MOTIVATION INTERVENTION THROUGH CALCULUS TASKS WITH SCIENCE AND ENGINEERING APPLICATIONS

by

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DEDICATION

To my mom Rukiye, my dad Mustafa and my brother Ahmet Emin, without whom this would have not been possible.

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ABSTRACT

Although national interest has been focused on increasing STEM graduates, calculus courses still pose a challenge for most STEM major students. As recent statistics show, only half of the students are successful in calculus courses. Many times, students in these courses do not see the relevancy of the material to their future careers and this inability to connect the two can be a cause of a lack of motivation. Recent research studies suggest that interventions might be a useful tool to improve student motivation.

The purpose of this quasi-experimental research study is to measure the impact of an intervention on three student motivational aspects - performance expectations, utility value, and interest. The intervention consisted of the engagement of students in calculus tasks with specific applications they will encounter in subsequent science and engineering courses. They were designed to explicitly connect calculus concepts to other disciplines. Six Calculus – I sections were selected for this study, three were randomly assigned to a treatment group where the intervention was implemented twice during a semester and student motivational aspects were measured through surveys.

The results indicate that the impact of the intervention on student motivation was not statistically significant by considering instructor as a random effect. However, there were some instances where the intervention significantly influenced student utility value and interest. However, student performance expectations constantly decreased throughout the semester. Moreover, the results showed that the intervention improved female students’ utility value and interest more than it did male students. The implications and limitations of this study also discussed in further detail.

I. INTRODUCTION

Context of the Study

Over the past several decades, college student retention in science, technology, engineering, and mathematics (STEM) majors has emerged as one of the major focus on undergraduate education in the United States. Statistics show that forty-eight percent of bachelor's degree students and sixty-nine percent of associates degree students who entered STEM fields between 2003 and 2009 had left these fields by Spring 2009. Roughly one-half of these students switched their major to non-STEM fields, and the rest of them left STEM fields by exiting college before earning a degree or certificate (NCES, 2014 & NCES, 2009).

There is an increasing demand for graduates in STEM majors. However, low retention rates are part of the cause of the low number of graduates from these fields (Daemplfe, 2002). Seymour and Hewitt (1997) identify STEM students' performance in introductory courses as one of the key indicators as to whether they switch out of their intended STEM majors during their college experience.

In the U.S., students who are in their first or second year of STEM studies take introductory science, mathematics, and engineering courses, which includes calculus courses (PCAST, 2012). In 1987, and still current to this date (Bressoud, Mesa, & Rasmussen, 2015; Jeffrey, Lyle, Chariker, 2015), the Mathematical Association of America (MAA) stated that calculus acts as a filter to the STEM pipeline, which in turn blocks access to STEM careers (Steen, 1987). Researchers claim that calculus still continues to pose a challenge for most STEM students (Jeffrey, Lyle, Chariker, 2015). In general, calculus courses are required introductory courses for most STEM field majors.

Therefore, a strong foundation and understanding of calculus concepts is an important requirement for all STEM degrees (Young et al., 2011).

The Research Problem

Almost anyone who has taught a mathematics course would recognize that students often ask, “why are we learning this” or “when would I need this?” In particular, this situation occurs in college calculus courses since many of them will go into applied fields. Students who are taking introductory STEM courses, including calculus, might not see the value or the connections between course material and their lives (Wulf, 2007; Brophy, 1999). If students are not given the opportunity to see this connection, they might become disengaged, thereby lacking the motivation to study the subject (Harackiewicz, Tibbetts, Canning & Hyde, 2014). Hence, making mathematics and science courses personally relevant and meaningful may engage students in the learning process, enable them to identify with future science careers, foster the development of interest, and promote science related academic choices and career paths (Hulleman & Harackiewicz, 2009).

The Mathematical Association of America (MAA) conducted a nationwide study in 2015 entitled “Characteristics of Successful Programs in College Calculus”. The study investigated students experience in Calculus I courses and how this affects their confidence, enjoyment of mathematics and intention to persist in the study of mathematics (Bressoud, Mesa, & Rasmussen, 2015). The study included 663 instructors and over 14,000 students from 213 colleges and universities in the United States. They found that only 50% of the students earned an “A” or a “B” in the course, and 23% of them earned a “C” and 27% of the students earned a “D”, “F”, or withdrew from the course. Hence, only half of the students were considered as successful in calculus courses if the standard is at least a "B" in the course. Furthermore, around 27% of the students were unable to pass calculus courses, which is almost a third of students studying calculus. Ultimately, students who are not able to pass calculus cannot remain in STEM fields.

The institution where this study took place has similar student performance statistics in calculus courses. According to the statistics from the fall 2016 semester, 61% of the students earned an A, B, or C, and 39% of the students earned a D, an F, or withdrew from the Calculus I courses. In the same semester, 45% of those students who earned a D, 85% of those who earned an F, and 72% of the ones that withdrew dropped out of the institution or switched their starting majors. In the fall 2017 semester, the latest statistics from the institution, 60% of students earned an A, B, or C, and 40% of the students earned a D, F, or withdrew. Approximately 60% of the students from those semesters can be considered successful in Calculus I courses if they earn a C or above, meeting the grade criteria. In this respect, students' performance in these courses match with the national data shown previously.

Sternberg (2005) argues that motivation is key for school success; in its absence the student may not succeed in school. Motivation is seen as a pre-requisite of, and a necessary element for, student engagement in learning (Saeed & Zyngier, 2012). If educators have a sound understanding of different types of student motivation possible in any given context, then they are in a better position to provide a more conducive learning environment to students that better promotes their learning (Marsh, 2000).

Many contemporary theories of motivation recognize the instrumental role of expectancies and values on student's effort, choice, and persistence. The expectancy-value model by Eccles et al. (1983) argues that individuals take on challenging tasks if they see the value of it, and if they expect to succeed on it. The theory assumes that individuals' values and expectancies on a task directly affect their performance and persistence on it. The model consists of four components of value - attainment, intrinsic, utility and cost.

Utility value is related to how a person sees the relevance of a task to their goals. When individuals perceive utility value in a task, they may connect the task to important personal goals and outcomes in an intrinsically regulated way that improves interest (Vansteenkiste, Lens, & Deci, 2006). Since utility value may have a strong potential for students' learning process, it might help STEM students relate calculus concepts to their fields. In the educational psychology field, there are some intervention studies that address students' motivation and interest.

The study by Puruhito et al. (2011) developed interventions to provide information about the utility of calculus topics. Using a 5-minute video segment, the study related the use of mathematics to engineering in Calculus II courses including four hundred and sixty-three engineering major students in the southern United States. They found that the intervention increased students' perceived utility of the curriculum without significantly decreasing the instruction time and making extensive changes to the courses. Although the 5-minute video segment is a practical method to increase the instrumentality of calculus for engineering students, it does not provide opportunities to academically engage and motivate students during calculus courses.

In a similar study, Hulleman and Harackiewicz (2009) created classroom science activities encouraging high school students to connect course materials, emphasizing the utility value, to increase student motivation and learning. They designed an intervention where the students were asked to write a summary of what they learned from science topics. The participants of the study were two hundred and sixty-two students taught by seven science teachers from two high schools in a small Midwestern city in the United States. The results showed that the intervention increased interest in science and improved course grades for students with low success expectations. As the authors recommend, a single study requires replication before generalizations can be made about more diverse settings and students. In addition, the study was done on high school students studying science, so it would be compelling to see whether a related intervention in calculus would produce similar results.

While some studies focus solely on utility value, others incorporate interest into the values being measured. Vansteenkiste, Lens, and Deci (2006) believe that when an individual perceives utility value in a task, they might connect the task to some important personal goals and outcomes in an intrinsically regulated way that improve interest. In addition, Pintrich and De Groot (1990) state that the more students believe the subject is ‘interesting and important’, the more motivated and engaged they are in the learning process. Therefore, interest could be an important aspect of students’ motivation to learn calculus courses.

The following study examines interest through motivational intervention. Durik and Harackiewicz (2007) designed two studies to examine the effects of situational factors on interest, employing catch and hold, and how these effects vary as a function of individual interest. Individual interest was examined as a moderator of effects of situational factors designed to catch and hold task interest. The study was conducted on ninety-six college students who were enrolled in introductory psychology courses in the United States. Their outcome variable was participants' subjective interest in the mental mathematics technique (their interest on this task). The results showed that catch promoted student interest by stimulating their attention and arousal. The effects of catch and hold differed based on students' individual interest. This study only focused on student interest and deeply investigated different aspects of interest. Since this study was conducted at the undergraduate level, and it was not in a STEM subject, it did not provide information about calculus courses. In addition, the study only focused on interest and it did not incorporate utility value as a motivational construct.

Another study by Hulleman, Godes, Hendricks, and Harackiewicz (2010) incorporated both utility value and interest in the same framework. They developed a utility value intervention to increase interest and performance on a task. Students' utility value was manipulated through writing tasks. The participants of this study were approximately four hundred and fifty undergraduate students enrolled in several psychology courses in a university in the United States. They found that the intervention increased students' perceptions of utility value and interest. In addition, their analysis revealed that utility value explained the effects of the intervention on students interest and predicted performance. However, the result of this study is based on students from psychology courses, which is not a STEM field. Even though psychology is not with the STEM fields, the intervention provides insight into motivational interventions as it investigates utility value of college students. Consequently, it is necessary to see whether these same results can be obtained by having a similar intervention in calculus courses.

So far, the need for increasing students' motivation in calculus courses has been discussed by the guidance of research studies. Now it is necessary to ask - how do we improve student motivation? Some research studies documented here have shown the effectiveness of motivation interventions, such as relevance interventions, on student motivation in subjects like psychology and other subjects. The other question then becomes - what kind of intervention is necessary to improve students' motivation, specifically in calculus?

There are some calls to incorporate concepts from other STEM disciplines within mathematics. The National Council of Teachers of Mathematics (NCTM) recommends that K-12 schools should provide opportunities to learn about mathematics by working on problems arising in contexts outside of mathematics. These connections can be applied to other subject areas and disciplines as well as to students' daily lives (NCTM, 2000). In order for students to demonstrate depth of understanding, their learning experiences must provide them with the proper tools and contexts to do so (Schwalbach & Dosemagen, 2000). The literature published about the idea of assimilation of science and mathematics concepts shows that there continues to be a support for integrated science and mathematics education in the reform documents. However, more empirical research grounded in these theoretical models is needed (Berlin & Lee, 2005).

In a research study discussing K- 12 curriculum, Rogers (1997) encouraged using a sense of knowledge based in the real world as well as based on student's experiences. He suggests that such a curriculum would engage students in rigorous and deep learning and encourage them to begin mapping their own understandings as a result of their experiences. He also argues that if students were given a real-world application problem, engineering or science related, this could then provide students with the opportunity to acknowledge how interdisciplinary frames are useful.

Research studies support the idea of real world application situations and mathematics. Becker and Park (2011) state that integration of mathematics with science, technology, and engineering provides students with the context in which they can make meaningful connections between these subjects. They argue that such integrative approaches could bridge abstract concepts in mathematics to practices in science, technology and engineering subjects. For instance, Judson and Sawada (2000) implemented an action research study where they investigated the impact of integrating mathematics into a science class to improve student's achievement in mathematics. The participants were fifty-two junior high school students in the United States. They found that students in the integrated courses attained higher achievement scores. However, this integrated approach was implemented at a junior high school setting, not in a college level course.

Furthermore, Elliott et al. (2001) designed an experimental research to investigate the effect of an interdisciplinary course called "Algebra for the Sciences" on students critical thinking skills, problem-solving skills, and attitudes towards mathematics. The participants were two hundred and eleven students attending a university in the southwestern United States. Their study shows no significant difference in problem-solving skills between students in the interdisciplinary course and students in the college algebra course, but students in the interdisciplinary course had slightly larger gains in critical thinking and significantly higher positive attitudes toward mathematics. Therefore, it is necessary to investigate how applying science and engineering, for instance in an instructional task, into calculus courses could potentially influence student motivation.

Overall, as previously discussed, designing a motivation intervention study that connects mathematics to STEM disciplines might be a way to improve student motivation in calculus. In particular, applying real world concepts and situations into calculus courses might cultivate student motivation and hence be a practical and useful way to accomplish a motivation intervention.

Purpose of Study

The purpose of this study is to test an intervention, as an instructional task, that aims to improve student motivation by increasing students' utility value, interest and performance expectations. Research has shown that motivation interventions help students to find value and meaning in learning and increase student motivation and performance (Eccles & Harold, 1991; Eccles & Wigfield 1995).

Existing studies in research literature investigate motivation and relate it to engagement (Saeed & Zyngier, 2012; Singh, Granville & Dika, 2002). Some studies design motivational interventions to examine constructs of utility value and interest in different class levels and courses (Hulleman, Godes, Hendricks, & Harackiewicz, 2010; Hulleman & Harackiewicz, 2009; Durik & Harackiewicz, 2007). However, there are few studies (Puruhito et al., 2011) that look at motivation through intervention in calculus courses. Therefore, the need exists to investigate student motivation and interest through interventions, specifically in college level calculus courses due to the importance of student motivation in calculus for STEM fields.

The intervention designed for this study has students engaging in the Calculus Tasks with Science and Engineering Applications. In order to accomplish the purpose of this study, the following research questions are investigated.

1. How do the Calculus Tasks with Science and Engineering Applications impact students' motivational aspects, including utility value, interest, and performance expectations in college Calculus I courses?
2. How does the impact of the Calculus Tasks with Science and Engineering Applications differ based on student gender, intended majors, and race in college Calculus I courses?
3. How do students' motivational aspects, including utility value, interest, and performance expectations change within a semester in college Calculus I courses?

Definitions

Some of the key terms that were used throughout this study are described below.

1. Calculus: Introductory mathematics courses typically taught in mathematics departments. These courses are a prerequisite for further mathematics courses and are requirements for most STEM majors.
2. Calculus I: A beginning calculus course that focuses on differential and integral calculus taught in the mathematics department.
3. Interest: In this study, it is referred as an emotional state aroused by specific features on an activity of a task (Hidi, 2000; Renninger, 2000)
4. Lab – A separate component of a calculus course sometimes referred to as a recitation session and is typically led by a teaching assistant.

5. Instructor – The faculty member, usually holding a PhD degree, who instructs the calculus courses.
6. Instructor of Record – The main instructor who is responsible for teaching the course (Teaching assistants might not necessary be Instructor of Records)
7. Performance Expectations – Refers to calculus students' expectations for their own course performance.
8. STEM – An acronym for Science, Technology, Engineering, and Mathematics fields of study at the collegiate level. The acronym has changed from Science, Mathematics, and Engineering (SME) to SME&T and SMET, and finally to STEM. Technology was added after the 1990s when computer science became an emerging field.
9. TA – An acronym for a graduate Teaching Assistant.
10. Utility Value – In general, refers to how well a task or activity is related or connected to students' current or upcoming goals (Eccles et al., 1983). In this study, it is defined as how well calculus students relate calculus material to their goals and future careers.

II. A REVIEW OF THE LITERATURE

A Conceptual Map of the Literature Review

The following map (Figure 1) depicts a conceptual structure of the review of the literature. It starts from the broad perspective on STEM fields, which discusses the historical focus on STEM fields and student retention in those fields. It then narrows to calculus courses as introductory courses for STEM fields. After that, narrowing even further, it includes the approach taken in this study which is motivation. Finally, it ends by looking at motivational constructs – performance expectations, interest and utility value, which are the focal points of investigation in this study.

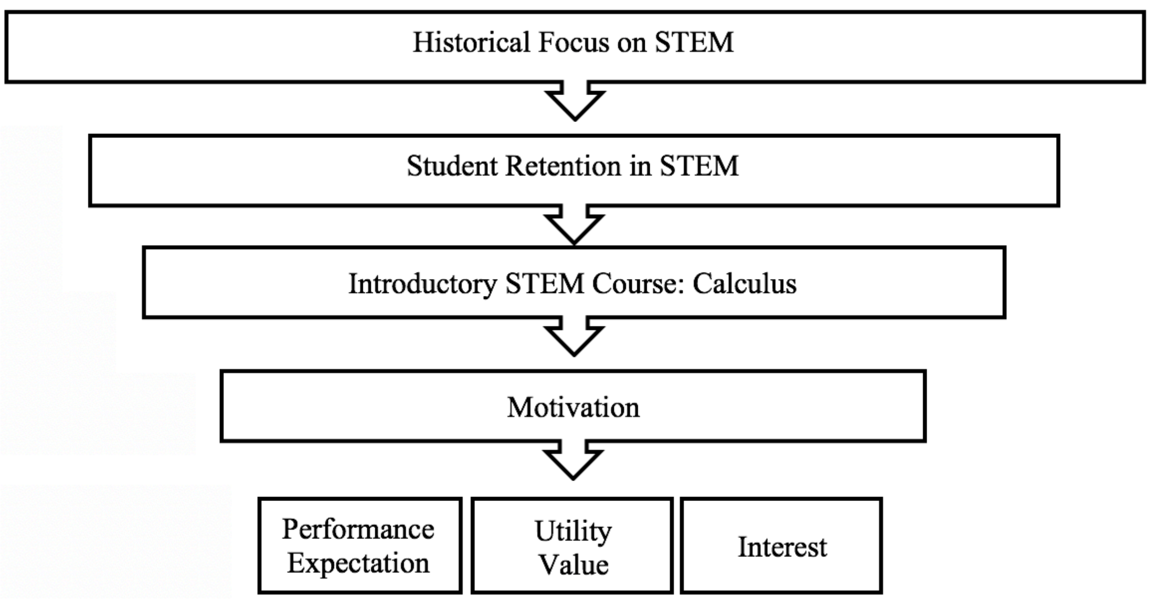


Figure 1. Conceptual map of the literature review

Historical Focus on STEM

The number of students starting and completing (STEM) related majors in the United States has received increased attention from educational researchers, politicians, and businessmen. Reports from Tapping America's Potential (TAP, 2008), the Business Higher Education Forum (BHEF, 2014; BHEF, 2013; BHEF, 2010), and the President's

Council of Advisors on Science and Technology (PCAST, 2012) call for improving STEM education and increasing the number of STEM college graduates. The increasing flow of STEM workers into job markets keeps the U.S. economy competitive within the global economy (Chen, 2009).

A National Science Foundation report from 1986 stated the need for improvements in teaching practices in STEM fields and provided several recommendations for institutions (NSF, 1986). The report emphasized investments needed in high quality education in science, mathematics, and engineering. Specifically, reconsidering curriculums to meet student's needs that would improve college education. Since NSF's report (1986), there have been multiple other reports (American Association of Physics Teachers, 1996; National Research Council, 1989; Steen, 1987) that state the need for improvement in undergraduate education in STEM fields. Quality of education in STEM fields in higher education institutes influence students' retention in these fields. Hence, it is important to look at students' retention rates in STEM fields.

Student Retention in STEM

Student retention in science, engineering, mathematics and technology (STEM) majors has emerged as one of the most important issues in undergraduate education in the United States. Forty-eight percent of bachelor's degree students and 69% of associate degree students who entered STEM fields between 2003 and 2009 had left these fields by Spring 2009 (NCES, 2014). Almost half of the students switched their major to a non-STEM field, and the rest of the students left STEM fields by leaving institutions before earning a degree or certificate.

The Program for International Student Assessment (PISA) is a system of international assessment that compares fifteen-year-old students' performance in science, reading and mathematics from participating countries. In PISA 2015, seventy-three education systems from around the world participated in the assessment. United States performance in science literacy in PISA 2015 was lower than 18, and higher than thirty-nine other education systems. In addition, U.S. performance in mathematics literacy in PISA 2015 was lower than in more than half of other education systems (36/69) but higher than twenty-eight education systems. In conclusion, the United States has fallen behind thirty-six other countries in math and eighteen other countries in science, according to the report (PISA, 2015). Thus, student performance in science and mathematics in high school might also impact student retention in STEM fields.

Introductory STEM Course: Calculus

Students who are in their first or second year of STEM studies usually take introductory science, mathematics, and engineering courses, including mandatory calculus courses (Sonnert, Sadler, & Bressoud, 2015; PCAST, 2012). A strong foundation and understanding of calculus is an important requirement for almost every STEM field degree (Young et al., 2011). Every year, more than 300,000 students in two- and four-year college and universities enroll in calculus courses.

In 1987, the Mathematics Association of America (MAA) stated that calculus acts as a filter to the STEM pipeline, which in turn blocks access to STEM careers if students are not successful (Steen, 1987). There are empirical research studies that also support this argument. For instance, the findings of Tobias (1990), Strenta et al. (1994), and Seymour and Hewitt (1994) provide evidence that introductory STEM courses eliminate low performing students from the STEM fields. These studies address the issue in introductory STEM courses, yet they do not examine students' motivation in these courses. Additionally, Seymour and Hewitt (1997) identify STEM students' performance in introductory courses as one of the key indicators as to whether they remain in their intended STEM majors during their college experience. Scholars have attributed high attrition rates to several factors including students' motivation to learn, instructional practices, and institutional factors.

Further research by Glasson and Lalik (1993) discusses the need of skills such as reflecting, relating, and examining concepts as they are taught in an active constructive course. However, Beswick and Ramsden (1987) argue that this kind of student engagement is less likely to happen in traditional lectures where the stream of information leads students to focus on taking instant notes with less time to understand the questions and concepts during the course. So far these studies address classroom and instructional issues in calculus courses that provide recommendations that require extensive curriculum and instructional efforts. The essential question is then how to promote student motivation to learn calculus in a less reconstructive way?

Motivation Theories

Gasiewski (2012) draws attention to theories of motivation and learning in order to investigate and gain insights into student learning in introductory STEM courses. Motivation is an inner power that requires an individual to reach a goal that strengthens and directs the individual's behaviors (Basaran, 1982). According to Ryan and Deci (2000) to be motivated means to be moved to do something - "a person who feels no impetus or inspiration to act is thus characterized as unmotivated, whereas someone who is energized or activated toward an end is considered motivated" (p. 54). Motivation is a highly complex concept. Ryan and Deci (2000) indicate that individuals are not only motivated at different levels, but that their motivation orientations are different. There can be different attitudes and goals behind the motivations of individuals demonstrating the same action. Motivation is also seen as a situational construct depending on a person's moment-to-moment thoughts, experiences and the interpretation of what is happening (Kiemer, Groschner, Pehmer, & Seidel, 2015).

Motivation research literature classifies motivation as either intrinsic or extrinsic. Learning for the sake of learning is intrinsic motivation, while learning as a way to be praised or rewarded is extrinsic motivation (Corpus, McClintic-Gilbert, & Hayenga, 2009). Ryan and Deci (2000) note that intrinsically motivated students have a greater likelihood of having quality educational experiences because of their interest and enjoyment. According to Eccles and Wigfield (2002), when individuals are intrinsically motivated, they engage in an activity because they are interested in and enjoy the activity. If the students are performing the task because they take pleasure in doing so, the motivation orientation is internal, and the motivation type is referred to as intrinsic motivation.

However, every student might not always be intrinsically motivated in classrooms. According to Krause, Bochner and Duchesne (2006) teachers frequently use extrinsic motivation like rewards, praise, free time, food and even punishment to encourage and stimulate their students towards learning. Researchers also claim that when extrinsically motivated, individuals engage in activities for instrumental reasons, meaning, for the usefulness or relatedness of the activity, or some other reasons including receiving a reward (Eccles & Wigfield, 2002).

Therefore, both intrinsic and extrinsic motivation could be important aspects of students' motivation toward learning calculus material. The aim of this study is to focus on how students value calculus, and how those values impact their motivation to learn. Since this study was based on students' challenge on valuing or connecting calculus concepts to their lives or future careers, Expectancy-Value Theory was utilized.

Expectancy-Value Theory

Jaqueline Eccles and collaborators developed the Expectancy-Value Theory of achievement-related choices for motivation (Eccles et al., 1983). The theory argues that individuals take on challenging tasks, such as taking calculus courses or persisting in STEM fields, if they a) value the task or the activity, and b) expect to succeed the task or the activity. In Eccles and collaborators' Expectancy-Value model, expectancies and values are assumed to directly impact performance, persistence, and choice of educational tasks. They define expectancies for success as individuals' beliefs about how well they perform on immediate and future tasks.

The collaborators of the theory outlined four components of task value: attainment value, intrinsic value, utility value, and cost. They defined attainment value as the personal importance of doing well on the task, and linked attainment value to the relevance of engaging in a task. Intrinsic value is the enjoyment that the individual feels through an activity or the subjective interest the individual has on the subject. This particular construct is similar to intrinsic motivation by Deci and Ryan (1985) and to the constructs of interest by Renninger et al. (1992). Another component of Eccles et al.

(1983) is cost. Cost is defined as the negative aspect of engaging in the task, such as anxiety, fear of failure, and effort required. The last component of the model, and the one focused in this study, is utility value and it will be described next.

Utility value. Utility value is one of the components of the Expectancy-Value model (Eccles et al., 1983) and it is sometimes referred as perceived utility, or instrumentality. It is determined by how well a task relates to current and upcoming goals (Eccles et al., 1983). According to Eccles and Wigfield (2002), a task can have positive value to a person since it triggers important future goals, even if they are not interested in the task at the time. Students might attempt instructional activities, only because it was required for them to do them. This aspect of their utility value model can be linked to the more extrinsic motivational reasons for engaging in a task (Deci & Ryan, 1985). Eccles and colleagues consider utility value as an extrinsic factor since it extends beyond the task itself to connections between that task and other tasks, activities, or goals (Wigfield & Eccles, 1992). This means that outside factors, such as the content being related to a future goal, might motivate students extrinsically to engage in the task.

What students usually ask in mathematics classes is "why are we learning this?". In particular, students who are taking mathematics have a hard time seeing the value or connection between course material and their lives (Brophy, 1999). If individuals believe a task is useful and relevant beyond their current condition, or for goals such as achievement, carrier goals, or aspects of the individuals' life, it can be said that the individual's utility value of the task is high. This same challenge of utility value potentially occurs in calculus settings.

Research studies have shown the relationship between utility value, performance, and achievement. For instance, Simons, Dewitte, and Lens (2003) designed a study where they examined whether the instrumentality (utility value) of a task could be a factor on student's motivation and performance. They collected data from six hundred and ninety-five college students who enrolled in physical education courses in Belgium. The researchers concluded that highlighting the usefulness of an activity (by telling students how it could help them on their future goals) increased their persistence and performance in the physical education class. Although this study has implications of the importance of utility value interventions, it does not provide much information regarding student motivation in calculus courses.

Bong (2001) investigated contributions of beliefs and task value in predicting college students' course achievement and students future course enrollments. The researcher collected data from one hundred and sixty-eight undergraduate students who were enrolled in an instructional methods course in the education department in a women's university in Korea. The results showed that students' perceived usefulness of the course predicted their self-efficacy in the course, which then predicted their exam performance. Hence, students' utility value of the subject has important implications for their performance in the course. Although the setting of this study is college level course, it does not reveal much about mathematics courses.

Furthermore, Malka and Covington (2005) conducted an exploratory study to investigate the effect of perceived instrumentality (utility value) on course performance of ninety-five psychology major students at a state university on the West Coast of the United States. The study collects data about some motivational variables such as perceived instrumentality, goals, and performance through self-reported forms. They found that the students' ability to relate school work to their future goals (i.e., perceived instrumentality) predicted their classroom performance. Malka and Covington's study (2005) found that perceived instrumentality appears to be a salient and empirically distinct aspect of college students' motivation to achieve their goals. Moreover, they claimed that perceived instrumentality is a useful construct for addressing how students' motivation maps onto student course performance. Even though this study provides strong empirical evidence on the impact of perceived instrumentality (PI) on student performance, it does not inform about mathematics courses.

Therefore, as these studies indicate, there is a relationship between students' perception of utility in a task and their performance consequently. However, since the purpose of the study is to investigate utility value as a motivational variable in a calculus course, the research studies conducted so far have revealed further research is needed.

One of the few studies related to motivation in calculus was done by Puruhito et al. (2011) They developed interventions to provide information about the utility of calculus topics through a 5-minute video segment related to the use of mathematics in engineering. Administered to four hundred and sixty-three Calculus II engineering major students, the researchers found that the intervention increased students perceived utility of the curriculum without significantly decreasing the instruction time and making extensive changes to courses. This study informs how a possible intervention may impact calculus student utility value. Although it is a practical method to increase the instrumentality of calculus for engineering students, it does not provide opportunities to academically engage students during calculus. Another important aspect of the Expectancy-value Theory is expectancies which will be defined in the next section.

