Effects of Motivational Beliefs and Instructional Practice on Students' Intention to Pursue Majors and Careers in Engineering

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ABSTRACT

This dissertation examined the differences in group mean scores of traditional and pilot groups on the students' motivational beliefs and their intention to pursue majors and careers in engineering. The difference between the two groups was in terms of instruction techniques used. The instructional techniques used for the traditional group was that of traditional engineering design (TED), while the technique used for the pilot group had more features of an active learning approach. Further, it tested the tenability of the domain identification model. The domain identification model was used to understand students' decision-making processes in committing to engineering majors and engineering careers. The data for this study was collected via online survey from first-year engineering students enrolled in an introductory engineering course at a research-intensive university located in southeastern US. The sample sizes of the traditional group and pilot group at the beginning of the semester were 875 and 188, respectively. The sample sizes of the traditional group and pilot group at the end of the semester were 812 and 242, respectively. The mean differences between the two groups were computed using *t*-tests via SPSS version 22.0. The causality hypothesized among variables in the domain identification model were tested using structural equation modeling (SEM) techniques. The measurement and structural models were estimated using LISREL version 9.1. This study followed the two-step SEM approach that Anderson and Gerbing (1988) suggested. A measurement model with an acceptable fit to the data was obtained followed by an estimation and evaluation of structural models. All the independent sample *t*-tests were not statistically significant indicating that the mean scores of students in the two groups did not differ significantly on any of the motivational and intention variables. The hypothesized measurement and structural models provided a good fit to the data. A few post-hoc revisions were made to the models. This study brought empirical evidence that the domain identification model can be used to understand students' major-and career-decision making processes. Engineering identification was a better predictor of major intention and career intention compared to engineering program utility, engineering program belonging, and engineering program expectancy.

Dedication

To my wife, Migmar Tsamchoe la and our two children, Tenzin Dawa Chosang la and Tenzin Yangdoen Chosang la, and my brother, Tsewang Gyaltsen la.

Acknowledgement

My educational journey to earn this Ph.D. degree began nine years ago. His Holiness the Dalai Lama called for Tibetans to pursue the highest university degrees to serve the needs of the Tibetan community and build strong human capital, and I responded. His call stoked my personal desire to become a teacher, a researcher, and a productive member of the world community. These two factors motivated me as I worked through the Ph.D. program.

I have met many wonderful individuals during this journey; more than I can name here. I thank all of the people who supported me, but I'd would like to call out a few names for special recognition. This educational journey could have not begun without the gracious support of Dr. Don Roth, former dean of the graduate school of the University of Wyoming. I consider him to be a dear friend. Don and his wife Leslie, made our time in Laramie memorable. I consider it a special honor to be earning my doctorate from the same university where Don got his Master's and Ph.D. degrees from. You both have my thanks!

When I started down this path, I did not understand how long and hard the road to Ph.D. would be. I earned admission based purely on my merits and survived the many rigors of doctoral training. I faced many hardships, both financial and otherwise, during the last nine years. However, I did not waiver from my goal.

It took more than personal commitment to achieve this success. My wife, Migmar Tsamchoe la, and my brother, Tsewang Gyaltsen la stood by me and helped me stay focused throughout the journey. I could not have reached the finish line without their support and coaching, and I thank them from the bottom of my heart.

My wife's support was unconditional and unwavering. She saw my determination, and believed that I could achieve any goals I set for myself. We met as teenagers (she was in ninth grade and I was in eighth grade when we first dated), and have never looked back. She raised our

two children with unlimited love and compassion and her commitment to the family is unparalleled. She is our rock! I thank you, Migmar la, and I look forward to many fulfilling years ahead with you and our two beautiful children.

Raising a family in the US while going through this program is not an easy task, and we have sacrificed much to follow my dream. Winter breaks, Summer breaks, Fall breaks, Spring breaks, or breaks of any nature did not mean much to us. Financial challenges limited our ability to travel for fun, so the occasional trip to Minnesota to see family was the highlight. They also kept us from visiting our ageing parents and family members back in India. Our children are growing up without ever meeting some of their grandparents, and that is heart-ache on both sides of the world.

Going out to dinner has been a rare luxury, and generally meant quick run to Taco Bell or McDonald’s. My brother, Tsewang Gyaltsen la, would sometimes send a check with special instructions to take the family out for a treat. His love and support for my family made it possible for me to pursue my advanced degree. I dedicate this dissertation to my wife and brother as a way of paying respect to what they have done for me, and for our family.

My children, Tenzin Dawa Chosang la and Tenzin Yangdoen Chosang la, supported me and sustained me while I studied. I am proud of them for exceeding our expectations in school, and for understanding that we had to live within our means. With our extremely limited financial resources, we could not enroll them in any extracurricular activities, including summer camps, gymnasium classes, and music classes. However, we tried to buy educational materials for them during every summer to help them prepare ahead of time for the upcoming year and beyond. Those limited investment yielded handsome returns in the form of their exceptional performance

in school. We hope to keep this momentum going for them so that they will also become productive members of this world community.

Next, I would like to thank my committee members, Drs. Kusum Singh, Elizabeth Creamer, Brett Jones, and Marie Paretti. They all played an active and significant role in helping me complete this study. Some were instrumental in helping me conceive and refine the idea for this study, while others were instrumental in helping me find data. Many played an active role in making this dissertation a work of high quality. It was my honor to have Dr. Singh as the chair of my dissertation committee. I had multiple meetings with her throughout the entire writing process. Her ability to provide clear guidance and to hone my ideas was amazing. Dr. Singh held me to a high standard and pushed me even when I was nervous or hesitant. She did not make my journey easy, but certainly made it enriching and enlightening. She is an accomplished scholar and researcher, and I came out of every meeting I had with her with new knowledge to add to my knowledge bank. Thank you, Dr. Singh.

Finally, I met many good friends at VT, both in the community and within the EDRE program. I developed friendships with many individuals from the country I came from. Rajesh, Daljit, Atul, Sharad, Karthik, Vishwas, Kiran, and Sandeep—these are but a few of the many who helped me along the way. My wife and I have had opportunities to invite them for dinner at our home, and we shared a lot of laughter and good times over the momo (Tibetan dumpling) we served them. I also have had the opportunity to serve on the Indian Student Association (ISA) committee as the liaison officer and as vice president. I had wonderful working experiences with the ISA committee members, such as Abhijit, Shyam, Mahesh, Aditya, Pallavi, Akshay, Sreyoshi, Ashima, and Harmish. It was my honor to serve the small Indian community at Virginia Tech and I thank them for making me feel at home.

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Chapter 1: Introduction

Background

The US needs a sufficient number of graduates and professionals in the Science, Technology, Engineering, and Mathematics (STEM) fields for it to succeed in the 21st century, to maintain a leading position in the global marketplace, and to solve pressing issues related to, energy, the environment, and national security (Rollins, 2011). However, the US struggled with shortages of STEM professionals over the last six decades. Serious attention to science and math education by policy makers in the US began with the 1959 launch of the Sputnik satellite by the former Soviet Union (Drew 2011; Miller & Kimmel, 2012). Some of the major initiatives to improve education in the scientific fields as a result of serious attention science and math education received led to the creation of the National Defense Education Act (NDEA) and the National Science Foundation (NSF). These organizations channel federal money to colleges and universities to support various research initiatives, including increasing enrollment of students in STEM majors and reducing attrition rates from these majors.

Extensive research in the area of STEM fields, specifically those factors that contribute to students continuing in or switching out of STEM majors, has been conducted over the last six decades (Steinberg, 1949; Lucena, 2005). This research has resulted in a large body of knowledge, which can be broadly classified as focused on cognitive and non-cognitive factors. The literature in this area demonstrates that there are numerous cognitive and non-cognitive variables that influence students' decisions to commit to engineering majors and engineering careers.

Some of the cognitive factors investigated to understand and to predict students' intentions to pursue engineering majors were students' GPA (Tyson, 2011; Zhang, Anderson, Ohland, Carter, & Thorndyke, 2004), math ability (Grandy, 1998; Kokkelenberg & Sinha, 2010; Pascarella & Terenzini, 2005), and ACT/SAT scores (Adelman, 1985; Suresh, 2006; Zhang et al., 2004). These cognitive factors have been found to have strong predictive relationships with students' persistence in STEM majors (French, Immekus, & Oakes, 2005; Schaefers, Epperson, & Nauta, 1997; Suresh, 2006; Tyson, 2011; Zhang, Anderson, Ohland, & Thorndyke, 2004).

Similarly, researchers have studied non-cognitive factors, specifically the impact of motivational theories (Eccles et al., 1983; Eccles & Wigfield, 2000; Osborne & Jones, 2011; Lent, Brown, & Hackett, 1994) and proactive personality (Major, Holland, & Oborn, 2012) on students' academic decisions to pursue STEM degrees. Some of the motivational theories that were used were social cognitive career theory (SCCT; Lent, Brown, & Hackett, 1994), expectancy-value theory (Eccles et al., 1983; Eccles & Wigfield, 2000), and the domain identification model (Osborne & Jones, 2011). Through these motivational theories, research has consistently shown that motivation has a significant impact on students' persistence in STEM fields.

In addition to motivational beliefs, other non-cognitive variables studied included classroom and academic climate, social pressures, departmental culture, and institutional structures in STEM programs (Geisinger & Raman, 2013; Goodchild, 2004). Many authors have looked at attrition issues in the late 1980s and early 1990s (e.g., Brush, 1991; Hewitt & Seymour, 1991; Manis, Thomas, Sloat, & Davis, 1989). These researchers found that a traditional lecture format in classes for STEM majors was detrimental to students' persistence in the fields (e.g. Bernold, Spurlin, & Anson, 2007; Cabrera, Colbeck, & Terenzini, 1998; Seymour & Hewitt, 1997). Similarly, other issues found to be associated with attrition were lack of opportunity for questioning, poor teaching, and unresponsive faculty members (Lichtenstein, Loshbaugh, Claar, Bailey, & Sheppard, 2007; Seymour & Hewitt, 1997; Strenta, Elliott, Adai, Matier, & Scott, 1994).

As a result of the findings of the studies cited above, many innovative initiatives have been undertaken to overcome retention and attrition issues. For instance, in many Colleges of Engineering, new programs have been developed to respond to the greater need for more engineers and some of the efforts in this area have been through programmatic design. Numerous innovative programs, such as learning communities, pre-college programs, summer bridge sessions, supplemental courses, externally funded undergraduate research programs, and mentoring have been initiated to increase students' interest in STEM and to ultimately retain them (Brewe, Kramer, & Sawtelle, 2012; Fortenberry, Sullivan, Jordan, & Knight, 2007; Koenig, 2009; Maton, Hrabowski, Schmitt, 2000; Pierrakos, Beam, Constantz, Johri, & Anderson, 2009). These programs were designed to give students increased opportunities to learn through interactive activities, more interaction with faculty members, and larger engagement in collaborative learning. Further, several major universities established Departments of Engineering Education and/or Schools of Engineering Education within Colleges of Engineering to develop and research new ways of teaching engineering subjects. Some of the new developments included starting doctoral programs in Engineering Education. For instance, Purdue University and Virginia Tech started their doctoral programs in Engineering Education in 2005 and 2008, respectively (Haghighi et al., 2008).

In addition, innovative instructional pedagogies, such as active learning, were experimented with to counter the issue of students' poor experiences in their introductory STEM courses. The problem-based learning (PBL) and peer instruction (PI) are a part of active learning pedagogies. These instructional pedagogies have repeatedly been shown to have positive influences on students' experiences in their introductory classes (Felder, Forrest, Baker-Ward, Dietz, Mohr, 1993; Hoit & Ohland, 1998; Matusovich et al., 2012; Watkins & Mazur, 2013). These teaching techniques directly address most of the issues identified by Seymour and Hewitt (1997) and Strenta et al. (1994), such as poor teaching, unresponsive faculty members, and lack of opportunity for questioning. When used appropriately, they boost students' motivation (Jones, Epler, Mokri, Bryant, & Paretti, 2013; Matusovich et al., 2012), enhance their skills in areas, such as problem-solving, communication, and teamwork (Knight, Fulop, Marquez-Magana, & Tanner, 2008), and increase their chances of persisting in STEM fields (Hoit & Ohland, 1998; Springer, Stanne, & Donovan, 1997; Jones, Osborne, Paretti, & Matusovich, 2014; Watkins & Mazur, 2013). Even though these instructional pedagogies have different names, they are closely related (Knight et al., 2008). Many studies have found that positive experiences in a single course could influence students' decisions to stay in the STEM majors (Hoit & Ohland, 1998; Springer, Stanne, & Donovan, 1997; Watkins & Mazur, 2013).

Further, to improve scholarly research and teaching in engineering education and to improve the learning of engineering and science, numerous centers were established at universities, such as the University of Washington Center for Engineering Learning and Teaching in 1998, the Colorado School of Mines Center for Engineering Education in 2000, and the NSF funded Center for the Advancement of Engineering Education in 2003 (Haghighi, Smith, Olds, Fortenberry, & Bond, 2008). In addition to these centers, some universities started a common first-year program. The purpose of such a program was to help students make connections among engineering, science, and mathematics (Froyd & Ohland, 2005). These initiatives were often described as integrated curricula and are often taught using active learning strategies (Froyd & Ohland, 2005; Roedel et al., 1995).

A large body of research has accumulated on cognitive and non-cognitive factors that affect students' decisions to continue in STEM majors or switch out of those majors and the research in this area continues to grow. Researchers have a better understanding of the nature of problems affecting recruitment and retention efforts as a result of decades of research. They have found some workable and innovative solutions to the problems.

However, the problem of recruitment and retention in STEM fields given increasing demand has not been fully resolved. A demand-supply gap exists and continues to enlarge because of problems affecting recruitment and retention of students in those fields. The concerted efforts at the national and institutional level have not been entirely successful in preventing decreased enrollment in engineering fields (Pierrakos et al. 2009) and also in increasing retention (Watkins & Mazur, 2013). The National Science Foundation (2010) published the Science and Engineering indicators and it showed that the number of students enrolled in science and engineering is unchanging, while jobs in those fields are on the rise. Additional evidence has pointed in the same direction. For instance, it was projected that it would be hard to replace STEM positions vacated because of retirements and also because of students' reduced interests in STEM fields (Bureau of Labor Statistics, 2005; 2010; Melsa, 2007). Students' reduced interest in STEM fields, which is leading to a dearth of students joining STEM fields, was highlighted by Chang (2009), the National Science Foundation (2007), and Ohland et al. (2008).

Despite the fact that a body of research is growing, all the research findings are not consistent. One of the major inconsistencies was that some of those who defected from engineering were performing well academically (Besterfield-Sacre, Atman, Shuman, 1997; Seymour & Hewitt, 1997). The results of these studies indicate that students switch out to other majors for reasons other than academic performance and an acceptable level of preparedness. What complicates the context further is that studies have found that a degree in engineering does not necessarily translate into an engineering career (e.g., Lichtenstein et al., 2009; Ngambeki, Dalrymple, & Evangelou, 2008).

Rationale for the Study

The continuing problems of shortages of STEM professionals and inconsistent research findings demonstrates a need for more research in this area. The decision-making process to commit to engineering majors and careers is complex, involving many cognitive and non-cognitive factors. Lichtenstein et al. (2007) pointed out that multiple bodies of research in the last few decades have produced knowledge that outlined complexities associated with students' decision-making, but definitive insight is still lacking.

Therefore, there continues to be a need for more research to further understand factors that influence students' decision-making processes related to joining, continuing, and/or switching out of STEM majors. Further, more research on the effectiveness of the innovative instructional pedagogies should be conducted so that the federal government can promote the use of effective instructional practices, such as active learning, on a wider scale. Gates Jr. and Mirkin (2012) recommended that the federal government encourage educational institutions to embrace active learning approaches in introductory STEM courses because they are empirically validated to be effective.

There are many theories regarding students' decision to discontinue their college education (e.g., Tinto, 1987;), their persistence in chosen majors (e.g., Eccles, 2009; Seymour

Hewitt, 1997) and making their career choices (e.g., Lent, Brown, & Hackett, 1994, 2000). Identity and values have been demonstrated to have a positive influence on students' goal intentions in numerous domains (Eccles et al., 1983; Kaplan & Flum, 2009; Ruff, 2013), such as engineering (e.g., Jones et al., 2010). Domain specific identification is not a part of many theories, such as expectancy-value theory and social cognitive career theory (SCCT), but has potential to contribute to the existing body of knowledge on major and career decision-making. Therefore, the domain identification model can be a new lens to study factors related to students' goal intentions and can contribute to the current literature on commitment to STEM majors and career theory.

The problems of recruitment and retention are equally prevalent in the field of engineering as in other STEM areas, and lead to shortages of qualified engineers in the market. Therefore, this study focuses on engineering majors, specifically on students' intention to continue in engineering majors and pursue engineering careers using the domain identification model (Osborne & Jones, 2011) as a theoretical framework. This study also investigates the impact of active learning as an instructional technique by comparing the level of students' academic motivation, as measured with five components of the MUSIC Model of Academic Motivation (Jones, 2009) and other motivation-related variables.

The domain identification model has been applied to study students' choices in many majors. For instance, this model has been used to investigate the impact of students' motivational beliefs on their intention to pursue majors and careers in engineering (e.g, Jones, Osborne, Paretti, & Matusovich, 2014) as well as in other careers, such as music teaching and performance (e.g, Jones & Parkes, 2010). This model can also be applied to study other specific academic and non-academic domains, such as job performance, mathematics, and statistics (Osborne & Jones, 2011).

The present study extends the prior work of Hoit and Ohland (1998), Osborne and Jones (2011), Springer, Stanne, and Donovan (1997), and Watkins and Mazur (2013) by testing the model with two different groups—traditional and pilot groups—in an introductory engineering class. The instructional techniques used in the pilot group had more features of an active learning approach and, therefore, students in that group were expected to have higher motivation. The other important goal of this study is to contribute to understanding complex decision-making processes of students to persist in their engineering majors.

Research Questions (RQs)

The following research questions were formed for this study:

R-Q-1. Are there mean differences between the two types of instruction on motivation-related beliefs, engineering identification, the three engineering-related motivational factors, and the two intention variables (major intention and career intention)?

R-Q-2. Do students' motivation-related beliefs in an introductory engineering course influence engineering identification and the three engineering-related motivational factors?

