard, data=data_FG1)
summary(regmod5)

####Check assumptions
##VIF
vif(regmod5)

length(regmod5$fitted.values)
plot(regmod5$fitted.values,data_FG1$PP_final)
reg.line=lm(data_FG1$PP_final~regmod5$fitted.values)
abline(reg.line$coef)
lines(lowess(data_FG1$PP_final~regmod5$fitted.values), lwd=2,
col="red")
```

```
fit.mod = lm(data_FG1$PP_final~regmod5$fitted.values)
confband = as.data.frame(predict(fit.mod, interval="confidence"))
confband$fitted.values=regmod5$fitted.values

confband=arrange(confband, fitted.values)
lines(cbind(confband$fitted.values, confband$lwr), col="blue",
      lwd=2,lty="dashed")
lines(cbind(confband$fitted.values, confband$upr), col="blue",
      lwd=2,lty="dashed")

##check residuals
plotResiduals(regmod5)

##normality of residuals
hist(regmod5$residuals)
plot(density(regmod5$residuals))
qqPlot(regmod5$residuals)
##homogeneity of variance
plot(regmod5$fitted.values,regmod5$residuals)
abline(h=0)
#########Levene's test
cutIncrement = 0.01
minN = 20
theMax = minN
theN = 0
cutValue = min(regmod5$fitted.values)
cutoffs = NULL
while(cutValue < max(regmod5$fitted.values)){
  while(theN < theMax & cutValue < max(regmod5$fitted.values)){
    cutValue = cutValue + cutIncrement
    theN = sum(regmod5$fitted.values <= cutValue)}
  cutoffs = c(cutoffs, cutValue)
  theMax = theN + minN
}
cutoffs
min(regmod5$fitted.values)
max(regmod5$fitted.values)
#ADD A GROUPING VARIABLE BASED ON
#THE FITTED CUTOFF VALUES TO regmod5

regmod5$resid.group = 0
for(i in 1:nrow(data_FG1)){
  for(n in length(cutoffs):1){
    if(regmod5$fitted.values[i] <= cutoffs[n]){
      regmod5$resid.group[i] = round(cutoffs[n], 2)
    }
  }
}
table(regmod5$resid.group)
regmod5$resid.group = ifelse(regmod5$resid.group ==
                               2.99, 2.97, regmod5$resid.group)
table(regmod5$resid.group)

leveneTest(regmod5$residuals, regmod5$resid.group)
####p-values is greater than .05 which is good
VARIANCE = tapply(regmod5$residuals, regmod5$resid.group, var)
```

```
max(VARIANCE)/min(VARIANCE)
#####this is under 4 which is good

################################
######Regression - TASint#######
################################
regmod6 <- lm(TASint_final_transf ~ White_Asian + Latino_mixed +
Black_AsianURM + section + gender_bin + fin_hard, data=data_FG1)
summary(regmod6)
####Check assumptions
##VIF
vif(regmod6)

length(regmod6$fitted.values)
plot(regmod6$fitted.values,data_FG1$TASint_final_transf)
reg.line=lm(data_FG1$TASint_final_transf~regmod6$fitted.values)
abline(reg.line$coef)
lines(lowess(data_FG1$TASint_final_transf~regmod6$fitted.values),
lwd=2, col="red")
fit.mod = lm(data_FG1$TASint_final_transf~regmod6$fitted.values)
confband = as.data.frame(predict(fit.mod, interval="confidence"))
confband$fitted.values=regmod6$fitted.values

confband=arrange(confband, fitted.values)
lines(cbind(confband$fitted.values, confband$lwr), col="blue",
      lwd=2,lty="dashed")
lines(cbind(confband$fitted.values, confband$upr), col="blue",
      lwd=2,lty="dashed")

##check residuals
plotResiduals(regmod6)

##normality of residuals
hist(regmod6$residuals)
plot(density(regmod6$residuals))
qqPlot(regmod6$residuals)
##homogeneity of variance
plot(regmod6$fitted.values,regmod6$residuals)
abline(h=0)
#########Levene's test
cutIncrement = 0.01
minN = 20
theMax = minN
theN = 0
cutValue = min(regmod6$fitted.values)
cutoffs = NULL
while(cutValue < max(regmod6$fitted.values)){
  while(theN < theMax & cutValue < max(regmod6$fitted.values)){
    cutValue = cutValue + cutIncrement
    theN = sum(regmod6$fitted.values <= cutValue)}
  cutoffs = c(cutoffs, cutValue)
  theMax = theN + minN
}
cutoffs
min(regmod6$fitted.values)
max(regmod6$fitted.values)
```

```
#ADD A GROUPING VARIABLE BASED ON
#THE FITTED CUTOFF VALUES TO regmod6

regmod6$resid.group = 0
for(i in 1:nrow(data_FG1)){
  for(n in length(cutoffs):1){
    if(regmod6$fitted.values[i] <= cutoffs[n]){
      regmod6$resid.group[i] = round(cutoffs[n], 2)
    }
  }
}
table(regmod6$resid.group)
regmod6$resid.group = ifelse(regmod6$resid.group ==
                               .71, .61, regmod6$resid.group)
table(regmod6$resid.group)
library(car)
leveneTest(regmod6$residuals, regmod6$resid.group)
####p-values is greater than .05 which is good
VARIANCE = tapply(regmod6$residuals, regmod6$resid.group, var)
max(VARIANCE)/min(VARIANCE)
#####this is under 4 which is good

################################
######Regression - Diverse_back#######
################################
regmod7 <- lm(Diverse_back_final ~ White_Asian + Latino_mixed +
Black_AsianURM + section + gender_bin + fin_hard, data=data_FG1)
summary(regmod7)

####Check assumptions
##VIF
vif(regmod7)

length(regmod7$fitted.values)
plot(regmod7$fitted.values,data_FG1$Diverse_back_final)
reg.line=lm(data_FG1$Diverse_back_final~regmod7$fitted.values)
abline(reg.line$coef)
lines(lowess(data_FG1$Diverse_back_final~regmod7$fitted.values), lwd=2,
col="red")
fit.mod = lm(data_FG1$Diverse_back_final~regmod7$fitted.values)
confband = as.data.frame(predict(fit.mod, interval="confidence"))
confband$fitted.values=regmod7$fitted.values

confband=arrange(confband, fitted.values)
lines(cbind(confband$fitted.values, confband$lwr), col="blue",
      lwd=2,lty="dashed")
lines(cbind(confband$fitted.values, confband$upr), col="blue",
      lwd=2,lty="dashed")

##check residuals
plotResiduals(regmod7)

##normality of residuals
hist(regmod7$residuals)
plot(density(regmod7$residuals))
qqPlot(regmod7$residuals)
```