Performance expectations. The Eccles et al. model shows that expectancy and value are independent constructs that are often positively related. Positive expectancies, or the idea of competence, can enable students to perceive value in educational activities (Hulleman, Godes, Hendricks, Harackiewicz, 2010). Research has shown that finding value and meaning in activities might increase task engagement and the development of competence and positive performance expectations (e.g., Eccles & Harold, 1991; Eccles & Wigfield, 1995). Since performance expectations is a construct considered to influence student success and task choices, as it was implied by the Expectancy-value Model (Eccles et al., 1983), it might be considered to be an important aspect influencing student motivation in calculus courses.

The Expectancy-value theory acknowledges intrinsic value as another type of value that involves enjoyment and interest, but theories of interest development provide a more nuanced picture of how students generate interest and enjoyment. Vansteenkiste, Lens, and Deci (2006) also found that when an individual perceives utility value in a task, they might connect the task to some important personal goals and outcomes in an intrinsically regulated way that foster the development of interest. Therefore, interest might be an invaluable aspect of students' motivation. Interest development theories will be examined in the next part.

Interest Development

Interest theories generally study why individuals focus on engaging in certain tasks. According to Eccles and Wigfield (2002) there are two types of interests, individual interest and situational interest. Individual interest is a relatively stable evaluative orientation towards certain domains. Situational interest is an emotional state aroused by specific features of an activity or a task. According to Hidi (2000) and Renninger (2000) individual interest refers to an individual psychological disposition associated with his/her preferences for activities/actions. Alternately, situational interest refers to the appealing effect of characteristics in an activity or object that triggers responses from the moment of person - activity interaction.

Researchers have claimed that the potential for interest and motivation lies within the person, but content and environment impact the strength and direction of interest (Hidi & Renninger, 2006; Renninger & Hidi, 2011). In a different study, Hidi and Renninger (2006) developed a four-phase model of interest development (a well-known model in the field) that includes the transition from situationally-based interest to individual interest.

In the first phase, a trigger is necessary (usually from content or environment) to spark a temporary affective and cognitive change that results in a short-term increase in interest. In phase two, when this triggered situational interest is further supported, then it can develop into a more maintained situational interest. In order to develop emerging individual interest (phase 3) and well-maintained individual interest (phase 4), the individual must play a more active role in their own interest development. This model of interest is useful when considering student learning in calculus courses. If students are triggered to study the material they might maintain interest, and then it may ultimately transform to a more individual or personal interest. Although the interest development schemes of Hidi and Renninger (2006) have important implications for student motivation, this study focuses solely on how the two early phases of interest could be impactful in calculus courses.

Further research by Mazer (2013) explains that, “Students who experience cognitive interest are pulled toward a subject because they possess a clear structural understanding of the content,” whereas, “Students who experience heightened emotional interest are pulled toward a content area because they are energized, excited, and emotionally engaged by the material” (p. 256). These statements are showing emotional and cognitive aspect of interest that might improve student learning.

Additionally, the more students believe the course work is ‘interesting and important’, the more motivated and engaged they are in the learning process (Pintrich & DeGroot, 1990). Therefore, interest is an important aspect of student motivation that may influence student learning in undergraduate courses. If calculus students believe that the material is “interesting and important” then they might become more motivated and engaged in classrooms.

Recent research studies have examined interest as a construct that influences student learning. For instance, Mazer (2012) conducted a study with two hundred and fifty-two undergraduate students enrolled in an introduction to human communication course at a university in the midwest United States. The researcher aimed to develop and validate an interest and engagement scale, as well as to collect data about students’ interest and engagement. The results of the study showed that students who experienced higher levels of interest in the material were more likely to be engaged in classroom and other educational learning activities. This study informs us about the importance of interest in undergraduate course settings. However, it does not provide much information about student interest in calculus courses.

Researchers believe that well-developed interests can motivate students to engage with the material through an educational activity. For example, Harackiewicz, Barron, Tauer, Carter, and Elliot (2002) designed a study to examine the impact of achievement goals on predicting interest and performance over time. They collected data from three hundred and fifty-five students who enrolled in psychology courses at a university in the midwestern United States. They found that interest was associated with performance in the short term and was relevant to student learning. However, this study only examined students interest in psychology courses, which are not STEM courses.

Research has shown many studies on situational interest that have focused on the characteristics of academic tasks that create interest (Eccles & Wigfield, 2002). For instance, the study by Durik and Harackiewicz (2007) examined interest by designing experimental studies. They used an educational task, which was a mental mathematics technique, as an intervention. The study aimed to investigate the effects of situational factors on interest, and to test how these effects vary as a function of individual interest. Individual interest was examined as a moderator of effects of situational factors designed to *catch* and *hold* task interest. They collected data from ninety-six college students who were enrolled in introductory psychology courses in the United States. Their focal dependent variable in the intervention was the participants' subjective interest in the mental mathematics technique (task interest).

The results showed that *catch* promoted interest by stimulating attention and arousal; however, *hold* operated at a deeper and more self-involved level of interest toward the task. However, this study only informs us about students' interest in psychology courses, hence there is a need to investigate student interest in calculus courses. If calculus students are provided such educational activities, it may catch their attention and therefore lead to a higher level of interest in studying calculus subjects.

Among the studies documented here, some of them investigate only the construct utility value and relate it to some other variables, while other studies only examine the construct interest. However, the following study examines both utility value and interest. Hulleman, Godes, Hendricks, and Harackiewicz (2010) investigated the impact of an intervention on interest and performance by designing two intervention studies. In the first study, students were taught a new mental mathematics technique. Next, students were randomly assigned to the relevance and control conditions. Participants in the relevance condition were asked to write an essay describing how the math activity could relate to their life. In total, one hundred and seven undergraduate students enrolled in introductory psychology courses at a state university in the U.S. participated in this study. The results showed that, through an intervention, utility value could play a causal role in triggering and maintaining interest.

In their second study, the researchers extended a similar investigation to a larger student sample with a slightly different method. They collected data from three hundred and fifty students who were enrolled in psychology courses at a large midwestern university in the U.S. At mid-semester, participants were randomly divided into two sets of writing conditions - relevance and control. The students in the relevance condition were asked to write about the relevancy of the topic that they learned in class connecting to their real life. The results found that the relevance intervention increased perceptions of utility value, which then impacted students' interest. In addition, it demonstrated an association between utility value and performance. Even though these two studies did not take place in calculus courses, they have important implications and potentials in terms of student utility value and interest. Hence, related research is needed to investigate whether the same results could be replicated in calculus courses.

Another important aspect of motivation is student engagement. Most motivation studies consider engagement as an essential construct. However, for the most part, the engagement literature tends to be broader and definitions of engagement are not differentiated well. According to Fredricks et al. (2004), emotional engagement overlaps considerably with interest and value constructs in motivational research. A recent report, “Engaging Schools”, considers motivation and engagement as synonyms and uses the words interchangeably (National Research Council & Institute of Medicine, 2004).

Student Engagement

Engagement refers to the quality of a student’s involvement in their pursuit of education and hence connection with people, activities, goals, and values (Skinner, Kindermann, & Furrer 2009). A research study by Handelsman et al. (2005) defines student engagement as an interaction between student and course content in both inside and outside classroom environments. Kuh (2009) further states that engagement refers to the quality of effort and participation in authentic learning activities. Student engagement also refers to a “student's willingness, need, desire and compulsion to participate in, and be successful in, the learning process promoting higher level thinking for enduring understanding” (Bomia, Beluzo, Demeester, Elander, Johnson, & Sheldon, 1997, p. 294). According to Robinson and Hullinger, (2008) student engagement is defined as “efforts of the student to study a subject, practice, obtain feedback, analyze and solve problems” (p. 101). Delialioglu (2011) defines student engagement as a process that involves students in activities that are considered “academically meaningful” that contribute to both learning and personal development.

According to Fredricks et al. (2004) academic engagement is a construct that includes three dimensions: behavioral, emotional, and cognitive. Student involvement in class such as asking questions, and paying attention are characteristics of behavioral engagement (Birch & Ladd, 1997). Emotional engagement relates to students’ feelings of boredom, anxiety, and excitement in the classroom (Connell & Wellborn, 1991; Skinner & Belmont, 1993). Cognitive engagement is conceptualized as students’ investment in learning and the individual’s commitment to hard work.

Gasiewski, Eagan, Garcia, Hurtado and Chang (2012) designed a research study of student academic engagement in introductory STEM courses and drew attention to theories of motivation and learning to offer insight into psychological traits that promote undergraduate students’ academic engagement in mathematics. They collected data from 2,973 students enrolled within seventy-three introductory STEM courses across fifteen colleges and universities in the United States. They found that student engagement was truly vital to student performance. However, they pointed out that there should have been more consideration on various methods for gathering data in introductory STEM courses to enable rich explorations about student motivation to learn.

Kuh et al. (2008) investigated the effects of student engagement by examining first-year college students grades and persistence. They merged student-level records from eighteen different types of higher education institutions between 2000 and 2003 to examine the links between student engagement and two key outcomes of college - academic achievement and persistence. They found that student engagement in educational activities was positively related to academic performance. In addition, they noticed that student engagement had an even bigger effect on lower achieving students.

Overall, the studies documented here constitute a basis for the importance of student engagement in college classrooms. Most engagement research studies pay more attention to the cognitive side of student learning, but this is not the focus of this study. However, some of the research in engagement literature focusing on emotional aspects of engagement overlaps considerably with interest and value constructs in the motivation research and shows similar results in both areas of research. Hence, engagement is not being investigated since emotional engagement overlaps considerably with motivation research. Engagement is only considered as an important aspect that influences student motivation but will not be investigated in this study.

A National Study on Calculus

In order to better understand the current situation in calculus courses in the U.S., a recent national study was examined. The Mathematical Association of America released a study in 2015 titled "Characteristics of Successful Programs in College Calculus", which was the first large scale investigation of Calculus I courses in the U.S. It provided a considerable amount of knowledge of who enrolled in Calculus I, what their preparation had been, and what they experienced during one semester (Bressoud, Mesa, & Rasmussen, 2015).

The researchers collected data in 2010 from four types of higher education institutions including PhD-granting universities, MA-granting universities, BA-granting universities, and AS-granting two-year colleges across the U.S. They documented that almost 300,000 students were enrolled in Calculus I in those institutions at the time and the distribution of the number of students in each type of institution was 110,100 in PhD-granting universities, 82,300 in BA-granting universities, 40,900 in MA-granting universities, and 65,000 in AS-granting institutions. They reported that majority of the students who enrolled in Calculus I were White (77%) or Asian-American (15%). Also, majority of the students' parents hold college degrees (mother completed college 62% and father completed college 65%).

In addition, a lot of the students taking Calculus I had done well in high school mathematics in a track that led them to calculus by 12th grade. In Calculus I courses, they found, in the fall semester measured, only 50% of the students earned an "A" or a "B" for the course, 23% of them earned a "C", and 27% of the students earned a "D", an "F", or withdrew from the course. It can be concluded that only half of the students were successful in calculus courses nationwide. The study also examined the impact of instructor and institutional factors on student attitudes. They investigated three affective outcome variables from students, which are - confidence, enjoyment of mathematics, and intention to persist in the study of mathematics in calculus courses. After some statistical analyses, they formed a composite mathematics attitude variable based on mathematics confidence, enjoyment, and persist, and called it "mathematics attitude".

Since not all of the students and instructors that participated in the national project completed all the surveys, Sonnert and Sadler (2015) only included 3,103 students in 308 classrooms and 123 institutions. They measured the variables of confidence, enjoyment of mathematics, and intention to persist by assigning two or three items for each of the variables included in the surveys. Students then rated those items on point-scales such as ranging from 0: (strongly disagree) to 5: (strongly agree). The same items were included in both pre-survey and post survey. Pre-survey was implemented at the beginning of Fall 2010 semester and post-survey was implemented at the end of the same semester.

Sonnert and Sadler (2015) found that student confidence, enjoyment of mathematics, and desire to persist in studying mathematics decreased between the beginning and end of their calculus courses. Hence, the mathematics attitude composite also decreased significantly. The researchers ran hierarchical linear models to determine how the outcome (student attitude in calculus) was partitioned into three levels - students, classrooms, and departments. They showed that students' prior experience with mathematics, their preparation in calculus, and prior attitudes towards mathematics shaped students attitude at the end of their calculus courses.

What they found in classrooms level was that *Good Teaching* (defined in the instructor impact section) improved students' attitudes about mathematics. Whereas, they noticed that *Ambitious Teaching* (collection of teaching characteristics such as the use of group projects, the inclusion of unfamiliar problems, and requirements for students to explain how they found their answers etc.) was negatively related to students' attitudes. In addition, they found that the use of technology in calculus classrooms did not influence student attitudes about mathematics one way or the other. As far as the impact of institution levels on student attitude, they found it to be limited. They argued that the impact of departmental characteristics on students' mathematics attitudes were mediated by the instructors' pedagogical practices. For instance, *Student-Centered* departments (promote student involvement) were associated with instructors *Good Teaching* (Sonnert & Sadler, 2015).

Overall, the MAA's study illuminated aspects of learning and teaching in calculus courses nationwide. In particular, the variables they investigated (confidence, enjoyment and persistence) are, to some degree, related to the motivational variables of this proposed study because these concepts are also affective factors for students. Hence, the results have some implications for future investigations in calculus classrooms. In addition, the national calculus project might be a guideline for the design of this study since it revealed a bigger picture of what is happening in calculus courses across the nation. By looking at the results of the project, it can be assumed that, for the most part, students are not performing well in Calculus I courses and it could be due to affective or motivational reasons.

The calculus project considered three affective variables of students, which were confidence, enjoyment, and intention to persist in mathematics. It only measured these variables and reflected on the changes that happened within the semester of data collection in 2010. Enjoyment could be well related to the interest concepts in motivation research; persistence could be related to the academic expectancies in the Expectancy-Value model. In addition, confidence is a concept that has been studied by motivation researchers previously.

It is necessary to focus more on student motivation using advanced items that measure specific motivation concepts such as utility value and interest, and to test how a possible intervention would influence student motivation to study Calculus - I.

Gender and Motivation in Mathematics

Gender difference in mathematics performance, attitude, and affect is a concern for the female presence in many areas of STEM fields (Halpern et al., 2007; National

Academy of Science, 2006). Some research in the United States has shown that the gender gap in mathematics performance has narrowed in K-12 settings (Hyde, Fennema, & Lamon, 1990; Hyde et al., 2008). However, the number of women pursuing higher education in math and science is declining (Panteli, Stack, & Ramsay, 2001).

Researchers commonly used Expectancy-value theory as a framework for investigating gender difference in student motivation and achievement related outcomes (Gaspard et al., 2015). According to this theory, value beliefs are a key factor in explaining gender differences in academic choices (Eccles, 2005, 2009). Research studies have investigated student utility value and examined differences in utility value in gender. For instance, Watt (2004) designed a longitudinal study investigating mathematics and English self-perceptions, values (intrinsic and utility), and task perceptions among adolescents in Australia. This study found no differences in gender among students from grades 7 to 11. Whereas Steinmayr and Spinath (2010) investigated three subjective task value components including importance, utility value, and intrinsic values between genders of German students in regard to German language, mathematics, physics and chemistry. The authors found that the differences in the students' utility value in mathematics favored males for 11th graders.

Watt, Eccles, and Durik (2006) examined student choices regarding mathematics participation by gender in high school settings both in Australia and the United States. They found that boys selected higher levels of mathematics more than girls in the Australian setting, but not in the U.S. sample. However, they found no difference between males and females in utility value and attainment value in Grades 9 and 10 in both Australian and the U.S. settings. Moreover, further motivation studies investigating differences in gender in both the United States and Germany found that girls reported less intense affectional constructs such as anxiety, hopelessness, and shame in mathematics than boys (Frenzel et al., 2007; Meece et al., 1990). These studies only give information about gender differences in mathematics in K - 12 settings, not higher education. Although the previous research studies discussed here took place in lower level education levels, they provide insights into how motivational differences occurred in between males and females.

Some previously discussed motivation intervention studies in higher education settings considered gender as a potential motivational aspect. Although their focus was not investigating gender differences, they did not find any differences between male and female students' motivation (Hulleman & Harackiewicz, 2009; Hulleman et al., 2009; Puruhito, 2011; Durik & Harackiewicz (2007). However, as it was discussed in this section, some studies found that males had higher motivation than females, and others showed no difference between males and females. Even though the main focus of this study is not investigating differences in motivation in gender in college setting, gender impact was considered as a potential impact on student motivation.

Applications of Mathematics

According to Muller and Burkhardt (2007), mathematics is taught to develop a competency in using mathematics concepts and skills to deal with problems from the "real world". Most mathematics curriculums use "illustrative applications" where the focus is on a particular mathematical topic showing the various practical contexts where it can be useful and practicing its use in those situations. One of the roles of applications of mathematics is, indirectly, *enhancing student motivation* (Muller & Burkhardt, 2007).

Students who encounter appealing applications will learn answers to the universal question: "Where am I going to use this?"

In this study, calculus tasks with science and engineering applications will be used as an example of illustrative applications. This means providing opportunities to connect science and engineering concepts to calculus, but not necessary designing a brand-new curriculum. Application approach is sometimes referred to as contextualizing. There are some calls to contextualize mathematics concepts in classrooms. The National Council of Teachers of Mathematics recommends that K-12 schools should provide opportunities to learn about mathematics by working on problems arising in contexts outside of mathematics. These connections can be applied to other subject areas and disciplines as well as to the student daily lives (NCTM, 2000, p. 65). In order for students to demonstrate depth of understanding, their learning experiences must provide them with the proper tools and contexts to do so (Schwalbach & Dosemagen, 2000).

There are research studies involving the idea of applications of science in mathematics courses. Literature published from 1990-2001 shows that there has been continuous support for science and mathematics education in the reform documents. However, more empirical research grounded in these theoretical models is clearly needed as we continue in the 21st century (Berlin & Lee, 2005).

Rogers (1997) states that curriculum, specifically in a K-12 setting, should use a sense of knowledge based in the real world as well as based on student experiences. He suggests that such a curriculum would engage students in rigorous and deep learning and encourage them to begin mapping their own understandings as a result of their experiences. Other literature supports the idea of applying real world situations into mathematics, in other words, contextualizing. Becker and Park (2011) state that the application of mathematics to science, technology, and engineering provides students with a context in which they can make meaningful connections between these subjects. They argue that such approaches could bridge abstract concepts in mathematics to practices in science, technology and engineering subjects.

For instance, Judson and Sawada (2000) implemented an action research, where they investigated the impact of applying mathematics into a science class to improve student achievement in mathematics. The participants were fifty-two junior high school students in the U.S. They found that students in these courses attained higher achievement scores. Although these studies exhibit applications of science with mathematics, they took place in K-12 settings. The focus of this study being higher education, they serve a perfunctory role for examination of this concept.

More importantly, Elliott et al. (2001) designed an experimental research to investigate the effect of an interdisciplinary course titled “Algebra for the Sciences” that measured students critical thinking skills, problem-solving skills, and attitudes towards mathematics. The participants were 211 students attending a university in the southwestern United States. Their study showed no significant difference in problem-solving skills between students in the interdisciplinary course and students in the college algebra course, whereas students in the interdisciplinary course had slightly larger gains in critical thinking and significantly higher positive attitudes toward mathematics. Therefore, it is necessary to see how applications of science and engineering, in some forms of practical tasks, into calculus courses might influence student attitudes and motivation.

Additionally, Marrongelle (2004) investigated how undergraduate students in an integrated calculus and physics class use physics to help them solve calculus problems. They followed a case study designed to examine different ways that students use the concepts in physics as they worked through calculus tasks. Data was gathered from four interviews that had eight student participants who studied at a public university in the northeastern U.S. The participants were enrolled in a class that followed The Integrated Calculus and Physics (ICP) curriculum of that university. This was a year-long program designed for undergraduate science, mathematics, and engineering majors at the university. The course was team-taught by a mathematician and a physicist and assisted by mathematics and physics graduate students. Their team organized topics from the standard first-year university calculus and physics curriculums at their institution in order to determine the maximum number of complementary topics.

In Marrongelle's (2004) case study, twenty-one calculus tasks were used to elicit information about how the students used physics to help them solve calculus problems presented in various contexts. The results showed that some of the students were able to successfully make connections between the physics and mathematics as they solved problems. This study has implied how science concepts helped calculus students to make connections. However, they designed an entire curriculum to accomplished that, which is not the scope of this proposed study. If integrating physics problems into calculus is a way to improve student learning, then a similar approach could potentially improve their motivation in calculus courses.

Instructional Tasks

In mathematics education, instructional tasks or activities are utilized as part of teaching. Maciejewski and Merchant, (2016) claim that instructional tasks assigned by instructors and experienced by students, impact student conceptions of the subject and their approaches to study the subject. They also argue that tasks impact student academic performance.

Alvarez (2002) conjectures that if K-12 students are engaged when doing academic tasks, then they may acquire a good amount of knowledge, since engaged students are prepared to take a personal risk in the learning task. These claims might also hold in college settings. When college education is considered, it is common sense to recognize that most classrooms in colleges are traditional, lacking in academic tasks that can engage students. Researchers claim that in traditional calculus courses, the constant stream of information leaves students scrambling to take accurate notes with little time to process questions and concepts (Beswick & Ramsden, 1987). Therefore, instructional tasks within calculus classrooms, in particular the ones that provide students with the opportunity to contextualize the content, might be useful to improve student conceptions of calculus topics and their motivation to study the subject.

Instructor Impact

In general, first year STEM field students find introductory courses meaningless and unrelated to their career plan. One of the common complaints is the lack of quality faculty as well as the absence of quality teaching at the undergraduate level of education (Wulf, 2007). Several studies found that poor teaching and lack of supportive faculty and demanding workload of STEM programs have led to low retention rates (Astin, 1993;

Hayes, 2002). Another example is from Hong & Shull (2010), who conducted an exploratory study on six successful engineering students through a case study approach. The study found that the students' frustration stemmed from the lack of quality faculty and the absence of quality teaching in the undergraduate engineering program. They found that students perceived their professors as either a significant source of support or the root of their frustrations. Findings from the study revealed that faculty significantly influenced the sustainability of STEM students.

Sonnert, Sadler, Sadler and Bressoud (2015) investigated changes in students' attitudes toward mathematics during a calculus course while controlling for student backgrounds. The data used in this study originated from the Characteristics of Successful Programs in College Calculus (CSPCC) project which was conducted by the Mathematical Association of America (MAA). The study considered data from 3,103 students at 123 colleges and universities in the U.S. They measured students' self-ratings of their mathematics confidence, interest, and enjoyment of mathematics. They found that teachers who employed *Good Teaching* practices had a positive impact on students' attitude. From the data collected as part of the national calculus project, Sonnert, Sadler, Sadler and Bressoud (2015) investigated the components of *Good Teaching* practices. Their analysis showed twenty-two items related to *Good Teaching* consolidated into three factors: Classroom Interactions that Acknowledge Students, Encouraging Instructors, and Fair Assessments.

Classroom Interactions that Acknowledge Students was a component of *Good Teaching* that encouraged students' participation by presenting various methods for solving problems, helping them to improve their problem-solving skills, asking questions to measure student understanding, and listening to students' questions and comments. Encouraging Instructors referred to students' perceptions that their instructors encouraged them to take Calculus 2, their instructors invited them to office hours, and made themselves available outside of their office hours as needed. Lastly, Fair Assessments referred to students' ratings of the assignments and examinations in Calculus I courses. In addition, it included student perceptions about the grading and feedback on their exams and homework.

Thus far the research documented here gives insight into the potential instructor impact in calculus courses. Therefore, it is important to consider the potential impact of instructors in calculus, but it is not the focus of this study. Moreover, instructor impact in this study will be minimized and the reasons for this will be explained in the methodology chapter.

Conceptual Framework

This study investigates student motivation in Calculus I courses. As it was discussed earlier, the Expectancy-Value Model and the interest theories guide this study to better understand students' motivational aspects. A conceptual framework was adapted from the way Hulleman et. al. (2010) investigated interest, utility value, and performance expectations based on the Expectancy-Value Model and the existing motivation research (Appendix A for their framework). Utility value, interest and performance expectations were chosen for investigation and hence, these concepts were included in the conceptual framework of this study (Figure 2).

The conceptual framework was the main argument of this study where these chosen concepts were relevant to address the research questions designed for the scope of the study (Lester 2005).

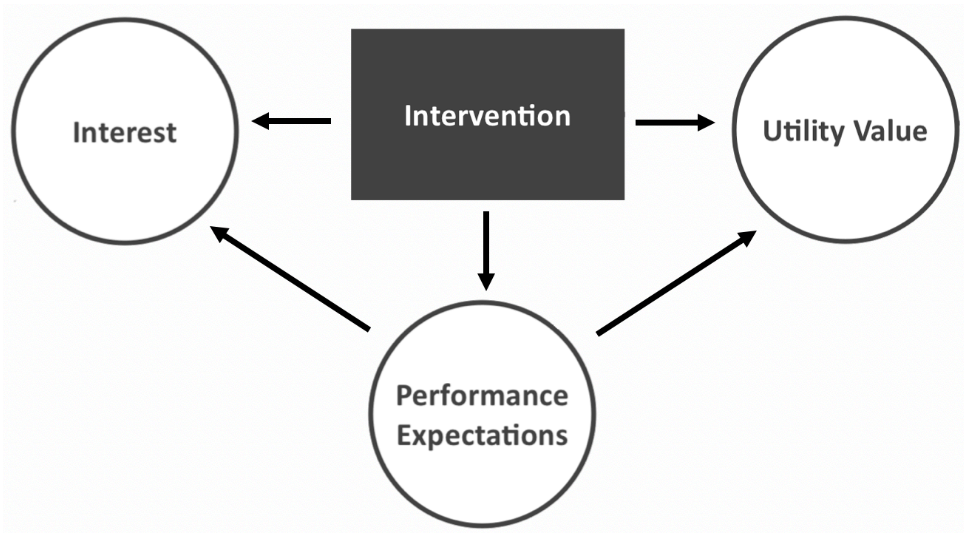


Figure 2: Conceptual framework of the study

III. METHODOLOGY

Introduction

As several reports and studies addressed, student retention in STEM fields has emerged as an important issue in the United States (NCES, 2014; NCES, 2009; BHEF, 2014; TAP, 2008, Baldwin, 2009). Introductory STEM field courses, in particular calculus courses, are seen as a roadblock to STEM fields (Steen, 1987). Research is needed to better understand and address issues in calculus courses since it is related to student retention in STEM fields. Some students in calculus courses do not see the relevance of the material and they encounter topics that may appear useless to their own lives and future careers. Therefore, making science and mathematics courses personally relevant and meaningful may engage students in the learning process.

This study investigates motivational aspects including performance expectations, utility value, and interest in calculus courses. The study followed a quasi-experimental research design. The purpose of the study was to measure the impact of an intervention, which is the implementation of the Calculus Tasks with Science and Engineering Applications in calculus courses in order to improve student motivation. To accomplish the purpose of this study, following research questions were investigated:

1. How do the Calculus Tasks with Science and Engineering Applications impact students' motivational aspects, including utility value, interest, and performance expectations in college Calculus I courses?
2. How does the impact of the Calculus Tasks with Science and Engineering Applications differ based on student gender, intended majors and race in college Calculus I courses?

3. How do students' motivational aspects, including utility value, interest, and performance expectations change within a semester in college Calculus I courses?

Figure 3 has been provided to show the timeline of this study. Each step in this process will be described in the following sections.

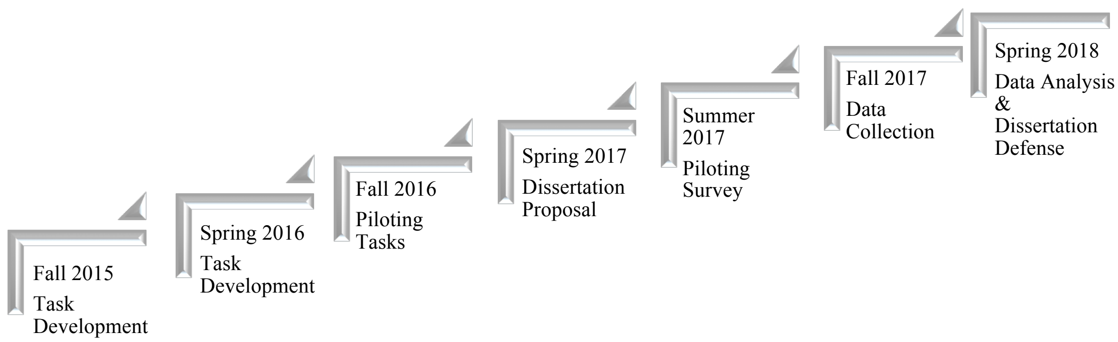


Figure 3: Timeline of the study

Pilot Study

In preparation for the main study, pilot studies were conducted during the fall 2016, spring 2017, and summer 2017 semesters. The pilot study consists of two components. The first component was to pilot a motivation survey that was adapted from surveys used in previous studies (Hulleman et al., 2010; Pintrich, 1991). The second component of the pilot study was to pilot the Calculus Tasks with Science and Engineering Applications in order to improve their clarity, accessibility of the content, and notation.