R-Q-3. Do engineering identification and the three engineering-related motivational factors affect students' intentions to pursue majors and careers in engineering?

R-Q-4. To what extent are the relationships in research questions two and three different across the two different types of instruction?

Domain Identification Model

The Domain Identification model is used as a conceptual framework for this study. Domain identification refers to "the extent to which an individual defines the self through a role or performance in a particular domain" (Osborne & Jones, 2011, p. 132). The domain identification model has identified a number of antecedents and consequences of a domain specific identification. Some of the antecedents are school climate, group membership, and formal and informal educational experiences. The formal and informal educational experiences as antecedents were included in the model used in this study. Specifically, students' motivation-related beliefs (i.e., the five components of the MUSIC Model of Academic Motivation) in an introductory engineering class were used as antecedents of engineering identification and three engineering-related motivational factors. The three engineering-related motivational factors took the place of "goals, beliefs, and self-schemas" in the original model. According to the original model, other consequences of domain specific identification and motivational beliefs are "choices, effort, and persistence." Major intention and career intention were used in place of "choices, efforts, and persistence". In sum, the partial domain identification model hypothesized that the five factors of the MUSIC model can predict engineering identification and three motivational beliefs. And these four variables in turn are hypothesized to predict students' engineering major intention and engineering career intention. The causal relationships hypothesized among these variables is presented in Figure 1.1.

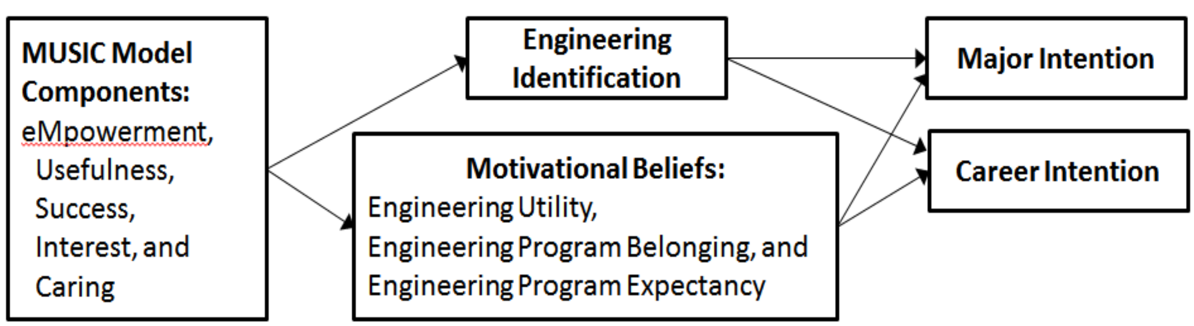

Figure 1.1. Variables included in the present study and paths examined. Structural paths are present from each component of the MUSIC model to engineering identification and three motivational beliefs, as well as from engineering identification and three motivational beliefs to major and career intention.

Outline of the Dissertation

This study was organized into five chapters. The first chapter begins with an introduction, underscores the rationale for the study, and presents the research questions and theoretical framework. The second chapter consists of the literature review related to all of the variables included in the partial domain identification model tested in this study. This chapter contains definitions and the intellectual history of the five components of the MUSIC Model of Academic Motivation. Similarly, definitions and the historical background of engineering identification, engineering utility, engineering program belonging, and engineering program expectancy, and their effects on the outcome variables of interest are also discussed. Further, the meaning and components of active learning and its usefulness in enhancing students' positive experiences are covered in the second chapter. The methodology of the study is presented in chapter three, which contains information about the sample and instrument. Further, it highlights the data collection techniques and analytical procedures. In chapter four, results of the data analyses are presented. This included descriptive statistics for all the variables in the study, intercorrelations among them, construct reliability of each scale with Cronbach's alphas, and fit indices of the measurement and structural models. The final chapter covers the conclusions of the study and included discussions of the results, implications for practice, limitations, and directions for future research.

Chapter 2: Review of Literature

Introduction

This chapter deals with review of relevant scholarly literature that provides the background and theoretical framework for this study. This review process is organized into three major divisions. First, the history of shortages of STEM graduates and professionals in STEM fields are presented. This is followed by the problems identified for declining enrollments in STEM programs and increasing attrition rates in these fields and the attempts made to ameliorate the underlying problems. Second, literature related to an innovative instructional technique, specifically Active Learning, will be examined. In this review process, the definition of Active Learning, its origin, its uses in the STEM programs, and its impact on student motivation and creating a conducive learning environment will be described. Third, this section is related to the definition of domain identification and intellectual history of the domain identification model. Further, definitions of the components of the domain identification model and their influence on students' persistence in STEM fields will be explored. The latent variables that are included in this study as part of the domain identification model are the five components of the MUSIC Model of Academic Motivation (eMpowerment, Usefulness, Success, Interest, and Caring), Engineering Identification, three motivational beliefs (engineering utility, engineering program belonging, and engineering program expectancy), engineering major intention, and engineering career intention. The relationships among these latent variables in the domain identification model are presented in Figure 1.

The following three research questions guided the process of this literature review.

1. Do five elements of the MUSIC Model influence engineering identification and specific engineering related motivational factors?
2. Do engineering identification and specific engineering related motivational factors affect

students' intentions to pursue a major and career in engineering?

3. Are these relationships the same in the two groups (traditional vs. treatment group)?

4. Are there mean differences between treatment and control groups on MUSIC Model, domain identification, specific engineering related motivational factors and intention variables?

Shortages of Professionals in STEM Fields

American technological leadership came into question when the Soviet Union, during the height of the Cold War, successfully launched Sputnik in space in 1957 (Drew, 2011; Miller & Kimmel, 2012). Sputnik was a satellite measuring 22 inches in diameter, which by today's standard is a tiny satellite. However, its psychological and political impacts on Americans were huge. Since then the issue of whether or not a sufficient number of individuals pursue careers in STEM fields has been continually discussed. Science education became a national priority with the voyage of Sputnik. Some of the measures undertaken in support of scientific education and scientific research included instituting the National Defense Education Act (NDEA) and the National Science Foundation (NSF). These organizations provide funding to colleges and universities to investigate techniques that would help improve a science and mathematics education in America, a trend that continues today.

A science and mathematics education in America is significant because an adequate number of STEM professionals are essential for the future prosperity of the US (The National Academies, 2007). The quality of STEM education in the US will determine whether it can continue to be one of the technological leaders in the world and be capable of solving challenges in the areas of national security, energy, environmental protection, and health (Rollins, 2011). Therefore, it is important to produce a highly capable and flexible workforce in the STEM fields to be competitive in a globalized, high-tech information economy.

Historically, the US has an astonishing record of achievement. However, US students lag behind their foreign counterparts in STEM education, especially at the elementary and secondary level (Drew 2011; Rollins, 2011). Specifically, our students' rankings have been low in most of the international standardized tests, such as The Trends in International Mathematics and Science Study (TIMSS) and the Program for International Student Assessment (PISA). TIMSS surveys focus on fourth and eighth grades in the areas of mathematics and science. The PISA assesses the ability of students to apply the science and technological knowledge they have gained. The purpose of this assessment is to test whether or not students have the requisite knowledge to be competitive in today's workplace. The ranking of the US students were at the bottom among those nations that participated in the test in 2006 (Rollins, 2011). The two other international surveys that the United States' students participate in are the Adult Literacy and Life Skills Survey (ALL) and Progress in International Literacy Study (PIRLS). The former survey is intended for those between 16 and 65 years old, while the latter is intended for fourth graders. Table 2.1 demonstrates the historical ranking of the U.S in mathematics and science assessments.

In addition to US students' participation in those international surveys, they participate in the national assessment program called the National Assessment of Educational Progress (NAEP). It is also called the Nation's Report Card. Unfortunately, less than one-third of eighth graders have attained proficiency in mathematics and science (Rollins, 2011).

Table 2.1

Performance of American High School Students in International Mathematics and Science Achievement Assessment

Year	No. of Countries in Study	US Rank
Math Assessments		
1965	12	12
1989	12	12
1991	15	12
2003	29	24
Science Assessments		
1973	14	14
1988 (biology)	13	13
1988 (Chemistry)	13	9
1991 (Physics)	15	13
2003	29	19

Source: Drew (2011). STEM the Tide: Reforming Science, Technology, Engineering, and Math Education in America.

The US students' lack of interest and poor performance in science and mathematics fields at the elementary and secondary schools level is reflected in the proportion of American students interested in graduate studies in STEM fields. More than 50% of the graduate students enrolled in science and engineering programs in US universities are from foreign countries (Rollins, 2011). Due to a lack of qualified professionals in the country, US businesses have been hiring non-US citizens to fill hundreds and thousands of positions of scientists and engineers every year for the last few decades (Drew, 2011).

In light of the problems plaguing STEM education, many commissions, committees, and task forces have been established to investigate the underlying problems and are assigned the responsibility of making recommendations to overcome those problems. For instance, presidential commissions, congressional committees, national academy task forces, disciplinary societies, and business groups investigated the issue and came up with several recommendations (The national Academies, 1993; 1999; National Academy of Engineering and the National Research Council, 2005; National Research Council, 1999a, 1999b, 2001; National Science Board, 2006).

An eminent group of scientists and business leaders, which the National Academy of Sciences commissioned, produced a report entitled *Rising Above the Gathering Storm: Energizing and Employing America for a Brighter Economic Future* in late 2005 (Byko, 2007; Drew, 2011; Rollins, 2011). This report lists four recommendations (Byko, 2007): (1) "10,000 Teachers 10 Million Minds" aimed at adding 10,000 qualified K-12 math and science teachers in US schools; (2) "Sowing the Seeds" looked for increased federal funding for basic research; (3) "Best and Brightest" recommended increasing the numbers of US citizens earning science, engineering, and math degrees and making it easier for international students to study in the United States; and (4) "Incentives for Innovation" addressed economic policies that reward innovation.

The *Gathering Storm* report emphasized the importance of young adults entering scientific, engineering, and related fields as this is the precursor to the future prosperity of the country (The National Academies, 2005 as cited in Miller and Kimmel, 2012). It is essential to maintain a competitive scientific workforce to prevent a decline in the standard of living. The report was important because it associated the decline in math and science education with national security and its consequences on future economic prosperity (Byko, 2007). US Representative Sherwood Boehlert's, comment best exemplified this: "This report took Washington by surprise. I can't remember another report on another subject…that so immediately intensified and gave focus to a policy discussion." (as cited in Byko, 2007).

Problem Identification (Cognitive and Non-Cognitive Factors)

Researchers investigated both cognitive and non-cognitive factors in understanding students' interest in pursuing majors in the STEM fields and also in predicting their retention in STEM fields. Research in these areas has been conducted for more than 50 years (Steinberg, 1949). Researchers in the last few decades have produced a body of literature. For instance, some of the reasons why students leave engineering degree programs and how the rate of retention can be increased has been associated with classroom and academic climate, grades and conceptual understanding, and self-efficacy and self-confidence (Geisinger & Raman, 2013).

Cognitive Factors

Both cognitive and non-cognitive factors were found to explain variability in engineering retention. In terms of cognitive factors, sufficient mathematics preparation at the high school level has been found to be important because it is related to attrition or retention (Grandy, 1998; Kokkelenberg & Sinha, 2010; Steinberg, 1949). Some researchers have also found that enrolling in and obtaining high grades in sciences classes (Grandy, 1998), chemistry (Levin & Wyckoff, 1990), social sciences (Moller-Wong & Eide, 1997), calculus (Levin & Wyckoff, 1990), and physics (Levin & Wyckoff, 1990; Moller-Wong & Eide, 1997) are significant in explaining variations in retention in engineering programs. Further, some argued that the overall high school GPA (Tyson, 2011; Zhang, Anderson, Ohland, Carter, & Thorndyke, 2004) and high school class rank (French, Immekus, & Oakes, 2005; Moller-Wong & Eide, 1997) had predictive relationships with retention in engineering program. Still others found ACT scores (Adelman, 1985) and SAT scores (Suresh, 2006; Zhang et al., 2004) to be predictive of student persistence in engineering programs, particularly the SAT math score (French et al., 1997; Suresh, 2006; Zhang et al., 2004). Beyond high school preparation in mathematics and science, numerous studies indicated that students' performances in those subjects in college, such as physics, chemistry, and calculus also predict students' attrition from engineering (Leuwerke, Robbins, Sawyer, & Hovland, 2004; Levin & Wyckoff, 1990; McDade, 1988).

Non-Cognitive Factors

In addition to proactive personality, numerous motivational theories have been tested to understand students' motivation to continue in STEM majors, such as the social cognitive career theory (SCCT; Lent Brown, & Hackett, 1994), the expectancy-value theory (Eccles et al., 1983; Eccles & Wigfield, 2000), and the domain identification model (Osborne & Jones, 2011).

Proactive personality. According to Bateman and Crant (1993), a person with a prototypic proactive personality is, "one who is relatively unconstraint by situational forces, and who effects environmental change" (p. 105). People with a proactive personality look for opportunities, exhibit initiative, take action, and persist until they effect substantive changes in their area of living (Bateman & Crant, 1983). It has been demonstrated that a proactive personality is a better predictor of individuals' motivation to learn when compared with the Big Five personality factors (neuroticism, extraversion, openness, conscientiousness, and agreeableness; Major, Turner, & Fletcher, 2006). The proactive personality has been investigated mainly in workplace settings and it has been shown to have strong relationships with positive outcomes, such as higher quality exchange relationships with leaders, job satisfaction, number of promotions, and job performance (Chan, 2006; Li, Liang, & Crant, 2010; Seibert, Crant &

Kraimer, 1999). The features of proactive personality that enable individuals to succeed in the workplace should likewise enable individuals to be successful in challenging majors at the university level (Major, Holland, & Oborn, 2012). Individuals with a proactive personality see challenges as learning opportunities (Elliot & Harackiewicz, 1996). Therefore, they have the tendency to engage in building new skills. Such an attitude could be valuable in rapidly changing technology fields. Major et al. (2012) found that a proactive personality was strongly related to students' commitment to STEM majors.

Social cognitive career theory (SCCT). The SCCT (Lent, Brown, & Hackett, 1994) has been widely used as a theoretical framework in studying students' decisions regarding their academic majors and career choices in a wide variety of fields (Betz, 2008; Lent et al. 2005; Lindley, 2005; Patrick, Care, & Ainley, 2011; Wang, 2013). The application of this theory to engineering students (Lent et al., 2003; Lent et al., 2008; Trenor, Yu, Waight, Zerda, & Ting Ling, 2008) included students' persistence in engineering fields and focused on underrepresented groups (Carrico & Tendhar, 2012; Lent et al., 2005; Trenor et al., 2008). The SCCT has a number of variables in its model and the relationships among those variables are specified *a priori*. However, the model was rarely tested with all the variables. The researchers test only select variables of the SCCT at a time depending on their research interests and research questions. For instance, Carrico and Tendhar (2012) tested relationships among self-efficacy, outcome expectations, interests, and goals. In their model, self-efficacy was hypothesized to predict outcome expectations, interests, and goals. Outcome expectations were expected to predict interests and goals. Interests, in turn, were hypothesized to predict goals.

The SCCTemerged from Bandura's Social Cognitive Theory (SCT; Lent et al., 1994). The SCT describes human behavior in terms of triadic reciprocal causation (Bandura, 1986). In this dynamic model of reciprocal determinism, cognitive, external environment, and behavior influence one another bidirectionally. The authors stated that bidirectionality does not occur simultaneously. Further, the sources of influences cannot be assumed to be of equal strength in reciprocality. Wood and Bandura (1989) further stated that the influence of causality takes time and so does activation of reciprocal influences. The reciprocality of influence makes people both products and creators of their environment. In this reciprocal causal structure, cognitive, vicarious, self-regulatory, and self-reflective processes are the key elements of the SCT.

Expectancy-value theory of motivation. Similarly, there are other motivational theories, such as the expectancy-value theory (Eccles et al., 1983; Wigfield & Eccles, 2000), that are employed to study students' choice of domain and their performance in those domains. Eccles' et al. (1983) expectancy-value theory of achievement performance and choices was initially tested in the mathematics achievement domain. The model hypothesizes relationships between numerous variables. However, the partial model has been often tested using expectation of success, subjective task value, and achievement-related choices as variables. Ability and expectancy are crucial aspects of this model. The operational definitions of these variables vary slightly across theoretical perspectives. Therefore, measures of these constructs also vary, especially with regard to the specificity of beliefs being measured and the question regarding the exact nature of ability. In terms of the values part of the model, Eccles et al. (1983) described different aspects of achievement values: attainment value, intrinsic value, utility value, and cost (Eccles et al., 1983; Wigfield & Eccles, 1992). The attainment value was defined as the importance of performing well on given tasks. The authors defined intrinsic value as the enjoyment one derives from doing the given task. Utility value indicates how a task aligns with one's short- and long-term goals. Cost in the value aspect of the model refers to other activities that one has to forego for choosing to be engaged in a certain activity.

Domain identification model. Yet another motivational theory that was recently introduced and used to understand processes through which students make decision to pursue majors and careers in engineering was the domain identification model (Osborne & Jones, 2011). The definition of domain identification model, its intellectual history, and its positive association with other variables will be discussed later in this chapter.

Causes of Attrition – Non-Cognitive Factors

In addition to high school GPA, math ability, ACT and SAT scores, there are other factors that predict attrition, such as classroom and academic climate, self-efficacy and self-confidence, social pressures, departmental culture, institutional structure, and interest and career goals (Geisinger & Raman, 2013; Goodchild, 2004). Some of the major studies that investigated the retention problems were carried out by Brush (1991), Hewitt and Seymour (1991), Manis, Thomas, Sloat, & Davis, (1989), Tobias (1990), and Widnall (1988). The major themes that emerged from these studies were that science and engineering courses were considered as "too large, too competitive and critical, and not very open to student input" (Strenta, Elliot, Adair, Matier, & Scott, 1994, p. 532). In an extensive review of the literature related to retention of engineering students published over the last five decades, Geisinger and Raman (2013) listed five major factors that are associated with weak retention in engineering programs: classroom and academic climate, grades and conceptual understanding, self-efficacy and self-confidence, interest and career goals, and race and gender.