```
##homogeneity of variance
plot(regmod7$fitted.values,regmod7$residuals)
abline(h=0)
#########Levene's test
cutIncrement = 0.01
minN = 20
theMax = minN
theN = 0
cutValue = min(regmod7$fitted.values)
cutoffs = NULL
while(cutValue < max(regmod7$fitted.values)){
  while(theN < theMax & cutValue < max(regmod7$fitted.values)){
    cutValue = cutValue + cutIncrement
    theN = sum(regmod7$fitted.values <= cutValue)}
  cutoffs = c(cutoffs, cutValue)
  theMax = theN + minN
}
cutoffs
min(regmod7$fitted.values)
max(regmod7$fitted.values)
#ADD A GROUPING VARIABLE BASED ON
#THE FITTED CUTOFF VALUES TO regmod7

regmod7$resid.group = 0
for(i in 1:nrow(data_FG1)){
  for(n in length(cutoffs):1){
    if(regmod7$fitted.values[i] <= cutoffs[n]){
      regmod7$resid.group[i] = round(cutoffs[n], 2)
    }
  }
}
table(regmod7$resid.group)
library(car)
leveneTest(regmod7$residuals, regmod7$resid.group)
####p-values is greater than .05 which is good
VARIANCE = tapply(regmod7$residuals, regmod7$resid.group, var)
max(VARIANCE)/min(VARIANCE)
#####this is under 4 which is good


####Compile regressions into 1 table
library(stargazer)
stargazer(regmod1, regmod2, regmod3, regmod4, regmod5, regmod6,
regmod7,
          type="html", dep.var.labels=c("Prof-stud int","Stud-stud
int","Discrim","Physical",
                                        "Partic","TA-stud int","Diverse
back"), star.cutoffs = c(.05, .01, .001),
          out="regressions_all_vars.htm")
####Redo in right order

stargazer(regmod1,regmod6,regmod2,regmod5,regmod3,regmod7,regmod4,
          type="html", dep.var.labels=c("Prof-stud int","TA-stud int",
                                        "Stud-stud
int","Partic","Discrim",
```

```
                                        "Diverse
back","Physical"),star.cutoffs = c(.05, .01, .001),
          out="regressions_all_vars.htm")
#######################################################
#       5. Interpret SS coefficients                  #
#######################################################

###SSint - fin_hard (transformed variable)
#values for fin_hard are 0, 1, 2, 3 - so find median, not mean
median(data_FG$fin_hard)
##Average transformed value for "average" student:
## a White/nonURM Asian woman with prof 2 with fin_hard value of 1:
(coefs = as.numeric(regmod2$coef))
val1 = c(1, 1, 0, 0, 1, 1, 1)
(fh1 = sum(coefs*val1))
fh1

##Average transformed value for a White/nonURM Asian woman with prof 2
with fin_hard value of 2:
val2 = c(1, 1, 0, 0, 1, 1, 2)
(fh2 = sum(coefs*val2))
fh2

##reverse transform values
fh1.rev = fh1^2
fh1.rev = fh1.rev + 0.99
(fh1.rev = 4.125 - fh1.rev)

fh2.rev = fh2^2
fh2.rev = fh2.rev + 0.99
(fh2.rev = 4.125 - fh2.rev)

fh2.rev - fh1.rev
(fh2.rev - fh1.rev)/sd(data_FG$Isol_SSint_final, na.rm=TRUE)

##all other variables held constant, increasing financial hardship
variable from 1 to 2
##is associated with an increase on SSint score of 0.058729

#######Prof-stud int - Lat/mixed was SS
## Estimate change in Prof-stud int for a person who is
## not White/non-URM_Asian and not Latino/mixed race
## and not Black/Asian_URM, and a person who is
## Latino/mixed race
summary(regmod1)
(coefs = as.numeric(regmod1$coef))
## Not in any of the three race groups
val1 = c(1, 0, 0, 0, 1, 1, 1)
(not.lat.mix = sum(coefs*val1))

## Is in the White_AsianWhite/non-URM_Asian group
val1 = c(1, 0, 1, 0, 1, 1, 1)
(is.lat.mix = sum(coefs*val1))

is.lat.mix - not.lat.mix
(is.lat.mix - not.lat.mix)/sd(data_FG$TSint_final, na.rm=TRUE)
```

```
########Participation (regmod5) - white/non-URM Asian was SS
(coefs = as.numeric(regmod5$coef))
## Not in any of the three race groups
val1 = c(1, 0, 0, 0, 1, 1, 1)
(not.wh.as = sum(coefs*val1))

## Is in the White_AsianWhite/non-URM_Asian group
val1 = c(1, 1, 0, 0, 1, 1, 1)
(is.wh.as = sum(coefs*val1))

is.wh.as - not.wh.as
(is.wh.as - not.wh.as)/sd(data_FG$PP_final, na.rm=TRUE)

######Diverse_back (regmod 7) - Latinx/mixed race was SS
(coefs = as.numeric(regmod7$coef))
## Not in any of the three race groups
val1 = c(1, 0, 0, 0, 1, 1, 1)
(not.lat.mix = sum(coefs*val1))

## Is in the White_AsianWhite/non-URM_Asian group
val1 = c(1, 0, 1, 0, 1, 1, 1)
(is.lat.mix = sum(coefs*val1))

is.lat.mix - not.lat.mix
(is.lat.mix - not.lat.mix)/sd(data_FG$Diverse_back_final, na.rm=TRUE)

######Diverse_back (regmod 7) - PROF2 was SS
(coefs = as.numeric(regmod7$coef))
## Has Prof 1
val1 = c(1, 0, 0, 0, 0, 1, 1)
(prof1 = sum(coefs*val1))

## Has Prof2
val1 = c(1, 0, 0, 0, 1, 1, 1)
(prof2 = sum(coefs*val1))

prof2-prof1
(prof2-prof1)/sd(data_FG$Diverse_back_final, na.rm=TRUE)

#######################################################
#       6. Regressions - take out White_Asian         #
#######################################################

##Suspected collinearity between White_Asian and Black_AsianURM,
gender_bin

########################################
#####Regression - TSint########
########################################

data_FG1 <- subset(data_FG, !is.na(TSint_final) & !is.na(race) &
!is.na(section) & !is.na(gender_bin) & !is.na(fin_hard))

regmod1 <- lm(TSint_final ~ Latino_mixed + Black_AsianURM + section +
gender_bin + fin_hard, data=data_FG1)
```

```
summary(regmod1)

####Check assumptions
##VIF
vif(regmod1)

length(regmod1$fitted.values)
length(data_FG1$TSint_final)
par(mfrow=c(1,1))
plot(regmod1$fitted.values,data_FG1$TSint_final)
reg.line=lm(data_FG1$TSint_final~regmod1$fitted.values)
abline(reg.line$coef)
lines(lowess(data_FG1$TSint_final~regmod1$fitted.values), lwd=2,
col="red")
fit.mod = lm(data_FG1$TSint_final~regmod1$fitted.values)
confband = as.data.frame(predict(fit.mod, interval="confidence"))
confband$fitted.values=regmod1$fitted.values
confband=arrange(confband, fitted.values)
lines(cbind(confband$fitted.values, confband$lwr), col="blue",
      lwd=2,lty="dashed")
lines(cbind(confband$fitted.values, confband$upr), col="blue",
      lwd=2,lty="dashed")