Piloting the Calculus Motivation Survey

The survey, titled "Calculus Motivation Survey", was adapted and developed in order to gather information about student motivation in calculus (see Appendix B for the pilot survey). The survey was piloted in Calculus I and Calculus II courses during summer 2017 at a public university in central Texas. Although the focus of the intervention was on Calculus I courses, there was a need to have more participants and Calculus II students were included. Total of 119 calculus students took the survey in June 2017 from two Calculus I courses and three Calculus II courses. The survey was administered at the beginning of their first-class day for all the calculus sections. Survey responses from all courses were used to test initial reliability and dimentiality properties of the survey.

The purpose of the piloting was to obtain initial reliability and dimensionality properties by conducting an exploratory (factor) analysis, but the survey was also tested for these properties with only Calculus I students that actually participated in the study. The results of the Confirmatory Factor Analysis and reliability are consistent with the results obtained in the piloting stages (See Chapter IV).

Survey development. Survey development took place during the piloting phase of this study in Summer 2017. Most of the items in the survey were adapted from Hulleman, Godes, Hendricks, and Harackiewicz (2010) study (Appendix C). They developed a survey for psychology courses to measure student motivational aspects. Since the theoretical base of this study was aligned with the Hulleman et al. (2010) study, it was appropriate to adapt the survey that they used in their study. However, since the context in which they used the survey was different, adaption efforts were necessary in order to implement it in calculus courses.

At first, a pilot survey was developed (Appendix B). The items that measured utility value and interest were adapted from Hulleman et al. (2010). The items 4, 5, and 6 in this study were utility value items that were tested in the Hulleman et al. (2010) study. The alpha scores of these utility value items were 0.88 combined. The items 7, 8, 9, 10, 11, 12, and 13 in the pilot survey tested for interest. The alpha scores of the interest items were 0.92 combined in the Hulleman et al., (2010) study.

The performance expectation items in the pilot survey were adapted from *A Manuel for the Use of the Motivated Strategies for Learning Questionnaire* (Pintrich, Smith, Duncan, & Mckeachie, 1991). Only three items were selected from many other items about performance expectations. The top three performance expectations items in Pintrich et al. (1991) that best predicted student performance were selected for this study. The alpha scores of the chosen items in Pintrich et al. (1991) was 0.93 combined. Therefore, the initial survey consisted of thirteen items, three of which were performance expectation items, three were utility-value items, and seven items were interest items. The items in the initial scale had response scale ranging from -3 (strongly disagree) and 3 (strongly agree).

Exploratory factor analysis and internal reliability. After administering the initial pilot survey to collect data, statistical analysis techniques were used in order to analyze the survey responses. The statistics software SPSS version 25 was used in this study. As was discussed earlier, 119 students took the initial survey as part of the piloting. The reliability of the initial pilot survey was 0.90 (Cronbach's Alpha), which is considered as very high (Table 1).

Table 1

Reliability statistics of the pilot survey.

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.901	.897	13

The mean scores of each item in the pilot survey is listed in Table 2. While the items int13, utv5, pef2, and pef3 had higher mean scores, the items int7, utv6, and int9 had lower mean scores in the piloting stage.

Table 2

Item statistics in the pilot survey.

	Mean	Std. Deviation	N
pef1	.71	1.508	119
pef2	1.10	1.324	119
pef3	1.05	1.241	119
utv4	.99	1.639	119
utv5	1.18	1.584	119
utv6	.16	1.771	119
int7	.11	1.789	119
int8	.53	1.682	119
int9	.19	1.653	119
int10	.55	1.863	119
int11	.82	1.577	119
int12	.24	1.650	119
int13	1.92	1.592	119

In addition, item total statistics for each item in the pilot survey is listed in Table 3. This table provides information about potential change if a particular item deleted from the pilot survey. It is interesting to note that if the item int13 was deleted, the survey would have resulted the highest reliability score.

Table 3

Item-total statistics for each item in the pilot survey.

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
pef1	8.85	180.621	.440	.779	.900
pef2	8.46	183.573	.429	.796	.900
pef3	8.51	186.252	.382	.659	.902
utv4	8.57	172.010	.605	.782	.893
utv5	8.38	168.576	.721	.829	.888
utv6	9.40	165.988	.693	.638	.889
int7	9.45	165.419	.698	.650	.889
int8	9.03	163.389	.803	.784	.884
int9	9.37	165.608	.761	.738	.886
int10	9.01	161.093	.765	.752	.885
int11	8.74	172.042	.633	.596	.892
int12	9.33	162.900	.833	.796	.882
int13	7.65	194.349	.086	.164	.915

Exploratory factor analysis was run in order to find underlying dimensions of the pilot motivation survey. In other words, it was aimed to test whether performance expectations, utility value and interest formed three dimensions. It was also aimed at reducing unnecessary data. In addition, Principal Axis Factoring was selected as an Extraction Method to be able to reduce data. Table 4 shows the Factor Matrix for the pilot survey.

Table 4

Factor matrix in the pilot survey.

	Factor		
	1	2	3
pef1	.483	**.764**	.100
pef2	.470	**.820**	.042
pef3	.398	**.712**	.116
utv4	**.672**	.013	-.560
utv5	**.808**	-.029	-.564
utv6	**.736**	-.128	-.195
int7	**.730**	-.157	.197
int8	**.846**	-.186	.142
int9	**.813**	-.208	.149
int10	**.815**	-.221	.220
int11	**.668**	-.169	.230
int12	**.871**	-.207	.149
int13	.098	-.154	.137

Note. 3 factors extracted. 19 iterations required.

Table 5 provided pattern matrix that showed three distinct components for each of the motivation dimensions that were hypothesized. Since patterns matrices are considered as reliable sources for determining factor loadings for dimensions, this table was used to make judgements about the items used. According to Table 6, the item pef1 had .90, pef2, .94, and pef3 had .94 factor loadings for the component 2. Thus, all the performance expectations items fell into the same component.

The utility value items, utv3, utv4, and utv5 had the factor loadings 0.954, 1, .597 accordingly. Thus, these items perfectly fit into the same component. In addition, the interest items int7, int8, int9, int10, int11, and int12 had the factor loadings of .77, .81, .80, .89, .77, and .84 accordingly. Therefore, all of these items fell into the same component. However, the item int13 had negative factor loading for the component 1. It was not strongly correlated to the other interest items (items 7, 8, 9, 10, 11, and 12). In addition, the deletion of this item resulted in higher overall reliability (Table 3). Therefore, item 13 needed to be deleted from the pilot survey.

Table 5

Pattern matrix in the pilot survey.

	Component		
	1	2	3
pef1	.026	**.906**	-.013
pef2	-.073	**.946**	.058
pef3	.012	**.840**	-.058
utv4	-.132	.008	**.954**
utv5	-.023	-.008	**1.004**
utv6	.261	-.031	**.597**
int7	**.776**	.037	-.023
int8	**.812**	.016	.088
int9	**.808**	-.011	.070
int10	**.890**	-.006	-.023
int11	**.774**	.020	-.086
int12	**.846**	.002	.088
int13	-.288	-.104	-.144

Note. Rotation converged in 5 iterations.

In addition, Table 6 shows the total variance explained by each item and by considering all the items cumulatively. As it can be seen, 74% of the variation was accounted for the first three components, this means that the majority of the variation was account for the three components that were hypothesized before.

Table 6

Total variance explained by each component in the pilot survey.

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.305	48.499	48.499	6.049	46.532	46.532
2	2.245	17.272	65.771	2.027	15.592	62.123
3	1.179	9.066	**74.837**	.918	7.062	69.185
4	.919	7.068	81.905			
5	.565	4.345	86.251			
6	.448	3.446	89.697			
7	.334	2.569	92.266			
8	.277	2.135	94.400			
9	.197	1.518	95.919			
10	.166	1.280	97.198			
11	.146	1.120	98.318			
12	.116	.895	99.213			
13	.102	.787	100.000			

Note. When factors are correlated, sums of squared loadings cannot be added to obtain a total variance.

At the conclusion of the survey analysis work, it was determined that the instrument was reliable, and a slight modification was needed. As explained earlier, the item int13 was removed. Hence, the instrument that was used for the main study consisted of the remaining 12 items, and the order of the items on the survey was kept exactly the same. During the actual study, the survey was administered, and a Confirmatory Factor Analysis and reliability test was conducted providing similar results (see the Instruments section).

Piloting the Calculus Tasks with Science and Engineering Applications

Piloting the Calculus Tasks with Science and Engineering Applications consisted of several efforts to determine their potential to impact student motivation. This study utilizes Calculus Tasks with Science and Engineering Applications as a way to help students connect calculus concepts to their future careers, and hence student performance or engagement on the tasks was not of interest. The purpose of piloting the Calculus Tasks with Science and Engineering Applications was to investigate the clarity and content appropriateness of the tasks and to have insights on student thoughts and feelings about the tasks. However, these were not analyzed since the focus of the study was to investigate student motivation.

During the spring 2017 semester two of the Calculus Tasks with Science and Engineering Applications, a physics task and a computer science task, were piloted in Calculus I courses. Tasks were implemented during the lab portion of three different Calculus I courses. The Instructor of Record for those courses was not present at the time. Students were divided into groups to work on the tasks with their groupmates. The researcher facilitated this process, provided any contextual knowledge necessary, and addressed any difficulties that the students had. The students were asked to voluntarily work on these tasks and provide feedback about the clarity of the content. Students were not graded for their performance.

The third calculus task, the engineering task, was piloted on a Calculus III student during the Summer 2017. This particular student was chosen because they had just passed Calculus I at the time, and they volunteered to be part of the pilot study. The student volunteered to work on the task and provide feedback during the informal meetings. The student was expected to perform the task and interact with the researcher. Again, the purpose of this interview was to gather information about the clarity and appropriateness of the task from a student perspective. For instance, the researcher asked questions like "How do you feel about this task?" or "Is there any part that is not clear to you in this task?". The student did not get any grades, and their performance was not measured.

Overall, the piloting stage of the tasks provided critical information about the tasks. The researcher was able to fix some of the issues including typos and number errors, and to provide more description about the context of the tasks. For instance, in the physics task, students were not able to remember some of the necessary formulas at the piloting stage. After piloting the tasks in classrooms, the researcher was able to edit the tasks and to determine the best way to implement them in the actual data collection process of this research project. See the final versions of the tasks in Appendix D, E and F.

Design of the Study

The goal of this study is to test the impact of an intervention, which is the implementation of the Calculus Tasks with Science and Engineering Applications in calculus courses in order to measure the impact on student motivation. To accomplish this goal, the study followed a quasi-experimental research design.

Three Calculus I Instructors of Record were selected to participate in the study based on the fact that they were teaching more than one section of the course. Each of the instructors had two sections of calculus courses, each section was randomly assigned to a treatment and comparison group. Figure 4 represent this structure for each instructor. The intervention was implemented during the lab portion of the courses. The treatment group was exposed to the implementation of tasks, while the comparison group did "business-as-usual". What this means is that the TAs for the comparison groups covered what was normally planned. In the Department of Mathematics at this institution, TAs for Calculus I courses typically lead the lab portions by solving problems from the textbook, facilitating question and answer sessions and group work, and reviewing for examinations.

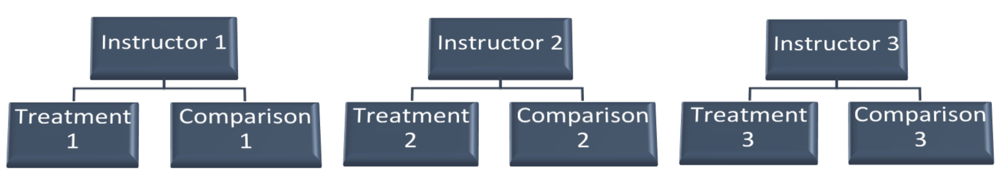


Figure 4: Setting of the treatment and comparison groups

According to the national calculus study (Bressoud, D., Mesa, V., & Rasmussen, C., 2015) instructor impact was found to be a significant factor on student attitude and beliefs in calculus courses. Therefore, it was aimed to minimize the instructor impact in this study by including treatment and comparison groups within each instructor's calculus course and to be able to compare treatment and comparison groups within each instructor's course.

Setting

This study took place at a public university in central Texas in Fall 2017. At this institution, calculus courses are being taught in the Department of Mathematics and these courses are required for most STEM field students. There are various calculus courses offered at the department including differential and integral calculus, calculus for life sciences, and calculus for business and economics.

This study only focuses on a differential and integral calculus course, which is called Calculus I, at this institution. In the Department of Mathematics at this institution, Calculus I courses have a lecture component taught by an Instructor of Record and a lab component that is led by a teaching assistant (TA). Typically, the instructors are PhD's in mathematics or mathematics education and TAs can be undergraduate, masters, or doctoral students holding different teaching positions.

The instructors in this study had varying background and teaching experiences. Instructor 1 holds a PhD degree in mathematics education and was working as a Lecturer in the Department of Mathematics. Although 2017 was his first-year teaching calculus as an Instructor of Record, he had many experiences teaching it as lab instructor before. Instructor 2 holds a PhD degree in mathematics. He has more than ten years of experience in teaching college level mathematics and taught calculus several times. Instructor 3 holds a PhD degree in mathematics. He has more than five years of teaching experience in mathematics and taught calculus courses before. Even though this study does not investigate instructor practices, this information is provided in order to provide an insight into the instructor's background.

In the Department of Mathematics at this institution, the adapted textbook, James Stewart's Calculus (8^{th} edition), is being used in all the calculus courses. This textbook is widely known for their mathematics precision and accuracy, clarity of exposition, and problem sets. All the instructors in this study assigned weekly and daily home-works from the textbook. Instructor 1 assigned home-works from the textbook and collected during the courses. Instructor 2 assigned and collected homework from the online website of this textbook. Instructor 3 assigned home-work from the textbook but did not collect them.

In this study, even though each treatment and comparison group had the same Instructor of Record, they did not have necessarily the same lab teaching assistant. The treatment and comparison groups in Instructor 1's courses were taught by two different teaching assistants who were both undergraduate mathematics students. However, in Instructor 2's courses, the same teaching assistant taught both treatment and comparisons groups. The TA for Instructor 2 was a doctoral student in mathematics education. In Instructor 3's courses, the same teaching assistant taught both treatment and comparisons groups. The TA for Instructor 3 was a masters student in mathematics. Since each instructor had both treatment and comparison groups, it was valid to compare the treatment and comparison groups within each instructor. Even though the TAs were different for some instructors, students in both treatment and comparison groups had very similar learning experience, since they attended the main lecture from the same instructor.

Participants

Participants in this research are students who were enrolled in Calculus I courses in the Department of Mathematics at the institution in Fall 2017. Approximately 178 students were involved in this study, however varying number of those students were considered for the data analysis since not all the participants responded to the instrument used to collect data. The participants were asked to sign a consent form.

Table 7 shows the distribution of the students to each of instructors and their labs which were treatment and comparisons groups. 178 students responded to Survey 1, 119 students responded to Survey 2, and 98 students responded to Survey 3 in total. Also, the number of participants from each instructor's comparison and treatments groups were provided in Table 7. As it can be seen from Table 7, the number of students in comparison and treatment groups were close for the most part for each instructor's course.

Table 7

Distribution of the number of participants responded to all the surveys.

survey			Groups		Total
			Comparison	Treatment	
1	Instructor	1	33	23	56
		2	29	22	51
		3	38	33	71
	Total		100	78	**178**
2	Instructor	1	20	26	46
		2	15	20	35
		3	22	16	38
	Total		57	62	**119**
3	Instructor	1	11	16	27
		2	15	17	32
		3	22	17	39
	Total		48	50	**98**

Note. (treatment=0 is comparison group and treatment=1 is treatment group).

Table 8 shows the distribution of students that responded to each survey based on their gender. Forty-eight female students responded to Survey 1, with 27 of them in comparison groups and 21 of them in treatment groups. Likewise, 30 female students responded to Survey 2 and 13 were in comparison groups, while 17 were in treatment groups. 30 female students responded to Survey 3, with 12 in comparison groups and 30 in the treatment groups.

According to Table 8, 130 male students responded to Survey 1, with 73 in the comparison groups and 57 in the treatments groups. Likewise, 86 male students responded to Survey 2, and 42 were in the comparison groups with 44 in treatment groups. Lastly, 66 male students responded to Survey 3, and 36 were in comparison groups while 30 were in the treatment groups.

Table 8.

Number of male and female participants responded to all the surveys.

Survey			Groups		Total
			Comparison	Treatment	
1	Gender	Female	27	21	48
		Male	73	57	130
	Total		100	78	178
2	Gender	Female	13	17	30
		Male	42	44	86
	Total		55	61	116
3	Gender	Female	12	18	30
		Male	36	30	66
	Total		48	48	96

Note. (gender=0 is female and gender=1 is male, and treatment=0 is comparison group and treatment=1 is treatment group).

Table 9 provides information about the participants who responded to all the surveys based on each race categories. The majority of the students that responded to Survey 1 were in the race category of White (81 students), Hispanic (54 students), and mixed race (19 students). Similarly, most students that responded to Survey 2 were in the race categories of White (51) and Hispanic (40). Finally, most students that responded to Survey 3 were in the race category of White (41) and Hispanic (25). Also, Table 9 shows the race distribution of the students within each instructors' course.

Table 9

Number of participants responded to the surveys categorized by race.

Survey			Race 1	2	3	4	5	6	Total
1	Instructor	1	2	1	18	9	26	0	56
		2	1	5	15	2	28	0	51
		3	5	8	21	8	27	2	71
	Total		8	14	54	19	81	2	178
2	Instructor	1	2	2	18	3	19	0	44
		2	1	4	11	2	17	0	35
		3	6	5	11	1	15	0	38
	Total		9	11	40	6	51	0	117
3	Instructor	1	2	2	6	3	12	0	25
		2	0	4	10	2	16	0	32
		3	5	6	9	5	13	1	39
	Total		7	12	25	10	41	1	96

Note. (1=Asian, 2=Black, 3=Hispanic, 4=Mixed, 5=White, and 6=Other).

Table 10 provides information about the participant race in the comparison and treatment groups for each instructor. In total, the majority of the students in the comparison groups were in three race categories: 92 students were White, 59 students were Hispanic, and 21 students mixed race. In the treatment groups, most students were in the three race categories: 81 students were White, 60 students were Hispanic, and 19 students were Black.

Table 10

Number of participants in treatment and comparison groups categorized by race.

Groups			Race						Total
			1	2	3	4	5	6	
Comparison	Instructor	1	0	2	21	9	31	0	63
		2	0	5	15	3	36	0	59
		3	13	11	23	9	25	1	82
	Total		13	18	59	21	92	1	204
Treatment	Instructor	1	6	3	21	6	26	0	62
		2	2	8	21	3	25	0	59
		3	3	8	18	5	30	2	66
	Total		11	19	60	14	81	2	187

Note. (1=Asian, 2=Black, 3=Hispanic, 4=Mixed, 5=White, and 6=Other).

An additional table that provides information about the background of the participants of this study is Table 11. It shows the number of male and female participants distributed to each major category for each survey.

Table 11.

Number of male and female participants categorized by each major.

Gender			Major					Total
			1	2	3	4	5	
Female	Survey	1	10	10	7	4	17	48
		2	8	6	4	1	11	30
		3	8	7	2	1	12	30
Male	Survey	1	65	38	6	5	15	129
		2	49	27	2	1	6	85
		3	34	22	3	1	6	66
Total	Survey	1	75	48	13	9	32	177
		2	57	33	6	2	17	115
		3	42	29	5	2	18	96

Note. (1=engineering, 2=computer science, 3=mathematics, 4=physics, 5=other).

Table 12 provides information about the distribution of the participants in the comparison and treatment groups categorized by each major. It is important to note that most students were in engineering and computer science majors, confirming the initial assumption when selecting the tasks.

Table 12

Number of participants in treatment and comparison groups categorized by major.

Groups			Major					Total
			1	2	3	4	5	
Comparison	Survey	1	40	26	7	8	19	100
		2	25	16	4	2	9	57
		3	21	12	3	2	10	48
Treatment	Survey	1	35	22	6	1	13	77
		2	33	19	2	0	8	62
		3	22	17	2	0	8	49
Total	Survey	1	75	48	13	9	32	177
		2	58	35	6	2	17	119
		3	43	29	5	2	18	97

Note. (1=engineering, 2=computer science, 3=mathematics, 4=physics, 5=other).

Intervention

The mechanism of the intervention is students engaging in the *Calculus Tasks with Science and Engineering Applications.* These tasks were science and engineering problems in nature, but they required calculus knowledge to perform. They were developed in order to motivate students to study calculus. It is hypothesized that two interventions of about 80 minutes each would be sufficient to change student motivation. Previous motivation researchers found positive impact with small interventions such as short writing assignments. The background of the development of the tasks and some of the characteristics of the tasks will be described next.

Development of the Calculus Tasks with Science and Engineering Applications

These tasks were developed by a team of instructors and professors from the Mathematics, Physics, Computer Science, and Engineering departments at this institution. The development of the tasks was a part of a research grant project (NSF STEM Rising Starts) that aimed to improve the quality of instruction in STEM courses in part by designing interdisciplinary curricula at the institution where this study was conducted. Several workshops were organized as part of the task development, and the professors and instructors spent hours together to come up with useful calculus tasks that could potentially motivate students. The researcher of this study also attended those workshops to collaborate with the other project people and examine the early stages of the tasks.

The Calculus Tasks with Science and Engineering Applications were only validated in terms of their content by the authors of the tasks. Hence, they may only be appropriate for students at the institution where this study took place. Since the authors of the tasks were not necessarily calculus or mathematics instructors, the tasks may include some mathematical content that students were not familiar with and this may in turn affect their motivational aspects. Best efforts were made during revision in the piloting process and implementation of the tasks to ensure that students were comfortable with the technical notation and wording of the different fields outside of calculus. Moreover, the tasks were content validated by two mathematics instructors but there was no systematic approach before the tasks were developed to ensure this aspect.

Features of the Calculus Tasks with Science and Engineering Applications

The tasks used in this study were homegrown, meaning they were developed by the professors who work at the institution where this study took place. These professors were dedicated to motivating their own students, therefore they were part of this initiative to develop calculus tasks. This situation itself describes how much they were concerned about their students learning in calculus courses; and not only the mathematics professors, but the science and engineering professors as well.

Another unique feature of the tasks is that they were designed to provide authentic problems from science and engineering disciplines and they were developed by the instructors teaching those fields and discussed in their own courses. The calculus students at this institution were likely to have those instructors in their future courses because most of the students involved in this study were engineering and computer science majors. For instance, the engineering task was written by the engineering professor who teaches manufacturing engineering courses (Appendix F). The professor claimed that he had used similar problems in his engineering courses before many times. Moreover, these tasks were a product of collaboration of instructors from different STEM fields and they all were aware that student performance in calculus courses was a key factor in their students' retention in these fields.

Rationale for the Selection of Tasks

While several tasks were designed by the team of instructors, only three were selected and adjusted for this study. In this study, three Calculus Tasks with Science and Engineering Applications were used as means of an intervention for the treatment groups. One was the physics task (Appendix D), one was the computer science task (Appendix E) and the third one was the engineering task (Appendix F).

The physics task involved a free-kick of an object context where students applied optimization techniques using derivatives. The computer science task was a problem where students compared the growth of computational algorithms (similar to function concepts in mathematics) using limits. The engineering task involved a real-world situation where students used inverse functions and linearization to design thermometers.

The rationale behind selecting these tasks was based on the number of students who typically enroll in calculus courses, and the distribution of that number to each intended major. In the Department of Mathematics at the institution where the study was conducted, the number of students who intended to major in computer science and engineering and were taking Calculus I were highest compared to other majors (Data provided by the Department of Mathematics). Therefore, the computer science and engineering tasks were used in order to target the majority of students who might have potentially been more interested in these tasks based on their future career plans. The Physics problem was chosen because it was a task that the physics professors use in their Mechanics courses; a requirement for not only the science major students, but also for the most engineering students at this institution.

It was hypothesized that using these three tasks as an intervention would have great potential for changing the targeted students' motivation to study calculus. The intervention provided opportunities for the students to experience science and engineering concepts related tasks during their mathematics coursework. As discussed earlier, contextualizing and making applications more explicit are critical aspects in mathematics courses and this intervention aimed to help students to see the relevancy of calculus topics and this, in turn, improve their motivation.

Alignment of the Tasks with Motivation Theories

These tasks were developed in order to provide the opportunities for the students to relate the calculus topics to their goals or future careers, to promote their interest to engage in calculus material, and, ultimately, keep them in STEM fields.

Some of the unique features of the tasks address the main motivational aspects that this study investigated. The tasks provide authentic science and engineering applications that require calculus knowledge and skills as a tool. In this respect, the tasks relate to the utility value concept of motivation. The students were expected to relate and connect the calculus material to their goals and future careers through the interaction with the tasks. For instance, through the physics task, the students were expected to optimize the distance a ball travel by applying derivative knowledge. Although the physics task is similar to problems in many existing calculus texts, it is different in terms of its ability to provide a window into the content and expectations of the next course in Mechanics with the possibility of the students having the authors of the tasks as their future instructors.

Moreover, the tasks were aimed to spark student interest in calculus material, which is related to the interest aspect of the motivation theories. Participation was expected to trigger responses from the appealing characteristics of the tasks through student interaction with the tasks. For instance, in the engineering task, the students were supposed to solve a problem related to a digital thermometer in real life. This situation creates an opportunity for students to feel like they are engineers solving a real-life problem. In fact, during the piloting stage of the tasks, one of the students stated that:

> "I really enjoyed it. It kind of put me in the situation where my job would ask me to do something it's not just a straight a math question. It test the concepts of math but it's a question that test your logic and your reasoning and how you can use math to apply it to a real-world scenario, so it was enjoyable".

This observation implies that the task was enjoyable for the student.

Implementation of the Intervention

As this is a quasi-experimental study in nature, the intervention was designed to measure the extent to which the intervention had an impact on student motivation. The purpose of the intervention was to help students connect why they need to learn calculus with why they will need the calculus knowledge in their goals or future careers, and also to trigger their interest in studying calculus. The idea behind the implementation was to provide opportunities for the students to see the relevancy of the calculus material. Student performance or reasoning on the particular tasks was not considered in this study.

Another piece that was aimed to promote student motivation was the background of the development, and characteristics of the tasks. The tasks were implemented in a way that showed how involved the faculty were with the students at the institution, and how much they cared about student motivation in calculus courses. The intervention engaged students in the chosen tasks during the lab portion of their calculus courses. The treatment groups were given Intervention 1 and Intervention 2 during the Fall 2017 semester.

Timing of the intervention was determined based on the content of each of the tasks, and the materials covered during the calculus courses. The physics and the computer science tasks were implemented in Intervention 1 in late October, because the instructors covered the topics of limits and derivatives completely in their calculus courses at that time. The engineering task was implemented early December because the calculus courses covered inverse functions in late November.

Implementation protocol. The protocol is attached in Appendix G. Each step in the protocol will be described in this section in order to provide insights into how these tasks were planned to be implemented during Calculus I courses. The protocol was designed in order to be able to implement in a classroom size around 20-30, but it could also work in a smaller class.

The introduction of the task is one of the motivational parts of the study. First, it aimed to provide details about the background of the study by including the information about the instructors (all the instructors from the science, engineering and mathematics departments) and how they developed the tasks. Also, some information about the instructors that was provided including the courses they teach and the department in which they work. Their pictures were also provided for the students to show they are actual instructors working at the institution.

Then the development stage of the tasks was discussed. The interdisciplinary collaboration between the instructors was stated and the fact that science and engineering professors value students learning calculus was also emphasized. Additionally, it was stated that these tasks were being implemented during the class to help students to connect and relate calculus concepts to their goals and future careers.

After introducing the task, the context and story of the task is presented to the class. Then, necessary exploration about the context, including required definitions and formulas, for the task was provided. The students were not expected to know about the tasks. For instance, a computer simulation was planned to present the idea of free kick in the physics problem. Also, the formulas and definitions were prepared to provide opportunities for the students.