Within the broader classroom and academic climate, Geisinger and Raman's (2013) research synthesis identified many factors that are detrimental to students' persistence in STEM fields. For instance, a traditional lecture format in STEM courses does not appear to suit the learning needs of the students in these fields (Bernold, Spurlin, & Anson, 2007; Cabrera, Colbeck, & Terenzini, 1998; Felder & Silverman, 1988; Seymour & Hewitt, 1997). Students find the course less alluring, for instance, when it is not interactive, and when it does not involve team projects. Many studies revealed that science and engineering students perceived a lack of opportunities for them to engage with other engineering students in particular and with engineering communities in general (Fleming, Engerman, & Williams, 2006). According to Manis, Thomas, Sloat, and Davis (1989), students' experiences in their first year courses determine whether students will stay in STEM fields or switch to non-STEM majors. Seymour and Hewitt (1997) found that students exit STEM majors during their first two years in college. The attrition in the first two years is mostly attributable to adverse experiences in their introductory courses, such as poor teaching, "coldness" of the classroom, lack of opportunity for questioning, and unresponsive faculty members (Seymour & Hewitt, 1997; Strenta, Elliott, Adai, Matier, & Scott, 1994). The findings on poor teaching were consistent with Lichtenstein, Loshbaugh, Claar, Bailey, & Sheppards' (2007) study. Lichtenstein et al. found that poor teaching in preengineering courses can lead the students to think that courses in engineering fields would also be poorly taught. This in turn makes them reconsider their decision to continue in STEM majors. Interestingly, most of the courses in colleges of engineering are still taught in a lecture format, an instructional technique that does not help gain insight into the way people learn and where engagement with students is minimal (Haghighi et al., 2008).

Common First Year Program

One of the major responses by institutions to combat the problems of the mismatch between demand and supply for qualified engineers was to initiate a common first year program. One of the factors that affected high attrition rate was the fact that students spent the first two years studying math and science before they were exposed to engineering. Therefore, one of the purposes of first-year engineering courses was to familiarize students with the engineering profession at the beginning of their engineering program so that they could see how engineering is different from math and science (Sorby & Hamlin, 2001). Students took common courses in colleges and universities where first-year programs were established. The goal was to help students make connections among engineering, science, and mathematics (Froyd & Ohland, 2005). These initiatives are often described as integrated curricula and are often taught using active learning strategies (Froyd & Ohland, 2005; Roedel et al., 1995).

Several universities started experimenting with an integrated curricula to enhance student learning. For example, Drexel University began an enhanced educational experience for engineering students in 1988 (Quinn, 1995), the Colorado School of Mines (CSM) initiated the Connections program in 1994 (Olds & Miller, 2004), Louisiana Tech University started an integrated freshmen engineering program in 1997 (Nelson & Napper, 1999), and Michigan Technological University (MTU) initiated a first year engineering program in 2000 (Hein et al., 2003). Further, the NSF sponsored a number of Coalitions around the country, one of which was an Engineering Education Coalition called the Foundation Coalition. The Coalition had been tasked with number of activities one of which was to develop new and high quality curricula (Al-Holou et al., 1998). Some of the member institutions of the Foundation Coalition were Arizona State University, Texas A&M University, and University of Alabama (Roedel et al., 1995). The member institutions were required to implement integrated engineering curricula at their universities. The learning outcomes specified by the Coalition, as an example, were (1) improved learning in the fundamentals, (2) improved teamwork skills, and (3) improved communication skills (Pendergrass et al., 2001).

It was believed that a one-size fits all approach would not work due to the variations in prevailing culture, mission, and student population at each university (Al-Holou et al., 1998). Therefore, Al-Holou et al. further added that, many different models of integrated curricula have been adopted at different colleges. Efforts of individual universities and the NSF lead to a proliferation of first-year engineering programs in the country. In the absence of a common definition for first year models, materials covered and expected outcomes vary widely (Reid & Reaping, 2014). They believed that first-year engineering programs are not successfully incorporated into an engineering curriculum even though they are prerequisites to courses in the second year. In order to overcome the diversity of first-year engineering courses, Reid and Reaping attempted to establish a common framework. Their goal was to enable “universities, community colleges, funding agencies, etc. to use the developed classification scheme to accurately determine specific course content when considering credit awarded for transfers, to develop introductory engineering coursework, formulate course foci, and to identify and fund efforts towards appropriate assessment gaps” (p. 1).

Innovative Instructional Techniques

Innovative instructional techniques such as Active Learning received serious attention from researchers in the last few decades because they have been shown to have a predictive association with retention of students. Active Learning is considered a meaningful method for increasing students’ academic performance and building supportive relationships among students and between instructors and students. This teaching technique was also found to be useful for promoting students’ interests in STEM majors (Al-Bahi, 2006; Johnson, Johnson, & Smith, 1998 as cited in Schneider et al., 2008). *Active Learning* is defined as a technique employed in the classroom that uses student-student and student-facilitator interaction in numerous forms to alter the learning environment from passive to active (Al-Bahi, 2006). This teaching technique was found suitable to meet the requirements of the Accreditation Board of Engineering and Technology's (ABET) Engineering Criteria 2000 (EC2000; Felder & Brent, 1992). Some of the significant features of the Active Learning strategies are (Bonewell & Eison, 1991): (1) students are involved in more than passive listening, (2) students are engaged in activities (e.g., reading, discussing, and writing), (3) there is less emphasis placed on information transmission and greater emphasis placed on developing student skills, (4) there is greater emphasis placed on the exploration of attitudes and values, (5) students' motivation is increased (especially for adult learners), (6) students can receive immediate feedback from their instructors, and (7) students are involved in higher order thinking skills (analysis, synthesis, and evaluation).

Such an instructional technique alleviates the problems of attrition to some extent because it has the potential to address numerous concerns associated with lecture format and other perceived detrimental features found in the learning environment in engineering programs. This teaching style significantly predicted students' success in the classroom (Cabrera et al. 1998). This suggests that engineering instructors and students' perceptions of success can lead to increased retention (Cabrera et al. 1998; Tendhar & Jones, 2014). Further, it was believed that a nominal change in instructional techniques could increase the chances of students completing their degrees in engineering (Lichtenstein et al. 2007). In terms of innovative instructional techniques, the active learning approaches such as problem-based learning (PBL) and peer instruction (PI) have been associated with an increased motivational level and a better understanding of conceptual knowledge in addition to providing positive experiences in introductory STEM courses for students (Matusovich et al., 2012; Watkins & Mazur, 2013). Lichtenstein et al. (2007) and Watkins and Mazur (2013) found that constructive and encouraging experiences in a single course could have a positive impact on students' decision to continue with engineering.

The influence of active learning methods, such as problem-based learning (PBL), peer instruction (PI; Watkins & Mazur, 2013), and the Karplus learning cycle (Hake, 1992; Karplus, 1964) on students for getting and keeping them interested in STEM fields have been investigated, and those studies produced positive results. These are student-centered instructional techniques wherein their participation in class discussions and interactive and group projects are normally key features. These instructional techniques differ from a traditional instructional technique wherein lectures, exams, and individual assignments are used more often. These different instructional techniques go by different names, but they are closely related (Knight, Fulop, Marquez-Magana, & Tanner, 2008). The definitions of PBL and PI, their distinctive features, and consequences are discussed below.

Problem-Based Learning (PBL)

The PBL as an instructional method was first used in medical schools. However, this method was later used in a variety of educational settings, such as secondary and post-secondary education (Barrows, 2000; Hmelo-Silver, 2000). Using this instructional technique (Hmelo-Silver, & Barrows, 2006; Hmelo-Silver, 2004), instructors assume the role of a facilitator of knowledge, rather than a supplier of knowledge. This instructional technique requires that students work in groups on complex and ill-structured problems. Such problems rarely have one correct answer. Students normally do not possess the requisite knowledge and skills to solve the problems assigned to them. However, by engaging in self-directed learning and receiving appropriate guidance from the instructors, students gather the necessary information and knowledge to solve the problems. Students' reflection on the process they used to find solutions is also an important aspect of the learning process in this kind of instructional technique.

Peer Instruction (PI)

PI is an instructional technique that engages students through activities during the class and addresses challenging parts of the course material (Crouch & Mazur, 2001; Crouch, Watkins, Fagen, & Mazur, 2007; Mazur, 1997; Watkins & Mazur, 2013). Using PI, instructors design several short presentations with each focusing on a single concept. Each presentation is then followed by a conceptual question called a Concept Test. The idea behind a concept test is to gauge students understanding of the materials presented and also to provide them with opportunities to think about difficult concepts. After each presentation, students are generally given one or two minutes to develop their answers. After they are done thinking, students report their answers to instructors through clickers, flashcards, a simple raising of hands, or writing down the answers on a piece of paper. This is followed by students discussing answers among themselves. Such a discussion generally lasts two to four minutes. Depending on how many students had a good grasp of the materials presented, the instructor would make a decision whether to revisit the concept or not. An instructional technique like this promotes student interaction leading to reduced "coldness" and increased "openness" in introductory STEM courses. Students would find class less "dull" when they are engaged in learning throughout their class time. Such an instructional technique helps students gain positive experiences (Lichtenstein et. al., 2007). Further, this teaching style boosts students' scores on concept tests (Crouch & Mazur, 2001; Hake, 1998) and enhances the rate of retention (Watkins & Mazur, 2013).

Domain Identification Model

Domain Identification

Domain identification has a long history. More than a century ago, William James (1892/1968) discussed the ideas of "self" and identity. According to James, individuals can have an unlimited number of possible selves. However, one pursues a manageable set of selves that influence their overall self-perceptions and self-feelings, specifically those that have a higher probability of producing positive results for the self. Energy is then directed towards improving those selves. Similarly, one of the assumptions in the self-esteem literature is that individuals identify themselves with numerous domains at various levels. It is not, however, healthy to commit oneself to several domains at the same time because it is not feasible to excel in all the domains simultaneously, and this can lead to a decreased level of motivation to perform (Osborne & Jones, 2011). On the other hand, it may not be healthy for an individual to be identified with just one domain. The over-reliance on one domain could bring significant instability in one's self-esteem, especially if obtaining desirable outcomes in that one domain is difficult. In the absence of other valuable alternative domains, it is difficult to switch to other domains when the conditions in the domain that one was originally pursuing change. There does not appear to be any research on this subject yet, but Osborne and Jones opined that being strongly identified with 5-10 domains is perhaps reasonable for healthy functioning.

The notion of domain identification and its relationship with the concept of the self has been seriously debated since William James' time by psychologists. The domain identification is also referred to as domain relevance, psychological centrality, and selective valuing in the literature. Domain identification refers to "the extent to which an individual defines the self through a role or performance in a particular domain" (Osborne & Jones, 2011, p. 13). Domain identification was found to have associations with many positive outcomes, such as deep cognitive processing of course material and self-regulation (Osborne & Rausch, 2001; Walker, Greene, & Mansell, 2006), grade point average and academic honors (Osborne, 1997), classroom participation and achievement (Voelkl, 1997), decreased behavioral referrals and absenteeism

(Osborne & Rausch, 2001), and intention to pursue majors and careers in engineering (Jones et al., 2010).

In addition to investigating the positive impacts of domain identification, several studies were conducted examining a wide array of factors to investigate how domain specific (engineering) professional identities were developed (e.g., Beam, Pierrakos, Constantz, Johri, & Anderson, 2009). Eliot and Turns (2011) for example found that certain learning activities shape engineering professional identities. However, the value component was missing from both of these studies, i.e., the values students assign to building professional identities and the value of "fitting" within engineering. Aside from research on how domain specific identities were impactful, there does not appear to be any research on how domain identification is developed and the ways in which it influences other variables.

The model explains the mechanism through which social and academic factors influence students' domain identification and motivational beliefs and how these variables in turn impact behavioral and academic outcomes. In other words, this model lists precursors and consequences of academic identification. This model, however, can be applied to other domains as well, such as parenting (e.g. Pasley et al., 2002) and job performance (e.g., Kanungo, 1979). Osborne and Jones' domain identification model is presented in Figure 2.1.

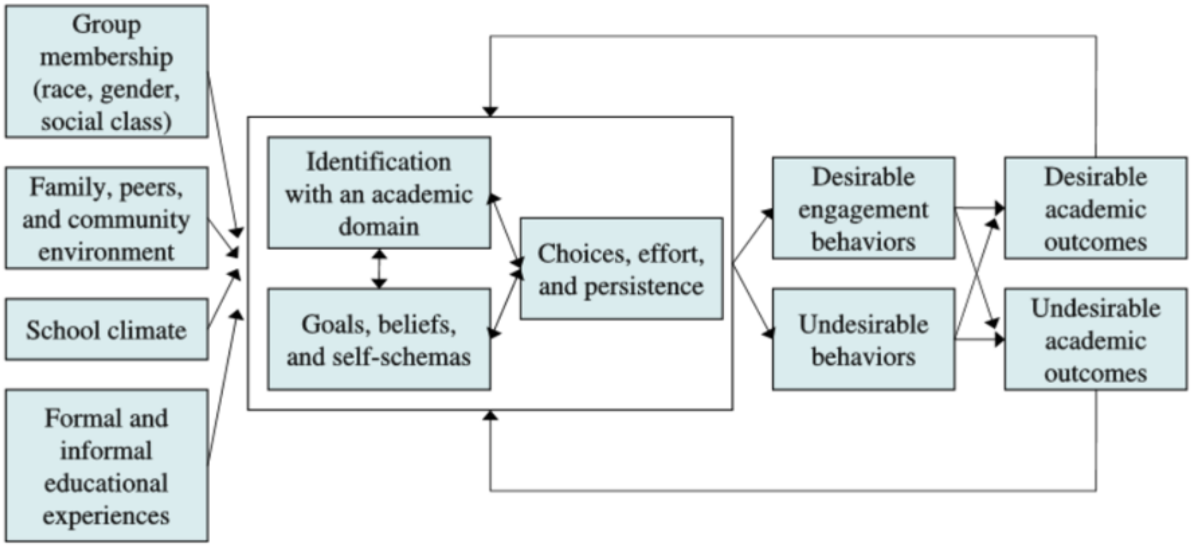

Figure 2.1. Precursors and consequences of identification with an academic domain

MUSIC Model of Academic Motivation

The MUSIC Model of Academic Motivation contains five motivation components: (1) eMpowerment; (2) Usefulness; (3) Success; (4) Interest; and (5) Caring. These components are well established motivational theories. Therefore, the MUSIC Model is not a new theory in itself. However, Jones' (2009) unique contribution in introducing the MUSIC Model of Academic Motivation was having all those five components in one cohesive model. The author calls this model an academic motivation model because the focus of application was in academic settings. However, this model can be applied to a variety of behaviors, including those in athletics and work settings, because of the research and theoretical foundation on which the MUSIC Model was built. This will become clearer later when definitions of each component, its related constructs, and its consequences are described.

The purpose of developing a model of academic motivation was to assist instructors in designing their courses. Designing courses in a way that boosts students' academic motivation is critical for students' learning outcomes. Motivation is a process that can be inferred from activities and expressions, whereby one is engaged in a sustained physical or mental activity to achieve the goals (Schunk, Pintrich, & Meece, 2008). The five components were included in the MUSIC Model based on the current motivation research and theories because each MUSIC element explains distinct features of students' motivation (Jones, 2009). An exact figure cannot be put on the number of components to be activated for students' motivation and there is no evidence to suggest that all the five components are essential at the same time. On the other hand, research indicates that students become more engaged in their learning environment when at least one or more of the MUSIC components are fostered (Jones, 2009). The five components of the MUSIC Model of Academic Motivation are discussed below.

eMpowerment. Empowerment refers to students' perceptions of the degree to which they have control over their learning. Research in this area has been undertaken by those who study self-determination theory (Deci & Ryan, 1985, 1991; Ryan & Deci, 2000). A key tenet of this theory states that people enjoy activities when they perceive that they have some control over them. Those who are highly self-determined (autonomous) will have more choices in managing their activities or goals, while those on the other end of the continuum would have fewer or no choices. Therefore, individuals who are fully self-determined are said to have an internal locus of control, while those whose perception of self-determination is low are said to have an external locus of control. Students who felt empowered and were given some autonomy reaped several benefits, such as enhanced conceptual learning, a higher sense of self-worth and self-esteem, a more positive emotional tone, greater perceived academic and social competence, a preference for challenging tasks, greater creativity, increased school attendance, and higher grades (Amabile, 1985; Boggiano, Main, & Katz, 1988; Csikszentmihalyi, 1985; deCharms, 1976; Deci, Schwartz, Sheinman, & Ryan, 1981; Filak & Sheldon, 2008; Flink, Boggiano, & Barrett, 1990; Grolnick & Ryan, 1986; Shapira, 1976, Vallerand & Bissonnette, 1992).

Usefulness. The usefulness refers to the extent to which students perceive the coursework to be helpful for reaching their short- or long-term goals. Research in the area of usefulness has been of interest to future time perspective theorists in their study of the instrumentality construct (De Volder & Lens, 1982; Kauffman & Husman, 2004; Lens, 1987; Tabachnick, Miller, & Relyea, 2008). Eccles and her colleagues have also investigated this construct in connection with their work on the expectancy-value model of motivation (Eccles et al., 1983; Eccles & Wigfield, 1995; Wigfield & Eccles, 2000). It was found that students who perceived their school work to be less relevant to their future goals were less motivated than those who did see the association between the two. That resulted in positive outlook on their future for those students (Simons, Vansteenkiste, Lens, & Lacante, M et al., 2004; Van Calster, Lens, & Nuttin, 1987). In first-year college students, those who perceived a course to be highly useful were found to be internally regulated, and they attained more positive learning outcomes (as cited in Simons et al., 2004).

Success. Success is defined as the extent to which students believe that they can attain success if they invest necessary effort. Individuals' self-perception of ability is a key part of many motivation theories, such as the theories of self-concept (Marsh, 1990; Marsh & Yeung, 1997; Schavelson & Bolus, 1982), self-efficacy (Bandura, 1986), self-worth (Covington, 1992), goal orientation (Ames, 1992), and expectancy-value (Wigfield & Eccles, 2000). Instructors can design courses in ways that promote the development of students' success belief in a number of ways. Some of the things that instructors can do in this regard, according to Jones (2009), are communicating course expectations clearly and explicitly to students, challenging students at a level suitable to them, and giving them feedback regularly. Meeting with both success and failure are important so that the feedback can be used to assess and adjust their sense of competence. The perception of success fostered in students can lead them to expend more energy in an activity, persist with that activity longer despite challenges, be strong in the face of tough situations, find the activity enjoyable, set challenging goals and be committed to them, approach difficult tasks without much anxiety, and achieve more than others (see Schunk & Pajares, 2005).