##check residuals
plotResiduals = function(mod){
  library(dplyr)
  if(length(labels(mod)) > 1){
    the.title = NULL
    for(i in 1:(length(labels(mod)) - 1)){
      the.title = paste(the.title,labels(mod)[i], "+")
    }
    the.title = paste(the.title,
                      labels(mod)[length(labels(mod))])
  } else{
    the.title = labels(mod)
  }
  plot(mod$fitted.values,mod$residuals, main = the.title)
  abline(h=0)
  lines(lowess(mod$residuals~mod$fitted.values), lwd=2, col="red")
  #create a 95% confidence band
  resid.mod = lm(mod$residuals~mod$fitted.values)
  confband = as.data.frame(predict(resid.mod,
                                   interval="confidence"))
  confband$fitted.values= mod$fitted.values
  confband=arrange(confband, fitted.values)
  lines(cbind(confband$fitted.values, confband$lwr), col="blue",
        lwd=2,lty="dashed")
  lines(cbind(confband$fitted.values, confband$upr), col="blue",
        lwd=2,lty="dashed")
} #end of plotResiduals()

plotResiduals(regmod1)

##normality of residuals
hist(regmod1$residuals)
plot(density(regmod1$residuals))
```

```
qqPlot(regmod1$residuals)
##homogeneity of variance
plot(regmod1$fitted.values,regmod1$residuals)
abline(h=0)
#########Levene's test
cutIncrement = 0.01
minN = 20
theMax = minN
theN = 0
cutValue = min(regmod1$fitted.values)
cutoffs = NULL
while(cutValue < max(regmod1$fitted.values)){
  while(theN < theMax & cutValue < max(regmod1$fitted.values)){
    cutValue = cutValue + cutIncrement
    theN = sum(regmod1$fitted.values <= cutValue)}
  cutoffs = c(cutoffs, cutValue)
  theMax = theN + minN
}
cutoffs
min(regmod1$fitted.values)
max(regmod1$fitted.values)
#ADD A GROUPING VARIABLE BASED ON
#THE FITTED CUTOFF VALUES TO regmod1

regmod1$resid.group = 0
for(i in 1:nrow(data_FG1)){
  for(n in length(cutoffs):1){
    if(regmod1$fitted.values[i] <= cutoffs[n]){
      regmod1$resid.group[i] = round(cutoffs[n], 2)
    }
  }
}
table(regmod1$resid.group)
regmod1$resid.group = ifelse(regmod1$resid.group ==
                              2.91, 2.62, regmod1$resid.group)
table(regmod1$resid.group)
leveneTest(regmod1$residuals, regmod1$resid.group)
####p-values is greater than .05 which is good
VARIANCE = tapply(regmod1$residuals, regmod1$resid.group, var)
max(VARIANCE)/min(VARIANCE)
#####this is under 4 which is good

################################
#######Regression - SSint#######
################################
regmod2 <- lm(Isol_SSint_final_transf ~ Latino_mixed + Black_AsianURM +
section + gender_bin + fin_hard, data=data_FG1)
summary(regmod2)

####Check assumptions
##VIF
vif(regmod2)

data_FG2 <- subset(data_FG1, !is.na(Isol_SSint_final_transf))
length(regmod2$fitted.values)
plot(regmod2$fitted.values,data_FG2$Isol_SSint_final_transf)
```

```
reg.line=lm(data_FG2$Isol_SSint_final_transf~regmod2$fitted.values)
abline(reg.line$coef)
lines(lowess(data_FG2$Isol_SSint_final_transf~regmod2$fitted.values),
lwd=2, col="red")
fit.mod = lm(data_FG2$Isol_SSint_final_transf~regmod2$fitted.values)
confband = as.data.frame(predict(fit.mod, interval="confidence"))
confband$fitted.values=regmod2$fitted.values
library(dplyr)
confband=arrange(confband, fitted.values)
lines(cbind(confband$fitted.values, confband$lwr), col="blue",
      lwd=2,lty="dashed")
lines(cbind(confband$fitted.values, confband$upr), col="blue",
      lwd=2,lty="dashed")

##check residuals
plotResiduals(regmod2)

##normality of residuals
hist(regmod2$residuals)
plot(density(regmod2$residuals))
qqPlot(regmod2$residuals)
##homogeneity of variance
plot(regmod2$fitted.values,regmod2$residuals)
abline(h=0)
#########Levene's test
cutIncrement = 0.01
minN = 20
theMax = minN
theN = 0
cutValue = min(regmod2$fitted.values)
cutoffs = NULL
while(cutValue < max(regmod2$fitted.values)){
  while(theN < theMax & cutValue < max(regmod2$fitted.values)){
    cutValue = cutValue + cutIncrement
    theN = sum(regmod2$fitted.values <= cutValue)}
  cutoffs = c(cutoffs, cutValue)
  theMax = theN + minN
}
cutoffs
min(regmod2$fitted.values)
max(regmod2$fitted.values)
#ADD A GROUPING VARIABLE BASED ON
#THE FITTED CUTOFF VALUES TO regmod2

regmod2$resid.group = 0
for(i in 1:nrow(data_FG2)){
  for(n in length(cutoffs):1){
    if(regmod2$fitted.values[i] <= cutoffs[n]){
      regmod2$resid.group[i] = round(cutoffs[n], 2)
    }
  }
}
table(regmod2$resid.group)
regmod2$resid.group = ifelse(regmod2$resid.group ==
                               .77, .55, regmod2$resid.group)
table(regmod2$resid.group)
```

```
library(car)
leveneTest(regmod2$residuals, regmod2$resid.group)
####p-values is greater than .05 which is good
VARIANCE = tapply(regmod2$residuals, regmod2$resid.group, var)
max(VARIANCE)/min(VARIANCE)
#####this is under 4 which is good

################################
#####Regression - Descrim#######
################################

regmod3 <- lm(Descrim_final ~ Latino_mixed + Black_AsianURM + section +
gender_bin + fin_hard, data=data_FG1)
summary(regmod3)

####Check assumptions
##VIF
vif(regmod3)

length(regmod3$fitted.values)
data_FG2 <- subset(data_FG1, !is.na(Descrim_final))
plot(regmod3$fitted.values,data_FG2$Descrim_final)
reg.line=lm(data_FG2$Descrim_final~regmod3$fitted.values)
abline(reg.line$coef)
lines(lowess(data_FG2$Descrim_final~regmod3$fitted.values), lwd=2,
col="red")
fit.mod = lm(data_FG2$Descrim_final~regmod3$fitted.values)
confband = as.data.frame(predict(fit.mod, interval="confidence"))
confband$fitted.values=regmod3$fitted.values
confband=arrange(confband, fitted.values)
lines(cbind(confband$fitted.values, confband$lwr), col="blue",
      lwd=2,lty="dashed")
lines(cbind(confband$fitted.values, confband$upr), col="blue",
      lwd=2,lty="dashed")

##check residuals
plotResiduals(regmod3)

##normality of residuals
hist(regmod3$residuals)
plot(density(regmod3$residuals))
qqPlot(regmod3$residuals)
##homogeneity of variance
plot(regmod3$fitted.values,regmod3$residuals)
abline(h=0)
#########Levene's test
cutIncrement = 0.01
minN = 20
theMax = minN
theN = 0
cutValue = min(regmod3$fitted.values)
cutoffs = NULL
while(cutValue < max(regmod3$fitted.values)){
  while(theN < theMax & cutValue < max(regmod3$fitted.values)){
    cutValue = cutValue + cutIncrement
    theN = sum(regmod3$fitted.values <= cutValue)}
```