After introducing the story of the task and necessary knowledge about the task, the students were broken into groups. They were expected to collaborate with their groups members to perform the tasks. Meanwhile, the researcher aimed to facilitate the class discussions and provide any help that was necessary for the students. During this stage the researcher aimed to make connections to calculus and tried to spark student' interest about the tasks. For instance, the researcher prompted questions including: "In order to optimize the function that you found for the distance, what tool do we need?" or "For the computational algorithms, what computation d we need in order to be able to compare algorithms?”. The purpose of these prompts is to have students notice why they need calculus as a tool.

After students completed their work, the aim was to discuss the task as a class and to have students share their work and thoughts. During that process, the researcher aimed to motivate students by revisiting the idea of the why they needed calculus as it was seen in the given task. The researcher informed the instructors about the implementation protocol before going into classrooms to do intervention. In the next part, how the three tasks were actually implemented in the classrooms is documented.

Intervention 1. Intervention 1 was given in late October in the lab portion (it was called treatment groups) of the selected Calculus I courses. Two tasks, the engineering task and the computer science task, were implemented in the same class day in the treatment groups. Typically, each class days for Calculus I labs are 80 minutes in the Department of Mathematics. Ample time provided for the students to work on tasks during the implementation. The lab instructors did not show up on the day Intervention 1 was implemented, but they showed up on the day that Intervention 2 was implemented. The principal researcher facilitated the labs when implementing the treatments for all the three treatment groups. The Intervention 1 was implemented as follows exactly the same in all the three treatment groups.

The researcher first started the class by introducing himself and the research project. Then, he went over the consent form and talked about the design of the study and how this experience would help the students. Also, the development phase of these tasks was described. Tasks were printed out in a handout including the consent form and was given to each participant. The emphasis was given on the professors who were involved with the task development team and how the students might potentially end up taking those professors' courses in the future. The pictures of the professors and the information on the courses that they teach were provided at the beginning on the handout, so that students could see it physically. It was also brought up that the Department of Mathematics cared about their learning and motivation in calculus courses.

The students were broken into groups of 3-4 students. Although there was a possibility that students had not likely to had worked in groups, Instructor 2 required group work per the course syllabus and in the other sections, the lab assistants often conducted recitation session in pairs or groups. The researcher started with the Physics task. The students were expected to know basic knowledge of physics, such as the distance formula and the decomposition of forces. The researcher provided a brief overview of these topics in the context of the problem and assisted students with any challenges related to the comprehension of the physics situation. This way, it was aimed to have students relaxed and focused on how to use calculus to work this task.

As a class, the given story, which was a free kick in soccer, was discussed. Then the researcher asked questions about the movement of the ball after kicking it to stimulate students to think about the movement. There were some interactions among the students at that moment. Then the researcher showed a website on the computer where for any values of angle and initial speed, the movement of the ball was simulated (question 1 in the task, see Appendix D). The purpose of that simulation was to have students to explore and visualize the movement of the ball.

The next part of the task was defining variables and parameters. The researcher went over those things in detail on board. In the part 3, the formulas for both x and y variables were derived together. The students were reminded how to use the physics knowledge to accomplish that. After that, the students were asked to work on the remaining parts in their groups. Meanwhile, the researcher walked around and watched their progress. The role of the researcher was more like a facilitator during group work. At the end of this task, the researcher asked the groups to bring up their work and ideas verbally to the public classroom forum. Those ideas were discussed as a whole class. The researcher specifically addressed why they needed calculus tools to be able to solve this task, in particular, the part 4 of the task required the students to take the derivate of the function that they found before.

The physics task typically took 30-40 minutes in all the treatment groups. Right after the physics task, the students were asked to move on to the next task, the computer science task, on their handouts (Appendix E). Similar introduction about the task was given to the students including information about the professors who wrote the tasks, and information about the type of computer science courses in which the students may potentially encounter the given task.

Then, the researcher presented the idea of algorithms and its meaning in the field of computer science. He went over the given example about computational algorithms in the first page of the handout. The students were then asked to work on the parts 1 and 2 in their groups. The researcher facilitated this session by walking around and answering any questions. When the students completed parts 1 and 2, the researcher had students bring up what they found. He emphasized the need to be able to compare growths, and the mathematical skills necessary in such computer science scenarios. For the most part, students were easily able to perform the part 1 and 2. After that, the researcher introduced the definition of using limits to compare rates of growth of two functions and emphasized that limits are useful where there are no graphs for algorithms to compare. Then the students worked on the part 3 in their groups.

At the end of this task, the researcher asked students to share what they found and how they found it. In some classes, the researcher was able to have students present their work on the board but in some classes that didn't happen due to the time constraints. Students kept the handouts in case they wanted to work on them later on since the handouts also included some extension problems. When the implementation of the Intervention 1 was done, the students were asked to fill out the Calculus Motivation Survey that was described earlier.

Intervention 2. Only one Calculus Tasks with Science and Engineering Applications was given in Intervention 2, which is the engineering task (Appendix F). It was implemented in late November in the lab portion of the same Calculus-1 courses. It was given exactly to the same treatment groups, and the formatting of the implementation was exactly the same.

The researcher introduced the context of the task, talked about the professors who wrote the tasks, and provided information about the type of engineering courses in which the students might work on such a task. Before having students work on the problems, one of the calculus ideas, linearization, was mentioned on the board. Linearization was the main calculus tool needed to accomplish the given engineering task. Then the students were asked to perform the first part of the task in their groups. Approximately 20 minutes was given for that part. After, the student work was brought up to the whole class for discussion.

The next part of the task was discussed as a class. The researcher asked the class to perform this part together since the second part of the task was challenging. This was anticipated because of the student reactions at the piloting stage of the task. Therefore, the researcher used the board to work on the task and the class contributed. When this was done, the researcher summarized what they did as a whole, while overall emphasizing the idea of why they needed calculus as a tool in such engineering scenarios. The engineering task took approximately 30-40 minutes in the treatment groups. Right after the task, the researcher asked the students to fill out the survey again. The surveying part took 7-10 minutes. Since the Intervention 2 did not take the entire lab time, 80 minutes, the researcher left the classroom to the lab instructors to cover their planned material of the day.

Instruments

Surveys

The *Calculus Motivation Survey* was used in this study in order to measure student motivation (Appendix H). The survey includes items to measure the motivation constructs including performance expectations, utility value, and interest. All the participants in this study were asked to take this survey during their regular class time. The participants were asked to choose the best option that described their feelings about each of the 12 items in the survey. In addition, the survey included three questions about student demographic information: gender, race, and intended major. The development of the survey occurred during the piloting stage of this study, and necessary adjustments were made before using it in the actual study based on the piloting results.

Confirmatory factor analysis and internal reliability. Exploratory Factor Analysis was conducted during the piloting stage of this study and this was reported earlier in this chapter. After that, Confirmatory Factor Analysis was conducted following the administration of the modified survey for the first time at the beginning of the semester when this study took place. The purpose of conducting Confirmatory Factor Analysis was to validate the dimensionality of the survey and to examine the factor loadings for the motivational aspects.

The results have shown that the reliability of the survey was .91 (Cronbach's Alfa), which is considered as a high reliability score (Table 13). This score was aligned with the reliability score of the initial survey, which was .90 (Table 1). Table 14 provides information about item statistics including mean and standard deviation in Survey 1 for each item and Table 15 informs about the situation in which if any of the items were deleted, how it would impact the survey.

Table 13

Reliability statistics of Survey 1.

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.918	.916	12

Table 14

Item statistics of Survey 1.

	Mean	Std. Deviation	Sample
pef1	1.29	1.171	173
pef2	1.63	1.111	173
pef3	1.47	1.081	173
utv4	1.30	1.343	173
utv5	1.51	1.270	173
utv6	.51	1.409	173
int7	.28	1.615	173
int8	.58	1.510	173
int9	.38	1.440	173
int10	.58	1.698	173
int11	.82	1.548	173
int12	.29	1.489	173

Table 15

Item-total statistics of Survey 1.

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
pef1	9.34	133.354	.524	.666	.916
pef2	9.01	133.866	.537	.746	.916
pef3	9.17	135.198	.499	.667	.917
utv4	9.34	130.422	.544	.595	.916
utv5	9.13	131.321	.549	.578	.916
utv6	10.13	126.123	.657	.500	.911
int7	10.36	118.720	.784	.697	.905
int8	10.05	120.026	.804	.816	.904
int9	10.26	120.915	.819	.763	.904
int10	10.05	120.247	.692	.628	.910
int11	9.82	121.694	.727	.598	.908
int12	10.35	120.821	.790	.756	.905

Another feature of the survey, as it was provided in Table 16 showed that 78% percent of the variability was explained by the three components detected.

Table 16

Total variance explained by each component in Survey 1.

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.348	52.896	52.896	6.070	50.585	50.585
2	1.789	14.907	67.803	1.551	12.921	63.507
3	1.274	10.614	**78.417**	1.000	8.335	71.842
4	.516	4.297	82.714			
5	.451	3.757	86.471			
6	.341	2.839	89.310			
7	.307	2.555	91.865			
8	.271	2.255	94.120			
9	.220	1.832	95.952			
10	.190	1.584	97.536			
11	.161	1.338	98.874			
12	.135	1.126	100.000			

Principal Axis Factoring and Promax Rotation were used in order to examine the dimension and validate the components in the survey. The Factor Matrix in Survey 1 is given in Table 17. According to Table 18, items pef1, pef2, and pef3 fell under the performance expectations component perfectly with high factor loadings .818, .947, .859, respectively. The items uv4, uv5, and uv6 fell under the utility value component with the factor loadings .886, .845, and .430 accordingly. The items int7, int8, int9, int10, int11, and int12 fell into the interest component with high factor loadings .761, .993, .889, .797, .710, and .901 accordingly.

Table 17

Factor matrix in Survey 1.

	Factor 1	Factor 2	Factor 3
pef1	.584	.594	-.092
pef2	.606	.712	-.012
pef3	.556	.644	-.006
utv4	.589	-.111	.624
utv5	.590	-.070	.594
utv6	.675	-.100	.227
int7	.813	-.169	-.084
int8	.855	-.223	-.286
int9	.857	-.156	-.213
int10	.725	-.256	-.132
int11	.748	-.184	-.066
int12	.830	-.214	-.203

Note. Extraction Method: Principal Axis Factoring.
3 factors extracted. 11 iterations required.

Table 18

Pattern matrix in Survey 1.

	Components		
	Interest	Performance Expectations	Utility Value
pef1	.084	**.818**	-.061
pef2	-.046	**.947**	.024
pef3	-.040	**.859**	.029
utv4	-.017	-.031	**.886**
utv5	-.020	.018	**.845**
utv6	.361	.041	**.430**
int7	**.761**	.029	.100
int8	**.993**	-.001	-.124
int9	**.889**	.067	-.047
int10	**.797**	-.085	.035
int11	**.710**	-.006	.109
int12	**.901**	-.005	-.032

However, the item uv6 was a little problematic since it loaded to both interest (0.36) and utility value (0.43) components, but these values were relatively small. This problem was ignored because of two reasons. First, the model overall had a good fit as it will be showed in this section next. Second, this particular item was located right before the interest items and that might have caused the factor loading towards interest component.

Additional analysis was run in order to determine whether the data was a good fit in the Confirmatory Factor Analysis stage. The fit indices in Table 19 showed that CFI and TLI are greater than .95, RMSEA is smaller than .10, SRMR is smaller than 0.10. Also, Chi-squared is significant (p=0.0) which means that the model fits well.

Table 19

Test statistics and indices of Survey 1.

	dF	Chi-squared	CFI	TLI	RMSEA	SRMR
Model	51	0.00	0.963	0.952	0.08	0.06

Overall, after the Confirmatory Factor Analysis process, it was determined that the survey was measuring what it was supposed to measure. Therefore, the survey was administered in the next data collection phases.

Data Collection

The main data for the study came from the instrument, Calculus Motivation Survey, that was developed in Summer 2017 (Appendix H). The survey was administered three times in the Fall 2017 semester where the main study took place. Figure 5 shows the timing of data collection process in this study.

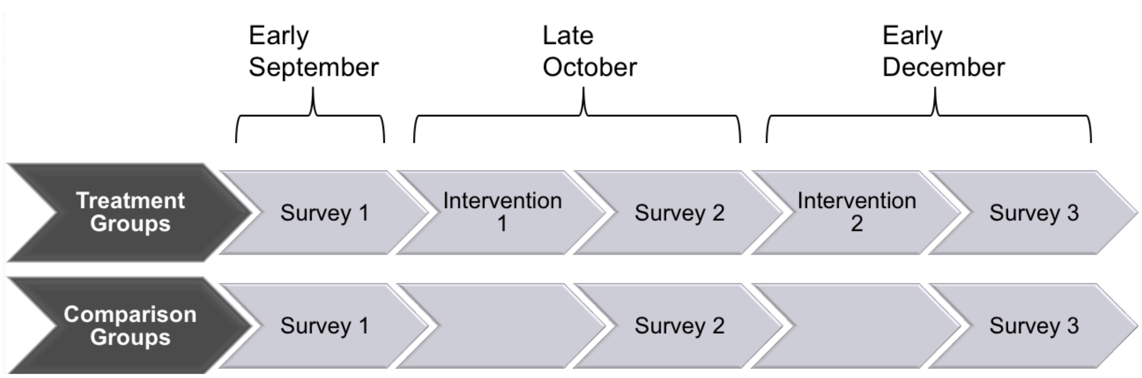


Figure 5: Timeline of the data collection

Recruitment of the Instructors

The three instructors chosen for this study were informed about the study in advance. The design and setting of the study were introduced in detail and the expectations from them were stated. In addition to the instructors, the teaching assistants for each of the lab portions were also contacted in advance. They were informed about the study and the expectations from them. The implementation protocol was shared with the instructors for their information.

They were all willing to collaborate with the researcher, and they were ready to provide anything that was needed for the design and the setting of the study. Both the instructors and lab assistants were told not to talk about the intervention in the comparison groups. However, the students in the comparison and treatment groups took the lecture from the same Instructor of Record and hence, there was the possibility of students interacting with each other about the tasks. The students were not told in advance that an intervention would take place in their labs.

Survey Administration

The survey was administered in both treatment and comparison groups three times throughout the semester (Survey 1, Survey 2, and Survey 3). The first survey was administered in the second week of the semester to measure students' initial measures on motivational concepts. The second survey was administered around late October because this was the time where the treatment groups were expose to Intervention 1. The third survey was administered early December, which was the week before their final week, and it was also the week that the treatment groups were exposed to Intervention 2. The researcher administered all the surveys in all the Calculus I sections.

The timing of Survey 2 and Survey 3 was determined by the timing of implementing the interventions. It was aligned with the timing of the interventions since it was aimed to measure the change in motivation right after the treatment groups had the interventions. It is important to note that even though comparison groups did not have any intervention, all the surveys were administered in these groups around the same times as the treatment groups.

Data Analysis

The purpose of this study was to test the impact of the treatment on student motivation and to investigate the potential change in their motivation over time. In order to accomplish that, quantitative data were collected through instruments. This is a quasi-experimental study where there are three different courses taught by different instructors. In quantitative research literature, this situation is considered as *split-plot* designs where grouping (or sometimes referred as blocks) is included as a variable. In this study, instructor is included as a variable because of its potential influence on student motivation. In statistics literature this situation is defined as *between variable*.

The statistical analysis technique that is recommended in split-plot designs is Repeated Measures when looking at a trend over time (Pituch & Stevens, 2016). Another technique that is used is Linear Mixed Effects Models and it is recommended when analyzing variance and measuring the impact of random and fixed effects (Barr, 2014).

During the data analysis, the impact of the fixed effects which are intervention, gender, major and race, were investigated. The outcome variables were the motivational aspects: performance expectations, utility value, and interest. In addition to these variables, a new motivation variable was created and named “composite motivation”.

This variable was computed based on the average score of the responses to the entire survey. In other words, student responses to each item were added and then divided by twelve to calculate the average score from all the items. Since the survey has not been validated for measuring motivation as an overall construct, the analysis for this particular variable is presented in an exploratory fashion with the purpose of generating possible future research questions and hypotheses. In this study, both Linear Mixed Effects Model and Repeated Measures Analysis were utilized to analyze the collected quantitative data.

Linear Mixed Effects Model

In general, Linear Mixed Effects Models are used when doing Analysis of Variance (ANOVA) on split-plot designs. This model is convenient when estimating fixed and random effects of multiple factors (Barr, 2014). This model incorporates both fixed- and random-effects in a linear predictor from the outcome variables. By the design of this study, there are blocks (three instructors or levels) which can be treated as a random effect. In addition, there are other variables: treatment, gender, major, and race which were the main fixed effects on student motivation.

The model allows examination of the impact of the variables on determined outcome variables by incorporating the fixed and random effects. The model assigns different starting motivation scores for each block (instructor) and tests the impact of fixed effects (intervention, gender, race etc.) based on different starting outcome scores. This approach eliminates the potential impact of beginning motivation scores of students in each block.

Some other advantages of this statistical technique include its efficiency on unbalanced data, meaning having uneven number of sample in groups. Also, the method is highly effective when analyzing individual differences (Bates, Machler, Bolker, & Walker, 2014). In this study, Linear Mixed Effects Model was conducted on the statistical software package, R, in order to analyze the quantitative survey data.

Repeated Measures Analysis

In repeated measures analysis, blocking (in this study, having different instructors) occurs on each subject. Therefore, variability among the participants due to the individual differences is removed from the consideration. Such designs make analysis much more powerful than completely randomized designs (Pituch & Stevens, 2016).

Repeated measures are used in situations where the same participants are compared under different treatments. One of the advantages of repeated measures is that it is a better fit when the concern is performance, or trend, over time. Also, it requires far fewer subjects than other methods since the same subjects are being used repeatedly. Therefore, repeated measures analysis is a good fit to analyze data in this study.

Repeated measures designs have varying complexities based on the number of groups and the number of treatments considered. (Pituch & Stevens, 2016). In this study, gender, treatment, and instructor effects were considered as between-subject factors and measuring the outcome variable (motivation) three times, which is considered as within-subjects factor. In other words, time is the within-subjects measure since the instrument was implemented three times to measure the motivational aspects throughout the semester. It is important to recall that the motivational aspects measured in this study were performance expectations, utility-value, and interest.

In order to compute the relationships between the motivational concepts, Repeated Measures Analysis tools were used on the statistical software SPSS. After getting the results from the software, the results were analyzed.

Assumptions for repeated measures analysis. Before analyzing the results from this particular statistical analysis technique, it was necessary to discuss the assumptions about this technique and address how this research project met with the assumptions.

All the dependent variables in this study were measured at the continuous levels. Therefore, it meets with the assumption that dependent variables should be measured at the continuous levels. Some of the initial motivation scores were not normally distributed but overall it is approximately normal data.

In addition, the independent variables in this study consisted of more than two categorical related groups. The independent variables, treatment (treatment or comparison), instructors (three instructors), gender (male or female), race (six race groups), and intended majors (five categories) all had at least two categories. Therefore, this study met with this assumption.

There was no outlier problem in this study since the range of the outcome variables ranged from -3 to +3 (from -3 corresponding to strongly disagree to +3 corresponding to strongly agree). Although the outcome motivation variables were continuous, the maximum and minimum values of those variables were not greater than 3 and smaller than -3. Hence, it meets with this assumption.

The *sphericity* assumption states that the variances of the differences between all combinations of related groups must be equal. In this study, Mauchly's Test was run to determine the possibility of violating Sphericity. Since this assumption was violated in some instances, Greenhouse-Geisser results were examined in those instances.

IV. RESULTS

Introduction

In this chapter, the research questions will be answered based on the quantitative data collected through the Calculus Motivation Survey after the first and second interventions. The survey results will be presented in terms of the conceptual framework based on the Expectancy-Value Theory (Eccles et al. 1983) and the interest theories. The results from both Repeated Measures Analysis and Linear Mixed Effects Model will be presented in order to answer the following research questions:

1. How do the Calculus Tasks with Science and Engineering Applications impact students' motivational aspects, including utility value, interest, and performance expectations in college Calculus I courses?
2. How does the impact of the Calculus Tasks with Science and Engineering Applications differ based on student gender, intended majors, and race in college Calculus I courses?
3. How do students' motivational aspects, including utility value, interest, and performance expectations change within a semester in college Calculus I courses?

The purpose of this study was to measure the impact of the intervention on student motivation in calculus settings. Throughout the study, the term motivation was used as a broader term which includes utility value, interest, and performance expectations. This approach was based on Hulleman et al. (2010)'s approach to the Expectancy-Value Theory (Eccles et al. 1983) and the motivation research literature. Therefore, utility value, interest, and performance expectations were taken into account as different outcome variables and the results will be presented separately. In addition, a new variable for overall motivation was constructed and added to the analysis as an outcome variable. This overall motivation variable, labeled *composite motivation*, was defined as the average of the three different dimensions measuring utility value, interest, and performance expectations. Since the survey has not been validated for measuring motivation as an overall construct, the analysis for this particular variable is presented in an exploratory fashion with the purpose of generating possible future research questions and hypotheses.

First, initial analysis based on the information gathered in the first survey will be presented, with the purpose of comparing the treatment and comparison groups at the baseline. Second, results from Linear Mixed Effects Model and Repeated Measures Analysis will be presented to address the research question. Lastly, and even though not the focus of the study, an analysis of calculus score performance between the two groups will be presented to inquire into the possibility of adding this variable as an outcome variable for future research.

Initial Analysis

The purpose of the initial analysis was to determine whether the treatment and comparison groups were different at the baseline on all outcome motivational aspects, and in terms of the number of participants at the beginning of the treatment. An Analysis of Variance test (ANOVA) was conducted on student motivation scores by gender, race and intended majors.

Motivational Aspects Differences by Gender

Table 20 shows the distribution of male and female participants for the treatment and comparison groups that responded to Survey 1. The percentage of the female students in the comparison groups was 27%, with 26.9% in the treatment groups, while the percentage of males was 73% in the comparison groups and 73.1% in the treatment groups. Although the total number of participants in treatment and comparison groups were relatively close, there was a bigger difference when participants were identified by gender.

Table 20

Initial distribution of participants by gender

			Gender		
			Female	Male	Total
Groups	Comparison	Count	27	73	100
		% within treatment	27.0%	73.0%	100.0%
		% within gender	56.3%	56.2%	56.2%
		% of Total	15.2%	41.0%	56.2%
	Treatment	Count	21	57	78
		% within treatment	26.9%	73.1%	100.0%
		% within gender	43.8%	43.8%	43.8%
		% of Total	11.8%	32.0%	43.8%
Total		Count	48	130	178
		% within treatment	27.0%	73.0%	100.0%
		% within gender	100.0%	100.0%	100.0%
		% of Total	27.0%	73.0%	100.0%

Table 21 shows the initial differences of student motivation scores between male and females. According to the results, female and male students' interest was significantly different at the beginning of the semester (p=0.088). However, student composite motivation, performance expectations, and utility value were not significantly different between males and females.

Table 21

Initial motivation scores by gender.

		Sum of Squares	df	Mean Square	F	Sig.
Composite Motivation	Between Groups	1.706	1	1.706	1.654	.200
	Within Groups	181.536	176	1.031		
	Total	183.242	177			
Performance Expectations	Between Groups	.006	1	.006	.006	.939
	Within Groups	189.202	176	1.075		
	Total	189.208	177			
Utility Value	Between Groups	.462	1	.462	.350	.555
	Within Groups	232.361	176	1.320		
	Total	232.823	177			
Interest	Between Groups	5.278	1	5.278	2.952	**.088**
	Within Groups	314.682	176	1.788		
	Total	319.960	177			

Overall, gender distribution was not equal in the treatment and comparison groups, but the initial interest scores were statistically different between males and females. This situation leads to the conclusion that gender needed to be considered as a fixed effect on the all the models with Linear Mixed Effects Models and Repeated Measures Analysis to investigate the impact of the intervention.

Motivational Aspects Differences by Major

Table 22 provides the distribution of participants' intended major for both the treatment and comparison groups.

Table 22

Initial distribution of participants by major.

			Major					Total
			1	2	3	4	5	
Groups	Comparison	Count	40	26	7	8	19	100
		% within treatment	40.0%	26.0%	7.0%	8.0%	19.0%	100.0%
		% within major	53.3%	54.2%	53.8%	88.9%	59.4%	56.5%
		% of Total	22.6%	14.7%	4.0%	4.5%	10.7%	56.5%
	Treatment	Count	35	22	6	1	13	77
		% within treatment	45.5%	28.6%	7.8%	1.3%	16.9%	100.0%
		% within major	46.7%	45.8%	46.2%	11.1%	40.6%	43.5%
		% of Total	19.8%	12.4%	3.4%	0.6%	7.3%	43.5%
Total		Count	75	48	13	9	32	177
		% within treatment	42.4%	27.1%	7.3%	5.1%	18.1%	100.0%
		% within major	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
		% of Total	42.4%	27.1%	7.3%	5.1%	18.1%	100.0%

Note. (1=engineering, 2=computer science, 3=mathematics, 4=physics, 5=other).

In the comparison groups, 40% of students were engineering majors, 26% of students were computer science majors, 7% of students were mathematics majors, 8% of students were physics majors, and 19% of students were in other majors. While in the treatment groups, 45.5% of students were engineering majors, 28.6% of students were computer science majors, 7.8% of students were mathematics majors, 1.3% of students were physics majors, and 13% of students were other majors. By inspection only, the treatment and comparison groups are similar in terms of major distribution, with the majority of students majoring in engineering or computer science.

Table 23 shows the initial differences of student motivation scores among majors. The results showed that there were significant differences in all the student motivational aspects among majors.

Table 23

Initial motivation scores by major.

		Sum of Squares	df	Mean Square	F	Sig.
Composite Motivation	Between Groups	13.670	4	3.417	3.493	**.009**
	Within Groups	168.265	172	.978		
	Total	181.935	176			
Performance Expectations	Between Groups	8.759	4	2.190	2.088	**.084**
	Within Groups	180.410	172	1.049		
	Total	189.169	176			
Utility Value	Between Groups	12.546	4	3.136	2.655	**.035**
	Within Groups	203.169	172	1.181		
	Total	215.715	176			
Interest	Between Groups	20.563	4	5.141	2.954	**.022**
	Within Groups	299.293	172	1.740		
	Total	319.856	176			

Therefore, major was also considered as a fixed effect in all the models that were performed in order to measure the impact of the intervention.

Motivational Aspects Differences by Race

Table 24 shows the distribution of participants' self-reported race for the treatment and comparison groups.

Table 24
Initial distribution of participants by race.

			race						Total
			1	2	3	4	5	6	
Groups	Comparison	Count	4	7	30	11	47	1	100
		% within treatment	4.0%	7.0%	30.0%	11.0%	47.0%	1.0%	100.0%
		% within race	50.0%	50.0%	55.6%	57.9%	58.0%	50.0%	56.2%
		% of Total	2.2%	3.9%	16.9%	6.2%	26.4%	0.6%	56.2%
	Treatment	Count	4	7	24	8	34	1	78
		% within treatment	5.1%	9.0%	30.8%	10.3%	43.6%	1.3%	100.0%
		% within race	50.0%	50.0%	44.4%	42.1%	42.0%	50.0%	43.8%
		% of Total	2.2%	3.9%	13.5%	4.5%	19.1%	0.6%	43.8%
Total		Count	8	14	54	19	81	2	178
		% within treatment	4.5%	7.9%	30.3%	10.7%	45.5%	1.1%	100.0%
		% within race	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
		% of Total	4.5%	7.9%	30.3%	10.7%	45.5%	1.1%	100.0%

Note. (1=Asian, 2=Black, 3=Hispanic, 4=Mixed, 5=White, and 6=Other).

In the comparison groups, 4% of students identified as Asian, 7% of students identified as Black, 30% of students identified as Hispanic, 11% of students identified as a mixed race, 47% of students identified as White, and 1% of students identified as other. Whereas, in the treatment groups, 5.1% of students identified as Asian, 9% of students identified as Black, 30.8% of students identified as Hispanic, 10.3% of students identified as a mixed race, 43.6% of students identified as White, and 1.3% of students identified as other. Similar to gender and major, and by inspection only, the treatment and comparison groups categorized by race showed tendency towards one or two categories, with the majority of students identifying as White or Hispanic.

Table 25 shows the initial differences in the initial student motivation scores by race.

Table 25
Initial motivation scores by race.

		Sum of Squares	df	Mean Square	F	Sig.
Composite Motivation	Between Groups	1.098	5	.220	.207	.959
	Within Groups	182.144	172	1.059		
	Total	183.242	177			
Performance Expectations	Between Groups	3.069	5	.614	.567	.725
	Within Groups	186.139	172	1.082		
	Total	189.208	177			
Utility Value	Between Groups	2.893	5	.579	.433	.825
	Within Groups	229.930	172	1.337		
	Total	232.823	177			
Interest	Between Groups	5.264	5	1.053	.575	.719
	Within Groups	314.695	172	1.830		
	Total	319.960	177			

The results showed that none of the motivational aspects was statistically different between the race groups. Although there was no statistical difference between race groups, some models were run in order to determine if the interaction of race and intervention was a significant factor on motivational aspects.