Interest. Interest has a few different definitions in the literature (Krapp, Hidi, & Renninger, 1992). However, one general definition is provided by Schraw and Lehman (2001): "liking and willful engagement in a cognitive activity" (p. 23). Often, interest is distinguished between situational interest and individual interest. Situational interest refers to immediate, short-term enjoyment induced by instructional activities. Therefore, such an interest is not of long-term value, because they are environmentally activated and specific to context (Jones, 2009). Individual interest, on the other hand, refers to personal enduring values activated internally on a specific topic (Schraw & Lehman, 2001; Hidi & Renninger, 2006). It is feasible to develop situational interest in students through instruction and coursework by incorporating novelty, games, social interactions, surprising information, humor, and/or emotional content (Bergin, 1999). Jones (2009) believes that instructors can influence students' interest. Hidi and Renninger (2006) put this aptly when they wrote, "The potential for interest is in the person but the content and the environment define the direction of interest and contribute to its development" (p. 112). Interest was found to have positive associations with outcomes, such as attention, memory, comprehension, deeper cognitive engagement, thinking, goal setting, learning strategies, and achievement (Hidi & Renninger, 2006; Schunk, Meece, & Pintrich, 2014).

Caring. Caring consists of two components: (a) academic caring, and (b) personal caring. Academic caring refers to the extent to which students perceive that their instructors and/or colleagues care about their success in academia. Personal caring, on the other hand, refers to the extent to which students perceive that their instructors and friends care about their welfare (Johnson, Johnson, & Anderson, 1983; Jones et al., 2012). The concept of caring is similar to other constructs, such as belongingness, relatedness, connectedness, affiliation, involvement, attachment, commitment, bonding, and sense of community (e.g., Baumeister & Leary, 1995; Noddings, 1992; Ryan & Deci, 2000). Many researches show that all humans have a need to get into caring relationships with others and sustain them (Baumeister & Leary, 1995; Ryan & Deci, 2000). Caring relationships have several positive outcomes, which include intrinsic motivation, positive coping, relative autonomy, engagement in school, expectancies, values, effort, cognitive engagement, self-efficacy, persistence, and performance (Freeman, Anderman, & Jenson, 2007; Furrer & Skinner, 2003; Goodenow, 1993; Hyde & Gess-Newsome, 1999/2000; Levett-Jones, Lathlean, Higgins, & McMillan, 2009; Murdock, 1999; Osterman, 2000; Seymour & Hewitt, 1997; Ryan, Stiller, & Lynch, 1994; Walker & Greene, 2009). Instructors can demonstrate academic caring by showing that it is important for them to see that students meet all the course objectives. Personal caring can be supported by instructors making reasonable accommodations for students when they are faced with difficult situations in their lives and by demonstrating interest in students' lives (Jones, 2009).

Engineering-Related Motivational Beliefs

The three motivational beliefs that were tested in this study as a part of the domain identification model are engineering utility, engineering program belonging, and engineering program expectancy. These constructs were included in the domain identification model because they have been shown to have positive associations with engineering persistence (Marra, Bogue, Shen, & Rodgers, 2007; Marra, Shen, Rodgers, & Bogue, 2009; Stevens, O'Conner, Garrison, Jocuns, & Amos, 2008). However, the influence of these variables on students engineering persistence were inconsistent when tested in a single model (Jones et al., 2012; Tendhar & Jones, 2014). The definitions of these constructs, their historical backgrounds, and related constructs are presented below.

Engineering Program Utility

Utility value was derived from the Eccles and Wigfield (1995) value component of the expectancy-value theory. Their values could be divided into three groups: intrinsic interest value, attainment value, and extrinsic utility value. Of these, the utility value was investigated as a part of the wider domain identification model along with two other motivational beliefs. Wigfield and Eccles (2000) define the general utility value as "utility value or usefulness refers to how a task fits into individual's future plan (p. 72). However, engineering utility in particular refers to "the usefulness of engineering in terms of reaching one's short- and long-term goals" (Jones et al., 2010, p. 320). Utility values have been shown to predict occupational and future course choices (Eccles, 2005; Meece, Wigfield, & Eccles, 1990; Wigfield, Tonks, & Eccles, 2004). Specifically, engineering utility predicted students' intention to pursue engineering careers for first year engineering students (Jones, et al., 2010).

Engineering Program Belonging

Belonging refers to the degree to which an individual has a psychological connection to a group (Brown, Alpert, Lent, Hunt, & Brady, 1988; Mallinctrodt & Wei, 2005). Goodenow (1993) defined it as "the extent to which students feel personally accepted, respected, included, and supported by others in the school social environment" (p. 80). Specifically, engineering program belonging refers to "the degree to which students perceive that they feel accepted, respected, included, and supported by the engineering students and faculty in the engineering program at the university" (Jones et al., 2012, p. 8). Finn (1989) underlined the significance of school belongingness. Belongingness is similar to other concepts, such as relatedness, affiliation, involvement, attachment, commitment, and bonding. However, belongingness is theoretically distinct from identification in that the social connection to a group is highlighted in belongingness, while identification highlights the value of the domain to sense of self (Jones, et al., 2012). With a sense of belongingness to a class, students feel openness and encouragement from their faculty members (Freeman, Anderman, & Jensen, 2007). Further, a sense of belongingness in engineering contributes to students' positive learning experiences (Trenor, Yu, Waight, Zedra, & Sha, 2008) and predicts their performance on standardized tests (Fast et al. 2010). Conversely, a lack of sense of belonging in engineering and social and academic fit have been associated with students' intentions to switch to other majors (Marra, Rodgers, Shen, & Bogue, 2012; Wao, Lee, & Borman, 2010). Researchers have shown that students' sense of belongingness can be nurtured by teachers (Furrer & Skinner, 2003; Ryan & Patrick, 2001) as well as their classmates (Juvonen, 2006). Teachers can promote belongingness through building caring relationship with their students. Four teacher characteristics have been listed that were said to promote high-quality student-teacher relationships: attunement; relatedness; supportiveness; and gentle discipline (see Reeve, 2006 for details). In addition to student-teacher relationships, classmates can promote belongingness by socially accepting students with high academic achievement, especially if that achievement has value to students' peer groups (Wentzel, 2005).

Engineering Program Expectancy

Expectancy is a part of the expectancy-value theory (Eccles et al. 1983; Eccles, Adler, & Meece, 1984; Eccles & Wigfield, 1995; Wigfield, 1994; Wigfield & Eccles, 1992). This theory hypothesizes that expectancies for success and value affect students' performance. This theory was built on the expectancy and value constructs originally developed by Tolman (1932), Lewin, (1938), and Atkinson (1957, 1966). Within the engineering program expectancy construct, the expectancy part of the theory is of relevance. The expectancy belief is related to self-efficacy theory (Bandura, 1986). Expectancy for success has been defined as the expectation one has over one's performance on upcoming tasks in domains, such as mathematics or engineering (Wigfield & Eccles, 2000). Specifically, engineering program expectancy has been defined as "one's belief in the possibility of his or her success in engineering" (Jones et al., 2010, p. 320). The empirical testing of the theory shows that it predicted students' performance on tasks (Eccles, 1984a; 1984b; Meece et al., 1990) and also predicted subsequent grades for junior high school students (Meece et al., 1990). Further, the expectancy beliefs have also been shown to affect students' grades, persistence, and career intention (Lent, Brown, & Larkin, 1986; Wright, Jenkins-Guarnieri, Murdock, 2013).

Summary

This review of literature covered the history of discussions revolving around the shortages of STEM professionals and attempts made to overcome this problem. It also went over the intellectual history of the domain identification model, theoretical framework of this study, and the latent variables used as a part of this model. Many factors, both cognitive and non-cognitive, have been found to have an impact on students' to decisions persist in STEM majors and their career intentions. Some of the cognitive variables that had predictive relationships with persistence and career intention were students' GPA, math ability, and ACT/SAT scores. In the case of non-cognitive variables, numerous motivational theories have been used to understand students' decision making process and have been found to have a positive influence on the outcome variables. Further, the role of proactive personality has recently been investigated in connection with students' major persistence. Change in first-year engineering curriculum and teaching pedagogy lead to positive results on many fronts. However, the problem of workforce shortages in the STEM fields continues, including in engineering. The domain identification model, therefore, adds to the current literature on major persistence and career theory, and it gives a new lens through which to study old problems.

Chapter 3: Method

Introduction

There are three major purposes in this study. The first is to evaluate mean scores of students in two sections of an introductory engineering course—a traditional version and a pilot version—by comparing students' motivation-related beliefs (i.e., the five components of the MUSIC Model of Academic Motivation), engineering identification, the three engineering-related motivational factors (engineering utility, engineering program belonging, and engineering program expectancy) and the two intention variables (major intention and career intention). The students were assessed on engineering identification, three engineering-related motivational factors, and the two intention variables, both at the beginning and the end of the semester, while they were assessed on the five components of the MUSIC Model only at the end of the semester. The second purpose was to examine the tenability of the domain identification model, specifically causality hypothesized among the variables as presented in Figure 1. The third purpose was to compare individual structural paths in the domain identification model between the two groups of students. The domain identification model tested in this study was a causal model that consisted of 11 latent variables; five of them were exogenous variables and six were endogenous variables. The five components of the MUSIC Model form the five exogenous variables of the causal model. They are eMpowerment, Usefulness, Success, Interest, and Caring. These five components were hypothesized to predict the four mediating endogenous variables, which were engineering identification, and three engineering-related motivational factors. Those four mediating endogenous variables in turn were hypothesized to predict the final two endogenous variables, namely students' intention to pursue majors and careers in engineering. This study, therefore, addressed the following four research questions.

Research Questions (RQs)

R-Q-1. Are there mean differences between the two approaches to instruction on motivation-related beliefs, engineering identification, three engineering-related motivational factors, and the two intention variables (major intention and career intention)?

R-Q-2. Do students' motivation-related beliefs in an introductory engineering course influence engineering identification and three engineering-related motivational factors?

R-Q-3. Do engineering identification and three engineering-related motivational factors affect students' intentions to pursue majors and careers in engineering?

R-Q-4. To what extent are the relationships in research questions two and three different across the two groups of different types of instruction?

This chapter contains information about samples and instruments. Further, the data collection technique is explained in this chapter. The procedures followed in analyzing the data are also included in this chapter, including conducting *t*-tests, Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and Structural Equation Modeling (SEM). Finally, this chapter includes a discussion on the differences between the traditional and pilot groups.

Research Design

A quasi-experimental design was adopted in this cross-sectional study. Using a survey, information about students' demographics were collected. In addition, their responses to motivation-related beliefs, engineering identification, three engineering-related motivational factors, and the two intentional variables were collected through online surveys. Cross-sectional data is not the best option to investigate any causal relationships; inferences from such studies should be cautiously drawn, especially with regard to making causal statements. However, such studies can be helpful in gaining understanding of plausible realtionships between numerous variables in *a priori* or a prespecified causal model.

This was a quasi-experimental study, in that there were two different groups: a traditional group and a pilot group of an introductory engineering class. Students were not randomly assigned to the two groups following any random sampling approach. However, a treatment was administred to students in the pilot group. The treatment administered was an innovative instructional pedagogy called active learning approach. Students in the traditional group were taught the way that this class had been taught in prior years, while instructional techniques used in the pilot group had some features of an active learning appraoch. More differences between the two groups will be discussed in greater detail later in this chapter. In short, a quasi-experiment is an experiment that shares most features of a true experimental design except that research participants were not assigned to different groups randomly (Pedhazur & Schmelkin, 1991).

Research Participants

The data for this study were collected from students in the two groups—a traditional group and a pilot group—of an introductory engineering course at a research-intensive university located in southeastern U.S. This study examined students' experiences in their first-year engienering courses and its impacts on their motivational beleifs and their engineering major and engineering career intentions. The administrators of the large engineering program at the said university collected data regularly from students in their introductory engineering course for their internal, departmental assessment purposes. Completing such a questionnaire is a part of a class assignment for students. An administrator of the engineering program was approached and it was discussed with her the possibility of including additional measures of interest to the researcher in the questionnaire that the administrators were going to administer as a part of the introductory engineering course. The administrator accepted the request to add measures of relevance to this study in their questionnaire.

The engineering program's administrator specifically included an item in the questionnaire asking students whether or not they would allow their data to be used for research purposes. Data from students who have consented for their data to be used for research purposes were used for the final analyses. It was also made known to students that they could discontinue their participation in the research study at any point without any consequences.

The descriptions of the samples from the two groups (traditional and pilot groups), specifically from the data collected at the beginning of the semester are provided below.

Beginning of Semester Sample—Traditional Group

One thousand eighty seven (1,087) students responded to the questionnaire administered at the beginning of the semester where students responded to questions measuring six constructs: (1) major intention; (2) career intention; (3) engineering identification; (4) engineering utility; (5) engineering program belonging; and (6) engineering program expectancy. Of those 1,087 students, 188 did not provide permission to use their data for research. Further, 20 of the research participants did not provide any data. and four of them completed the survey twice. Therefore, those three groups of students were excluded and the final analyses of descriptive and *t*-tests were performed on 875 cases. A second response sets of students who completed the survey twice were deleted.

In terms of gender, 655 (74.86%) of them were male, while 205 (23.43%) of them were female. There were 15 (1.71%) students who did not report their gender. The race composition of this data was: 602 (68.8%) were white; 155 (17.7%) were Asian; 47 (5.4%) were Hispanic; 21 (2.4%) were African Americans; 13 (1.5%) were Native American; and 37 (4.2%) of the respondents did not report their race.

Beginning of Semester Sample—Pilot Group

In the beginning of the semester survey, 247 students from the pilot group participated in the survey. However, students did not provide consent to use their data for research. Further, 24 students had missing information of over 80%. Therefore, excluding students from those two groups, 188 of them have been included in the final analyses. Student in the pilot group were also assessed on those six constructs that students in the traditional group were assessed on.

Out of 188 students retained for the final analyses from the pilot group, 161 (85.6%) were male, and 26 (13.8%) were female. One of them one (0.5%) did not report his/her gender. In terms of race, 144 (76.6%) identified as white, 25 (13.3%) were Asian, nine (4.8%) indicated that they were Hispanic/Latino, two (1.1%) of them were African Americans, and one (0.5%) was Native American. Seven (3.7%) of the participants did not report their race.

The purpose of assessing students in the two groups in the beginning of the semester on those six construct was to investigate the mean differences between the two groups. This baseline information collected at the beginning of the semester will enable us to determine the impact of an instructional design, that had some features of an active learning approach on the pilot group at the end of the semester. Specifically, the baseline information was used to determine whether or not students in the pilot group had more favorable perceptions of the five elements of the MUSIC Model in addition to the six constructs.

The descriptions of the samples from the two study groups (traditional and pilot groups), specifically from the data collected at the end of the semester are provided below.

End of Semester Sample—Traditional Group

The total number of students from the traditional group that responded to the survey at the end of the semester was 1,084. However, in the final analyses, only 812 cases were retained. Of 1,084 students, 188 students did not permit their data to be used for research. Further, 18 participants did not provide any information. In other words, they started the process of completing the survey, but quit it without responding to any of the survey questions. It was difficult to figure out what really happened with those 18 research participants, but it is possible that they got distracted by something when they began the survey process. Two of the participants completed the survey twice. Therefore, it was decided to exclude them from the final data analyses (1) who did not provide consent for their data to be used for research, (2) those who did not provide any response to the survey questions, and (3) the second response set of those participants who completed the survey twice.

The 812 cases retained for the final analyses were randomly divided into three groups using a systematic sampling approach. This was achieved using the MOD(#CASENUM) function in SPSS 22.0. This function resulted in creating three groups by assigning the first case to group two, the second case to group one, and the third case to group zero. This pattern of assigning cases to the three groups were then repeated throughout the data. This grouping variable was later arranged in an ascending order using the Sort Cases function in the SPSS. All 273 cases that were assigned to group zero came on the top and this group was used to conduct exploratory factor analysis (EFA) for all the latent variables. This group was called an estimation sample. All the 539 cases that were in groups one and two were then separated from those belonging to group zero and were used as the validation sample. The factor models obtained through the EFA using the estimation sample was then validated on the validation sample using the confirmatory factor analysis (CFA) approach. An acceptable measurement and structural models obtained using data from the traditional group was cross-validated on the data from the pilot section.

Of those included in the final analyses (validation sample), 411 (76.3%) were male, while 128 (23.7%) of them were female. In terms of race, 385 (71.4%) constitutes White, 90 (16.7%) indicated themselves as Asian, 29 (5.4%) of them were Hispanic, 14 (2.6%) identified themselves as African American, and six (1.1%) of them were Native Americans. Fifteen (2.8%) participants chose not to report their race.

End of Semester Sample—Pilot Group

The pilot section was the treatment group and had a smaller sample size compared to the traditional section. The idea was to check the impact of active learning approach and other changes envisaged on students' learning outcomes and motivational beliefs on a small group of students to determine if such an approach can be widely implemented. Three hundred fourteen students from the pilot group responded to the survey. However, 242 of them were used for final analyses. Of those 72 cases deleted from the final analyses, 35 of them did not consent their data to be used for research purposes. Further, 10 research participants started the process of completing the survey, but did not respond to any of the questions. Again, it is difficult to determine what really happened, but it is possible that those 10 students got distracted by something when they started the survey and then did not finish it. Three respondents completed the survey twice and their second set of response was deleted. The final measurement and structural models arrived at using the data from the traditional group was cross-validated on this sample.

Of 242 research participants, 36 (14.9%) of them were female, and 206 (85.1%) of them were male. In terms of race, 177 (73.1%) were White, 37 (15.3%) were Asian, 16 (6.6%) were Hispanic/Latino, 3 (1.2%) were African Americans, and 2 (0.8%) were Native American. Seven (2.9%) of them did not report their race.

Measures

As Figure 1 in Chapter one shows, there are a total of 11 latent variables in the partial domain identification model tested in this study: (1) five components of the MUSIC Model of Academic Motivation—eMpowerment, Usefulness, Success, Interest, and Caring (students' motivation-related beliefs); (2) engineering identification and three engineering-related motivational factors (engineering utility, engineering program belonging, and engineering program expectancy); and (3) two intention variables (engineering major intention and engineering career intention). The complex relationships among those 11 variables were determined *a priori* and also depicted in Figure 1.