```
  cutoffs = c(cutoffs, cutValue)
  theMax = theN + minN
}
cutoffs
min(regmod3$fitted.values)
max(regmod3$fitted.values)
#ADD A GROUPING VARIABLE BASED ON
#THE FITTED CUTOFF VALUES TO regmod3

regmod3$resid.group = 0
for(i in 1:nrow(data_FG2)){
  for(n in length(cutoffs):1){
    if(regmod3$fitted.values[i] <= cutoffs[n]){
      regmod3$resid.group[i] = round(cutoffs[n], 2)
    }
  }
}
table(regmod3$resid.group)
regmod3$resid.group = ifelse(regmod3$resid.group ==
                               3.28, 3.12, regmod3$resid.group)
table(regmod3$resid.group)
leveneTest(regmod3$residuals, regmod3$resid.group)
####p-values is LESS THAN .05 WHICH IS BAD
VARIANCE = tapply(regmod3$residuals, regmod3$resid.group, var)
max(VARIANCE)/min(VARIANCE)
#####this is under 4 which is good

################################
##Regression - Physical#########
################################
regmod4 <- lm(Physical_final ~ Latino_mixed + Black_AsianURM + section
+ gender_bin + fin_hard, data=data_FG1)
summary(regmod4)

####Check assumptions
##VIF
vif(regmod4)

length(regmod4$fitted.values)
plot(regmod4$fitted.values,data_FG1$Physical_final)
reg.line=lm(data_FG1$Physical_final~regmod4$fitted.values)
abline(reg.line$coef)
lines(lowess(data_FG1$Physical_final~regmod4$fitted.values), lwd=2,
col="red")
fit.mod = lm(data_FG1$Physical_final~regmod4$fitted.values)
confband = as.data.frame(predict(fit.mod, interval="confidence"))
confband$fitted.values=regmod4$fitted.values

confband=arrange(confband, fitted.values)
lines(cbind(confband$fitted.values, confband$lwr), col="blue",
      lwd=2,lty="dashed")
lines(cbind(confband$fitted.values, confband$upr), col="blue",
      lwd=2,lty="dashed")

##check residuals
plotResiduals(regmod4)
```

```
##normality of residuals
hist(regmod4$residuals)
plot(density(regmod4$residuals))
qqPlot(regmod4$residuals)
##homogeneity of variance
plot(regmod4$fitted.values,regmod4$residuals)
abline(h=0)
#########Levene's test
cutIncrement = 0.01
minN = 20
theMax = minN
theN = 0
cutValue = min(regmod4$fitted.values)
cutoffs = NULL
while(cutValue < max(regmod4$fitted.values)){
  while(theN < theMax & cutValue < max(regmod4$fitted.values)){
    cutValue = cutValue + cutIncrement
    theN = sum(regmod4$fitted.values <= cutValue)}
  cutoffs = c(cutoffs, cutValue)
  theMax = theN + minN
}
cutoffs
min(regmod4$fitted.values)
max(regmod4$fitted.values)
#ADD A GROUPING VARIABLE BASED ON
#THE FITTED CUTOFF VALUES TO regmod4

regmod4$resid.group = 0
for(i in 1:nrow(data_FG1)){
  for(n in length(cutoffs):1){
    if(regmod4$fitted.values[i] <= cutoffs[n]){
      regmod4$resid.group[i] = round(cutoffs[n], 2)
    }
  }
}
table(regmod4$resid.group)
regmod4$resid.group = ifelse(regmod4$resid.group ==
                              3.33, 3.13, regmod4$resid.group)
table(regmod4$resid.group)

leveneTest(regmod4$residuals, regmod4$resid.group)
####p-values is greater than .05 which is good
VARIANCE = tapply(regmod4$residuals, regmod4$resid.group, var)
max(VARIANCE)/min(VARIANCE)
#####this is under 4 which is good

################################
#########Regression - PP########
################################
regmod5 <- lm(PP_final ~ Latino_mixed + Black_AsianURM + section +
gender_bin + fin_hard, data=data_FG1)
summary(regmod5)

####Check assumptions
##VIF
```

```
vif(regmod5)

length(regmod5$fitted.values)
plot(regmod5$fitted.values,data_FG1$PP_final)
reg.line=lm(data_FG1$PP_final~regmod5$fitted.values)
abline(reg.line$coef)
lines(lowess(data_FG1$PP_final~regmod5$fitted.values), lwd=2,
col="red")
fit.mod = lm(data_FG1$PP_final~regmod5$fitted.values)
confband = as.data.frame(predict(fit.mod, interval="confidence"))
confband$fitted.values=regmod5$fitted.values

confband=arrange(confband, fitted.values)
lines(cbind(confband$fitted.values, confband$lwr), col="blue",
      lwd=2,lty="dashed")
lines(cbind(confband$fitted.values, confband$upr), col="blue",
      lwd=2,lty="dashed")

##check residuals
plotResiduals(regmod5)

##normality of residuals
hist(regmod5$residuals)
plot(density(regmod5$residuals))
qqPlot(regmod5$residuals)
##homogeneity of variance
plot(regmod5$fitted.values,regmod5$residuals)
abline(h=0)
#########Levene's test
cutIncrement = 0.01
minN = 20
theMax = minN
theN = 0
cutValue = min(regmod5$fitted.values)
cutoffs = NULL
while(cutValue < max(regmod5$fitted.values)){
  while(theN < theMax & cutValue < max(regmod5$fitted.values)){
    cutValue = cutValue + cutIncrement
    theN = sum(regmod5$fitted.values <= cutValue)}
  cutoffs = c(cutoffs, cutValue)
  theMax = theN + minN
}
cutoffs
min(regmod5$fitted.values)
max(regmod5$fitted.values)
#ADD A GROUPING VARIABLE BASED ON
#THE FITTED CUTOFF VALUES TO regmod5

regmod5$resid.group = 0
for(i in 1:nrow(data_FG1)){
  for(n in length(cutoffs):1){
    if(regmod5$fitted.values[i] <= cutoffs[n]){
      regmod5$resid.group[i] = round(cutoffs[n], 2)
    }
  }
}
```

```
table(regmod5$resid.group)
regmod5$resid.group = ifelse(regmod5$resid.group ==
                               2.99, 2.97, regmod5$resid.group)
table(regmod5$resid.group)

leveneTest(regmod5$residuals, regmod5$resid.group)
####p-values is greater than .05 which is good
VARIANCE = tapply(regmod5$residuals, regmod5$resid.group, var)
max(VARIANCE)/min(VARIANCE)
#####this is under 4 which is good

################################
######Regression - TASint#######
################################
regmod6 <- lm(TASint_final_transf ~ Latino_mixed + Black_AsianURM +
section + gender_bin + fin_hard, data=data_FG1)
summary(regmod6)
####Check assumptions
##VIF
vif(regmod6)

length(regmod6$fitted.values)
plot(regmod6$fitted.values,data_FG1$TASint_final_transf)
reg.line=lm(data_FG1$TASint_final_transf~regmod6$fitted.values)
abline(reg.line$coef)
lines(lowess(data_FG1$TASint_final_transf~regmod6$fitted.values),
lwd=2, col="red")
fit.mod = lm(data_FG1$TASint_final_transf~regmod6$fitted.values)
confband = as.data.frame(predict(fit.mod, interval="confidence"))
confband$fitted.values=regmod6$fitted.values

confband=arrange(confband, fitted.values)
lines(cbind(confband$fitted.values, confband$lwr), col="blue",
      lwd=2,lty="dashed")
lines(cbind(confband$fitted.values, confband$upr), col="blue",
      lwd=2,lty="dashed")