Results from Linear Mixed Effects Models

Linear Mixed Effects Models were conducted on the statistical software, R, to explore the impact of the intervention on student motivation. As an outcome variable for each of the models, the difference between motivational scores was considered and it can be interpreted as the *motivation change* after the interventions. The first measure of motivation change was the difference between initial motivational scores (Survey 1) and motivational scores after the first intervention (Survey 2). The second measure of motivation change was the difference between the initial motivational scores (Survey 1) and the second and final intervention (Survey 3).

This statistical technique requires subjects to take all the required motivation instruments to provide reliable results. However, only ninety-three participants responded to Survey 1 and Survey 2, and only eighty-one students responded to Surveys 1 and 3. Hence, the results presented in this section will be based on two different groups of participants labeled Intermediate and Final group, respectively. It is important to note that only sixty-six students responded to all the three surveys and this data was used to measure the change in scores by Repeated Measures Analysis, which will be presented later.

Several iterations were run on the software considering treatment, instructor (block impact), gender, major and race as independent variables and composite motivation, performance expectations, utility value, and interest is considered as dependent (outcome) variables. Results from each iteration will be presented in separate subsections. Each iteration will include information about the result of the model that was run. For the impact of each variable on each motivational aspect, there will be *p-values* and *estimates*. P-values are used to determine the statistical significance, and both $\alpha = .05$, and $\alpha = .10$ were considered for the level of significance. Estimates provide a measure of the average effects in the population. If estimate value is positive, then the direction of the effect is positive, if it is zero, then there is no effect.

In the results tables, there are interaction effects that will be showed as *Variable 1*Variable 2,* this represents the interaction effect of Variable 1 and Variable 2. Lastly, effect size is also provided for the Repeated Measures Analysis. *Partial Eta Squared* (also known as eta value in statistics) was used in order to provide the percent of variation explained in the outcome variable. For instance, the interaction of time by treatment accounted for 6% of the variation in the outcome (for effect size = .06). The cut-off for the effect size value is as following. If it is .01 or smaller, then the effect size is small. If it is in between .01 and .06 the effect size is medium. Likewise, if it is in between .06 and .14, then the effect size is considered large (again these numbers represents percentages of variation explained).

The Main Effects of Performance Expectations on Utility Value and Interest

This iteration examined the relationship between the dependent variables – performance expectations, utility value, and interest. The purpose of this model was to validate the impact of expectancies on motivation as it was hypothesized by the earlier researchers using the Expectancy-Value models. Table 26 shows the results of models that measure the effect of student's performance expectations on their utility value and interest. According to the results from the Intermediate group, student performance expectations significantly impacts students utility value ($p = 0.00$) and interest ($p = 0.02$). Also, the impact of the interaction of student performance expectations and treatment on motivation was conducted on the same model to determine if treatment made any change on the impact of performance expectations on student motivation. The results did not show any significant impact from this interaction.

Similar analysis was performed considering the Final group. The results showed that student expectations significantly impact their utility value ($p = 0.01$) and interest ($p = 0.08$). The impact of the interaction of student expectations and treatment did not significantly impact student utility value and interest.

Table 26
The main and interaction effects of performance expectations and intervention.

			Utility Value	Interest
Intermediate Group	Performance Expectations			
		estimate	**0.35**	**0.46**
		p-value	**0.00**	**0.02**
	Performance Expectations*treatment			
		estimate	0.04	0.03
		p-value	0.58	0.34
Final Group	Performance Expectations			
		estimate	**0.33**	**0.46**
		p-value	**0.01**	**0.08**
	Performance Expectations*treatment			
		estimate	0	0.27
		p-value	0.57	0.69

The Main Effects of Intervention

Table 27 shows the results from two different models. The first model was run to determine the impact of the intervention on student motivation by considering instructor as a random effect. Data from both Intermediate and Final groups were used in this particular analysis.

According to the results from both the Intermediate and Final groups, the impact of the intervention on student motivation, although positive in some cases, was not significant. The second model was conducted in order to examine the impact of the intervention within each of the instructors' courses. The results showed that the impact of the intervention was significant on student composite motivation only for Instructor 3 ($p=0.04$) for the Intermediate group and was not significant in other instructors' courses. There is no evidence of any significant impact of the intervention on student motivation for the Final group.

Table 27

The main effects of intervention on motivation.

			Composite Motivation	Performance Expectations	Utility Value	Interest
Intermediate Group	overall					
		estimate	0	0	0.04	0.26
		p-value	0.63	0.61	0.52	0.46
Final Group	overall	estimate	0	0	0.07	0.24
		p-value	0.80	0.49	0.72	0.91
Intermediate Group	Instructor 1					
		estimate	0	0	0.04	0.13
		p-value	0.56	0.26	0.43	0.45
	Instructor 2					
		estimate	0	0	0	0.27
		p-value	0.46	0.11	0.14	0.74
	Instructor 3					
		estimate	**0.28**	0.04	0.22	0.43
		p-value	**0.04**	0.14	0.16	0.13
Final Group	Instructor 1					
		estimate	0.34	0.09	0.42	0.41
		p-value	0.10	0.11	0.11	0.67
	Instructor 2					
		estimate	0	0	0	0.29
		p-value	0.33	0	0.17	0.76
	Instructor 3					
		estimate	0	0	0.16	0.03
		p-value	0.67	0.95	0.75	0.40

Note. The effects of the intervention were also showed within each instructors' course for Intermediate and Final group.

The Main and Interaction Effects of Intervention and Gender

Table 28 provides the results of the models used to analyze the impact of the interaction between treatment and gender from the Intermediate group. According to the results, the impact was positive (estimate=0.26) and significant on female performance expectations (p=0.04) while it was positive but not significant on composite motivation (0.44), utility value (0.35), and interest (0.57). There was no significant impact on male students.

Next, the interaction between treatment and gender on motivation was investigated in each instructors' courses. According to the results for male students in Instructor 2, there was no impact on composite motivation, performance expectations, or utility value. For females in Instructor 2's course, the impact was positive and significant (p=0.05) on student interest. It was also positive on student composite motivation (estimate=0.29) but not significant. For females in Instructor 3's group, the impact was positive and significant (p=0.02) on their performance expectations while it was positive on composite motivation (estimate=0.40), utility value (estimate=0.28), and interest (estimate=0.38) but not significant.

Table 28.

The interaction effects of intervention and gender on motivation in Intermediate Group.

			Composite Motivation	Performance Expectations	Utility Value	Interest
Treatment *male	overall					
		estimate	0	0	0	0.22
		p-value	0.18	0	0.58	0.78
Treatment *female	overall					
		estimate	0.44	**0.26**	0.35	0.57
		p-value	0.18	**0.04**	0.44	0.56
Treatment *male	Instructor 1					
		estimate	0	0	0	0.42
		p-value	0.4	0.16	0.61	0.80
	Instructor 2					
		estimate	0	0	0	0
		p-value	0.13	0.86	0.44	0.04
	Instructor 3					
		estimate	0.03	0	0.61	1.48
		p-value	0.93	0.03	0.61	0.20
Treatment *female	Instructor 1					
		estimate	0.66	0	0.88	0.61
		p-value	0.53	0.41	0.32	0.97
	Instructor 2					
		estimate	0.29	0	0	**1.33**
		p-value	0.26	0.65	0.86	**0.05**
	Instructor 3					
		estimate	0.40	**0.54**	0.28	0.38
		p-value	0.37	**0.02**	0.81	0.82

Note. Intermediate group data was used. The interaction effects were also showed within each instructors' course.

The results in Table 29 come from the analysis of the Final group on the interaction of treatment and student gender. According to the results, there was no impact on female or male students on this group.

Next, the interaction of treatment and gender on motivation was investigated in each instructor's course. According to the results from Instructor 1 for males, there was no impact on any of the motivational constructs. However, the impact was positive and significant for female composite motivation (p=0.06) and interest (p=0.08).

According to the results for male students in Instructor 2's section, there was no impact on their motivation. For females in Instructor 2'section, the impact was positive and significant (p=0.00) on student interest. There was no impact on their performance expectations and utility value. The results for Instructor 3 for males showed that the impact was positive on their utility value (estimate=0.11), interest (estimate=1.00), and composite motivation (estimate=0.64) but not significant.

Table 29

The interaction effects of intervention and gender on motivation in Final Group.

			Composite Motivation	Performance Expectations	Utility Value	Interest
Treatment*male	overall					
		estimate	0	0	0.08	0
		p-value	0.25	0.43	0.95	0.19
Treatment*female	overall					
		estimate	0.12	0	0.11	0.29
		p-value	0.42	0.83	0.89	0.28
Treatment*male	Instructor 1					
		estimate	0	0	0	0
		p-value	0.17	0.37	0.98	0
	Instructor 2					
		estimate	0	0	0	0
		p-value	0	0.86	0.55	0
	Instructor 3					
		estimate	0.64	0	1.11	1.00
		p-value	0.46	0.82	0.32	0.30
Treatment*female	Instructor 1					
		estimate	**0.70**	0.59	0.50	**0.84**
		p-value	**0.06**	0.13	0.44	**0.08**
	Instructor 2					
		estimate	0.12	0	0	**1.58**
		p-value	0.14	0.19	1	**0**
	Instructor 3					
		estimate	0	0	0.08	0
		p-value	0.42	0.94	0.59	0.28

Note. Final group data was used. The interaction effects were also showed within each instructors' course.

The Comparison of Female and Male Students

The next consideration was to compare the motivation scores of male and female students. The results showed higher initial motivation for the male students in the comparison groups; therefore, the male treatment, female treatment, and female comparison groups were compared to the male comparison groups. Only final group data was considered for this particular type of analysis since it revealed more significant results than data for the intermediate group.

According to the results in Table 30, the impact of the intervention on males in treatment groups was only positive on their interest (estimate=0.13) but not significant. There was no significant impact on their composite motivation, performance expectations, and utility value. The impact of the intervention on females was positive and significant on their composite motivation (p=0.02). The impact was positive for performance expectations (estimate=0.26), utility value (estimate= 0.35), and interest (estimate=0.57) but not significant.

Table 30

The comparison of student motivation scores to the males in the comparison groups.

		Composite Motivation	Performance Expectations	Utility Value	Interest
Male in treatments					
	estimate	0	0	0	0.13
	p-value	0.72	0.05	0.84	0.66
Female in treatments.					
	estimate	**0.44**	0.26	0.35	0.57
	p-value	**0.02**	0.12	0.08	0.09
Female in comparisons					
	estimate	0.02	0	0.02	0.34
	p-value	0.59	0.36	0.44	0.34

The motivation scores of female students who were in the comparison groups were not statistically different when compared to the motivation scores of male students in the comparison groups. However, only those female student' interest scores were higher than the males in the comparison groups, but it was not statistically significant.

In addition, the same comparison was done within each instructor's course. According to the results in Table 31, Instructor 1's course, only the utility value score of female students in the treatment group was statistically higher than (p=0.07) the male students in the comparison group. There was no difference in motivation scores in between male students in the treatment group and the male students in the comparison group.

The same comparison in Instructor 2's course showed that only the composite motivation and interest scores of the female students were higher than the male students in the comparison groups, but it was not statistically significant.

Table 31

The comparison of student motivation scores to the males in the comparison groups for each instructor.

			Composite Motivation	Performance Expectations	Utility Value	Interest
Instructor 1	Male in treatments					
		estimate	0	0	0	0.02
		p-value	0.56	0.16	0.48	0.58
	Female in treatments.					
		estimate	0.67	0.56	**0.89**	0.60
		p-value	0.15	0.19	**0.07**	0.59
	Fem in comparisons					
		estimate	0.33	0	0.06	0.56
		p-value	0.35	0.61	0.38	0.50
Instructor 2	Male in treatments					
		estimate	0	0	0	0
		p-value	0.21	0.12	0.10	0.66
	Female in treatments.					
		estimate	0.28	0	0	1.32
		p-value	0.89	0.15	0.53	0.19
	Fem in comparisons					
		estimate	0	0	0	0
		p-value	0.18	0.38	0.39	0.18
Instructor 3	Male in treatments					
		estimate	0.04	0	0.08	0.54
		p-value	0.31	0.49	0.34	0.11
	Female in treatments.					
		estimate	**0.39**	**0.46**	0.29	**0.37**
		p-value	**0.02**	**0.06**	0.11	**0.10**
	Fem in comparisons					
		estimate	0	0	0.13	**0.50**
		p-value	0.33	0.29	0.26	**0.10**

Lastly, the same comparison was implemented in Instructor 3's course as well. The results showed that the composite motivation (p=0.02), performance expectations (p=0.06), and interest scores (p=0.10) of the female students in the treatment groups were significantly higher than the male students in the comparison groups. Moreover, the interest scores of the female students in the comparison groups were significantly higher (p=0.10) than the male students in the comparison groups.

Results from Repeated Measures Analyses

Repeated Measures Analysis was run on SPSS software to compute the change in student motivation over the semester for all motivational aspects investigated in this study. Since this method was used in order to analyze the change in student motivation throughout the semester, sixty-six participants who responded to all the three surveys were included in this model. The overall number of participants is higher than that, but not all the participants completed the three motivation surveys. Thirty-five students were in the comparison groups, and thirty-one students were in the treatment groups.

As it was discussed before, Survey 2 was administered right after the first intervention to the Intermediate group, and Survey 3 was administered right after the second intervention to the Final group. The students in the comparison groups did not participated in the intervention, but surveys were administered around the same time as the treatment groups.

Several iterations were conducted on SPSS utilizing Repeated Measures Analysis using time, treatment, instructor, and gender as variables. In the analysis, time is referred to as a variable that represents repeating the same measure over time. For instance, students' interest scores were measured three times, as the Calculus Motivation Survey was administered three times through the data collection stage.

The results from each iteration will be presented using output tables and figures. The Tests of Within-Subjects Effects tables, which is a type of the ANOVA table, show whether the variables made significant impact on the outcome variable over time. The Pairwise Comparisons tables represent the change in between surveys (time 1, time 2, and time 3) quantitatively and show where the differences between the means of the survey results occurred. The figures provide visual representation for the data in order to understand the change over time.

The Main Effects of Time and Intervention on Motivational Aspects

Composite motivation scores. First, Repeated Measures Analysis was run using the composite motivation variable as a within-subject factor and considering treatment as a between-subjects factor. According to the results in Table 32, there was no significant difference between the composite motivations scores of treatment and comparison groups over time ($p=.87$). Table 33 includes information about the pairwise comparisons between different time points. According to the Pairwise Comparisons table, there was no significant change in composite motivation between surveys.

Figure 6 was provided to gain an easy understanding of the tabular results. As it can be seen in figure 6, the students in the treatment groups started with low motivation and the students in the comparison groups had much higher initial motivation. The change in motivation from the first survey to the second survey was positive in the treatment groups, but negative in the comparison groups. The change in student motivation from the second survey to the third survey was positive for comparison groups, but negative for the treatment groups.

Table 32

The main and interaction effects of time and intervention on composite motivation.

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
time	Sphericity Assumed	.089	2	.045	.134	.875
	Greenhouse-Geisser	.089	1.977	.045	.134	.872
time * treatment	Sphericity Assumed	.187	2	.093	.280	.756
	Greenhouse-Geisser	.187	1.977	.095	.280	.754

Table 33

Pairwise comparisons between time points for composite motivation.

(I) time	(J) time	Mean Difference (I-J)	Std. Error	Sig.[a]
1	2	-.045	.098	1.000
	3	-.045	.098	1.000
2	1	.045	.098	1.000
	3	-.001	.106	1.000
3	1	.045	.098	1.000
	2	.001	.106	1.000

Note. Based on estimated marginal means
a. Adjustment for multiple comparisons: Bonferroni.

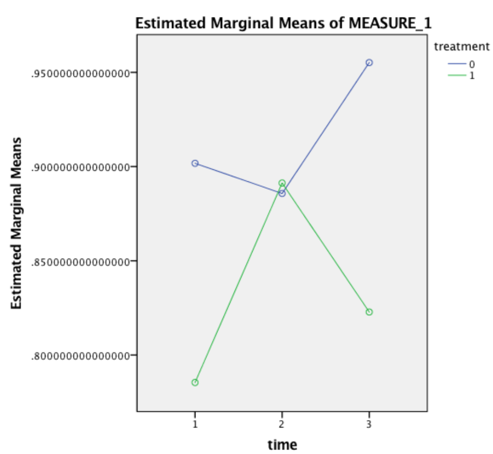


Figure 6: Change in student composite motivation over time. (The upper lines represent the comparison groups and the lower lines represent the treatment groups)

Performance expectations scores. In this model, student performance expectations scores were considered as the outcome variable. According to the results in

Table 34, time was a significant factor for change in student performance expectations (p=0.03, eta=.05). This means is that 5% of the variation in the performance expectations scores can be explained by the variable time (medium effect size). The results in Table 35 show that only the difference in performance expectations from the survey 1 and survey 3 was significant (p=0.07). As it can be seen on Figure 7, the student expectations keep decreasing for both treatment and comparison groups over time.

Table 34

The main and interaction effects of time and intervention on performance expectations.

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
time	Sphericity Assumed	4.568	2	2.284	3.609	.030
	Greenhouse-Geisser	4.568	1.799	2.540	3.609	.035
time * treatment	Sphericity Assumed	.101	2	.051	.080	.923
	Greenhouse-Geisser	.101	1.799	.056	.080	.906

Table 35

Pairwise comparisons between time points for performance expectations.

(I) time	(J) time	Mean Difference (I-J)	Std. Error	Sig.[a]
1	2	.246	.132	.200
	3	.366	.160	.076
2	1	-.246	.132	.200
	3	.120	.122	.988
3	1	-.366	.160	.076
	2	-.120	.122	.988

Note. Based on estimated marginal means
a. Adjustment for multiple comparisons: Bonferroni.

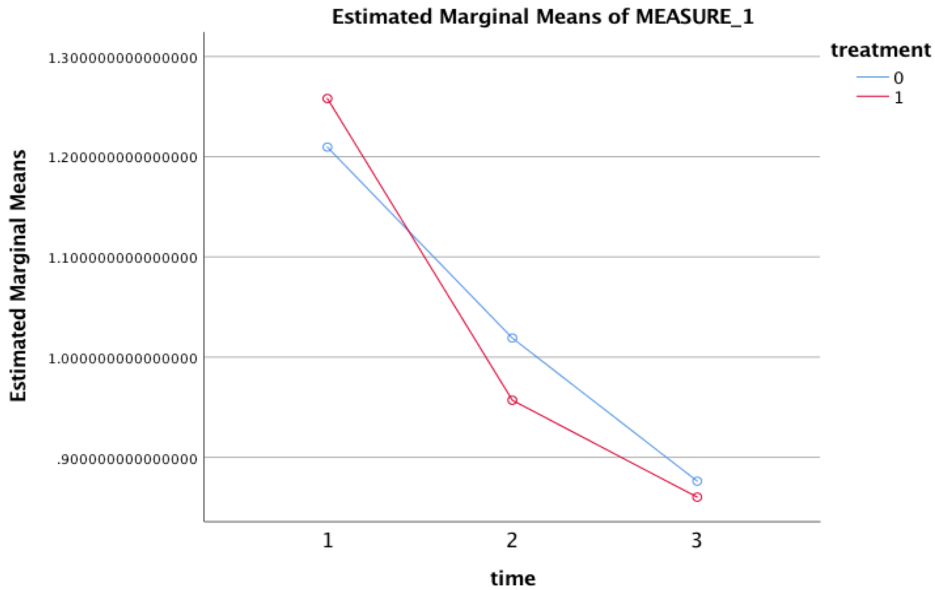


Figure 7: Change in student performance expectations over time. (the line that starts with lower motivation score is the comparison groups and the one starts with higher value is treatment groups)

Utility value scores. The results in Table 36 have shown that the impact of time itself, and the interaction of time and treatment were not significant. The change in student utility value in between the surveys was not significant (Table 37). According to the figure X, the change was positive from survey 1 to 2 for the treatment groups but negative for the comparison group. From the survey 2 to 3, the change was positive for the comparison group but negative for the treatment group. In addition, Figure 8 shows the change in student utility value over time.

Table 36

The main and interaction effects of time and intervention on utility value.

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
time	Sphericity Assumed	.247	2	.123	.239	.788
	Greenhouse-Geisser	.247	1.822	.135	.239	.767
time * treatment	Sphericity Assumed	.485	2	.242	.470	.626
	Greenhouse-Geisser	.485	1.822	.266	.470	.608

Table 37

Pairwise comparisons between time points for utility value.

(I) time	(J) time	Mean Difference (I-J)	Std. Error	Sig.[a]
1	2	.069	.143	1.000
	3	.080	.120	1.000
2	1	-.069	.143	1.000
	3	.011	.111	1.000
3	1	-.080	.120	1.000
	2	-.011	.111	1.000

Note. Based on estimated marginal means
a. Adjustment for multiple comparisons: Bonferroni.

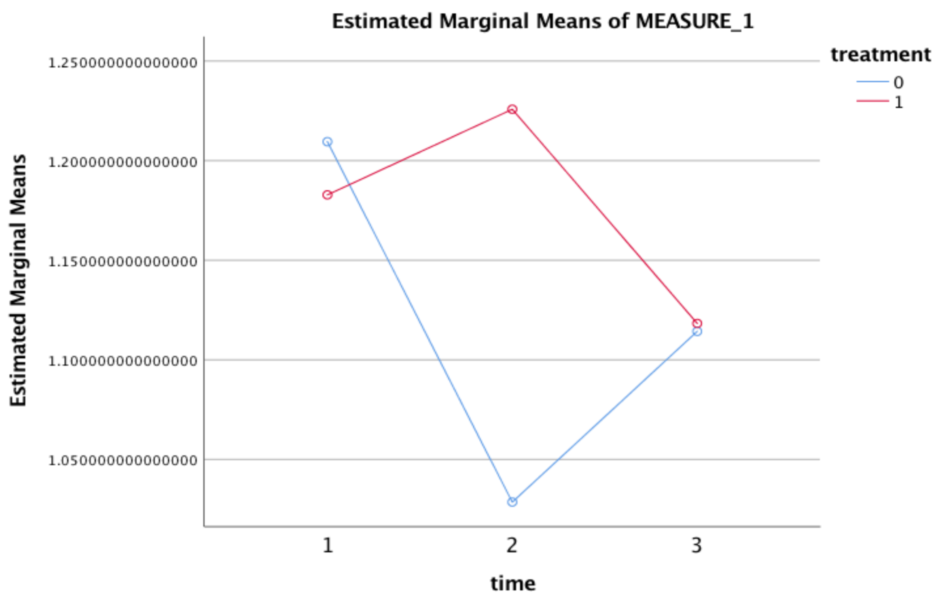


Figure 8: Change in student utility value over time. (the line that starts with lower motivation score is the treatment groups and the one starts with higher value is comparison groups)

Interest scores. According to the results in Table 38, only the impact of time (p=0.04, effect size .049) on student interest was significant. This means is that time was a medium effect on student interest and it explains approximately 5% of the variation in interest scores. Table 39 includes information about the change in between the surveys and the change was significantly different only in between the survey 1 and survey 3 (p=0.03). According to the Figure 9, student utility value increased for both treatment and comparison groups from survey 1 and survey 2. From the survey 2 to 3, students utility value decreased for the treatment groups but increased for the comparison groups.

Table 38

The main and interaction effects of time and intervention on interest.

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
time	Sphericity Assumed	3.498	2	1.749	3.275	.041
	Greenhouse-Geisser	3.498	1.915	1.826	3.275	.043
time * treatment	Sphericity Assumed	.418	2	.209	.391	.677
	Greenhouse-Geisser	.418	1.915	.218	.391	.668

Table 39

Pairwise comparisons between time points for interest.

(I) time	(J) time	Mean Difference (I-J)	Std. Error	Sig.[b]
1	2	-.240	.120	.146
	3	-.311*	.121	.038
2	1	.240	.120	.146
	3	-.071	.140	1.000
3	1	.311*	.121	.038
	2	.071	.140	1.000

Note. Based on estimated marginal means

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

b. Adjustment for multiple comparisons: Bonferroni.

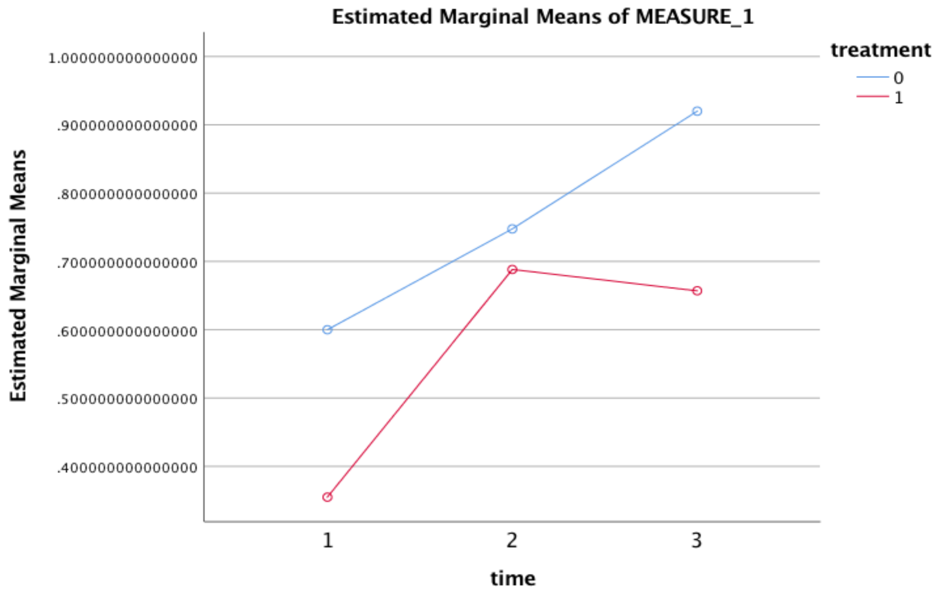


Figure 9: Change in student interest over time. (the line that starts with lower motivation score is the treatment groups and the one starts with higher value is comparison groups)

The Main and Interaction Effects of Time, Intervention, and Instructor

Composite motivation scores. This model explores the change in composite motivation over time by considering both treatment and instructors (blocks). According to the results from the Table 40, the only significant result was the interaction of time, treatment, and instructor (p=0.02, effect size .09). Thus, 9% of the variation in student composite motivation scores could be explained by the interaction of time, intervention, and time, which is a large effect size. Table 41 shows that there was no statistical difference in the means of the motivation responses between surveys. The change in student composite motivation can be examined for each instructor's course in Figures 10, 11, and 12.

Table 40

The main and interaction effects of time, intervention, and instructor on composite motivation.

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
time	Sphericity Assumed	.199	2	.100	.309	.734
	Greenhouse-Geisser	.199	1.986	.100	.309	.733
time * treatment	Sphericity Assumed	.141	2	.070	.218	.804
	Greenhouse-Geisser	.141	1.986	.071	.218	.803
time * instructor	Sphericity Assumed	.133	4	.033	.104	.981
	Greenhouse-Geisser	.133	3.973	.034	.104	.981
time * treatment * instructor	Sphericity Assumed	3.812	4	.953	2.960	.023
	Greenhouse-Geisser	3.812	3.973	.960	2.960	.023

Table 41

Pairwise comparisons between time points for composite motivation.

(I) time	(J) time	Mean Difference (I-J)	Std. Error	Sig.[a]
1	2	-.079	.097	1.000
	3	-.046	.101	1.000
2	1	.079	.097	1.000
	3	.032	.104	1.000
3	1	.046	.101	1.000
	2	-.032	.104	1.000

Note. Based on estimated marginal means

a. Adjustment for multiple comparisons: Bonferroni.