There are five exogenous variables and six endogenous variables in the causal model tested in this study. The five exogenous variables are the students' motivation-related beliefs in an introductory engineering class, and the six endogenous variables consisted of engineering identification and three engineering-related motivational factors, and two intention variables.

All the 11 latent variables in the model were assessed by a six-point agreement scale. Descriptions of the six-point rating scales are uniform for all of the 11 latent variables used in the domain identification model as presented in Table 3.1.

Table 3.1

A Description of the Six-Point Rating Scale

1	2	3	4	5	6
Strongly Disagree	Disagree	Somewhat Disagree	Somewhat Agree	Agree	Strongly Agree

Extant scales were used to measure all of the 11 constructs employed in this study. Specifically, the five elements of the MUSIC model were assessed by the MUSIC Model of Academic Motivation Inventory (Jones & Skaggs, 2012). The five elements (Empowerment, Usefulness, Success, Interest, and Caring) were measured with five (α=.91), five (α=.96), four (α=.93), four (α=.95), and six items (α=.93), respectively. Students' perception of engineering identification was assessed with the four-item of Identification with Engineering from Jones et al. (2014; α=.92). Similarly, research participants' perceptions of engineering utility (α=.97), engineering program belonging (α=.86), and engineering program expectancy (α=.93) were measured with scales used by Tendhar and Jones (2014). The three constructs were measured with six, eight, and five items, respectively. Two items each used to measure the two intention variables were based on indicator variables used in Jones (2010) and Jones et al. (2012). Eleven variables with their respective items are presented in Table 3.2.

Table 3.2

Fifty-Three Item Domain Identification Model Scale

Domain Identification Model's Scales
eMpowerment
1. I had the opportunity to decide for myself how to meet the course goals.
2. I had the freedom to complete the coursework my own way.
3. I had options in how to achieve the goals of the course.
4. I had control over how I learned the course content.
5. I had flexibility in what I was allowed to do in this course.
Usefulness
1. In general, the coursework was useful to me.
2. The coursework was beneficial to me.
3. I found the coursework to be relevant to my future.
4. I will be able to use the knowledge I gained in this course.
5. The knowledge I gained in this course is important for my future.
Success
1. I was confident that I could succeed in the coursework.
2. I felt that I could be successful in meeting the academic challenges in this course.
3. I was capable of getting a high grade in this course.
4. Throughout the course, I felt that I could be successful on the coursework.
Interest
1. The coursework held my attention.
2. The instructional methods used in this course held my attention.
3. I enjoyed the instructional methods used in this course.

4. The instructional methods engaged me in the course.
5. I enjoyed completing the coursework.
6. The coursework was interesting to me.

Caring

1. The instructor was available to answer my questions about the coursework.
2. The instructor was willing to assist me if I needed help in the course.
3. The instructor cared about how well I did in this course.
4. The instructor was respectful of me.
5. The instructor was friendly.
6. I believe that the instructor cared about my feelings.

Engineering Identification

1. Being good at engineering is an important part of who I am.
2. Doing well on engineering tasks is very important to me.
3. Success in engineering school is very valuable to me.
4. It matters to me how well I do in engineering school.

Domain Identification Model's Scale Continued

Engineering Utility

1. Knowing about engineering does not benefit me at all.
2. I see no point in me being able to do engineering.
3. Having a solid background in engineering is worthless to me
4. I have little to gain by learning how to do engineering.
5. After graduation, an understanding of engineering will be useless to me.
6. I do not need engineering in my everyday life.

Engineering Program Belonging

1. I feel like a real part of the General Engineering program.
2. Sometimes I feel as if I don't belong in the General Engineering program.
3. People in the General Engineering program are friendly to me.
4. I am treated with as much respect as other students in the General Engineering program.
5. I feel very different from most other students in the General Engineering program.
6. The instructors in the General Engineering program respect me.
7. I wish I were in a major other than engineering.
8. I feel proud of belonging in the General Engineering program.

Engineering Expectancy/Ability

1. Compared to other engineering students, I expect to do well in my engineering-related courses this year.
2. I think that I will do well in my engineering-related courses this year.
3. I am good at math, science, and engineering.
4. Compared to other engineering students, I have high engineering-related abilities.
5. I have been doing well in my engineering-related courses this year.

Major Intention

1. I don’t intend to change my major from engineering to a non-engineering major.
2. I plan to continue on in an engineering program.

Career Intention

1. My eventual career will directly relate to engineering.
2. In the future, I will have a career that requires me to have engineering skills.

Definitions of 11 Latent Variables

Empowerment denotes the level of control that students think they have over their learning environment (Jones, 2009). Usefulness represents students’ perception of the usefulness of engineering courses for their future use. Success refers to the students’ perception of their ability to succeed if they invest the required effort. Interest is a students’ perception that the course content and instructional techniques are interesting. Caring was defined as students’ perception that their instructors in their engineering courses care about their success. Engineering identification was defined as valuing engineering as part of their identity. Engineering Utility was defined as “the usefulness of engineering in terms of reaching one’s short- and long-term goals” (Jones et al., 2010, p. 320). Engineering program belonging refers to “the degree to which students perceive that they feel accepted, respected, included, and supported by the engineering students and in the engineering program at the university” (Jones et al., 2014, p. 1343-1344). Jones et al. (2010) described engineering program expectancy as “one’s belief in the possibility of his or her success in engineering” (p. 320). Engineering major intention was students’ intention to remain in engineering majors. Engineering career intention refers to students’ intention to pursue careers in the field of engineering post-graduation.

Data Collection

The administrator of a large engineering program at a research-intensive university located in southeastern U.S. had agreed to include the measures to be used in this study. They had already obtained the Institutional Review Board's (IRB) approval for their survey research. The administrator of the engineering program advised the researcher to submit an independent IRB application requesting permission to use data already collected under their department's IRB application. Therefore, a separate IRB application was filed and it was approved by the IRB.

As mentioned earlier, completing the questionnaire was a part of students' assignment in this class. They were given access to the online survey for one week; the web-based survey software called Qualtrics was used for the online survey. In other words, they had to complete the questionnaire within one week of it becoming available to them. However, within a period of that one week, there was no specific limit on the length of the time they could take to finish it. The overall questionnaire was intended to take about 15 minutes. The questionnaire was administered twice, one at the beginning of the semester and one at the end of the semester. The only difference between the two surveys was that students' motivation-related beliefs in an introductory engienering course was not included in the beginning of the semester survey.

Data Analysis

The data analysis began by performing preliminary analyses, such as descriptive statistics, intercorrelations among the latent variables, and reliabilities for all of the 11 latent variables used in the domain identification model. The preliminary data analyses were conducted using a statistical software called Statistical Package for the Social Sciences (SPSS) version 22.0.

The mean scores of students' motivation-related beliefs, engineering identification, three engineering related motivational factors, and the two intention variables in the two groups were compared using *t*-test via SPSS version 22.0. The comparisons of the mean scores between the two groups on those 11 latent variables pertain to the first research question.

Based on the research questions two through four, the appropriate data analytic strategy for this study was Structural Equation Modeling (SEM). The measurement and structural models were estimated using variance-covariance matrix and the Maximum Likelihood (ML) estimation method in LISREL version 9.1, to estimate SEM models and compare these across groups.

SEM describes a set of tools for data analysis. From a statistical perspective, traditional techniques for data analysis such as the analysis of variance, the analysis of covariance, multiple linear regression, canonicial correlation, and expoloratory factor analysis—and also measured variable path and confirmatory factor analysis—can be seen as special cases of SEM (Muller & Hancock, 2008). According to Mueller and Hancock, these data analytic techniques enable testing of theoretically derived causal hypotheses specified *a priori*. SEM allows for testing of a theoretical model that hypothesizes how certain items define factors and the relationships among the factors in the model (Schumacker & Lomax, 2010). Such hypothesis testing helps us gain insights into the complex relationships among factors. Therefore, SEM is an appropriate technique to be used in this study to examine relationships among those 11 latent variables, specified *a priori*, inlcuded as a part of the domain identification model tested.

The factor structures of the scales were investigated in this study on an estimation sample using the Exploratory Factor Analysis (EFA). The purpose of EFA is to find a theoretical model that provides a good fit to the data. Its analyses are considered data-driven. An estimation sample is a small percentage of the actual data that was randomly selected. In this study, one-third (1/3; 273 participants) of the sample from the traditional group, specifically from the end of the semester data was used as an estimation sample. An estimation sample was used to test the initial factor structure and the decisions to modify the model was made based on the results obtained. The principal component analysis with promax rotation was used to extract factors for each scale. The promax rotation is one of the oblique rotation methods. This rotation method is used when it is expected that correlations between factors could range from minor to moderate (Dimitrov, 2012). In other words, this rotation method does not require the rotation process to have uncorrelated factors (Meyers, Gamst, & Guarino, 2006), unlike orthogonal rotation method. The purpose of factor rotation is to obtain a simple structure for easily interpretable factors (Thurston, 1947). The goal of a simple structure is materialized when an item loads highly on one factor and its factor loading was negligible on all other factors. There exists many rules to determine the number of factors to be retained (cf. Zwick & Velicer, 1986), but in this study eigenvalue > 1 rule (Kaiser, 1960) was followed. The decision to delete items from the revised factor structure were made based on (1) items having high loadings on more than one factor, and (2) items with factor loadings below .4.

Then the CFA was used to confirm the revised factor structure on the validation sample. A validation sample is a sample that does not include those research participants who were a part of the estimation sample. A validation sample is used to confirm the model obtained from the estimation sample. In this study, two-third (2/3; 539 participants) of the sample from the traditional group, specifically from the end of the semester data was used as the validation sample. Unlike EFA, CFA is considered theory-driven. Its analyses strive to determine if the observed data provide a good fit to a prespecified theoretical model. The total expected number of factors, which manifest variable loads on which factor, and correlations, or lack thereof, between factors are determined *a priori* (Schumacker & Lomax, 2010).

To evaluate plausibility of proposed models, fit indices from the three major index classes were used, namely: absolute fit index, parsimonious fit index, and incremental fit index. Those three fit indices were represented by standardized root mean square residual (SRMR), root mean square error of approximation (RMSEA), and comparative fit index (CFI), respectively. There are different opinions on the cut off scores for the fit indices to retain a measurement model. For example, according to Hu and Bentler (1999), data-model fit is considered acceptable when SRMR and RMSEA values are equal to or less than .08 and .06, respectively. The CFI value, according to them, should be equal to or greater than .95. However, other authors such as Browne and Cudeck (1993) suggested that RMSEA value greater than .06 but less than .08 can be considered an adequate model fit, while MacCallum, Browne, and Sugawara (1996) contributed to these guidelines by suggesting that RMSEA value between .08 and .10 can be considered a mediocre fit. Browne and Cudeck (1993), however, suggested that any model with RMSEA value equal to or greater than .10 should be rejected. The chi-square difference test (James, Mulaik, & Brett, 1982) was used to compare different measurement and structural models.

The analyses of the measurements model was followed by the estimation and evaluation of structural models. This was the two-step SEM approach that Anderson and Gerbing (1988) suggested. It is imperative that any misspecification in the measurement model is fixed before analyzing the structural model because it is important to ensure that observed variables accurately reflect the constructs they are supposed to measure. In many instances, issues in the structural model are often related to measurement models and so they should be addressed with CFA before proceeding to analyze the structural models (Brown, 2006).

The measurement and structural models validated on the two-third (2/3; 539 participants) of the sample from the traditional group was then cross-validated on data from the pilot group with a sample size of 242. It is to be noted that the same fit indices and cut-off scores were used to assess the model data fit for both the measurement models and the structural models.

The model estimation and model evaluation may lead to model modification. One of the unique features of SEM is model modification. Modifications could include excluding non-significant parameters and/or adding unidirectional and/or bidirectional structural paths. This procedure is the final step in the SEM analyses. Modifications are performed to achieve a better model data fit. These techniques are technically data-driven. Model modifications should be considered cautiously and frugally. It is important that modifications are done one at a time whenever a decision to do so is made. The decision to modify an existing or a prespecified or evolving model should make both theoretical and statistical sense, however.

Distinction Between the Traditional and Pilot Group

Lecture and Workshop Groups

The data for this study was collected from an introductory engineering education class. This class had two versions: traditional and pilot. The pilot version was the treatment group. Both courses used lecture/small workshop format. With a lecture and a workshop, the class met twice a week. The lecture meetings were for 50 minutes, while workshop meetings were for one hour fifty minutes. There were 160 students in each traditional lecture group and 120 students in each pilot lecture group. The size of the workshop groups were smaller. Specifically, there were 32 students in each workshop group that were a part of the traditional version and 30 students in each workshop group that were a part of the pilot version. The traditional version had nine lecture groups and four workshop groups per lecture, while the pilot version had three lecture groups and four workshop groups per lecture. Lecture sessions in both the groups were taught by faculty members. In the case of workshops, traditional group's workshops were led by instructors and graduate teaching assistants (GTAs), while the pilot group's workshops were led by faculty, instructors, and GTAs.

Design and Intention of the Class

The major differences between the two versions of an introductory engineering class were their overall design and intention of the class as reflected in Appendices A through D. Specifically, the pilot version intentionally drew on research regarding student motivation (the MUSIC model), metacognition, problem-solving, and problem-based learning to plan both the lecture and workshop sessions. Some of the content and their differences will be presented in the subsequent few paragraphs.

Course objectives. Course objectives of the two classes are presented in Appendix A. Some of the objectives of the pilot version were to (a) compare and contrast the contributions of different types of engineers in the development of a product or process, (b) communicate information effectively, (c) synthesis information from several sources in addressing an issue, and (d) contribute to team efforts. Likewise, some of the objectives of the traditional version were to (a) demonstrate a basic understanding of the engineering design process, (b) demonstrate a knowledge of the disciplines of the Virginia Tech College of Engineering, (c) graph numeric data and derive simple empirical functions, and (d) demonstrate an understanding of professional ethics and application to real life situations.

Explicit similarities and differences. Explicit similarities and differences between the two versions of the class are presented in Appendix B. Some of the differences are in the areas of design, teamwork, and general problem sets. In the traditional version, there was one class on design where students were assigned readings on how to design a sustainable energy project. On the other hand, students in the pilot version spent a considerable amount of time on a problem solving project where they were given instructions on how to solve a problem rather than instructions on a design process. In terms of team, students in the traditional version spent one workshop session on a team activity. On the other hand, performing in teams were a part of several workshop sessions in the pilot version where students engaged in role playing and collectively dealing with conflicts. In the lecture sessions, opportunities were created for interaction between students, and students and instructors in both versions of the class. However, the pilot section typically involved a greater number of small group work and interactions. With the general problems, some knowledge of trigonometry and geometry and other knowledge were sufficient to solve problem sets presented to students in the traditional version. Students in the pilot version, on the other hand, were presented seven open-ended and ill-structured problems. Solutions to these problems were presented by students in a group of three to five. Students in this case had the autonomy to choose projects of their liking. The amount of knowledge in trigonometry and geometry required to resolve issues in those seven projects varied from project to project.

Course outline. Course outline of the traditional and pilot versions are presented in Appendix C and D, respectively. Topics covered differed between the two groups in a number of ways. Two such differences are as follows: first, a lecture session was devoted on information sources in the pilot section of the classes. The engineering college's librarian was invited to the class and made a presentation on using the library, and finding and evaluating sources. How to cite sources was also presented. Second, students in the pilot version had a guest speaker from the Career Services at their university. The speaker went over what their center could do for students and how to look up jobs relevant to engineering students.

Conclusion. Based on the differences between the two versions of the class presented above, we can conclude that the pilot version had more features of active learning. *Active learning* is defined as a technique employed in the classroom that uses student-student and student-facilitator interaction in numerous forms to alter the learning environment from passive to active (Al-Bahi, 2006). Therefore, active learning is considered a meaningful method for increasing students' academic performance and building supportive relationships among students, and between instructors and students. There are different instructional techniques (e.g., active learning, problem-based learning, and peer instruction) and they go by different names, but they are closely related (Knight, Fulop, Marquez-Magana, & Tanner, 2008).

The fact that the pilot version had more problem solving activities, team activities, and a greater number of small group work and interaction showed that it had more features of active learning. Further, the fact that students had autonomy to choose one of the seven open-ended and ill-structured problems would more than likely have an impact on their perceptions of empowerment, which is one of the components of the MUSIC Model of Academic Motivation. Students feel empowered when they perceive that they have a great amount of control over their learning (Jones, 2009). Similarly, a session with a guest speaker from the Career Services where students looked up job advertisements related to engineering degrees could increase perceived usefulness of their engineering degrees especially when they saw that there are plenty of job opportunities for engineering graduates. Usefulness is another component of the MUSIC model.

Chapter 4: Results

Introduction

There are five sections in this chapter. In the first section, descriptive statistics of the traditional and pilot groups from the beginning and end of the semester data are presented. Correlations among the 11 latent variables for the two groups at the end of the semester are also presented in this section. In the second section, results of the group mean differences between the two groups at the beginning and the end of semester on those 11 latent variables computed using *t*-test via SPSS version 22.0 are presented. This section pertains to research question one. In the third section, in order to answer research questions two and three, a discussion of the normality of the data is presented in addition to the results of the exploratory factor analyses (EFA). This section also contains a presentation of the comparisons between different measurement models. Students in the traditional group were divided into two parts. The estimation sample consisted of the one-third (273 participants) of the traditional sample. The EFA was conducted on the estimation sample to find a good-fitting solution. The revised factor model obtained as a result of the EFA was validated on two-third (539) of the traditional sample. This validated model was then cross-validated using the pilot sample.

In the fourth section, results of the relationships between students' motivation-related beliefs and engineering identification and three engineering-related motivational factors are presented and examined in this section. The relationships between these variables pertain to research question two. Further, results of the relationships between engineering identification and three engineering-related motivational factors and the two intention variables (major intention and career intention) are also presented and examined in this section. This part pertains to research question three. The two-step SEM approach suggested by Anderson and Gerbing (1988) was followed where an acceptable fit of the measurement model was first established before proceeding to estimating the structural model. Based on the types of research questions being addressed, the two major analytic techniques used were *t*-tests and structural equation modeling (SEM). The model data fit in the case of both measurement models and structural models were based on the fit indices of three major index classes—absolute fit index, parsimonious fit index, and incremental fit index—as represented by standardized root mean square residual (SRMR), root mean square error of approximation (RMSEA), and comparative fit index (CFI), respectively. Different measurement models and structural models were compared using the sequential chi-square difference test (James, Mulaik, & Brett, 1982).