##check residuals
plotResiduals(regmod6)

##normality of residuals
hist(regmod6$residuals)
plot(density(regmod6$residuals))
qqPlot(regmod6$residuals)
##homogeneity of variance
plot(regmod6$fitted.values,regmod6$residuals)
abline(h=0)
#########Levene's test
cutIncrement = 0.01
minN = 20
theMax = minN
theN = 0
cutValue = min(regmod6$fitted.values)
cutoffs = NULL
while(cutValue < max(regmod6$fitted.values)){
  while(theN < theMax & cutValue < max(regmod6$fitted.values)){
```

```
    cutValue = cutValue + cutIncrement
    theN = sum(regmod6$fitted.values <= cutValue)}
  cutoffs = c(cutoffs, cutValue)
  theMax = theN + minN
}
cutoffs
min(regmod6$fitted.values)
max(regmod6$fitted.values)
#ADD A GROUPING VARIABLE BASED ON
#THE FITTED CUTOFF VALUES TO regmod6

regmod6$resid.group = 0
for(i in 1:nrow(data_FG1)){
  for(n in length(cutoffs):1){
    if(regmod6$fitted.values[i] <= cutoffs[n]){
      regmod6$resid.group[i] = round(cutoffs[n], 2)
    }
  }
}
table(regmod6$resid.group)
regmod6$resid.group = ifelse(regmod6$resid.group ==
                               .71, .61, regmod6$resid.group)
table(regmod6$resid.group)
library(car)
leveneTest(regmod6$residuals, regmod6$resid.group)
####p-values is greater than .05 which is good
VARIANCE = tapply(regmod6$residuals, regmod6$resid.group, var)
max(VARIANCE)/min(VARIANCE)
#####this is under 4 which is good

################################
######Regression - Diverse_back#######
################################
regmod7 <- lm(Diverse_back_final ~ Latino_mixed + Black_AsianURM +
section + gender_bin + fin_hard, data=data_FG1)
summary(regmod7)

####Check assumptions
##VIF
vif(regmod7)

length(regmod7$fitted.values)
plot(regmod7$fitted.values,data_FG1$Diverse_back_final)
reg.line=lm(data_FG1$Diverse_back_final~regmod7$fitted.values)
abline(reg.line$coef)
lines(lowess(data_FG1$Diverse_back_final~regmod7$fitted.values), lwd=2,
col="red")
fit.mod = lm(data_FG1$Diverse_back_final~regmod7$fitted.values)
confband = as.data.frame(predict(fit.mod, interval="confidence"))
confband$fitted.values=regmod7$fitted.values

confband=arrange(confband, fitted.values)
lines(cbind(confband$fitted.values, confband$lwr), col="blue",
      lwd=2,lty="dashed")
lines(cbind(confband$fitted.values, confband$upr), col="blue",
      lwd=2,lty="dashed")
```

```
##check residuals
plotResiduals(regmod7)

##normality of residuals
hist(regmod7$residuals)
plot(density(regmod7$residuals))
qqPlot(regmod7$residuals)
##homogeneity of variance
plot(regmod7$fitted.values,regmod7$residuals)
abline(h=0)
#########Levene's test
cutIncrement = 0.01
minN = 20
theMax = minN
theN = 0
cutValue = min(regmod7$fitted.values)
cutoffs = NULL
while(cutValue < max(regmod7$fitted.values)){
  while(theN < theMax & cutValue < max(regmod7$fitted.values)){
    cutValue = cutValue + cutIncrement
    theN = sum(regmod7$fitted.values <= cutValue)}
  cutoffs = c(cutoffs, cutValue)
  theMax = theN + minN
}
cutoffs
min(regmod7$fitted.values)
max(regmod7$fitted.values)
#ADD A GROUPING VARIABLE BASED ON
#THE FITTED CUTOFF VALUES TO regmod7

regmod7$resid.group = 0
for(i in 1:nrow(data_FG1)){
  for(n in length(cutoffs):1){
    if(regmod7$fitted.values[i] <= cutoffs[n]){
      regmod7$resid.group[i] = round(cutoffs[n], 2)
    }
  }
}
table(regmod7$resid.group)
library(car)
leveneTest(regmod7$residuals, regmod7$resid.group)
####p-values is greater than .05 which is good
VARIANCE = tapply(regmod7$residuals, regmod7$resid.group, var)
max(VARIANCE)/min(VARIANCE)
#####this is under 4 which is good


####Compile regressions into 1 table
library(stargazer)
stargazer(regmod1, regmod2, regmod3, regmod4, regmod5, regmod6,
regmod7,
          type="html", dep.var.labels=c("Prof-stud int","Stud-stud
int","Discrim","Physical",
                                        "Partic","TA-stud int","Diverse
back"), star.cutoffs = c(.05, .01, .001),
```

```
        out="regressions_all_vars.htm")

################################RQ2B####################################

############# 2. Satisfaction questions         #################
##################################################################
ped_sat <- select(data_FG, Q10_1:Q10_11)
levels <- c("I haven't used this","Very ineffective","Somewhat
ineffective","Somewhat effective","Very effective")
ped_sat[] <- lapply(ped_sat, factor, levels=levels)
lapply(ped_sat, table)
ped_sat

data_long <- gather(ped_sat,question,answer,Q10_1:Q10_11)
head(data_long)
data_long$answer <- factor(data_long$answer,levels=levels)
levels1 <-
c("Q10_1","Q10_2","Q10_3","Q10_4","Q10_5","Q10_6","Q10_7","Q10_8","Q10_
9","Q10_10","Q10_11")
data_long$question <- factor(data_long$question,levels=levels1)
tbl <-
round(prop.table(table(data_long$question,data_long$answer),1)*100,0)
write.csv(apply(tbl,2,function(u) sprintf( "%.0f%%", u )),quote=FALSE)

###number of responses
apply(select(data_FG, Q10_1:Q10_11), 2, function(c)sum(!is.na(c)))

#convert to binary variables, append to data_FG
ped_sat_bin <- apply(ped_sat, 2, function(x) {ifelse(x == "Very
effective" | x == "Somewhat effective", 1,
                                                     ifelse(x ==
"Somewhat ineffective" |
                                                              x ==
"Very ineffective", 0, NA))})
ped_sat_bin <- as.data.frame(ped_sat_bin)
colnames(ped_sat_bin) <- paste(colnames(ped_sat_bin), "bin",sep = "_")
data_FG <- cbind(data_FG, ped_sat_bin)
head(data_FG)


#make ordinal variables too, append to data_FG
ped_sat_ord <- apply(ped_sat, 2, function(x) {ifelse(x == "Very
effective", 4,
                                                     ifelse(x ==
"Somewhat effective", 3,
                                                            ifelse(x ==
"Somewhat ineffective", 2,

ifelse(x == "Very ineffective", 1, NA))))})
ped_sat_ord <- as.data.frame(ped_sat_ord)
colnames(ped_sat_ord) <- paste(colnames(ped_sat_ord), "ord",sep = "_")
data_FG <- cbind(data_FG, ped_sat_ord)
head(data_FG)

##################################################################
###### 3. correlations between sat and climate scales ############
```