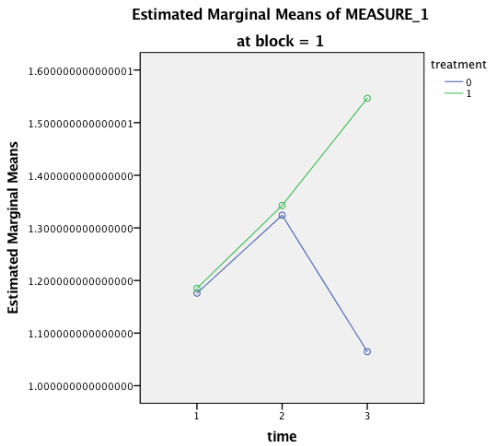


Figure 10: Change in student composite motivation for Instructor 1. (The line starting with lower score represents the treatment groups and the other one represents the comparison groups)

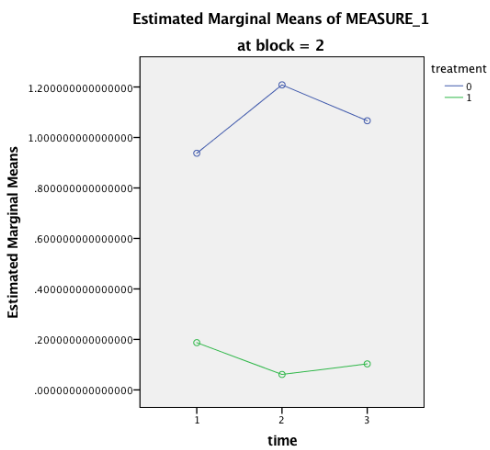


Figure 11: Change in student composite motivation for Instructor 2. (The line starting with lower score represents the treatment groups and the other one represents the comparison groups)

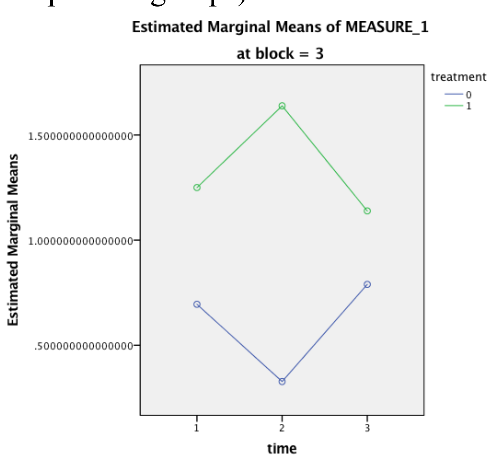


Figure 12: Change in student composite motivation for Instructor 3. (The line starting with lower score represents the comparison groups and the other one represents the treatment groups)

Performance expectation scores. According to the results from Table 42, time itself and the interaction of time, treatment and instructor were significant factors for the change in students' performance expectations (p=0.05, effect size .04, and p=0.00, effect size .118 accordingly). Therefore, approximately 12% of the variation in student performance expectation scores could be explained by the interaction of time, intervention, and time, which is a large effect size. According to Table 43, the difference between the means of student performance expectations between surveys was not significant. Figures 13, 14, and 15 provide the change in expectations in each instructors' courses.

Table 42

The main and interaction effects of time, intervention, and instructor on performance expectations.

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
time	Sphericity Assumed	3.436	2	1.718	2.921	.058
	Greenhouse-Geisser	3.436	1.776	1.935	2.921	.064
time * treatment	Sphericity Assumed	.065	2	.032	.055	.946
	Greenhouse-Geisser	.065	1.776	.037	.055	.930
time * instructor	Sphericity Assumed	1.275	4	.319	.542	.705
	Greenhouse-Geisser	1.275	3.552	.359	.542	.684
time * treatment * instructor	Sphericity Assumed	9.426	4	2.357	4.007	.004
	Greenhouse-Geisser	9.426	3.552	2.654	4.007	.006

Table 43

Pairwise comparisons between time points for performance expectations.

(I) time	(J) time	Mean Difference (I-J)	Std. Error	Sig.[a]
1	2	.193	.126	.395
	3	.327	.158	.129
2	1	-.193	.126	.395
	3	.133	.120	.814
3	1	-.327	.158	.129
	2	-.133	.120	.814

Note. Based on estimated marginal means

a. Adjustment for multiple comparisons: Bonferroni.

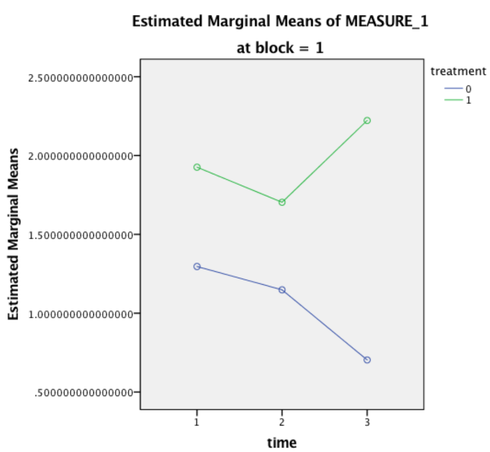


Figure 13: Change in student performance expectations for Instructor 1. (The line starting with lower score represents the comparison groups and the other one represents the treatment groups)

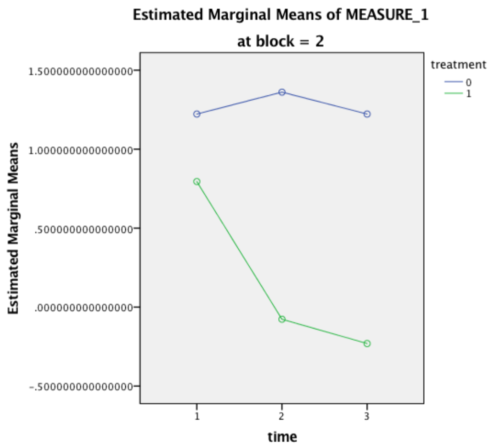


Figure 14: Change in student performance expectations for Instructor 2**.** (The line starting with lower score represents the treatment groups and the other one represents the comparison groups)

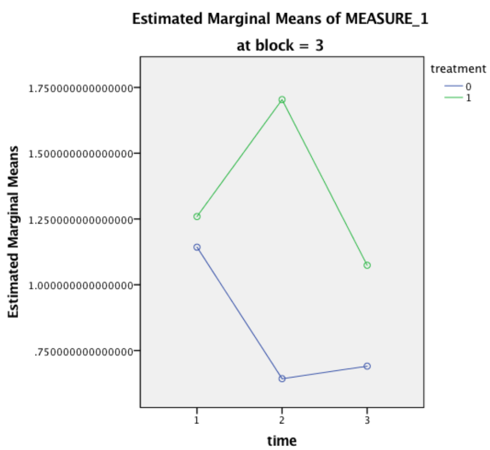


Figure 15: Change in student performance expectations for Instructor 3**.** (The line starting with lower score represents the comparison groups and the other one represents the treatment groups)

Utility value scores. The results (Table 44) have shown that only the interaction of time, treatment, and instructor over time was significant on students' utility value (p=0.03, effect size .08). Hence, 8% of the variation in student utility value scores could be explained by the interaction of time, intervention, and time, which is a large effect size. The change in student utility value in between the surveys was not significant (Table

45). The change in student utility value in all the instructors' courses can be examined in Figures 16, 17, and 18.

Table 44

The main and interaction effects of time, intervention, and instructor on utility value.

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
time	Sphericity Assumed	.137	2	.069	.137	.872
	Greenhouse-Geisser	.137	1.854	.074	.137	.857
time * treatment	Sphericity Assumed	.613	2	.307	.612	.544
	Greenhouse-Geisser	.613	1.854	.331	.612	.532
time * instructor	Sphericity Assumed	.204	4	.051	.102	.982
	Greenhouse-Geisser	.204	3.708	.055	.102	.977
time * treatment * instructor	Sphericity Assumed	5.498	4	1.375	2.742	.032
	Greenhouse-Geisser	5.498	3.708	1.483	2.742	.036

Table 45

Pairwise comparisons between time points for utility value.

(I) time	(J) time	Mean Difference (I-J)	Std. Error	Sig.[a]
1	2	.035	.142	1.000
	3	.066	.120	1.000
2	1	-.035	.142	1.000
	3	.030	.113	1.000
3	1	-.066	.120	1.000
	2	-.030	.113	1.000

Note. Based on estimated marginal means

a. Adjustment for multiple comparisons: Bonferroni.

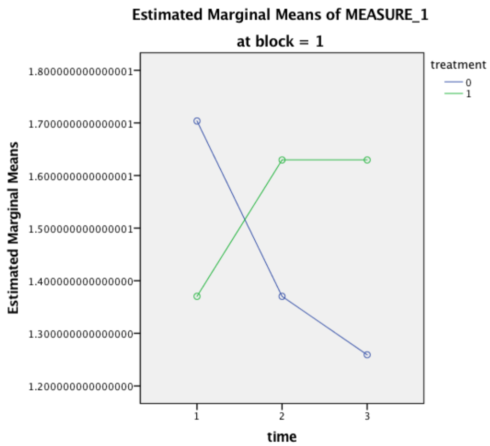


Figure 16: Change in student utility value for Instructor 1. (The line starting with lower score represents the treatment groups and the other one represents the comparison groups)

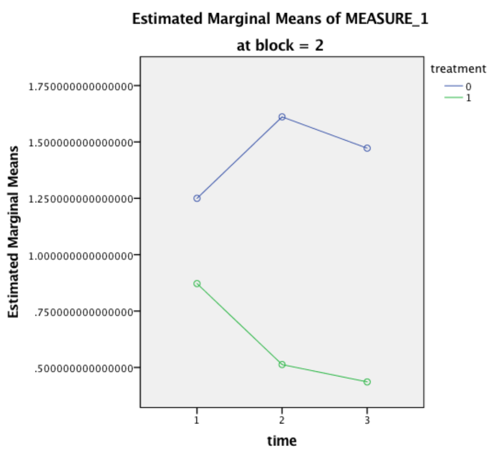


Figure 17: Change in student utility value for Instructor 2. (The line starting with lower score represents the treatment groups and the other one represents the comparison groups)

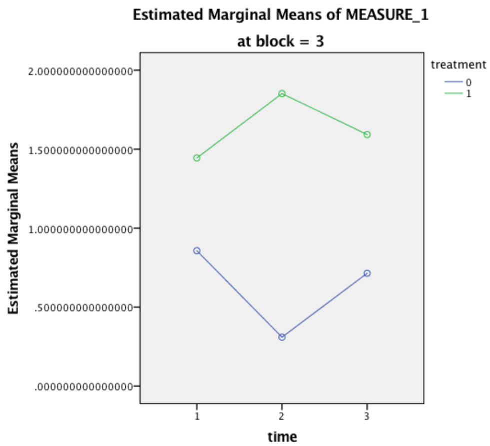


Figure 18: Change in student utility value for Instructor 3. (The line starting with lower score represents the comparison groups and the other one represents the treatment groups)

Interest scores. According to the results in Table 46, time and the interaction of time, treatment, and instructor were significant on the change in student interest over time ($p=0.04$, effect size .05, and $p=0.06$ effect size .07 accordingly). Thus, 7% of the variation in student interest scores could be explained by the interaction of time, intervention, and time, which is a large effect size. According to Table 47, only the difference between the means of survey 1 and survey 3 was significant ($p=0.07$). Figures 19, 20, and 21 provide the change in student interest in each of the instructors' courses.

Table 46

The main and interaction effects of time, intervention, and instructor on interest.

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
time	Sphericity Assumed	3.268	2	1.634	3.134	.047
	Greenhouse-Geisser	3.268	1.947	1.678	3.134	.049
time * treatment	Sphericity Assumed	.265	2	.133	.254	.776
	Greenhouse-Geisser	.265	1.947	.136	.254	.770
time * instructor	Sphericity Assumed	.770	4	.192	.369	.830
	Greenhouse-Geisser	.770	3.895	.198	.369	.825
time * treatment * instructor	Sphericity Assumed	4.857	4	1.214	2.329	.060
	Greenhouse-Geisser	4.857	3.895	1.247	2.329	.062

Table 47

Pairwise comparisons between time points for interest.

(I) time	(J) time	Mean Difference (I-J)	Std. Error	Sig.[a]
1	2	-.266	.122	.098
	3	-.287	.123	.070
2	1	.266	.122	.098
	3	-.021	.138	1.000
3	1	.287	.123	.070
	2	.021	.138	1.000

Note. Based on estimated marginal means

a. Adjustment for multiple comparisons: Bonferroni.

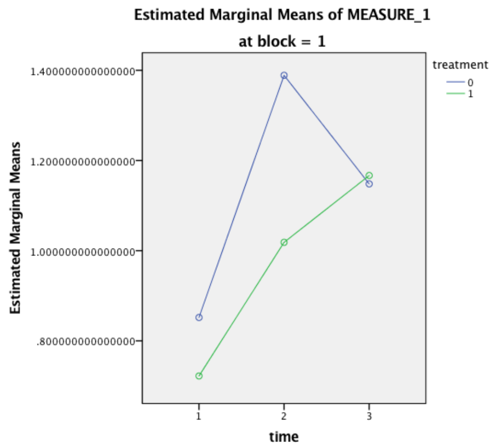


Figure 19: Change in student interest for Instructor 1**.** (The line starting with lower score represents the treatment groups and the other one represents the comparison groups)

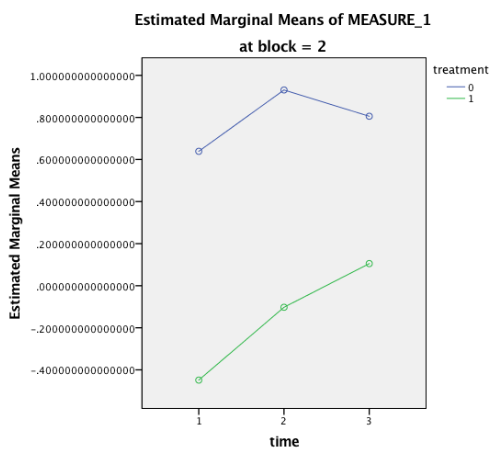


Figure 20: Change in student interest for Instructor 2. (The line starting with lower score represents the treatment groups and the other one represents the comparison groups)

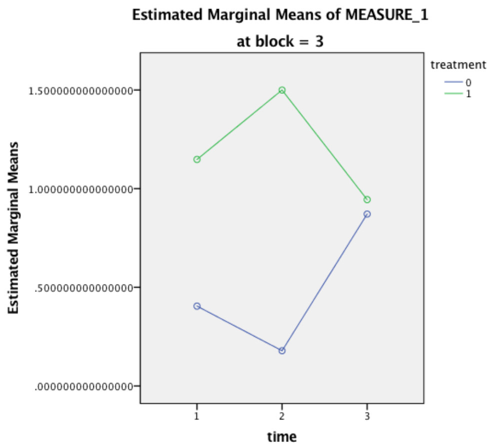


Figure 21: Change in student interest for Instructor 3**.** (The line starting with lower score represents the comparison groups and the other one represents the treatment groups)

So far, the main and interaction effects of time, intervention and instructor was presented. Additional analysis was done only on the interaction of time and instructor but that did not provide any significant result on any of the student motivational aspects. Now instead of instructor, gender was considered for the next iterations.

The Main and Interaction Effects of Time, Intervention, and Gender

Composite motivation scores. According to the results from Table 48, there was a significant effect of the interaction of gender and time (p=0.03, effect size .051). Thus, approximately 5% of the variation in student composite motivation scores could be explained by the interaction of gender and time, which is a medium effect size. However, all the other variables did not give us any significant results. Since the interaction of time and gender was significant, it is important to look at where those differences occurred. The following Table 49 shows those differences in between different time points and according to the comparisons, and there were no significant differences. Also, Figures 22 shows those differences for female students, while Figure 23 shows it for males.

Table 48

The main and interaction effects of time, intervention, and gender on composite motivation.

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
time	Sphericity Assumed	.373	2	.186	.576	.564
	Greenhouse-Geisser	.373	1.984	.188	.576	.563
time * treatment	Sphericity Assumed	.082	2	.041	.126	.882
	Greenhouse-Geisser	.082	1.984	.041	.126	.880
time * gender	Sphericity Assumed	2.175	2	1.087	3.359	.038
	Greenhouse-Geisser	2.175	1.984	1.096	3.359	.038
time * treatment * gender	Sphericity Assumed	.374	2	.187	.577	.563
	Greenhouse-Geisser	.374	1.984	.188	.577	.562

Table 49

Pairwise comparisons between time points for composite motivation.

(I) time	(J) time	Mean Difference (I-J)	Std. Error	Sig.[a]
1	2	-.102	.105	1.000
	3	-.002	.109	1.000
2	1	.102	.105	1.000
	3	.101	.114	1.000
3	1	.002	.109	1.000
	2	-.101	.114	1.000

Note. Based on estimated marginal means

a. Adjustment for multiple comparisons: Bonferroni.

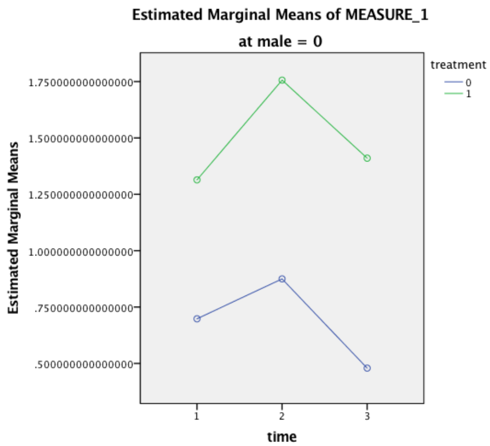


Figure 22: Change in student composite motivation for female students. (the line starting with lower score represents the female students in the comparison groups and the other one represents the students in the treatment groups)

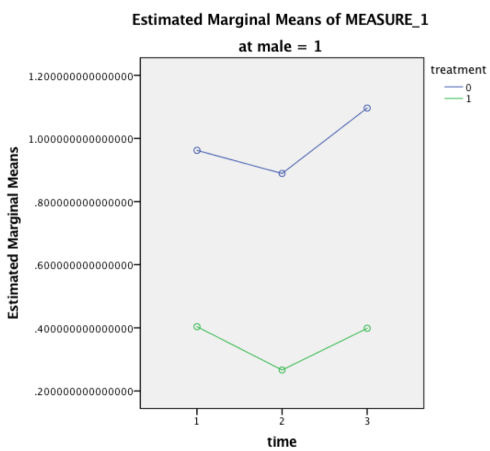


Figure 23: Change in student composite motivation for male students. (the line starting with lower score represents the male students in the treatment groups and the other one represents the students in the comparison groups)

Performance expectations scores. According to the results, there was a significant effect of time on student performance expectations (p=0.04 effect size .049). The interaction of the variables time, treatment, and gender were not significant (Table 50). The Pairwise Comparison Table (Table 51) did not show any significant difference between time points. Figure 24 includes a plot of the change in performance expectations of female students, and Figure 25 shows the same for male students.

Table 50

The main and interaction effects of time, intervention, and gender on performance expectations.

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
time	Sphericity Assumed	4.003	2	2.001	3.225	.043
	Greenhouse-Geisser	4.003	1.731	2.312	3.225	.051
time * treatment	Sphericity Assumed	.011	2	.005	.009	.992
	Greenhouse-Geisser	.011	1.731	.006	.009	.985
time * gender	Sphericity Assumed	1.119	2	.559	.901	.409
	Greenhouse-Geisser	1.119	1.731	.646	.901	.396
time * treatment * gender	Sphericity Assumed	2.570	2	1.285	2.071	.130
	Greenhouse-Geisser	2.570	1.731	1.485	2.071	.138

Table 51

Pairwise comparisons between time points for performance expectations.

(I) time	(J) time	Mean Difference (I-J)	Std. Error	Sig.[a]
1	2	.240	.140	.274
	3	.380	.178	.111
2	1	-.240	.140	.274
	3	.140	.131	.872
3	1	-.380	.178	.111
	2	-.140	.131	.872

Note. Based on estimated marginal means

a. Adjustment for multiple comparisons: Bonferroni.

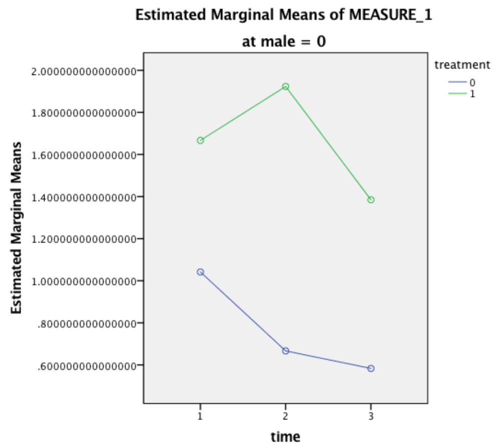


Figure 24: Change in student performance expectations for female students. (the line starting with lower score represents the female students in the comparison groups and the other one represents the students in the treatment groups)

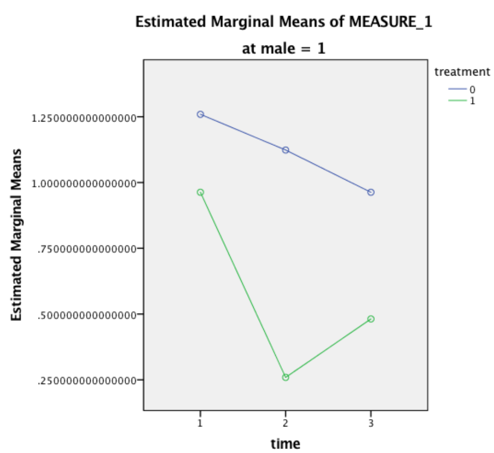


Figure 25: Change in student performance expectations for male students. (the line starting with lower score represents the male students in the treatment groups and the other one represents the students in the comparison groups)

Utility value scores. According to the results, the effect of interaction of time and gender was significant (p=0.06 effect size .044). Therefore, approximately 4% of the variation in student utility value scores could be explained by the interaction of gender and time, which is a medium effect size. The effect of time itself, the interaction of time and intervention, and the interaction of intervention and gender was not significant (Table 52). In addition, Table 53 did not show any significant differences between time points.

Figure 26 represents the change in student utility value between different times visually for females, while Figure 27 shows the same for males.

Table 52

The main and interaction effects of time, intervention, and gender on utility value.

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
time	Sphericity Assumed	.472	2	.236	.466	.629
	Greenhouse-Geisser	.472	1.816	.260	.466	.610
time * treatment	Sphericity Assumed	.082	2	.041	.081	.923
	Greenhouse-Geisser	.082	1.816	.045	.081	.907
time * gender	Sphericity Assumed	2.897	2	1.449	2.858	.061
	Greenhouse-Geisser	2.897	1.816	1.595	2.858	.067
time * treatment * gender	Sphericity Assumed	.335	2	.168	.331	.719
	Greenhouse-Geisser	.335	1.816	.185	.331	.698

Table 53

Pairwise comparisons between the time points for utility value.

(I) time	(J) time	Mean Difference (I-J)	Std. Error	Sig.[a]
1	2	-.036	.156	1.000
	3	.092	.133	1.000
2	1	.036	.156	1.000
	3	.128	.118	.854
3	1	-.092	.133	1.000
	2	-.128	.118	.854

Note. Based on estimated marginal means

a. Adjustment for multiple comparisons: Bonferroni.

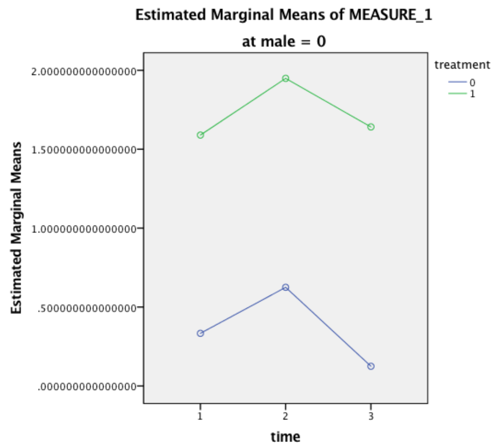


Figure 26: Change in student utility value for female students. (the line starting with lower score represents the female students in the comparison groups and the other one represents the students in the treatment groups)

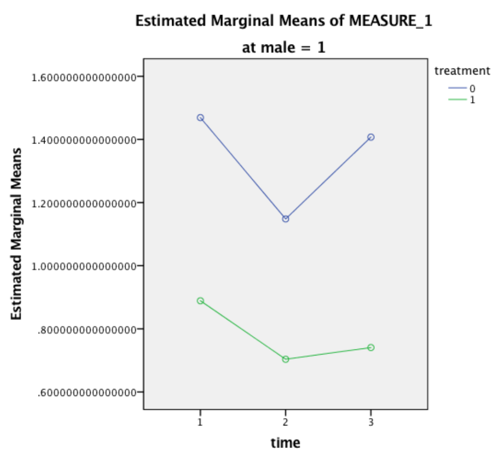


Figure 27: Change in student utility value for male students. (the line starting with lower score represents the male students in the treatment groups and the other one represents the students in the comparison groups)

Interest scores. According to the results, time was a significant change in student interest (p=0.07 effect size .04). Also, the interaction of time and gender was a significant factor in the change in student interest (p=0.07 effect size .04). Hence, 4% of the variation in student interest scores could be explained by the interaction of gender and time, which is a medium effect size. However, the interaction of time and intervention, and the interaction of time, intervention, and gender was not significant (Table 54).

Table 54

The main and interaction effects of time, intervention, and gender on interest.

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
time	Sphericity Assumed	2.732	2	1.366	2.602	.078
	Greenhouse-Geisser	2.732	1.937	1.410	2.602	.080
time * treatment	Sphericity Assumed	.158	2	.079	.151	.860
	Greenhouse-Geisser	.158	1.937	.082	.151	.854
time * gender	Sphericity Assumed	2.811	2	1.406	2.677	.073
	Greenhouse-Geisser	2.811	1.937	1.451	2.677	.075
time * treatment * gender	Sphericity Assumed	.606	2	.303	.577	.563
	Greenhouse-Geisser	.606	1.937	.313	.577	.558

Table 55 provides results about how the difference occurred between time points for student interest. The change in between Survey 1 and Survey 2 was significant (p=0.07).

Table 55

Pairwise comparisons between time points for interest.

(I) time	(J) time	Mean Difference (I-J)	Std. Error	Sig.[a]
1	2	-.301	.132	.077
	3	-.237	.134	.244
2	1	.301	.132	.077
	3	.064	.151	1.000
3	1	.237	.134	.244
	2	-.064	.151	1.000

Note. Based on estimated marginal means

a. Adjustment for multiple comparisons: Bonferroni.

Figure 28 below represents the change in student interest in between different time points for female students. Figure 29 shows the same for male students.

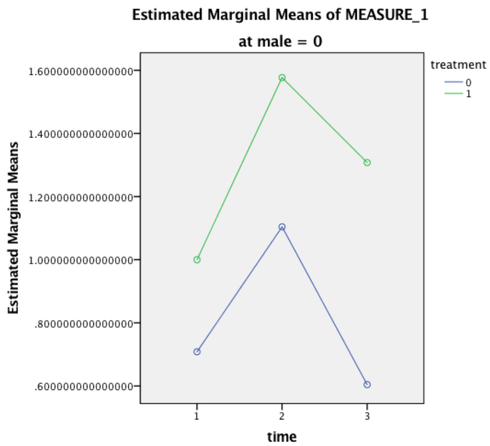


Figure 28: Change in student interest for female students. (the line starting with lower score represents the female students in the comparison groups and the other one represents the students in the treatment groups)

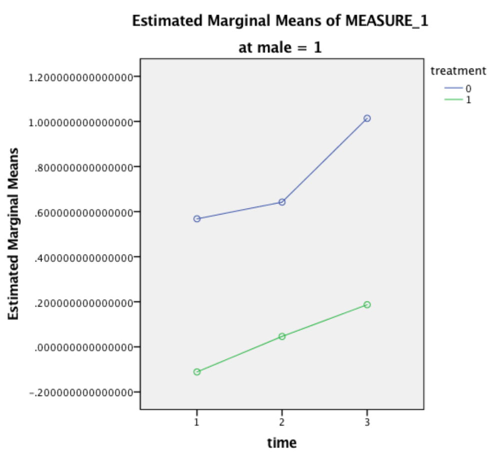


Figure 29: Change in student interest for male students. (the line starting with lower score represents the female students in the treatment groups and the other one represents the students in the comparison groups)

The Effects of Student Race and Major

The results presented so far explored the impact of the variables, including intervention, instructor, and gender on student motivational aspects. In addition to these variables, student race and intended majors were also investigated using the Linear Mixed Effect models. The impact of student race was not significant on their overall motivation (p=0.94), considering the instructor as a random effect. In addition, linear models were run to test the impact of race within each instructor's courses, but none of the models showed significant results. Even though these results were not significant, student motivation scores based on their race were plotted in order to gain insight into how it may have differed with the purpose of exploring relationships in future research. Figure 30 shows students' initial composite motivation for each race groups while Figure 31 shows students' post (Survey 3) composite motivation for each race groups. It is worthwhile to notice that the majority of the students self-identified in White and Hispanic race groups and the number of students in all the other race groups were lower. Not all the race groups were represented in all the instructors' courses.