The fifth and final section pertains to research question four. This question deals with comparing individual structural paths for the two groups.

Descriptive Statistics and Correlations among the 11 Latent Variables

In this section, descriptive statistics of the traditional and pilot groups from the beginning and end of semester data are presented. Correlations among the 11 latent variables for the two groups at the end of semester are also presented in this section.

Descriptive Statistics—Beginning of Semester

Descriptive statistics and reliabilities of the six scales for both the traditional group and pilot group are presented in Table 4.1 and Table 4.2, respectively. The descriptive statistics, specifically means and standard deviations, for the six constructs were obtained using their average scores. Major intention had two indicator variables, career intention was measured by two items, and engineering identification, engineering utility, engineering program belonging, and engineering program expectancy were measured by four, six, five, and five items, respectively.

Table 4.1

Descriptive Statistics and Reliabilities of Traditional Group—Beginning of the Semester

Variables	N	Mean	Standard Deviation	Cronbach's Alpha (α)
Major Intention	875	5.35	0.77	.85
Career Intention	875	5.08	0.85	.84
Engineering Identification	875	5.24	0.66	.84
Engineering Utility	875	5.49	0.68	.90
Engineering Program Belonging	875	4.97	0.62	.73
Engineering Program Expectancy	875	4.83	0.69	.88

Table 4.2

Descriptive Statistics and Reliabilities of Pilot Group—Beginning of the Semester

Variables	N	Mean	Standard Deviation	Cronbach's Alpha (α)
Major Intention	188	5.37	0.84	.92
Career Intention	188	5.08	0.84	.85
Engineering Identification	188	5.22	0.73	.85
Engineering Utility	188	5.32	0.95	.95
Engineering Program Belonging	188	4.94	0.63	.76
Engineering Program Expectancy	188	4.93	0.66	.87

Out of a maximum score of six for each latent variable, mean scores for the six latent variables ranged between 4.83 and 5.49 for the traditional group. Their scale reliabilities ranged between .73 and .90. On the other hand, the pilot group's mean scores of those six latent variables ranged between 4.93 and 5.37. Their scale reliabilities ranged between .76 and .95.

Descriptive Statistics—End of Semester

Descriptive statistics and reliabilities of the 11 scales for both the traditional group and pilot group, from their end of semester data, are presented in Table 4.3 and Table 4.5, respectively. The descriptive statistics (specifically means and standard deviations) for the 11 constructs were obtained using their average scores. Major intention had two indicator variables, career intention was measured by two items, and engineering identification, engineering utility, engineering program belonging, and engineering program expectancy were measured by four, six, five, and five items, respectively. The five components of the MUSIC Model (Empowerment, Usefulness, Success, Interest, and Caring) were measured with five, five, four, six, and six items respectively. The correlation matrices of the two groups are presented in Tables 4.4 and 4.6, respectively.

Out of a maximum score of six for each latent variable, mean scores for the 11 latent variables ranged between 4.05 and 5.39 for the traditional group. Their scale reliabilities ranged between .78 and .94. On the other hand, the pilot group's mean scores on those 11 latent variables ranged between 3.98 and 5.41. Their scale reliabilities ranged between .78 and .96.

Table 4.3

Descriptive Statistics and Reliabilities of Traditional Group—End of the Semester

Variables	N	Mean	Standard Deviation	Cronbach's Alpha (α)
Major Intention	539	5.39	0.89	.88
Career Intention	539	5.13	0.93	.87
Engineering Identification	539	5.17	0.73	.86
Engineering Utility	539	5.22	1.03	.96
Engineering Program Belonging	539	4.90	0.67	.78
Engineering Program Expectancy	539	4.72	0.77	.89
Empowerment	539	4.24	0.98	.90
Usefulness	539	4.08	1.12	.94
Success	539	4.64	0.85	.89
Interest	539	4.05	1.07	.93
Caring	539	4.98	0.78	.91

Table 4.4 (p. 61-62)

Correlations Among Latent Variables of Traditional Group—End of the Semester

	MI	CI	Idnt	Uti	Bel	Exp	Emp	Use	Suc	Int	Car
MI	-										
CI	$.67^{**}$	-									
Idnt	$.56^{**}$	$.62^{**}$	-								
Uti	$.40^{**}$	$.42^{**}$	$.43^{**}$	-							
Bel	$.30^{**}$	$.34^{**}$	$.50^{**}$	$.31^{**}$	-						
Exp	$.46^{**}$	$.40^{**}$	$.46^{**}$	$.22^{**}$	$.34^{**}$	-					

Emp	.18**	.24**	.32**	.09*	.51**	.26**	-				
Use	.23**	.28**	.34**	.14**	.50**	.22**	.70**	-			
Suc	.44**	.38**	.38**	.25**	.42**	.62**	.50**	.46**	-		
Int	.24**	.30**	.36**	.12**	.55**	.27**	.76**	.88**	.51**	-	
Car	.20**	.25**	.31**	.25**	.53**	.21**	.39**	.32**	.41**	.38**	-

Note. MI-Major Intention; CI=Career Intention; Idnt=Engineering Identification; Uti=Engineering Utility; Bel=Engineering Program Belonging; Exp=Engineering program Expectancy; Emp=Empowerment; Use=Usefulness; Suc=Success; Int=Interest; Car=Caring; *p < .05; **p < .01

Table 4.5

Descriptive Statistics and Reliabilities of Pilot Group—End of the Semester

Variables	N	Mean	Standard Deviation	Cronbach's Alpha (α)
Major Intention	242	5.41	0.87	.89
Career Intention	242	5.21	0.81	.84
Engineering Identification	242	5.23	0.74	.89
Engineering Utility	242	5.25	1.08	.96
Engineering Program Belonging	242	4.98	0.69	.79
Engineering Program Expectancy	242	4.82	0.67	.84
Empowerment	242	4.20	1.00	.91
Usefulness	242	4.08	1.15	.94
Success	242	4.53	0.91	.90
Interest	242	3.98	1.14	.93
Caring	242	5.09	0.77	.91

Table 4.6

Correlations Among Latent Variables of Pilot Group—End of the Semester

	MI	CI	Idnt	Uti	Bel	Exp	Emp	Use	Suc	Int	Car
MI	-										
CI	$.72^{**}$	-									
Idnt	$.62^{**}$	$.69^{**}$	-								
Uti	$.32^{**}$	$.33^{**}$	$.32^{**}$	-							
Bel	$.35^{**}$	$.32^{**}$	$.44^{**}$	$.15^{**}$	-						
Exp	$.55^{**}$	$.55^{**}$	$.54^{**}$	.12	$.24^{**}$	-					
Emp	.08	.05	$.18^{**}$	-.07	$.48^{**}$	.10	-				
Use	.10	.10	$.26^{**}$	-.03	$.44^{**}$	.05	$.67^{**}$	-			
Suc	$.29^{**}$	$.30^{**}$	$.38^{**}$	.07	$.31^{**}$	$.46^{**}$	$.58^{**}$	$.46^{**}$	-		
Int	.09	.08	$.23^{**}$	-.09	$.47^{**}$	.10	$.76^{**}$	$.84^{**}$	$.53^{**}$	-	
Car	.12	.10	.12	.01	$.50^{**}$	.11	$.51^{**}$	$.36^{**}$	$.39^{**}$	$.40^{**}$	-

Note. MI=Major Intention; CI=Career Intention; Idnt=Engineering Identification; Uti=Engineering Utility; Bel=Engineering Program Belonging; Exp=Engineering program Expectancy; Emp=Empowerment; Use=Usefulness; Suc=Success; Int=Interest; Car=Caring; $*p < .05$; $**p < .01$

The difference between the measurement of six and 11 latent variables between the two time-points was that the student-related motivational factors (MUSIC Model) was not assessed during the beginning of the semester. However, students were assessed on those five variables at the end of the semester to determine the impact of active learning approach used in the pilot group on those five variables. The correlation tables (4.4 and 4.6) exhibit high correlations among some of the variables. For example, the correlation between usefulness and interest was .88 in Table 4.4 and .84 in Table 4.6. Similarly, correlations between empowerment and interest, and major and career intentions were over .7. There appears to be issues of multicollinearity. Therefore, different measurement models will be compared where, for example, usefulness and interests would be collapsed into one factor.

Group Mean Differences

Group Mean Differences—Beginning of Semester

The first research question pertains to investigating the mean score differences between students in the traditional and pilot groups on the six variables at the beginning of the semester and on all of the 11 latent variables at the end of the semester.

Six independent sample *t*-tests were conducted to compare scores on six different constructs between students in the traditional and pilot groups at the beginning of the semester. The results of the *t*-tests are presented in Table 4.7, which included the names of the constructs, mean scores of the two groups, mean differences, *t* statistics, *p* values, and 95% confidence intervals (CI). Except for a difference in the mean scores between the two groups on engineering utility, no significant differences were found on the five other constructs. This suggests that students in the two groups had similar levels of perceptions of major intention, career intention, engineering identification, engineering program belonging, and engineering program expectancy) at the beginning of the semester.

Table 4.7

Group Mean Differences Between the Two Groups—Beginning of Semester

Variables	Traditional (Mean)	Pilot (Mean)	Mean Differences	*t*	*p*(two-tailed)	95% CI Lower	95% CI Upper
Major Intention	5.35	5.37	-.02	-.28	.77	-.14	.10
Career Intention	5.08	5.08	.00	-.03	.98	-.14	.13
Engineering Identification	5.24	5.22	.02	.45	.65	-.08	.13
Engineering Utility	5.49	5.32	.17	2.27	.02	.02	.31
Engineering Belonging	4.87	4.94	-.07	.58	.56	-.07	.13
Engineering Expectancy	4.83	4.93	-.10	-1.89	.06	-.21	.00

Note. CI=Confidence Interval

First, an independent-samples *t*-test was conducted to assess differences in the major intention mean scores for students in the traditional and pilot groups at the beginning of the semester. The data suggest that there were no significant differences in the mean scores for their perceptions of major intention between the traditional group (M = 5.35, SD = .77) and the pilot group (M = 5.37, SD = .84), $t(1063)$ = -.28, p = .77 (two-tailed). The mean difference was -.02 with a 95% confidence interval (CI) of -.14 to .10.

Second, an independent-samples *t*-test was conducted to assess differences in the career intention mean scores for students in the two groups at the beginning of the semester. The data suggest that there were no significant differences in the mean scores for their perceptions of career intention between the traditional group (M = 5.08, SD = .85) and the pilot group (M = 5.08, SD = .84), $t(1063)$ = -.03, p = .98 (two-tailed). The mean difference was -.001 with a 95% confidence interval (CI) of -.14 to .13.

Third, an independent-samples *t*-test was conducted to assess differences in the engineering identification mean scores for students in the two groups at the beginning of the semester. The data suggest that there were no significant differences in the mean scores for their perceptions of engineering identification between the traditional group (M = 5.24, SD = .66) and the pilot group (M = 5.22, SD = .73), t(1063) = .45, p = .65 (two-tailed). The mean difference was .02 with a 95% confidence interval (CI) of -.08 to .13.

Fourth, an independent-samples *t*-test was conducted to assess differences in the engineering utility mean scores for students in the two groups at the beginning of the semester. The data suggest that there were significant differences in the mean scores for their perceptions of engineering utility between the traditional group (M = 5.49, SD = .68) and the pilot group (M = 5.32, SD = .95), t(1063) = 2.27, p=.02 (two-tailed). The mean difference was .17 with 95% confidence interval (CI) of .02 to .31.

Fifth, an independent-samples *t*-test was conducted to assess differences in the engineering program belonging mean scores for students in the two groups at the beginning of the semester. The data suggest that there were no significant differences in the mean scores for their perceptions of engineering identification between the traditional group (M = 4.87, SD = .62) and the pilot group (M = 4.94, SD = .63), t(1063) = .58, p = .56 (two-tailed). The mean difference was .07 with a 95% confidence interval (CI) of -.07 to .13.

Sixth, an independent-samples *t*-test was conducted to assess differences in the engineering program expectancy mean scores for students in the two groups at the beginning of the semester. The data suggest that there were no significant differences in their perceptions of engineering program expectancy between the traditional group (M = 4.83, SD = .69) and the pilot group (M = 4.93, SD = .66), $t(1063) = -1.89$, p = .06 (two-tailed). The mean difference was -.10 with a 95% confidence interval (CI) of -.21 to .00.

Group Mean Differences—End of Semester

Eleven independent sample *t*-tests were conducted to compare scores on 11 different constructs between students in the traditional and pilot groups at the end of the semester. The results of the *t*-tests are presented in Table 4.8, which includes the names of the constructs, mean scores for the two groups, mean differences, *t* statistics, *p* values, and 95% confidence intervals (CI). None of the 11 *t*-tests were significant. This suggests that students in the two groups had similar levels of perceptions of motivation related beliefs, engineering identification, engineering-related motivational factors, and the two intentional variables.

Table 4.8

Group Mean Differences Between the Two Groups—End of Semester

Variables	Traditional (Mean)	Pilot (Mean)	Mean Differences	*t*	*p*(two-tailed)	95% CI Lower	95% CI Upper
Major Intention	5.39	5.41	-.02	-.29	.77	-.15	.11
Career Intention	5.13	5.21	-.08	-1.22	.22	-.22	.05
Engineering Identification	5.17	5.23	-.05	-.92	.36	-.16	.06
Engineering Utility	5.22	5.25	-.03	-.34	.73	-.19	.13
Engineering Belonging	4.90	4.98	-.08	-1.62	.11	-.19	.02
Engineering Expectancy	4.72	4.82	-.10	-1.94	.05	-.21	.00
Empowerment	4.24	4.20	.04	.52	.60	-.11	.19
Usefulness	4.08	4.08	.00	.01	.99	-.17	.17
Success	4.64	4.53	.11	1.63	.10	-.02	.24
Interest	4.05	3.98	.07	.93	.36	-.09	.24
Caring	4.98	5.09	-.11	-1.79	.07	-.23	.01

Note. 95% confidence interval used

First, an independent-sample *t*-test was conducted to assess differences in the mean scores of major intention for students in the traditional and pilot groups at the end of the semester. The data suggest that there were no significant differences in the mean scores for their perceptions of major intention between the traditional group ($M = 5.39$, $SD = .93$) and the pilot group ($M = 5.41$, $SD = .87$), $t(781) = -.29$, $p = .77$ (two-tailed). The mean difference was -.02 with a 95% confidence interval (CI) of -.15 to .11. The active learning approach did not seem to have positively and sufficiently affected students in the pilot group to have higher scores than students in the traditional group on major intention.

Second, an independent-sample *t*-test was conducted to assess differences in the mean scores for career intention between students in the traditional and pilot groups at the end of the semester. The data suggest that there were no significant differences in mean scores for their perceptions of career intention between the traditional group ($M = 5.13$, $SD = .89$) and the pilot group ($M = 5.21$, $SD =.81$), $t(781) = -1.22$, $p =.22$ (two-tailed). The mean difference was -.08 with a 95% confidence interval (CI) of -.22 to .05. The active learning approach did not seem to have positively and sufficiently affected students in the pilot group to have higher scores than students in the traditional group on career intention.

Third, an independent-sample *t*-test was conducted to assess differences in the mean scores for engineering identification between students in the traditional and pilot groups at the end of the semester. The data suggest that there were no significant differences in the mean scores for their perceptions of engineering identification between the traditional group ($M = 5.17$, $SD = .73$) and the pilot group ($M = 5.23$, $SD =.74$), $t(781) = -.92$, $p = .36$ (two-tailed). The mean difference was -.05 with a 95% confidence interval (CI) of -.16 to .06. The active learning approach did not seem to have positively and sufficiently affected students in the pilot group to have higher scores than students in the traditional group on engineering identification.

Fourth, an independent-sample *t*-test was conducted to assess differences in the mean scores for engineering utility between students in the traditional and pilot groups at the end of the semester. The data suggest that there were no significant differences in the mean scores for their perceptions of engineering utility between the traditional group (M = 5.22, SD = 1.03) and the pilot group (M = 5.25, SD = 1.08), $t(781)$ = -.34, p = .73 (two-tailed). The mean difference was -.03 with a 95% confidence interval (CI) of -.19 to .13. The active learning approach did not seem to have positively and sufficiently affected students in the pilot group to have higher scores than students in the traditional group on engineering utility.

Fifth, an independent-sample *t*-test was conducted to assess differences in the mean scores for engineering program belonging between students in the traditional and pilot groups at the end of the semester. The data suggest that there were no significant differences in the mean scores for their perceptions of engineering program belonging between the traditional group (M = 4.90, SD = .67) and the pilot group (M = 4.98, SD = .69), $t(781)$ = -1.62, p = .11 (two-tailed). The mean difference was -.08 with a 95% confidence interval (CI) of -.19 to .02. The active learning approach did not seem to have positively and sufficiently affected students in the pilot group to have higher scores than students in the traditional group on engineering program belonging.

Sixth, an independent-sample *t*-test was conducted to assess differences in the mean scores for engineering program expectancy between students in the traditional and pilot groups at the end of the semester. The data suggest that there were no significant differences in the mean score for their perceptions of engineering program expectancy between the traditional group (M

= 4.72, *SD* = .77) and the pilot group (*M* = 4.82, *SD* = .67), *t*(781) = -1.94, *p* = .05 (two-tailed). The mean difference was -.11 with a 95% confidence interval (CI) of -.21 to .00. The active learning approach did not seem to have positively and sufficiently affected students in the pilot group to have higher scores than students in the traditional group on engineering program expectancy.

Seventh, an independent-sample *t*-test was conducted to assess differences in the mean scores for empowerment between students in the traditional and pilot groups at the end of the semester. The data suggest that there were no significant differences in mean scores for their perceptions of empowerment between the traditional group (*M* = 4.24, *SD* = .98) and the pilot group (*M* = 4.20, *SD* = 1.00), *t*(781) = .52, *p* = .60 (two-tailed). The mean difference was .04 with a 95% confidence interval (CI) of -.11 to .19. The active learning approach did not seem to have positively and sufficiently affected students in the pilot group to have higher scores than students in the traditional group on empowerment.