```
####################################################################
library(Hmisc)
data_cors <- select(data_FG, Descrim_final:TSint_final,
Q10_1_ord:Q10_11_ord)
rcorr(as.matrix(data_cors))

##Also look at corrs between just ped satisfaction variables
data_cors1 <- select(data_FG, Q10_1_ord:Q10_11_ord)
rcorr(as.matrix(data_cors1))

#################################RQ3####################################

####################################################################
#############  3. Frequencies for all FG students   ##############
####################################################################
#Q12: Did you take this course with the intention of taking additional
math courses?
table(data$Q12)
prop.table(table(data$Q12))
table(data_FG$Q12)
prop.table(table(data_FG$Q12))
#Major at beg. of course: STEM or non-STEM
table(data$Q13_coded)
prop.table(table(data$Q13_coded))
table(data_FG$Q13_coded)
prop.table(table(data_FG$Q13_coded))
#Q14: At the beginning of the semester, how certain or uncertain were
you that you would complete the major(s) you listed above?
table(data$Q14)
prop.table(table(data$Q14))
table(data_FG$Q14)
prop.table(table(data_FG$Q14))
#Q15: At this point, has your intended major(s) changed from the one(s)
you listed above?
table(data$Q15)
prop.table(table(data$Q15))
table(data_FG$Q15)
prop.table(table(data_FG$Q15))
#Q17: For the major(s) you are most likely to complete at this time,
are additional math courses (e.g., trigonometry, calculus) required?
table(data$Q17)
prop.table(table(data$Q17))
table(data_FG$Q17)
prop.table(table(data_FG$Q17))
#Q18: Is this course a prerequisite for those additional math courses?
table(data$Q18)
prop.table(table(data$Q18))
table(data_FG$Q18)
prop.table(table(data_FG$Q18))
#STEM status throughout semester
table(data$EndofCourse_Discipline)
prop.table(table(data$EndofCourse_Discipline))
table(data_FG$EndofCourse_Discipline)
prop.table(table(data_FG$EndofCourse_Discipline))
#Q21: How important or unimportant is getting good math grades in
college for your future?
```

```
table(data$Q21)
prop.table(table(data$Q21))
table(data_FG$Q21)
prop.table(table(data_FG$Q21))
#Q19: To what extent, if any, has your experience in this course
influenced your
#intention to major in a science, technology, engineering, and
mathematics (STEM) field?
table(data$Q19)
table(data_FG$Q19)
prop.table(table(data_FG$Q19))
#Q20: To what extent, if any, has your experience in this course
influenced your
#intention to take additional math courses?
table(data$Q20)
table(data_FG$Q20)
prop.table(table(data_FG$Q20))

#################################################################
#  4. Frequencies for FG students broken down by addtl categories#
#################################################################
data_FG_leave <- subset(data_FG, EndofCourse_Discipline == "Left STEM"
| EndofCourse_Discipline == "Was STEM, now considering switching to
non-STEM major")
dim(data_FG_leave)
data_FG_stay <- subset(data_FG, EndofCourse_Discipline == "STEM" |
EndofCourse_Discipline == "Undecided, considering med school")
dim(data_FG_stay)
#Q19: To what extent, if any, has your experience in this course
influenced your
#intention to major in a science, technology, engineering, and
mathematics (STEM) field?
table(data_FG_leave$Q19)
prop.table(table(data_FG_leave$Q19))
table(data_FG_stay$Q19)
prop.table(table(data_FG_stay$Q19))
#Q20: To what extent, if any, has your experience in this course
influenced your
#intention to take additional math courses?
table(data_FG_leave$Q20)
prop.table(table(data_FG_leave$Q20))
table(data_FG_stay$Q20)
prop.table(table(data_FG_stay$Q20))
#Q21: How important or unimportant is getting good math grades in
college for your future?
table(data_FG_leave$Q21)
prop.table(table(data_FG_leave$Q21))
table(data_FG_stay$Q21)
prop.table(table(data_FG_stay$Q21))

#################################################################
# 5. compare leavers and stayers on climate scales           ####
#################################################################

##Create data set with just leavers and stayers
```

```
data_FG$stayleave <- ifelse(data_FG$EndofCourse_Discipline == "Left
STEM" | data_FG$EndofCourse_Discipline == "Was STEM, now considering
switching to non-STEM major",

"leave",ifelse(data_FG$EndofCourse_Discipline == "STEM" |
data_FG$EndofCourse_Discipline == "Undecided, considering med school",
                                           "stay","NA"))
data_FG$stayleave
data_FG_stayleave <- subset(data_FG, stayleave == "leave" | stayleave
== "stay")
dim(data_FG_stayleave)

#########T-TESTS
##Used bartlett.test to determine whether to use var.equal=TRUE per
these instructions:
#https://rcompanion.org/rcompanion/d_02.html

bartlett.test(Descrim_final ~ stayleave, data=data_FG_stayleave)
#p > .05 so use var.equal=TRUE
t.test(Descrim_final ~ stayleave, data=data_FG_stayleave,
var.equal=TRUE,
       conf.level=0.95)

bartlett.test(PP_final ~ stayleave, data=data_FG_stayleave)
#p > .05 so use var.equal=TRUE
t.test(PP_final ~ stayleave, data=data_FG_stayleave, var.equal=TRUE,
       conf.level=0.95)

bartlett.test(Physical_final ~ stayleave, data=data_FG_stayleave)
#p > .05 so use var.equal=TRUE
t.test(Physical_final ~ stayleave, data=data_FG_stayleave,
var.equal=TRUE,
       conf.level=0.95)

bartlett.test(TSint_final ~ stayleave, data=data_FG_stayleave)
#p < .05 so use var.equal=FALSE
t.test(TSint_final ~ stayleave, data=data_FG_stayleave,
var.equal=FALSE,
       conf.level=0.95)

bartlett.test(Diverse_back_final ~ stayleave, data=data_FG_stayleave)
#p > .05 so use var.equal=TRUE
t.test(Diverse_back_final ~ stayleave, data=data_FG_stayleave,
var.equal=TRUE,
       conf.level=0.95)

bartlett.test(Isol_SSint_final_transf ~ stayleave,
data=data_FG_stayleave)
#p > .05 so use var.equal=TRUE
t.test(Isol_SSint_final_transf ~ stayleave, data=data_FG_stayleave,
var.equal=TRUE,
       conf.level=0.95)

bartlett.test(TASint_final_transf ~ stayleave, data=data_FG_stayleave)
#p > .05 so use var.equal=TRUE
```

```
t.test(TASint_final_transf ~ stayleave, data=data_FG_stayleave,
var.equal=TRUE,
       conf.level=0.95)

#################################################################
# 6. compare leavers and stayers on demographics             ####
#################################################################
table(data_FG_leave$section)
prop.table(table(data_FG_leave$section))

table(data_FG_stay$section)
prop.table(table(data_FG_stay$section))

table(data_FG_leave$gender)
prop.table(table(data_FG_leave$gender))

table(data_FG_stay$gender)
prop.table(table(data_FG_stay$gender))

table(data_FG_leave$race)
prop.table(table(data_FG_leave$race))

table(data_FG_stay$race)
prop.table(table(data_FG_stay$race))

table(data_FG_leave$URM)
prop.table(table(data_FG_leave$URM))

table(data_FG_stay$URM)
prop.table(table(data_FG_stay$URM))

table(data_FG_leave$Pell)
prop.table(table(data_FG_leave$Pell))

table(data_FG_stay$Pell)
prop.table(table(data_FG_stay$Pell))

table(data_FG_leave$Promise)
prop.table(table(data_FG_leave$Promise))

table(data_FG_stay$Promise)
prop.table(table(data_FG_stay$Promise))

table(data_FG_leave$Loans)
prop.table(table(data_FG_leave$Loans))

table(data_FG_stay$Loans)
prop.table(table(data_FG_stay$Loans))