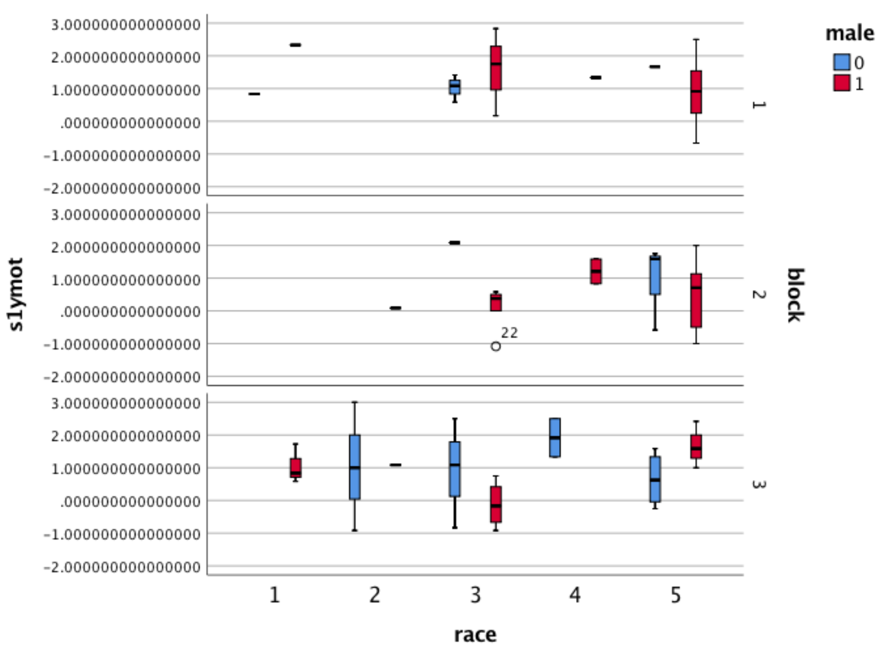


Figure 30: Student initial composite score distributed based on race. (1=Asian, 2=Black, 3=Hispanic, 4=Mixed, 5=White, and 6=Other)

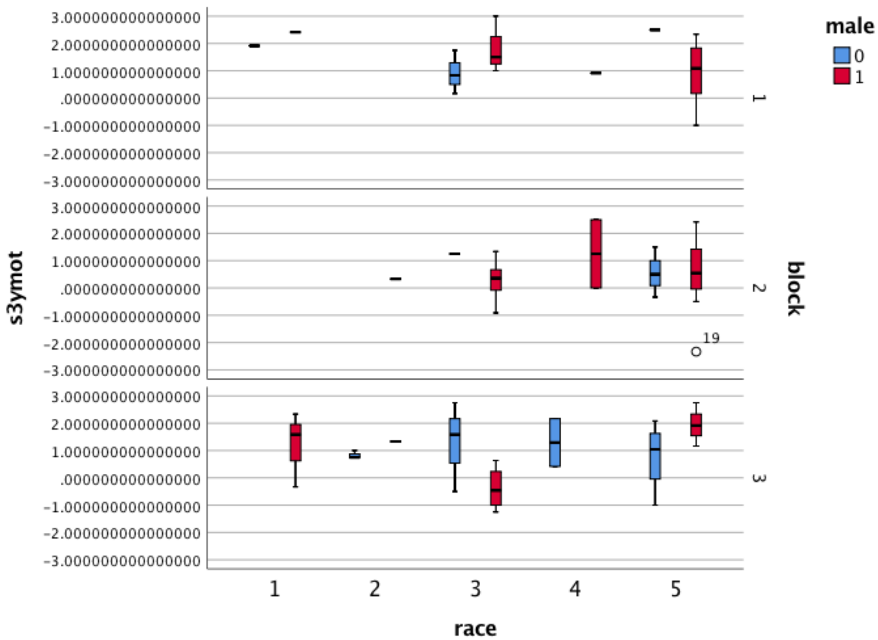


Figure 31: Student post composite score distributed based on race. (1=Asian, 2=Black, 3=Hispanic, 4=Mixed, 5=White, and 6=Other).

Linear Mixed Effects models were also run using student intended majors. The results showed that student major was not a significant factor on student motivation (p=0.99) when considering instructor as a random effect. In addition, various models were run to investigate the interaction of treatment and major within each instructor's course and none of the models showed any significant difference. Although these results were not significant, student motivation scores based on their majors were plotted in order to gain insight into how it may have differed. Figure 32 shows student initial composite motivation based on each student major. Similarly, Figure 33 represents student composite motivation scores for each major in Survey 3, which was administered at the end of the semester.

It is worthwhile to notice that students who intended to major in mathematics, physics, or other are few compared to engineering and computer science. This situation was typical in Calculus I courses at this institution.

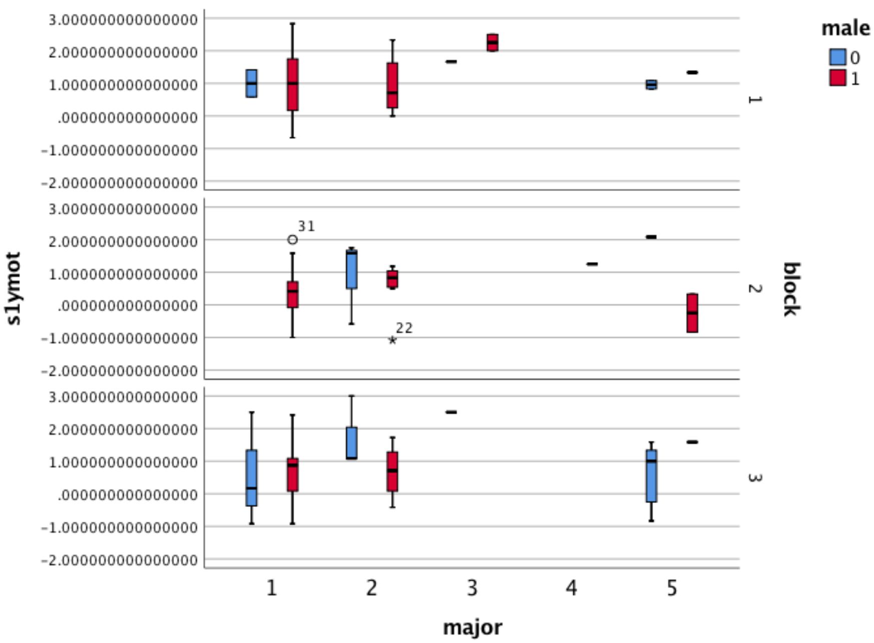


Figure 32: Student initial composite score distributed based on major. (1=engineering, 2=computer science, 3=mathematics, 4=physics, and 5=other).

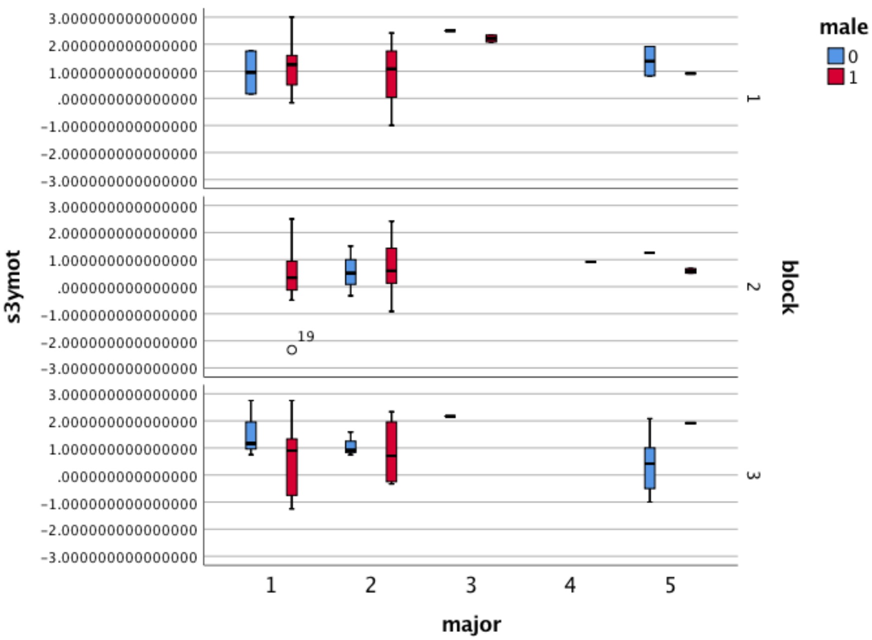


Figure 33: Student post composite score distributed based on major. (1=engineering, 2=computer science, 3=mathematics, 4=physics, and 5=other).

Student Final Performance

Although student performance was not included in the conceptual framework of this study, students' final exam scores were gathered in order to explore relationships that can be measured in future research questions. Table 56 below represents the number of students taking final exams in each instructor's treatment and comparison groups. It is important to note that some of the students who took the final examination might have partially participated in this study or they may not have participated in any stage of this study (students might only show up on exam days or skip lab portion of the course).

Table 56

Number of students took final exams for each instructor.

Instructors		Number
1	Comparison	32
	Treatment	27
2	Comparison	28
	Treatment	23
3	Comparison	31
	Treatment	26

Note. This distribution is regardless of participation in this study.

Figure 34 shows the distribution of student final exam scores for treatment and comparison groups within each instructor's course. The box plots provide insight into student final exam grades visually. In Instructor 1's course, there was an obvious difference between student scores. The median of the treatment group was higher than the comparison group and the overall box was much higher than the comparison group. In Instructor 2's course, the median of the treatment group was higher than the comparison group and the box for treatment group was comparatively shorter than the comparison group. The student scores in the comparison group were varied, but the scores in the treatment groups were relatively less varied although there were some outliers. In Instructor 3's course, the median of the treatment groups was higher than the comparison group. Although the scores in the upper whiskers of both groups were similar, lower whiskers were different. The treatment group in this class had more varying scores in the lower whiskers.

The exploratory analysis shows that the distribution of scores vary by treatment and comparison groups, and the tendency is for the treatment group to perform better by instructor.

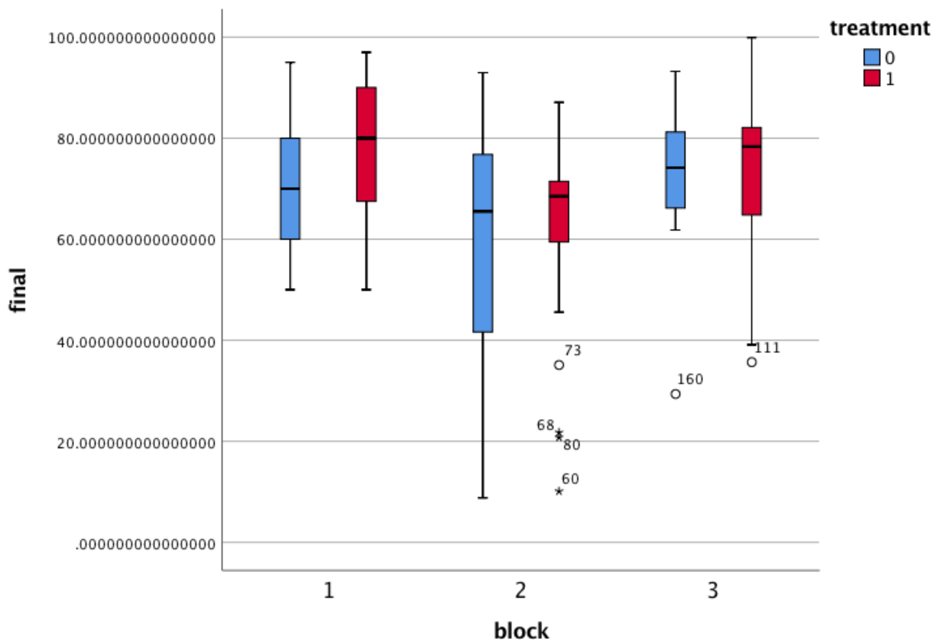


Figure 34: Student final exam scores for each instructor (Block 1, 2, and, 3 represents Instructor 1, 2, and 3 respectively and the box on the left is for comparison groups for each instructor).

Summary of Results

Based on the quantitative data collected through the surveys, the following research questions will be answered in this section:

1. How do the Calculus Tasks with Science and Engineering Applications impact student motivational aspects, including utility value, interest, and performance expectations in college Calculus I courses?

According to the results, the impact of the Calculus Tasks with Science and Engineering Applications on student motivation was not statistically significant overall. However, there were few cases where the impact was positive and significant on some of the student motivational aspects.

When the impact of the Calculus Tasks with Science and Engineering Applications were considered within each instructor's treatment and comparison groups there were varying results. The intervention had a positive and significant impact on students' composite motivation for Instructor 1 ($p=0.04$, in the Intermediate group). The intervention had a positive impact on student interest in all the instructor's courses, however that impact was not significant. Similarly, the intervention had a positive impact on performance expectations in some cases (Instructor 1 in Final group, and Instructor 3 in Intermediate group), but that was also not significant.

2. How does the impact of the Calculus Tasks with Science and Engineering Applications differ based on student gender, intended majors, and race in college Calculus I courses?

The impact of the intervention on student motivation significantly differed based on student gender. However, student motivation did not significantly differ based on students' intended major, or race ($p=0.99$, and $p=0.94$ accordingly). Therefore, a more in-depth analysis was performed using gender as a variable.

According to the results from the Intermediate group (participants in both groups that answered initial survey and the second survey after the first intervention), the intervention had a positive and significant impact on female student performance expectations ($p=0.04$). When each instructor's course is examined in terms of the impact of gender and intervention, the impact had a positive and significant impact on female student interest in Instructor 2's course ($p=0.05$) and female students performance expectations in Instructor 3's course ($p=0.02$).

The results from the Final group (participants in both groups that answered initial survey and final survey after the second intervention) showed that the intervention, although it had a positive impact, was not significant. When each instructor's course is considered, the intervention significantly impacts female student composite motivation ($p=0.06$) for Instructor 3, and interest ($p=0.08$) for Instructor 1 and Instructor 2.

Additional analysis was performed in order to compare the male and female students who were in the intervention groups to the male students in the comparison groups. According to those results, the intervention on female students' composite motivation had a positive and significant impact ($p=0.02$) when compared to the male students in the comparison groups.

3. How does student motivational aspects, including utility value, interest, and performance expectations change within a semester in college calculus courses?

Data from all the three surveys were analyzed to allow for analysis of change over time. Students' interest ($p=0.04$), and performance expectations ($p=0.05$) significantly changed throughout the semester. The direction of the change varied for different motivational aspects and student groups. Student performance expectations kept decreasing for both treatment and comparison groups throughout the semester. Student interest increased for both treatment and comparison groups.

When considering the instructor impact as a variable in addition to intervention, results were mixed. The interaction of time and instructor had no significant impact over time on student motivation. However, the interaction of the intervention and instructor over time had a positive and significant impact on composite motivation ($p=0.02$), performance expectations ($p=0.00$), utility value ($p=0.03$), and interest ($p=0.06$).

The change in student motivation based on student gender was examined to further address this question. The impact of gender on composite motivation, utility value, and interest was significant over time ($p=0.03$, $p=0.06$, and $p=0.07$ accordingly). Female student composite motivation, utility value, and interest increased from the first survey to the second survey and decreased from the second to the third surveys. Overall, final motivation scores for females were higher than initially observed.

The male student composite motivation decreased from the first survey to the second and increased from the second to the third. Overall, their composite motivation increased. The male student interest constantly increased over time. Their utility value decreased from the first survey to the second and then increased from the second to the third, but the at the end it was lower than the starting values. The male students' performance expectations decreased over time (except for the treatment groups).

V. DISCUSSION

Introduction

The purpose of this study was to measure the impact of a motivation intervention using the Calculus Tasks with Science and Engineering Applications. A quasi-experimental study was designed in a single public university in central Texas. The study was conducted during the course of one semester in three Calculus I courses. The students were surveyed to determine the impact of the intervention on their motivational aspects including utility-value, interest, and performance expectations as it is grounded in the Expectancy-Value Theory (Eccles et al., 1983). The survey results were then analyzed using multiple statistical techniques in order to reveal the impact of the intervention. In this chapter, the results will be discussed and interpreted thoroughly, and will be positioned within the existing motivation studies in the literature. Implications of the findings, limitations, and future research will be presented.

Summary of Findings

In this section of the chapter, the research questions of this study will be revisited to discuss conclusions based on the results. The results are a product of analyzing the data using two statistical techniques that were discussed in the previous chapter.

The first research question guiding this research study was "How do the Calculus Tasks with Science and Engineering Applications impact student motivational aspects, including utility value, interest, and performance expectations in college Calculus I courses?". The motivational aspects that were analyzed are composite motivation, performance expectations, utility value and interest.

Based on the Linear Mixed Effects Model, the impact of the Calculus Tasks with Science and Engineering Applications on student motivation was not statistically significant overall. The intervention had a positive and significant impact on student composite motivation in Instructor 1's course (in the intermediate group). The intervention had a positive impact on student interest in all of the instructors's courses, but it was not significant. Similarly, the intervention had a positive impact on performance expectations in some cases (Instructor 1 in Final group, and Instructor 3 in Intermediate group) but it was not significant.

The lack of significant results for the impact of the intervention on the overall treatment group, as well as having only one significant result in the case of an instructor's course after Intervention 1, requires further examination. A possible explanation could be related to the effect of the instructor on student motivation implicitly for the treatment and control groups. This study did not include mechanisms to control for this effect, and detailed data about instructors' practices related to student motivations was not gathered. Hence, this research question needs further examination in future research with more careful control over the instructors' practices related to motivation.

The second research question investigated in this research study was "How does the impact of the Calculus Tasks with Science and Engineering Applications differ based on student gender, intended majors and race in college Calculus I courses?".

The impact of the intervention on student motivation significantly differed based on student gender. However, student motivation did not significantly differ based on students' intended major, or race. It is possible that this was due to not having enough participants (in some cases no participation at all) for each race and major categories in the Calculus I courses (see Figure 30 – 33). Therefore, a more in-depth analysis was performed using gender as a variable.

According to the results from the Intermediate group (participants that answered initial survey and second survey after the first intervention), the intervention had a positive and significant impact on female student performance expectations. When each instructor's course is examined in terms of the impact of gender and intervention, the impact had a positive and significant impact on female student interest in Instructor 2's course, and female students' performance expectations in Instructor 3's course. The results from the Final group (participants that answered initial survey and final survey after the second intervention) showed that when each instructor's course was considered, the intervention significantly impacts female student composite motivation in Instructor 1's course, and interest in Instructor 1's and Instructor 2's courses.

Additional analysis was performed in order to compare the male and female students who were in the intervention groups to the male students in the comparison groups. According to those results, the impact of the intervention on female student composite motivation had a positive and significant impact when compared to the male students in the comparison groups.

Results give consistent evidence that the intervention had a positive and significant impact on female students in more aspects of student motivation than the male students. In particular, regarding the aspects of interest and composite motivation. Similar to the overall results, when the analysis is performed by instructor group, the positive and significant impact on the female student interest aspect of motivation needs further examination since not enough data was gathered to explain instructor effect. This might be due to female students not having as much opportunity as males to be engaged in science and engineering concepts.

The third research question investigated in this research study was "How does student motivational aspects, including utility value, interest, and performance expectations change within a semester in college calculus courses?". Student motivational aspects, utility value, interest, and performance expectations were analyzed over time to examine the change. Repeated Measures Analysis was conducted in order to address this research questions. The results showed that student interest, and performance expectations significantly changed throughout the semester. While the student performance expectations kept decreasing, their interest increased for both treatment and comparison groups over time.

The impact of the intervention was positive and significant on the change in student interest and utility value at the beginning of the semester, but it did not have a positive impact at the end of the semester. That is, a significant growth of interest and utility value was observed after the first intervention but not after the second. The interaction of intervention and instructor over time was significant on composite motivation, performance expectations, utility value, and interest. We again observe the evidence of instructor effect on the impact of motivational aspects that needs to be further investigated.

The change in student motivation based on student gender was also examined to further address this question. Gender had a positive and significant impact over time on composite motivation, utility value, and interest. The female student composite motivation, utility value, and interest increased from the first survey to the second survey and it decreased from second to the third survey. Overall, the final motivation scores for females were higher than initially observed. The male student composite motivation decreased from the first survey to the second and increased from the second to the third; their overall composite motivation was increased for both intervention and comparison groups. Male student interest constantly increased over time regardless of having the intervention or not. A possible explanation for that might be as the amount of calculus materials increased during the semester, male student expectations for getting good grades decreased.

As a whole, evidence suggests that student interest increased significantly over time, but their performance expectations significantly decreased at the end of the semester regardless of taking the intervention. Their utility value was decreased over time, but not significantly, and their composite motivation increased but not significantly. There is not enough evidence to account of these changes by the intervention since none of the interaction of time and intervention was significant for these motivational aspects.

Gender was a contributor for the change in student motivation over the semester. In general, female students' motivation scores were higher than male students. The intervention seems to have contributed to the increase in female student motivation aspects, except for the performance expectations after the first intervention in the treatment group. Although the number of females was low compared to males, the intervention was still effective on the change in female student motivation in some instructor's courses.

Finally, and as an exploratory analysis, the final performance of all students was examined independently of whether they participated in the intervention or not with the purpose of formulating new hypothesis and continuing this line of research. Observing the distribution of final examination scores, it can be seen that there is variation between treatment and comparison groups and among instructors. It would be interesting to investigate in future research the extent to which this variation is due to the intervention.

Discussion of Findings

The main purpose of this study was to measure the extent to which an intervention, Calculus Tasks with Science and Engineering Applications, extrinsically influenced student motivation. Student performance on these tasks was not the focus of this study, rather the impact of the intervention on their motivation was thoroughly investigated. Final calculus course performance was only considered as an exploratory factor for future research. The motivational concepts constituting the theoretical background of this study were performance expectations, utility value and interest. The results documented in this study were well positioned with the existing research studies in the literature. Even though the setting and the nature of the intervention in this study differed from the existing motivation intervention studies, the results and conclusions are, for the most part, consistent with them, contributing to the robustness of these findings.

The intervention was not a significant factor impacting student motivational aspects. However, the intervention had a stronger impact on female students, and significantly increased female students' motivation in some instructor's courses. The growth was significant in the composite motivation, performance expectations and interest. This suggests that their engagement in the calculus tasks with applications to science and engineering, written by potential science and engineering instructors, helps female students to relate the content to their goals or future careers and to get interested in studying calculus.

The positive and significant impact on some students is consistent with Puruhito et al. (2011) findings in Calculus II courses, and the impact of female students is consistent with the results of Durik and Harackiewicz (2007), where they found that the female participants showed greater interest and competency values than male participants on a mathematics task (although the participants came from psychology courses).

By the design of this study, intervention was also given to female students in STEM fields, which is an aspect that earlier motivation intervention research studies had not included (i.e. Hulleman and Harackiewicz, 2009; Hulleman et al., 2009; Puruhito, 2011). This is somewhat surprising since most of the research studies indicated that females tend to show more negative motivation and attitude towards mathematics, but students of those studies might not necessarily be STEM majors (Durik and Harackiewicz, 2007; Hyde, Fenema, Ryan, Frost, & Hopp, 1990).

Student performance expectations, which were also investigated as a motivational concept in this study, were not significantly impacted by the intervention. This result aligns with the national study of calculus courses (Bressoud, D., Mesa, V., & Rasmussen, C., 2015) where they found that student composite attitude (confidence, enjoyment and desire to persist) in calculus decreased at the end of the semester. This general tendency in calculus courses in the U.S. might explain the student low performance expectancy measures in this study.

This study procedured the idea of implementing tasks that use calculus concepts to solve science and engineering problems, created specifically by potential future instructors of students in computer science, physics, and engineering. After implementing the tasks to a treatment group and measuring motivational scores, however, there was no enough evidence to suggest that the intervention had a positive impact. Although this result is consistent with the Elliott et al. (2001) study where an interdisciplinary approach did not show any significant impact on students, it was different from the Marrongelle (2004) study where they found that providing interdisciplinary tasks helped students to make connections between calculus and physics.

This study also investigated the impact of the student's race and intended major on student motivation. The results showed that those variables did not have a significant effect on student motivation. In Hulleman and Harackiewicz (2009)'s study, race was also not a significant factor on student motivation. In addition, student's intended major was also not a significant factor on student motivation in calculus in this study. This might be due to most Calculus I courses being a before major course, and to the fact that most students do not commit to a major in their first few years. The existing motivation research studies did not consider student intended majors as a variable, and it may be because of most studies taking place in psychology courses.

Implications

The demand to increase STEM graduates has become a primary concern of researchers and policy makers in the United States, and calculus has been seen as a roadblock to graduating more STEM majors. Therefore, enriching the learning environment and motivating students in calculus courses is crucial for STEM fields.

Theoretical Implications

This study was grounded in the existing motivation intervention research studies and was mainly based on Hulleman et al. (2010)'s approach to the Expectancy Value theory (Eccles et al, 1983) and interest theories. The conceptual analytic model used in this study was adapted from Hulleman et al. (2010). The findings of this study aligned with the theoretical model and the existing studies for the most part, although differences occurred in some instances.

The positive and significant growth in student utility value and interest after the first intervention is consistent with Hulleman et al. (2010)'s findings. Also, the consistency of the relationship between student performance expectations and utility value supported the efforts of including expectancies in theoretical models (for a review, Hulleman et al., 2010; T. R. Mitchell, 1974). However, the intervention did not improve performance expectations of the Calculus I students in this study.

Since this study had students apply calculus in real world related science and engineering scenarios, this may have contributed to their engagement and feeling of involvement in mathematics. The literature on student engagement showed the relationship between student engagement and motivation for learning and student hope for better future and academic success (Furrer & Skinner, 2003; Van Ryzin, Gravely, & Roseth, 2009).

The results in this study give evidence that gender may play an important role in student motivation in calculus settings. In addition, this study overlaps with the results found in the national Calculus I study since the national study also investigated some affective factors (Bressoud, D., Mesa, V., & Rasmussen, C., 2015). However, the national study did not consider gender as a factor, they controlled the analysis for gender. In this aspect, the role of gender has important implications for future interventions in calculus courses.

Practical Implications

This study provided evidence that a theoretical approach based on motivation theories could be possible in calculus settings. Making use of interventions through the lenses of the Expectancy Value and interest theories was practical in terms of understanding student motivation and the interaction between the motivational constructs. This study provided opportunities for calculus students to be engaged in science and engineering tasks. These tasks were particularly related to their future careers since the tasks were developed by the science and engineering professors and instructors in the same institution. Calculus students that participated in the study were highly likely to take courses from those professors and encounter similar science and engineering tasks in those courses. Implementing those tasks in calculus courses provided the opportunity for the students to experience the use of calculus knowledge before they take relevant science and engineering courses.

In particular, the tasks seemed to be more impactful for female students than male students. It seems that similar interventions can provide an important change in female students' motivation to study calculus and ultimately keep them in the STEM fields. More research is needed to fully understand the reason why females benefit more, and better designs are needed to isolate other confounding factors that may be affecting the results, such as the effect of instructors' motivational practices and the timing of intervention.

Moreover, the evidence suggested that the interaction of intervention and instructor over a semester had a significant effect on composite motivation, performance expectations, utility value, and interest. Although the impact of instructor characteristics and practices on student motivation was not investigated in this study, there were possibilities based on some earlier research. According to the national Calculus I study, instructor skills such as *good teaching* improved students' attitudes about mathematics, and in this respect some instructors might have had good teaching skills that might have contributed to student motivation. Whereas the national study showed that *Ambitious Teaching* was negatively related to students' attitudes, hence, some instructors might have had these skills that negatively affected their student motivation.

Limitations

Since this study has many limitations, the results should be considered as a first step towards designing motivation interventions in calculus courses rather than conclusive claims. First, the results cannot be generalized or extended to populations beyond the group of students that participated. Although the assignment of treatment and comparison was conducted at random, instructors and students were not. It was a convenience sample of participants, they were the students of the instructors that had two sections of Calculus I. This selection facilitated the design of having treatment and comparison groups under the same instructor. In addition, the implementation of the tasks was conducted in a recitation or lab setting, which not all institutions have. The lab setting allowed for flexible time to introduce the tasks and give background about future courses and professor – a key component of the implementation in terms of impacting motivational aspects. Moreover, the teaching assistants for the lab portions of the Calculus I were not considered as a possible factor that impacts student motivation.

Second, the Calculus Motivation Survey that was adapted for this study did not undergo a full validation study. Even though the items that were used in the survey were based on previously validated instruments and tested for internal reliability and dimensionality in other settings, it is limited in terms of utility in calculus settings. In addition, the piloting stage of the survey included responses from Calculus II students. Although the target population of this study was Calculus I students, the sample from Calculus II was included in order to increase the number of sample size. This might have caused a slight limitation due to different student levels.