Eighth, an independent-sample *t*-test was conducted to assess differences in the mean scores for usefulness between students in the traditional and pilot groups at the end of the semester. The data suggest that there were no significant differences in mean scores for their perceptions of usefulness between the traditional group (*M* = 4.08, *SD* = 1.12) and the pilot group (*M* = 4.08, *SD* = 1.15), *t*(781) = .01, *p* = .99 (two-tailed). The mean difference was .00 with a 95% confidence interval (CI) of -.17 to .17. The active learning approach did not seem to have positively and sufficiently affected students in the pilot group to have higher scores than students in the traditional group on usefulness.

Ninth, an independent-samples *t*-test was conducted to assess differences in the mean scores for success between students in the traditional and pilot groups at the end of the semester.

The data suggest that there were no significant differences in the mean scores for their perceptions of success between the traditional group (*M* = 4.64, *SD* = .85) and the pilot group (*M* = 4.53, *SD* = .91), *t*(781) = 1.63, *p* = .10 (two-tailed). The mean difference was .11 with a 95% confidence interval (CI) of -.02 to .24. The active learning approach did not seem to have positively and sufficiently affected students in the pilot group to have higher scores than students in the traditional group on success.

Tenth, an independent-sample *t*-test was conducted to assess differences in the mean scores for interest between students in the traditional and pilot groups at the end of the semester. The data suggest that there were no significant differences in their perceptions of interest between the traditional group (*M* = 4.05, *SD* = 1.07) and the pilot group (*M* = 3.98, *SD* = 1.14), *t*(781) = .93, *p* = .36 (two-tailed). The mean difference was .08 with a 95% confidence interval (CI) of -.09 to .24. The active learning approach did not seem to have positively and sufficiently affected students in the pilot group to have higher scores than students in the traditional group on success.

Eleventh, an independent-sample *t*-test was conducted to assess differences in the mean scores for caring between students in the traditional and pilot groups at the end of the semester. The data suggest that there were no significant differences in the mean score for their perceptions of caring between the traditional group (*M* = 4.98, *SD* = .78) and the pilot group (*M* = 5.09, *SD* = .77), *t*(781) = -1.79, *p* = .07 (two-tailed). The mean difference was -.11 with a 95% confidence interval (CI) of -.23 to .01. The active learning approach did not seem to have positively and sufficiently affected students in the pilot group to have higher scores than students in the traditional group on caring.

The results of this study did not support the hypothesis that the pilot group would have a higher level of motivation at the end of semester as a result of using an active learning approach as an instructional technique.

Normality of Data, EFA, and Measurement Models

This section presents information on the normality of data, results of the EFA, and the comparisons of different measurement models using chi-square difference tests. This information is needed to answer research questions two and three which relate to estimating the structural model. It is important to examine the normality of the data to ensure that this assumption has been met. The result of such an examination will allow us to determine whether or not any correction measures need to be taken, such as Satora Bentler correction, if the normality assumption has been violated. This correction can be made adding ROBUST ESTIMATION in the syntax when estimating both the measurement and structural models. Similarly, EFA was conducted on the estimation sample to determine the factor structure, which was then confirmed on the validation sample. Based on the results of the EFA and the correlations among the latent variables, five different measurement models have been estimated with the 11 latent variables used as the baseline model. The most viable model among the five was then cross-validated with the pilot sample.

Normality of Data

Skewness and kurtosis are measures of normality. For the traditional group, skewness ranged between -.42 and -2.33, and kurtosis ranged between -.231 and 7.48. On the other hand, for the pilot group, skewness ranged between -.02 and -1.1 and kurtosis ranged between -.1 and .11. There does not appear to be a clear consensus on an acceptable level of nonnormality. However, univariately, it was found that major problems arise when univariate skewness and kurtosis exceed two and seven, respectively (Curan, West, & Finch, 1996; Muthen & Kaplan

1992). In this study, however, only one variable (MI1—Major Intention 1) had skewness and kurtosis over two and seven.

Rating scale data are widely used in social sciences. Likert scales output is often considered as an interval scale even though it is more of an ordinal scale in stricter sense (Malhotra, 1996). However, this practice is considered acceptable because it occurs quite often in social sciences research (Kinnear & Taylor, 1991). According to Stewart, Barnes, Cote, Cudeck, and Malthouse (2001), variables rarely follow normal distribution. The data that come from ordinal scales are usually not normal (Stewart et al., 2001; Hancock, 2014). If the normality assumption is not severely violated, Maximum Likelihood (ML) estimation method yields reasonable results (Bollen, 1989; Hancock, 2014). In the case of severe normality issue, Satorra-Bentler corrections could be used, but in this study this correction was not used based on the univariate skewness and kurtosis values of each variable.

Exploratory Factor Analysis

Table 4.9 represents the factor loadings of 26 items of the MUSIC Model of Academic Motivation. The 26 items of the MUSIC scale were subjected to principal component analysis (PCA) via SPSS 22.0. The results show the existence of four components as opposed to five components after promax rotation, specifically, usefulness items and interest items loaded onto a single factor. The four components explained 70.96% of the variance. The results of this study do not support the use of a five factor MUSIC scale because usefulness and interest items loaded onto a single factor. However, usefulness and interest are theoretically distinct constructs (Jones, 2009). Further, the five-factor MUSIC scale has been validated (Jones & Skaggs, 2012). Therefore, it was decided to confirm and compare the five-factor model with four-factor model by collapsing usefulness and interest into one factor.

Table 4.9 (p. 74-75)

Factor Loadings for Exploratory Factor Analysis with Promax Rotation of the MUSIC Model of Academic Motivation (n=273—Estimation Sample)

Variables	No. of Items	Factor Loadings	Scale Alpha	Variance Explained (%)
Usefulness Items:	5		.93	43.75
In general, the coursework was useful to me.		.96		
The coursework was beneficial to me.		1.01		
I found the coursework to be relevant to my future.		.79		
I will be able to use the knowledge I gained in this course.		.81		
The knowledge I gained in this course is important for my future.		.86		
Interest Items:	6			
The coursework held my attention.		.92	.93	
The instructional methods used in this course held my attention.		.73		
I enjoyed the instructional methods used in this course.		.58		
The instructional methods engaged me in the course.		.66		
I enjoyed completing the coursework.		.77		
The coursework was interesting to me.		.84		
Caring Items:	6		.91	14.36
The instructor was available to answer my questions about the coursework.		.77		
The instructor was willing to assist me if I needed help in the course.		.87		
The instructor cared about how well I did in this course.		.82		
The instructor was respectful of me.		.84		
The instructor was friendly.		.86		
I believe that the instructor cared about my feelings.		.89		
Empowerment Items:	5		.87	7.27
I had the opportunity to decide for myself how to meet the course goals.		.63		
I had the freedom to complete the coursework my own way.		.86		
I had options in how to achieve the goals of the course.		.80		
I had control over how I learned the course content.		.83		
I had flexibility in what I was allowed to do in this course.		.84		
Success Items:	4		.87	5.57

I was confident that I could succeed in the coursework.		.88		
I felt that I could be successful in meeting the academic challenges in this course.		.72		
I was capable of getting a high grade in this course.		.92		
Throughout the course, I felt that I could be successful on the coursework.		.83		

Note. Factor loadings < .40 are suppressed.

Table 4.10 represents the factor loadings of 20 items of engineering identification and three engineering-related motivational factors (engineering utility, engineering program belonging, and engineering program expectancy). The scale originally had 23 items, but all the three negatively worded items measuring engineering program belonging loaded onto a factor that was different from the rest of the items. Therefore, the three negatively worded items were excluded in the revised model. The extraction method and rotation method used were PCA and promax, respectively via SPSS 22.0. The four components explained 68.52% of the variance with component 1 contributing 37.76%, component 2 contributing 15.16%, component 3 contributing 9.10%, and component 4 contributing 6.5%. The correlations between the four factors were positive and ranged between small and medium.

Table 4.10 (p. 75-76)

Factor Loadings for Exploratory Factor Analysis with Promax Rotation of Engineering Identification and Three Engineering-Related Motivational Factors (n=273—Estimation Sample)

Variables	No. of Items	Factor Loadings	Scale Alpha	Variance Explained (%)
Engineering Utility Items:	6		.90	37.76
Knowing about engineering does not benefit me at all.		.79		
I see no point in me being able to do engineering.		.90		
Having a solid background in engineering is worthless to me.		.87		
I have little to gain by learning how to do engineering.		.84		
After graduation, an understanding of engineering will be useless to me.		.85		
I do not need engineering in my everyday life.		.65		

Engineering Program Expectancy Items:	5		.90	15.16
Compared to other engineering students, I expect to do well in my engineering-related courses this year.		.86		
I think that I will do well in my engineering-related courses this year.		.89		
I am good at math, science, and engineering.		.77		
Compared to other engineering students, I have high engineering-related abilities.		.76		
I have been doing well in my engineering-related courses this year.		.89		
Engineering Identification Items:	4		.88	9.10
Being good at engineering is an important part of who I am.		.86		
Doing well on engineering tasks is very important to me.		.93		
Success in engineering school is very valuable to me.		.87		
It matters to me how well I do in engineering school.		.67		
Engineering Program Belonging Items:	5		.77	6.50
I feel like a real part of the General Engineering program.		.43		
People in the General Engineering program are friendly to me.		.82		
I am treated with as much respect as other students in the General Engineering program.		.82		
The instructors in the General Engineering program respect me.		.72		
I feel proud of belonging in the General Engineering program		.48		

Note. Factor loadings < .40 are suppressed.

Table 4.11 represents the factor loadings of the two intention variables, major intention and career intention. They loaded onto a single factor. The amount of variance explained was 75.05. The extraction method and rotation method used were PCA and promax, respectively via SPSS 22.0. The four items did not load onto two factors as expected. Therefore, two measurement models were estimated to compare the model-data fit: one where the two variables were considered as distinct and the other where two variables were considered as a single factor.

Table 4.11

Factor Loadings for Exploratory Factor Analysis with Promax Rotation of the Major Intention and Career Intention (n=273—Estimation Sample)

Variables	No. of Items	Factor Loadings	Scale Alpha	Variance Explained (%)
Major/Career Intention Items:	4		.89	75.05
I plan to continue on in an engineering major.		.89		
I don't intend to change my major from engineering to a non-engineering major.		.84		
My eventual career will directly relate to engineering.		.88		
In the future, I will have a career that requires me to have engineering skills.		.85		

Measurement Models Compared and Cross-Validated

Five measurement models were estimated and compared against the baseline measurement model (model 1) with 11 latent variables. The fit indices of the three major index classes for the five measurement models and the chi-square difference tests are presented in Table 4.12. In two of the measurement models, usefulness and interest were collapsed into a single factor in model 2 and major and career intentions were collapsed in model 3 based on their factor loadings in EFA. In model 4, empowerment and interest were collapsed into a single factor based on their high correlations as presented in Tables 4.4 and 4.6. Model five is similar to the baseline model except the errors of usefulness items one and two were allowed to covary. This model was estimated for two reasons. First, the loading of usefulness item two in the EFA was over 1, which is problematic as it could be a sign of multicollinearity. Second, the modification indices of the baseline model suggested achieving the highest decrease in chi-square value by correlating the errors of usefulness items one and two. Therefore, a decision to revise the measurement model was made because the results of the EFA and modification indices of the baseline measurement model were consistent. In other words, the model modification was theoretically and statistically reasonable. The issue of correlated errors could arise when the items are “very similarly worded, reverse worded, or differentially prone to social desirability and so forth” (Brown, 2006, p. 181). In this case, the two items appear to be “similarly worded.” The two items are: (1) In general, the coursework was useful to me (usefulness item 1), and (2) the coursework was beneficial to me (usefulness item 2).

Results of the five measurement models were presented in Table 4.12, specifically their fit indices and chi-square difference tests. By collapsing two latent variables in models two (usefulness and interest were combined as a single factor), three (major intention and career intention were combined as a single factor), and four (empowerment and interest were combined as a single factor), the degrees of freedom increased by 10 each. For 10 degrees of freedom, the chi-square value of 18.307 is significant at the .05 level. The differences in chi-square values in the three models as compared to the baseline model were all greater than 18.307. Therefore, the less constraint baseline measurement model was better than models two, three, and four in explaining covariation in the data. The more constrained measurement

Table 4.12 (p. 78-79)

Chi-Square Difference Tests and Fit Indices of Competing Measurement Models

Models	χ^2	Df	$\Delta\ \chi^2$	Δ Df	SRMR	RMSEA	CFI
(1) Baseline measurement model (11 latent variables)	3463.57	1120			.056	.062	.971
(2) Usefulness and Interest Combined (10 latent variables)	3616.02	1130	152.54	10	.057	.064	.967
(3) Major and career intentions combined (10 latent variables)	3698.65	1130	235.08	10	.057	.065	.968
(4) Empowerment and interest combined (10 latent variables)	3896.15	1130	432.58	10	.058	.067	.966

(5) Errors of use1 and use2 covary (11latent variables)	3322.97	1119	140.60	1	.057	.060	.973

models two, three, and four would have been better if the increase in chi-square values were less than 18.307 for an increase of 10 degrees of freedom. However, model five, which is similar to the baseline measurement model except for the covarations of the errors between usefulness items one and two, was better than the baseline measurement model. One degree of freedom was lost, as compared to the baseline model, in model five because one additional parameter was added. For one degree of freedom, the chi-square value of 3.841 is significant at the .05 level. In this study, for the loss of one degree of freedom, the chi-square went down by 140.60. Further, its RMSEA was less by .001 and CFI was greater by .002 compared to the baseline model. Therefore, model five provided a better fit to the data than the baseline model and it can be described as “one tenable explanation for the associations observed in the data” (Mueller & Hancock, 2008, p. 506). This model was, therefore, accepted as a “good explanation of our data” (Keith, Hallam, Fine, 2004).

The multiple squared correlation coefficients ranged between .36 and .93 and are presented in Table 4.13. This refers to the amount of variance explained in the dependent variable by an independent variable or a group of them. In the context of the measurement model, it refers to the amount of variance explained in the observed variables by their respective latent variables. The factor loadings of the measurement model ranged between .60 and .91 and are presented in Table 4.13. After respecifying the measurement model with one correlated error between usefulness items one and two, the modification indices further suggested correlating error variances, for example, between caring items one and two. However, it was decided against making further modification to the measurement model for three reasons. First, the fit indices were within the acceptable range. Second, MacCallum, Roznowski, and Necowitz (1992) noted that respecifying a model that provides a good fit to the data may obtain better fit but increases the likelihood of "fitting small idiosyncratic characteristics of the sample" (p. 501). Third, Schumacker and Lomax (2010) advised against making changes to the initial model without substantive theoretical justification.

Table 4.13 (p. 80-82)

Factor Loadings for Confirmatory Factor Analysis of the MUSIC Model of Academic Motivation (n=539—Validation Sample)

Variables	No. of Items	Factor Loadings	Squared Multiple Correlation Coefficients
Empowerment Items:	5		
I had the opportunity to decide for myself how to meet the course goals.		.75	.56
I had the freedom to complete the coursework my own way.		.81	.66
I had options in how to achieve the goals of the course.		.89	.78
I had control over how I learned the course content.		.78	.61
I had flexibility in what I was allowed to do in this course.		.81	.65
Usefulness Items:	5		
In general, the coursework was useful to me.		.88	.77
The coursework was beneficial to me.		.86	.74
I found the coursework to be relevant to my future.		.85	.72
I will be able to use the knowledge I gained in this course.		.89	.79
The knowledge I gained in this course is important for my future.		.88	.77
Success Items:	4		
I was confident that I could succeed in the coursework.		.82	.67
I felt that I could be successful in meeting the academic challenges in this course.		.82	.67
I was capable of getting a high grade in this course.		.79	.63
Throughout the course, I felt that I could be successful on the coursework.		.85	.72
Interest Items:	6		
The coursework held my attention.		.83	.69
The instructional methods used in this course		.83	.70

held my attention.			
I enjoyed the instructional methods used in this course.		.81	.65
The instructional methods engaged me in the course.		.85	.72
I enjoyed completing the coursework.		.85	.72
The coursework was interesting to me.		.86	.73
Caring Items:	6		
The instructor was available to answer my questions about the coursework.		.76	.57
The instructor was willing to assist me if I needed help in the course.		.82	.68
The instructor cared about how well I did in this course.		.75	.56
The instructor was respectful of me.		.82	.68
The instructor was friendly.		.84	.71
I believe that the instructor cared about my feelings.		.81	.65

Variables	No. of Items	Factor Loadings	Squared Multiple Correlation Coefficients
Engineering Identification Items:	4		
Being good at engineering is an important part of who I am.		.70	.49
Doing well on engineering tasks is very important to me.		.82	.67
Success in engineering school is very valuable to me.		.85	.72
It matters to me how well I do in engineering school.		.78	.61
Engineering Utility Items:	6		
Knowing about engineering does not benefit me at all.		.83	.69
I see no point in me being able to do engineering.		.91	.83
Having a solid background in engineering is worthless to me.		.92	.85
I have little to gain by learning how to do engineering.		.95	.90
After graduation, an understanding of engineering will be useless to me.		.91	.84
I do not need engineering in my everyday life.		.79	.63

Engineering Program Belonging Items:	5		
I feel like a real part of the General Engineering program.		.65	.42
People in the General Engineering program are friendly to me.		.68	.46
I am treated with as much respect as other students in the General Engineering program.		.70	.49
The instructors in the General Engineering program respect me.		.70	.50
I feel proud of belonging in the General Engineering program		.60	.36
Engineering Program Expectancy Items:	5		
Compared to other engineering students, I expect to do well in my engineering-related courses this year.		.82	.68
I think that I will do well in my engineering-related courses this year.		.88	.77
I am good at math, science, and engineering.		.72	.52
Compared to other engineering students, I have high engineering-related abilities.		.71	.50
I have been doing well in my engineering-related courses this year.		.85	.72

Variables	No. of Items	Factor Loadings	Squared Multiple Correlation Coefficients
Major Intention Items:	2		
I plan to continue on in an engineering major.		.96	.93
I don't intend to change my major from engineering to a non-engineering major.		.83	.69
Career Intention Items:	2		
My eventual career will directly relate to engineering.		.88	.78
In the future, I will have a career that requires me to have engineering skills.		.89	.79

Measurement model five as presented in Table 4.12 was estimated using the validation sample (2/3 of the traditional group) and was then cross-validated with the pilot group. Schumacker and Lomax (2010) advocated using a different set of data to validate the modified model. The fit indices of the three major index classes for the measurement model is presented in

Table 4.14 and the results demonstrate that the measurement model was successfully replicated with an independent sample as the values of the fit indices met the requirements of the cut-off score criteria for good model-data fit based on the three major index classes.