##################################################################
#7. do table with original climate scales comparing stay and leave#
##################################################################

rm(list=ls())
setwd("/Users/Kate/Dropbox/School/Dissertation/ACTUAL
STUDY!!!/Survey/survey data")
```

```
data <- read.csv("data_final.csv", na.strings="")
library(psych)
library(car)
library(dplyr)

##select all classroom climate items
data1 <- select(data, Q3_1:Q8_8)
###Get the variables from character to numeric, then recode reverse-
coded items, then convert
#from numberic to ordinal for correct analysis in lavaan
#convert to numeric
levels <- c("Strongly disagree","Somewhat disagree","Somewhat
agree","Strongly agree")
data1[] <-  lapply(data1, factor, levels=levels)
data1[] <- lapply(data1, as.numeric)
#recode reverse-coded variables
data1$Q5_8 <- ifelse(data1$Q5_8 == 4,1,ifelse(data1$Q5_8 ==
3,2,ifelse(data1$Q5_8 == 2,3,ifelse(data1$Q5_8 == 1,4,NA))))
data1$Q3_4 <- ifelse(data1$Q3_4 == 4,1,ifelse(data1$Q3_4 ==
3,2,ifelse(data1$Q3_4 == 2,3,ifelse(data1$Q3_4 == 1,4,NA))))
data1$Q4_20 <- ifelse(data1$Q4_20 == 4,1,ifelse(data1$Q4_20 ==
3,2,ifelse(data1$Q4_20 == 2,3,ifelse(data1$Q4_20 == 1,4,NA))))
data1$Q3_5 <- ifelse(data1$Q3_5 == 4,1,ifelse(data1$Q3_5 ==
3,2,ifelse(data1$Q3_5 == 2,3,ifelse(data1$Q3_5 == 1,4,NA))))
data1$Q5_1 <- ifelse(data1$Q5_1 == 4,1,ifelse(data1$Q5_1 ==
3,2,ifelse(data1$Q5_1 == 2,3,ifelse(data1$Q5_1 == 1,4,NA))))
data1$Q3_8 <- ifelse(data1$Q3_8 == 4,1,ifelse(data1$Q3_8 ==
3,2,ifelse(data1$Q3_8 == 2,3,ifelse(data1$Q3_8 == 1,4,NA))))
data1$Q3_13 <- ifelse(data1$Q3_13 == 4,1,ifelse(data1$Q3_13 ==
3,2,ifelse(data1$Q3_13 == 2,3,ifelse(data1$Q3_13 == 1,4,NA))))
data1$Q4_3 <- ifelse(data1$Q4_3 == 4,1,ifelse(data1$Q4_3 ==
3,2,ifelse(data1$Q4_3 == 2,3,ifelse(data1$Q4_3 == 1,4,NA))))
data1$Q4_15 <- ifelse(data1$Q4_15 == 4,1,ifelse(data1$Q4_15 ==
3,2,ifelse(data1$Q4_15 == 2,3,ifelse(data1$Q4_15 == 1,4,NA))))
data1$Q5_19 <- ifelse(data1$Q5_19 == 4,1,ifelse(data1$Q5_19 ==
3,2,ifelse(data1$Q5_19 == 2,3,ifelse(data1$Q5_19 == 1,4,NA))))
data1$Q4_21 <- ifelse(data1$Q4_21 == 4,1,ifelse(data1$Q4_21 ==
3,2,ifelse(data1$Q4_21 == 2,3,ifelse(data1$Q4_21 == 1,4,NA))))
data1$Q4_16 <- ifelse(data1$Q4_16 == 4,1,ifelse(data1$Q4_16 ==
3,2,ifelse(data1$Q4_16 == 2,3,ifelse(data1$Q4_16 == 1,4,NA))))
data1$Q4_6 <- ifelse(data1$Q4_6 == 4,1,ifelse(data1$Q4_6 ==
3,2,ifelse(data1$Q4_6 == 2,3,ifelse(data1$Q4_6 == 1,4,NA))))
data1$Q5_13 <- ifelse(data1$Q5_13 == 4,1,ifelse(data1$Q5_13 ==
3,2,ifelse(data1$Q5_13 == 2,3,ifelse(data1$Q5_13 == 1,4,NA))))
data1$Q3_12 <- ifelse(data1$Q3_12 == 4,1,ifelse(data1$Q3_12 ==
3,2,ifelse(data1$Q3_12 == 2,3,ifelse(data1$Q3_12 == 1,4,NA))))

####Descrim
Descrim <- select(data1,Q3_5,Q5_1,Q3_8,Q3_13,Q4_3,Q4_15,Q5_19,Q4_21)
Descrim <- select(Descrim, Q5_1, Q3_8, Q3_13, Q4_21, Q4_15)
data$Descrim_final <- rowMeans(Descrim)


#####PP
PP <- select(data1, Q3_3,Q4_12,Q5_8,Q3_4,Q4_20,Q5_12)
PP <- select(PP, Q3_3, Q4_12, Q5_8)
```

```
data$PP_final <- rowMeans(PP)

#####Physical
Physical <- select(data1, Q3_12,Q4_9,Q4_18,Q4_7,Q5_17,Q5_20)
Physical <- select(Physical, Q4_18,Q5_17,Q5_20)
data$Physical_final <- rowMeans(Physical)

########TASint
TASint <- select(data1, Q8_1,Q8_2,Q8_3,Q8_4,Q8_5,Q8_6,Q8_7,Q8_8)
TASint <- select(TASint, Q8_1,Q8_2,Q8_4,Q8_5,Q8_6,Q8_7,Q8_8)
data$TASint_final <- rowMeans(TASint)

######ISOL_SSint
Isol_SSint <- select(data1, Q3_9, Q3_14, Q4_4, Q4_11, Q4_14, Q4_19,
Q5_2, Q5_4, Q5_5, Q5_11, Q5_14, Q5_15, Q5_18)
Isol_SSint <- select(Isol_SSint, Q4_4, Q4_14, Q5_2, Q5_5, Q5_11, Q5_14,
                     Q5_15, Q5_18)
data$Isol_SSint_final <- rowMeans(Isol_SSint)

###Diverse_back
Diverse_back <- select(data1,
Q3_10,Q4_8,Q4_17,Q3_7,Q3_11,Q4_5,Q5_3,Q5_6,Q5_10)
Diverse_back <- select(Diverse_back, Q3_10, Q4_5, Q4_8, Q5_10)
data$Diverse_back_final <- rowMeans(Diverse_back)