Third, the Calculus Tasks with Science and Engineering Applications were only validated in terms of their content by the authors of the tasks. Hence, they may only be appropriate for students at the institution where this study took place. Since the authors of the tasks were not necessarily calculus or mathematics instructors, the tasks may include some mathematical content that students were not familiar with and this may in turn affect their motivational aspects. Best efforts were made during revision and implementation of the tasks to ensure that students were comfortable with the technical notation and wording from the different fields outside of calculus. However, there was no systematic approach before the tasks were developed to ensure this aspect. Future use of these tasks in replication studies should be taken with great caution.

Finally, another limitation of the study was not including the relationship between motivation and student final calculus performance. Therefore, the impact of the intervention on student performance or finding any association of motivation and performance was not possible.

Future Research

Further research is needed to understand instructor's implicit or explicit impact on student motivational aspects and its relation to the intervention. Studies could be designed to gather information about instructors' beliefs and practices and include this information as particular variables.

Student performance and reasoning on the calculus tasks were not investigated in this study. Therefore, a different research project might explore student performance or reasoning on application problems, and its relationship to student motivation. In addition, in this study, some of the students may have started the semester with low motivation. There might be additional reasons for this low motivation, such as socio-economic status, high school GPA, and SAT scores. Further research might address detailed background information about calculus students and also follow up students on their next calculus or mathematics courses to determine retention.

One of the limitations of this study was not linking student motivation and their course performance. Therefore, a follow up study might be designed in order to explore how motivation interventions impact their end of semester performance in calculus courses.

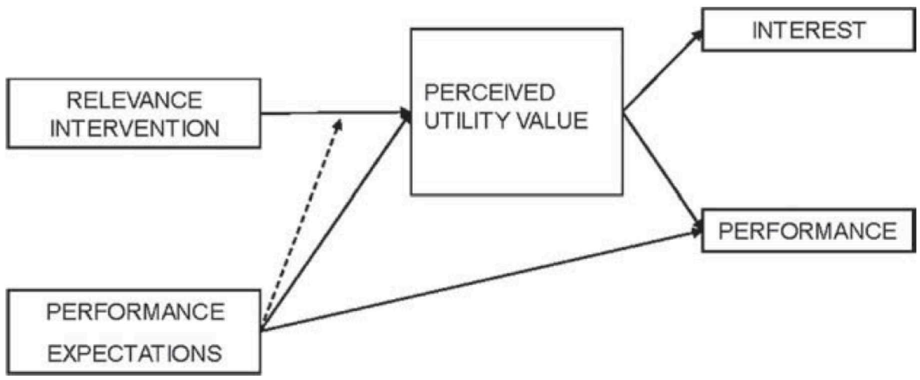
The implementation of the calculus tasks that were executed was done by a very particular implementation protocol. Therefore, other settings need to be explored where the implementation protocol is tested under ideal conditions in different institutions.

Moreover, a validation study could be designed for the Calculus Motivation Survey used in this study.

APPENDIX SECTION

Appendix A

The Framework in Hulleman et al. (2010) Study



Appendix B

Pilot Survey
Calculus Motivation Survey

This is a Likert scale that includes 12 questions. The questions are listed below, and they are about your experience in this course and Calculus overall. Please circle or cross the box that best describes what you think or feel.

	Strongly Disagree	**Disagree**	**Somewhat Disagree**	**Neutral**	**Somewhat Agree**	**Agree**	**Strongly Agree**
I believe that I will receive an excellent grade in this class.							
I expect to do well in this class.							
Considering the difficulty of this course, the teacher, and my skills, I think I will do well in this class.							
What I am learning in this course is relevant to my life.							
I think what we are studying in this course is useful for me to know							
I find the content of this course to be personally meaningful.							
I've always wanted to learn more about Calculus.							
I think the field of Calculus is very interesting							
I think what we're learning in this course is fascinating.							
To be honest, I just don't find this course interesting.							
I think the material in this course is boring.							
Calculus fascinates me.							
I am interested in majoring in a STEM field.							

BACKGROUND QUESTIONS

Please provide some details about your background.

What is your current intended major?	
What is your gender?	
What is your race/ethnicity?	

Appendix C

Motivation Scale in Hulleman et al. (2010)

Interest Items
I think psychology is an interesting subject.
I am not interested in psychology. (Reversed)
I think I will like learning about psychology in this course.
I think psychology will be interesting.
I've always wanted to learn more about psychology.
I think the field of psychology is very interesting.
I think what we're learning in this class is fascinating.
To be honest, I just don't find psychology interesting. (Reversed)
I think the material in this course is boring. (Reversed)
Psychology fascinates me.
I am interested in majoring in psychology.

Utility Value Items
What I am learning in this class is relevant to my life.
I think what we are studying in Introductory Psychology is useful for me to know.
I find the content of this course to be personally meaningful.

Appendix D

PROJECTILE MOTION

Authors:

Physics Department

Problem that arises in PHYS 1430 (mechanics) and PHYS 3311 (mechanics i)

PHYS 1430 This course covers the principles of classical mechanics through problem solving and laboratory investigations. It is designed for students majoring and minoring in physics and/or other disciplines within the college of science and engineering.

PHYS 3311 This course discusses the fundamentals of classical mechanics focusing on the physical description of the behavior of single and multiple particle systems. Topics included are advanced problem-solving strategies for systems with position and velocity dependent forces, simple harmonic oscillators, and non-inertial reference frames

In Classical Mechanics, we study the physical description of the behavior of single and multiple particle systems. One important example is the motion of a projectile in the presence of gravity. In this lab activity, we look at the *Free Kick in Soccer* problem that is discussed in PHYS 1430. We examine the vertical and horizontal position along path of kicked soccer ball.

Topics: Acceleration, Velocity, Position, Optimization

FREE KICK IN SOCCER

Story: After a foul, a soccer player is allowed a free kick. If you kick the soccer ball with an initial velocity (v_0), what launch angle (θ) will make the ball land the farthest from its launch point?

1. Explore: The website http://galileoandeinstein.physics.virginia.edu/more_stuff/Applets/Projectile/projectile.html has an applet you can use to simulate this problem. By moving the sliders on the right, you can change the initial velocity and angle of the ball. We will ignore air resistance for now. Click on the *Fire* button to see the trajectory. The goal is to land as far away from the starting point as possible. Use the website to discuss the following;
   a. Try different values for the initial velocity and angles. Discuss what do you notice about the range of the ball as you change the initial velocity and angle.

   b. For an initial velocity of 30 m/s, what angle gives the maximum range?

   c. Does the same angle work if the initial velocity is 50 m/s? Explain.

2. Defining Parameters and Variables.

Launch angle: θ in radians

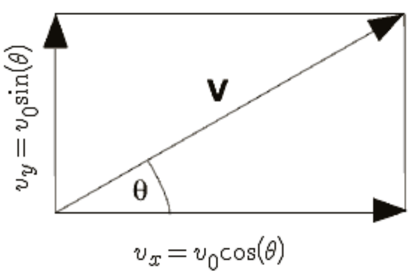
Initial velocity of ball: v_0 in m/s

Time: t in seconds

Position of ball: (x, y) where x represents the horizontal position of the ball and y represents the vertical position of the ball. Note that x and y are functions of θ and time t.

Force due to gravity: g in m/s^2

From physics knowledge, it is known that the velocity can be written in two directions: horizontal velocity and vertical velocity. The following diagram represents how the velocity is split into horizontal and vertical.



3. Finding formulas for the position of the ball as it moves. Find the general formulas for the position of the soccer ball. This part will be discussed as a class. [*Hint: Remember that* $distance(position) = rate\ (velocity) \times time$.].

$x =$

$y =$

4. Deriving the optimal launch angle (θ) to be able to kick the ball farthest distance. Discuss in your group and provide your reasoning in your answers.

    a. Find a formula for the time (t) when the ball hits the ground and call it t_{hit}. [*Hint: Set* $y = 0$*, that is, find* t *when the distance from the ground is 0 meters.*]

    b. Determine the total horizontal distance, x, for the time (t_{hit}) the ball travels before it hits the ground. [*Hint: Substitute the value you found in part (a) into the horizontal position function.*]

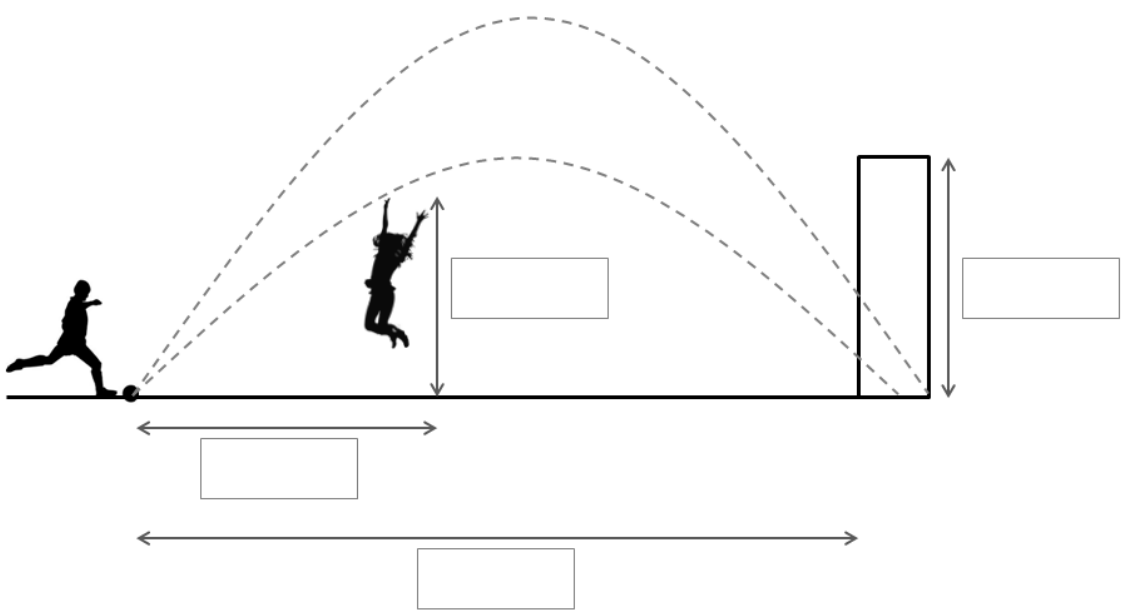
    c. Use the derivative of the horizontal distance function, x, to determine what angle θ maximizes the function x.

5. Discuss the following questions with your groups based on your previous work.
    a. Explain if kicking the ball harder (increase the initial velocity) would result in a change in the launch angle that maximizes the horizontal distance?
    b. Discuss if playing soccer on the moon instead of the earth (the gravitational acceleration was to change) would result in any change in the launch angle that maximizes the horizontal distance?
    c. Explain how increasing the initial velocity would impact the horizontal distance of the ball?
    d. Explain how decreasing the gravitational acceleration would impact the horizontal distance?

6. Extension: A soccer player is attempting to make a free kick over her opponents and into the goal (assume the goalie has fallen asleep!). The opponents must remain 9.15 meters (10 yards) from the soccer ball. The height of the goal bar is 2.44 m (8 feet) from the ground, and the opponents can jump 1.8 m high. The soccer ball will be kicked at a location from 20 m from the goal with an initial velocity of 25 m/s. For what range of angles must the ball be kicked, in order to land inside the goal?

   Video: https://www.youtube.com/watch?v=17CyPFbTVpU

   a. Use the values given above to label the side view of the situation shown in the diagram below.



   b. What is the minimum angle required to kick the ball over the head of the opponents?

c. What angles are required to kick the ball into the goal?

d. For what range of angles must the ball be kicked in order to land inside the goal without getting blocked?

Appendix E

COMPUTATIONAL ALGORITHMS

Authors:

Computer Science Department

Problem that arises in CS 2308 (Foundations of CS II) and CS 3358 (Data Structures and algorithms)

Computer Science is the study of computation applied to problem solving. There are often many computational algorithms that can be developed to solve a single problem, and choosing the best *algorithm* depends on developing a quick way to compare the performance of algorithms long before they have been implemented in a programming language.

It is possible to express the time performance of an algorithm as a mathematical function relating the number of computational "steps" the algorithm will perform as a function of the size of the input function. For example, the below *pseudo-code* describes a simple algorithm to calculate the sum of a sequence of numbers:

Sum = 0

For each element X_i in the sequence:

Sum = Sum + X_i

The algorithm begins with a single operation: the assignment of the value 0 to a variable named "Sum". For each of the N elements in the sequence, two operations are performed: an addition operation, and another assignment to the variable "Sum". Therefore, the following function determines the number of computation steps in the algorithm as a function of the input size: $f(N) = 1 + 2N$

In order to compare possible algorithms, we compare the growth (or rate of change) of these functions as N approaches infinity.

Topics: Limits involving infinity

1. Computer scientists often measure the efficiency of an algorithm by the mathematical function that determines the number of computations. These functions typically involve polynomial, exponential or logarithmic functions. The pictures below include the behaviors of these functions.

a) Identify each of the given functions on the picture and label them [four functions on the left given in the first picture and three functions on the right given in the second picture. Match which one is which]

I. $f(n) = n$

II. $g(n) = n^2$

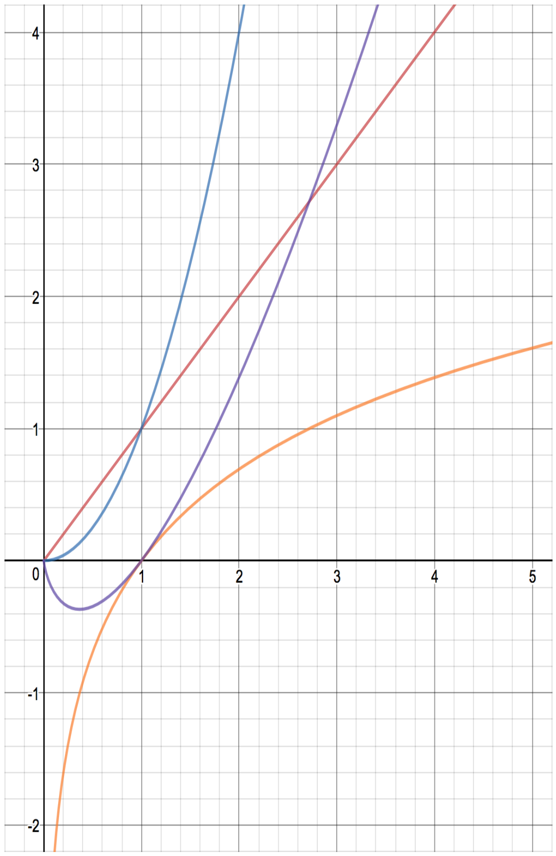
III. $k(n) = \ln(n)$

IV. $p(n) = n\ln(n)$

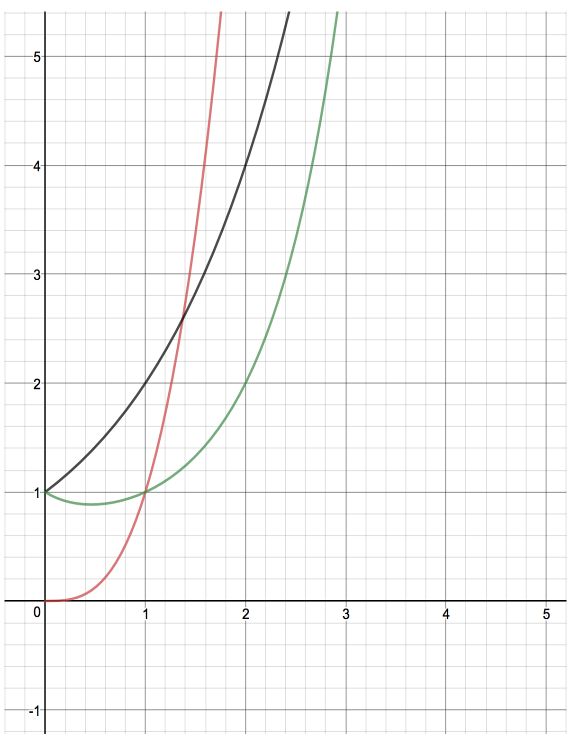
V. $h(n) = n^3$

VI. $q(n) = 2^n$

VII. $r(n) = n!$



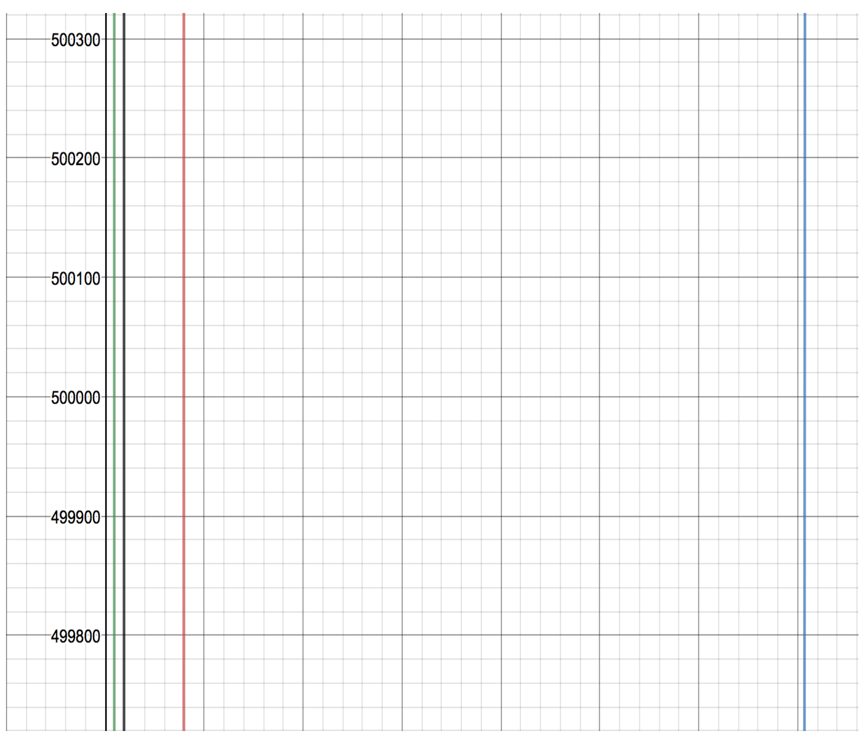
4
3
2
1
0
1
2
3
4
5
-1
-2



5
4
3
2
1
0
1
2
3
4
5
-1

b) Based on the same functions given on the picture previously, compare and contrast the behavior of the performance functions as n tends to infinity (that is, the size of the input grow without bound). Which one seems to be growing faster? How can you tell?

c) The following graph shows some section of a graph given for large values for the performance functions previously discussed. What do you notice about the behavior of the performance functions? Do you still support your claims in the part (a)?



2. Now we want to combine some of the algorithms above to see what happens to their behaviors. Imagine combining $h(n)$, $k(n)$, and $q(n)$ with $f(n)$.

i. $f(n) = n$

ii. $h(n) = n^3$

iii. $q(n) = 2^n$

iv. $k(n) = \ln(n)$

v. $f(n) + h(n) = n + n^3$

vi. $f(n) + k(n) = n + \ln(n)$

vii. $f(n) + q(n) = n + 2^n$

a) Identify each of the given algorithms on the picture and label them [match which one is which].

b) Compare the behavior of the following pairs of algorithms below as n tends to infinity. Do they look the same or different for large values of n? Which one grows faster? How can you tell?

- $f(n) + h(n) = n + n^3$ vs $f(n) + \ k(n) = n + \ln(n)$

- $f(n) + \ k(n) = n + \ln(n)$ vs $f(n) + q(n) = n + 2^n$

- $f(n) + q(n) = n + 2^n$ vs $f(n) + h(n) = n + n^3$

c) Based on the growth comparison you did previously, which of the algorithms is more efficient to use in computer science problems? [Hint: the slower the performance function grows, the more efficient it is

Definition: Rates of growth as $x \to \infty$

Let $f(x)$ and $g(x)$ be positive for large x.

1. f grows faster than g (or g grows slower than f) as $x \to \infty$ if:

   $\lim_{x\to\infty} \frac{f(x)}{g(x)} = \infty$ or $\lim_{x\to\infty} \frac{g(x)}{f(x)} = 0$

2. f and g grow at the same rate as $x \to \infty$ if:

   $\lim_{x\to\infty} \frac{f(x)}{g(x)} = L$ where L is finite and positive.

3. In a computer science problem, there are three different algorithms with three corresponding functions that measure the number of computation steps for a given input n.

I. $nlog_2^n$

II. $n^{3/2}$

III. $n(log_2^n)^2$

a) Determine the rate of the growth by comparing each pairs of the given algorithms [Hint: take the limit of the ratio of two algorithms as n goes to infinity].

d) Which of the algorithms is the most efficient in the long run? [Hint: the slower the performance function grows, the more efficient it is]

Appendix F

LINEARIZATION AND THERMOCOUPLES

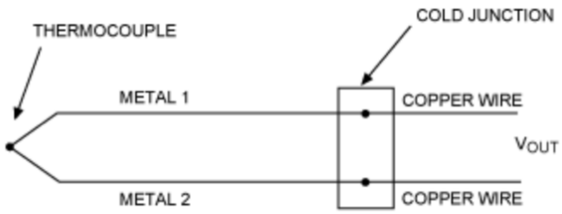
Author:

Engineering Department

Problem that arises in Manufacturing engineering courses

Do you care if the thermostat in your house is accurate at 160°F? At -57°F? What if a thermostat accurate from 30°F to 110°F costs $10 and one accurate from -57°F to 160°F costs $1,000? Which would you purchase? Have you ever wondered how your oven thermometer works? Heating a tube of mercury to a high temperature is not a particularly safe thing to do around food you will eat, so a different type of thermometer is needed.

This is where a **thermocouple** comes in. A thermocouple starts with two thin pieces of different types of metal that are parallel to each other. The tips of one side of each metal strip are bent until they touch. Now pass a current into the free end of one piece of metal, allow it to run through the connection, and measure the voltage that comes out the free end of the second piece of metal. This voltage will change based on the ambient temperature. If you start with two known types of metal, there will be a complicated equation that describes how the voltage changes with respect to the temperature. In the world of engineering, complicated equations lead to expensive equipment. Linear equations are very easy to solve and so using a linearization of the complicated equation of a thermocouple can allow you to build a less expensive thermometer.



But there is a catch. If you find the linearization of a function y=f(x) at x=a, the linear approximation of the function is valid "near" a, but might not be at all close far from a. When using linearization to produce a less expensive thermometer, you need to know the range for which it is accurate within a tolerance chosen based on the intended use of the thermometer. For example, an oven thermometer that is reads within 5°F of the true temperature is good enough for most household uses, but you wouldn't want your house thermometer to read 76°F if the actual indoor temperature was 81°F. And you really wouldn't want to take a child's temperature on a digital thermometer with a 5°F margin of error. In each of these 3 instances, the range for which you expect accuracy is also different.

Topics: Linearizations, approximations of functions

1. A thermocouple has an unknown governing equation. You are not daunted by this, and cleverly decide to use a linear approximation of the unknown function that is based on a secant line rather than a tangent line. You collect experimental data for two calibration points and come up with the data in the table below. [Suppose a linear output/input relationship is accurate only between for the temperature 100°C and 1000°C]

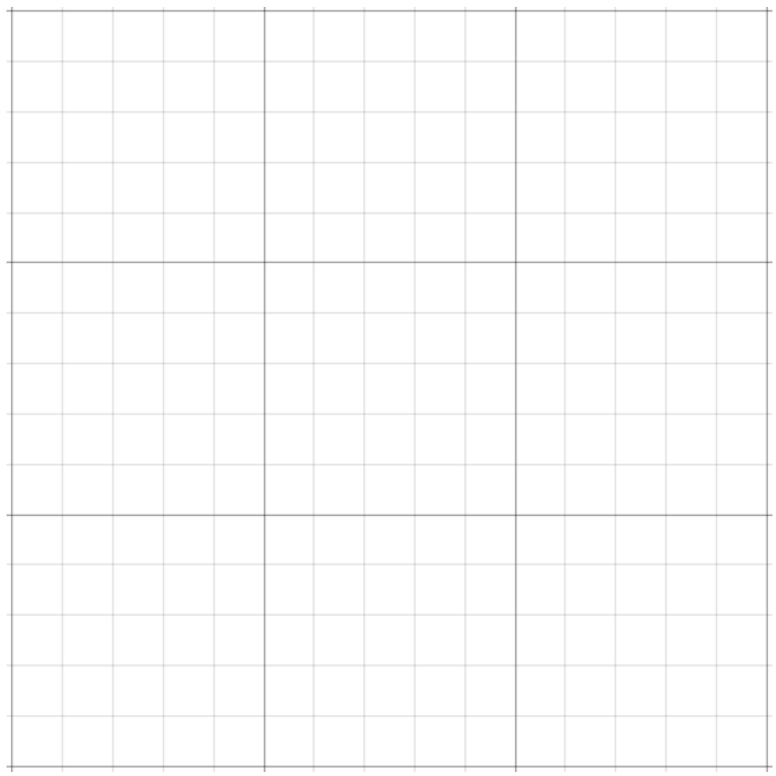
Calibration time	Temperature (°C)	Voltage (mV)
1	200	25
2	500	55

   a. Find the linear function of the thermocouple if the input is temperature and the output is voltage [It means to find the linear approximation for the unknown function based on the two points given].

b. Find the temperature corresponding to a voltage output of 200mV.

c. Is the result in (b) reasonable? Why or why not?

d. Sketch a graph of a function that could be the actual function associated with this thermocouple. Include all of the information from parts a, b, and c.



2. Suppose the actual equation governing a particular thermocouple is given by $f(x) = \sqrt{x}$.

a. Suppose you want to put the thermocouple in a digital thermometer used to take a child's temperature. Keeping in mind that a normal temperature is 98.6°F, so select this appropriate value for $x = a$ and calculate the linearization ($L(x)$) of $f(x)$ at the chosen $x = a$.

b. A typical digital thermometer gives readings of temperature with one decimal place. On what range of voltage given by the linearization, is your linearization valid with in 1/10th of one-degree Fahrenheit?

Notice that

$f(x) = V$ → true voltage

$L(x) = V$ → approximate voltage

$f^{-1}(V) = x$ → true temperature

$L^{-1}(V) = x$ → approximate temperature

I. We want the temperature read to be within 0.1 of the true temperature, therefore the following inequality is what we need. Simplify it to get the inequality located very below;

$$f^{-1}(V) - 0.1 < L^{-1}(V) < f^{-1}(V) + 0.1$$

$$|L^{-1}(V) - f^{-1}(V)| < 0.1$$

II. Now you need to find $f^{-1}(V)$ and $L^{-1}(V)$ to solve the above for V.

$f^{-1}(V) =$

$L^{-1}(V) =$

III. Now put $f^{-1}(V)$ and $L^{-1}(V)$ into the equation to solve for V;

$$|L^{-1}(V) - f^{-1}(V)| < 0.1$$

IV. Therefore, the range of voltage should be ($V_1 =$………, $V_2 =$………...).

c. Is this thermocouple appropriate for an oral thermometer? Why or why not?

Appendix G

Implementation Protocol

1. Introduction of the project
    a. Background of the project.
    b. Development of the tasks.
    c. Information about the instructors.
2. Working on the tasks
    a. Presenting the story.
    b. Exploration and definitions.
    c. Student group work.
        i. Facilitating the class.
        ii. Assisting groups.
        iii. Providing necessary help.
3. Class discussion
    a. Students share work.
    b. Bringing back the relevancy.

Appendix H

CALCULUS MOTIVATION SURVEY

This is a Likert scale that includes 12 questions. The questions are listed below, and they are about your experience in this course and Calculus overall. Please circle or cross the box that best describes what you think or feel.

	Strongly Disagree	**Disagree**	**Somewhat Disagree**	**Neutral**	**Somewhat Agree**	**Agree**	**Strongly Agree**
I believe that I will receive an excellent grade in this class.							
I expect to do well in this class.							
Considering the difficulty of this course, the teacher, and my skills, I think I will do well in this class.							
What I am learning in this course is relevant to my life.							
I think what we are studying in this course is useful for me to know							
I find the content of this course to be personally meaningful.							
I've always wanted to learn more about Calculus.							
I think the field of Calculus is very interesting							
I think what we're learning in this course is fascinating.							
To be honest, I just don't find this course interesting.							
I think the material in this course is boring.							
Calculus fascinates me.							

BACKGROUND QUESTIONS

Please provide some details about your background.

What is your current intended major?	
What is your gender?	
What is your race/ethnicity?	

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