###TSint
TSint <- select(data1, Q7_1,Q7_2,Q7_3,Q7_4,Q7_5,Q7_6,Q7_7,Q7_8)
TSint <- select(TSint, Q7_1,Q7_2,Q7_4,Q7_5,Q7_8)
data$TSint_final <- rowMeans(TSint)

data$FG <- ifelse(data$Q33 == "No",1,ifelse(data$Q33 == "Yes",0,NA))
data$FG <- as.factor(data$FG)
table(data$FG)
data_FG <- subset(data, FG == 1)
data_FG_leave <- subset(data_FG, EndofCourse_Discipline == "Left STEM"
| EndofCourse_Discipline == "Was STEM, now considering switching to
non-STEM major")
dim(data_FG_leave)
data_FG_stay <- subset(data_FG, EndofCourse_Discipline == "STEM" |
EndofCourse_Discipline == "Undecided, considering med school")
dim(data_FG_stay)

mean(data_FG_leave$Descrim_final)
mean(data_FG_leave$PP_final)
mean(data_FG_leave$Physical_final)
mean(data_FG_leave$TASint_final, na.rm=TRUE)
mean(data_FG_leave$Isol_SSint_final)
mean(data_FG_leave$Diverse_back_final)
mean(data_FG_leave$TSint_final, na.rm=TRUE)

sd(data_FG_leave$Descrim_final)
sd(data_FG_leave$PP_final)
sd(data_FG_leave$Physical_final)
sd(data_FG_leave$TASint_final, na.rm=TRUE)
sd(data_FG_leave$Isol_SSint_final)
sd(data_FG_leave$Diverse_back_final)
```

```
sd(data_FG_leave$TSint_final, na.rm=TRUE)

mean(data_FG_stay$Descrim_final, na.rm=TRUE)
mean(data_FG_stay$PP_final)
mean(data_FG_stay$Physical_final)
mean(data_FG_stay$TASint_final, na.rm=TRUE)
mean(data_FG_stay$Isol_SSint_final, na.rm=TRUE)
mean(data_FG_stay$Diverse_back_final)
mean(data_FG_stay$TSint_final, na.rm=TRUE)

sd(data_FG_stay$Descrim_final, na.rm=TRUE)
sd(data_FG_stay$PP_final)
sd(data_FG_stay$Physical_final)
sd(data_FG_stay$TASint_final, na.rm=TRUE)
sd(data_FG_stay$Isol_SSint_final, na.rm=TRUE)
sd(data_FG_stay$Diverse_back_final)
sd(data_FG_stay$TSint_final, na.rm=TRUE)

###cohen's d effect sizes
library(lsr)
cohensD(data_FG_stay$Descrim_final,data_FG_leave$Descrim_final)
cohensD(data_FG_stay$PP_final,data_FG_leave$PP_final)
cohensD(data_FG_stay$Physical_final,data_FG_leave$Physical_final)
cohensD(data_FG_stay$TASint_final,data_FG_leave$TASint_final)
cohensD(data_FG_stay$Isol_SSint_final,data_FG_leave$Isol_SSint_final)
cohensD(data_FG_stay$Diverse_back_final,data_FG_leave$Diverse_back_fina
l)
cohensD(data_FG_stay$TSint_final,data_FG_leave$TSint_final)

###################################################################
#8. do table with original climate scales comparing prof1 & prof2 #
###################################################################
data_FG$section <- ifelse(data_FG$Q42 == "Section 10 (meets MTW 8:00-
8:50AM)","Prof_1",
                       ifelse(data_FG$Q42 == "Section 20 (meets MTW
12:20-1:10PM)" |
                                data_FG$Q42 == "Section 30 (meets MTW
3:35-4:25PM)", "Prof_2", NA))

table(data_FG$section)

data_FG_prof1 <- subset(data_FG, section == "Prof_1")
dim(data_FG_prof1)
data_FG_prof2 <- subset(data_FG, section == "Prof_2")
dim(data_FG_prof2)

mean(data_FG_prof1$Descrim_final)
mean(data_FG_prof1$PP_final)
mean(data_FG_prof1$Physical_final)
mean(data_FG_prof1$TASint_final, na.rm=TRUE)
mean(data_FG_prof1$Isol_SSint_final, na.rm=TRUE)
mean(data_FG_prof1$Diverse_back_final)
mean(data_FG_prof1$TSint_final, na.rm=TRUE)

sd(data_FG_prof1$Descrim_final)
sd(data_FG_prof1$PP_final)
```

```
sd(data_FG_prof1$Physical_final)
sd(data_FG_prof1$TASint_final, na.rm=TRUE)
sd(data_FG_prof1$Isol_SSint_final, na.rm=TRUE)
sd(data_FG_prof1$Diverse_back_final)
sd(data_FG_prof1$TSint_final, na.rm=TRUE)

mean(data_FG_prof2$Descrim_final, na.rm=TRUE)
mean(data_FG_prof2$PP_final)
mean(data_FG_prof2$Physical_final)
mean(data_FG_prof2$TASint_final, na.rm=TRUE)
mean(data_FG_prof2$Isol_SSint_final, na.rm=TRUE)
mean(data_FG_prof2$Diverse_back_final)
mean(data_FG_prof2$TSint_final, na.rm=TRUE)

sd(data_FG_prof2$Descrim_final, na.rm=TRUE)
sd(data_FG_prof2$PP_final)
sd(data_FG_prof2$Physical_final)
sd(data_FG_prof2$TASint_final, na.rm=TRUE)
sd(data_FG_prof2$Isol_SSint_final, na.rm=TRUE)
sd(data_FG_prof2$Diverse_back_final)
sd(data_FG_prof2$TSint_final, na.rm=TRUE)


###cohen's d effect sizes
library(lsr)
cohensD(data_FG_prof1$Descrim_final,data_FG_prof2$Descrim_final)
cohensD(data_FG_prof1$PP_final,data_FG_prof2$PP_final)
cohensD(data_FG_prof1$Physical_final,data_FG_prof2$Physical_final)
cohensD(data_FG_prof1$TASint_final,data_FG_prof2$TASint_final)
cohensD(data_FG_prof1$Isol_SSint_final,data_FG_prof2$Isol_SSint_final)
cohensD(data_FG_prof1$Diverse_back_final,data_FG_prof2$Diverse_back_fin
al)
cohensD(data_FG_prof1$TSint_final,data_FG_prof2$TSint_final)

##################################################################
#9. compare FG and CG students on STEM intentions during course   #
##################################################################

rm(list=ls())
setwd("/Users/Kate/Dropbox/School/Dissertation/ACTUAL
STUDY!!!/Survey/survey data")
data <- read.csv("data_final.csv", na.strings="")
#################
data$FG <- ifelse(data$Q33 == "No",1,ifelse(data$Q33 == "Yes",0,NA))
data$FG <- as.factor(data$FG)
table(data$FG)
data_FG <- subset(data, FG == 1)
data_CG <- subset(data, FG == 0)

prop.table(table(data_FG$EndofCourse_Discipline))
##STEM Leaver:
0.04545455 + 0.10606061
#STEM stayer:
0.54545455 + 0.04545455
#non-STEM throughout:
0.21212121 + 0.03030303 + 0.01515152
```

```
prop.table(table(data_CG$EndofCourse_Discipline))
##STEM Leaver:
0.01030928 + 0.06185567
#STEM stayer:
0.51546392 + 0.02061856
#non-STEM throughout:
0.34020619 + 0.01030928 + 0.03092784 + 0.01030928
```