Table 4.14

Fit Indices of the Measurement Model—Cross-Validation Sample (Pilot Group)

Model	χ^2	Df	SRMR	RMSEA	CFI
Measurement Model	2559.099	1119	.069	.073	.955

The multiple squared correlation coefficients ranged between .35 and .95 and are presented in Table 4.15. This refers to the amount of variance explained in the dependent variable by an independent variable or a group of them. In the context of the measurement model, it refers to the amount of variance explained in the observed variables by their respective latent variables.

The factor loadings of the measurement model ranged between .59 and .97 and are presented in Table 4.15. There was some room for improvement in the measurement model with the pilot data based on the modification indices. However, it was decided against modifying the model for the three reasons listed earlier.

Table 4.15 (p. 83-86)

Factor Loadings for Confirmatory Factor Analysis of the MUSIC Model of Academic Motivation (n=242—Pilot Group)

Variables	No. of Items	Factor Loadings	Squared Multiple Correlation Coefficients
Empowerment Items:	5		
I had the opportunity to decide for myself how to meet the course goals.		.77	.59
I had the freedom to complete the coursework my own way.		.83	.69
I had options in how to achieve the goals of the		.87	.75

Variables	No. of Items	Factor Loadings	Squared Multiple Correlation Coefficients
course.			
I had control over how I learned the course content.		.80	.64
I had flexibility in what I was allowed to do in this course.		.79	.63
Usefulness Items:	5		
In general, the coursework was useful to me.		.88	.77
The coursework was beneficial to me.		.90	.81
I found the coursework to be relevant to my future.		.87	.76
I will be able to use the knowledge I gained in this course.		.86	.74
The knowledge I gained in this course is important for my future.		.86	.74
Success Items:	4		
I was confident that I could succeed in the coursework.		.85	.73
I felt that I could be successful in meeting the academic challenges in this course.		.83	.69
I was capable of getting a high grade in this course.		.81	.65
Throughout the course, I felt that I could be successful on the coursework.		.84	.71
Interest Items:	6		
The coursework held my attention.		.79	.63
The instructional methods used in this course held my attention.		.82	.68
I enjoyed the instructional methods used in this course.		.83	.68
The instructional methods engaged me in the course.		.86	.75
I enjoyed completing the coursework.		.86	.74
The coursework was interesting to me.		.86	.75
Caring Items:	6		
The instructor was available to answer my questions about the coursework.		.70	.48
The instructor was willing to assist me if I needed help in the course.		.77	.60
The instructor cared about how well I did in this course.		.72	.52
The instructor was respectful of me.		.86	.74
The instructor was friendly.		.86	.74
I believe that the instructor cared about my feelings.		.85	.73

Engineering Identification Items:	4		
Being good at engineering is an important part of who I am.		.72	.52
Doing well on engineering tasks is very important to me.		.87	.75
Success in engineering school is very valuable to me.		.91	.83
It matters to me how well I do in engineering school.		.83	.68
Engineering Utility Items:	6		
Knowing about engineering does not benefit me at all.		.89	.79
I see no point in me being able to do engineering.		.97	.93
Having a solid background in engineering is worthless to me.		.92	.85
I have little to gain by learning how to do engineering.		.97	.95
After graduation, an understanding of engineering will be useless to me.		.90	.81
I do not need engineering in my everyday life.		.78	.61
Engineering Program Belonging Items:	5		
I feel like a real part of the General Engineering program.		.59	.35
People in the General Engineering program are friendly to me.		.80	.65
I am treated with as much respect as other students in the General Engineering program.		.74	.55
The instructors in the General Engineering program respect me.		.65	.42
I feel proud of belonging in the General Engineering program		.59	.35
Engineering Program Expectancy Items:	5		
Compared to other engineering students, I expect to do well in my engineering-related courses this year.		.76	.57
I think that I will do well in my engineering-related courses this year.		.88	.78
I am good at math, science, and engineering.		.63	.40
Compared to other engineering students, I have high engineering-related abilities.		.61	.37
I have been doing well in my engineering-related courses this year.		.71	.51

Variables	No. of Items	Factor Loadings	Squared Multiple Correlation Coefficients
Major Intention Items:	2		
I plan to continue on in an engineering major.		.90	.80
I don't intend to change my major from engineering to a non-engineering major.		.90	.79
Career Intention Items:	2		
My eventual career will directly relate to engineering.		.85	.72
In the future, I will have a career that requires me to have engineering skills.		.87	.75

Structural Models

This section pertains to research questions two and three. These two research questions investigate the tenability of the domain identification model, specifically causality hypothesized among the variables as presented in Figure 1. In the model being tested, it was hypothesized that students' motivation-related beliefs would predict engineering identification and three engineering-related motivational factors. The engineering identification and three engineering-related motivational factors in turn are hypothesized to predict students' engineering major intention and engineering career intention. The structural model that provided the best fit to the validation sample after making modifications to the initial model was then cross-validated with the pilot data. The modification process and the final model are presented first, followed by discussions on the effects of exogenous latent constructs on the first set of endogenous constructs (elements of the gamma matrix), and the effects of the first set of endogenous latent variables on the second set of endogenous constructs (elements of the beta matrix).

Traditional Group

For the traditional group, the first structural model estimated was the model presented in Figure 1. This was the initial hypothesized model. A second structural model was estimated and compared against the first model. An additional parameter was added in the second model, specifically major intention was hypothesized to predict career intention. Thereafter, one parameter each was deleted in the subsequent models. Each model was compared with its immediate subsequent model using a chi-square difference test and the three fit indices. Table 4.16 presents the chi-square difference test and the fit indices of the competing structural models.

Table 4.16

Chi-Square Difference Tests and Fit Indices of Competing Structural Models (p. 87-88)

Models	$\chi^2(df)$	Df	$\Delta\ \chi^2$	Δ Df	SRMR	RMSEA	CFI
(1) Initial Model	3614.33	1136			.075	.063	.969
(2) Path from Major to Career Added	3512.49	1135	101.84	1	.074	.062	.971
(3) Path from Expectancy to Career deleted	3512.56	1136	.07	1	.074	.062	.971
(4) Path from Belonging to Career deleted	3512.73	1137	.17	1	.074	.062	.971
(5) Path from Empowerment to Belonging deleted	3512.75	1138	.02	1	.074	.062	.971
(6) Path from Interest to Expectancy deleted	3512.95	1139	.20	1	.074	.062	.971
(7) Path from Usefulness to Belonging deleted	3513.23	1140	.28	1	.074	.062	.971

(8) Path from Interest to Utility deleted	3513.78	1141	.55	1	.074	.062	.971
(9) Path from Usefulness to Expectancy deleted	3514.53	1142	.75	1	.074	.062	.971
(10) Path from Usefulness to Identification deleted	3515.45	1143	.92	1	.074	.062	.971
(11) Path from Caring to Expectancy deleted	3517.88	1144	2.43	1	.074	.062	.971
(12) Path from Usefulness to Utility deleted	3520.79	1145	2.91	1	.075	.062	.971
(13) Path from Empowerment to Identification deleted	3524.35	1146	3.56	1	.075	.062	.971

A parameter added in model two was a path from major intention to career intention. This makes theoretical sense because it is imperative for an individual to possess an engineering degree to pursue an engineering career. For loss of one degree of freedom, the chi-square value went down by 101.84 which was statistically significant at the .05 level. Further, the values of SRMR and RMSEA went down by .001 each while the value of CFI went up by .002. All these changes indicate that the proposed structural model two provided a better fit to the observed data compared to the initial model. Therefore, this model makes sense not just theoretically, but also statistically.

However, not all of the hypothesized relationships among the latent variables were supported in model two. In other words, some of the path coefficients were significant as expected, while others were not. Further, the initial hypothesized model was close to a fully saturated model. Therefore, a series of modifications were made to model two, specifically, deleting path coefficients that were insignificant, one at a time, to arrive at a parsimonious model. The path coefficients that had the lowest z values were deleted first. The output of model two showed that 13 path coefficients were not significant. However, in the final model, 11 path coefficients were excluded because two of the coefficients became significant after deleting insignificant path coefficients. Those two path coefficients were: (1) association between interest and engineering identification, and (2) association between empowerment and engineering program expectancy. Eleven deleted parameters were reflected in models three through 11. The final structural model for the traditional group with standardized path coefficients are presented in Figure 4.1.

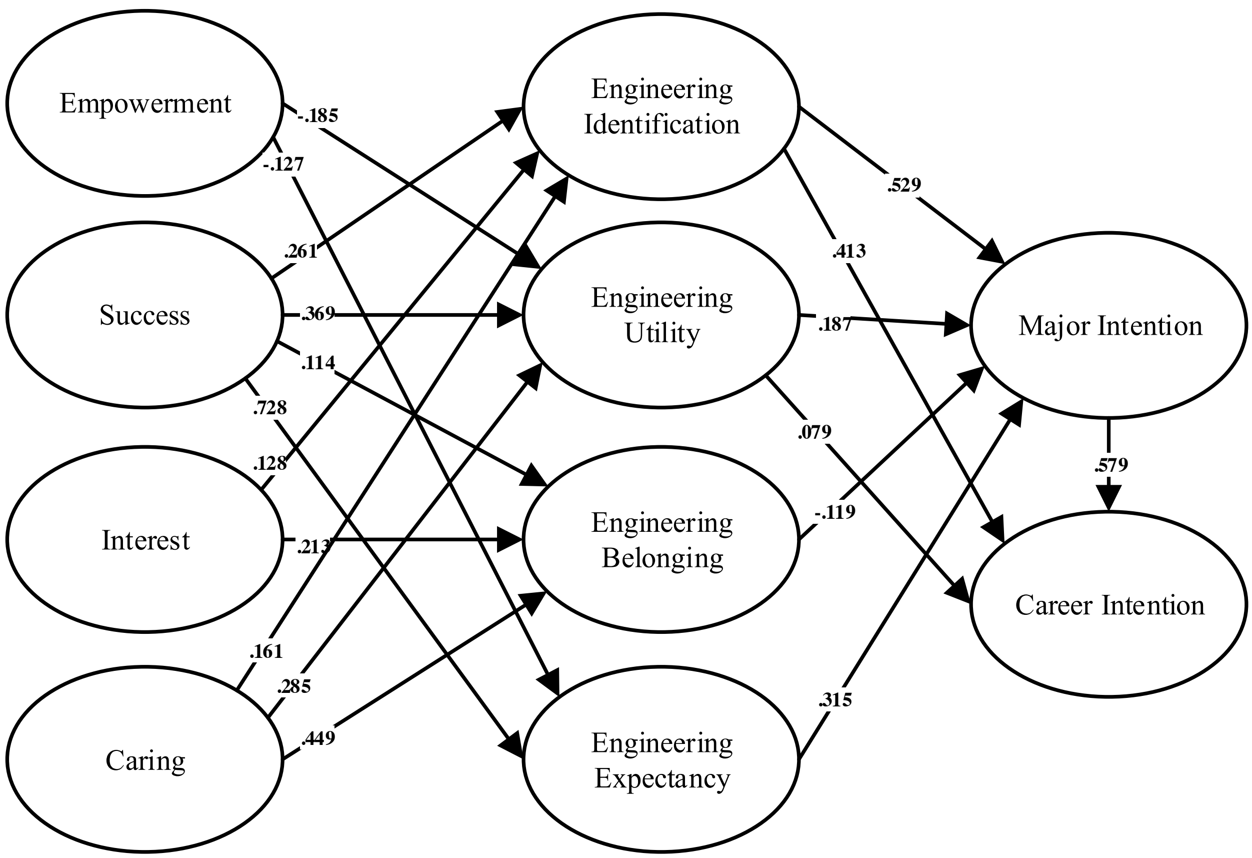

Figure 4.1. Final structural model-traditional group.

In model three, a model was estimated again excluding the path from engineering program expectancy to career intention. That path had the lowest z value. For an increase of one degree of freedom, the increase in chi-square value was less than 3.84. The three fit indices were similar between the two models. Therefore, the more parsimonious model three was better than model two. This pattern was consistent throughout the rest of the models. Beginning with model three, one parameter was excluded in each subsequent model. The chi-square value did not increase by more than 3.84 in any of the subsequent models. Based on chi-square difference tests and the three fit indices, model 13 was considered to be the best fitting and most parsimonious model explaining relations in the data reasonably well. All the hypothesized relationships in structural model 13 were significant.

Pilot Group

The model 13 estimated and presented in Table 4.16 was then cross-validated with the pilot data. The final structural model for the pilot group with standardized path coefficients are presented in Figure 4.2.

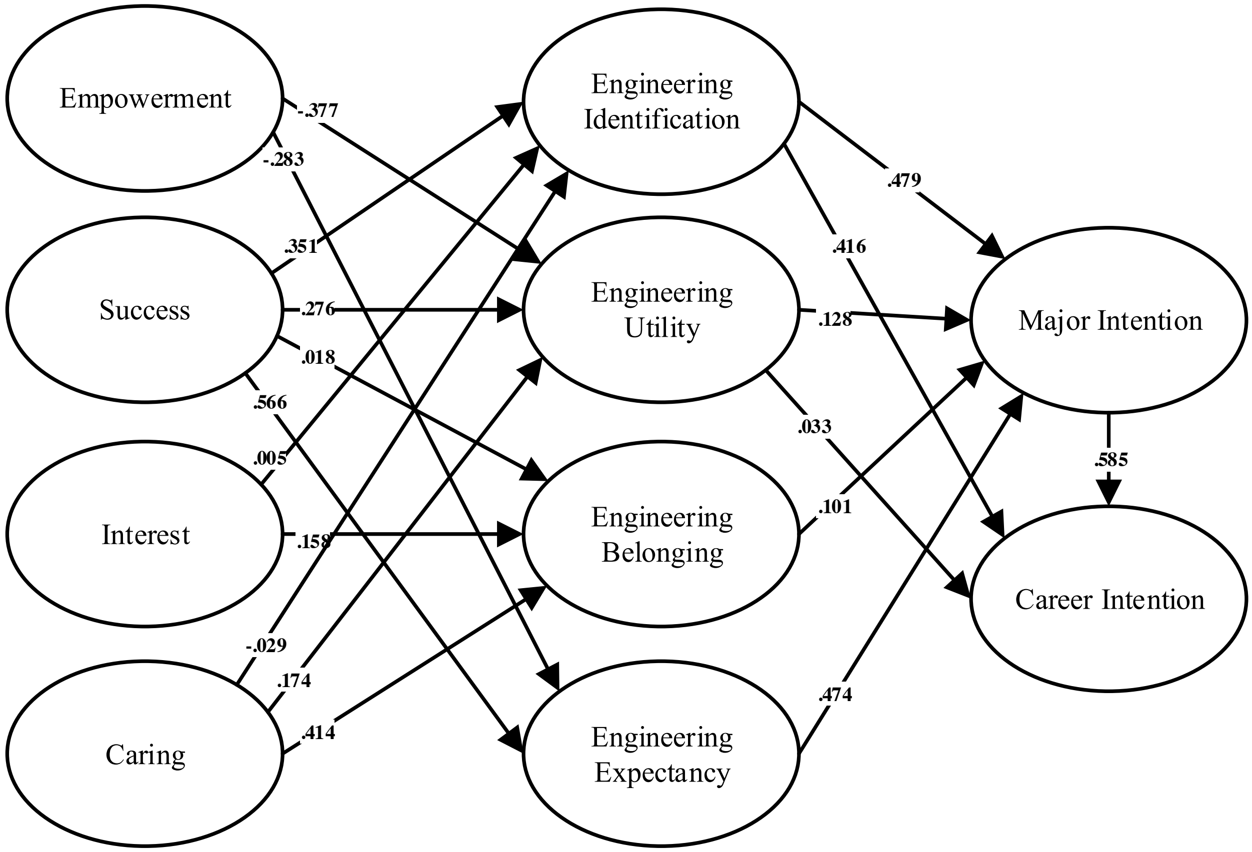

Figure 4.2. Final structural model—pilot group.

The fit indices of the cross-validation are presented in Table 4.17. The fit indices presented in Table 4.17 suggest a successful replication of the proposed model estimated with the traditional sample. The value of SRMR suggest a mediocre fit. However, the values of RMSEA and CFI indicate an adequate model-data fit. Schumacker and Lomax (2010) noted that the proposed model can be considered as being supported by the observed data if majority of the fit indices used for the study have adequately met the cut-off criteria for an acceptable model. In the case of the pilot data, two out of three fit indices indicate an acceptable model.

Table 4.17

Structural Model Validated on the Pilot Group

Models	χ^2	Df	SRMR	RMSEA	CFI
(2) Structural Model	2704.899	1146	.097	.075	.952

Research Question 2

Traditional group. Research question two focuses on the effect of the five MUSIC elements on engineering identification and three engineering-related motivational factors. Table 4.18 presents the path coefficients and their standard errors along with the variances explained (R^2). Of the five MUSIC elements, success, interest, and caring significantly predicted engineering identification. Controlling for other independent variables, empowerment and usefulness were not significant in predicting engineering identification. Therefore, these two variables were deleted from the final model to predict engineering identification. Success, interest, and caring together accounted for 27% of the variation in engineering identification. Engineering utility was significantly predicted by empowerment, success, and caring. The three explanatory variables accounted for 13.2% of the variance in engineering utility. The coefficient of empowerment was significant, however, it was not in the expected direction. Coefficients of usefulness and interest were not statistically significant while controlling for other elements of the MUSIC model. Therefore, these two variables were excluded from the final model to predict engineering program utility. Success, interest, and caring significantly predicted variation in engineering program belonging and the three independent variables explained 53.4% of the variation in engineering program belonging. Empowerment and usefulness were deleted from the final model to predict engineering program belonging. Success and interest were the only

MUSIC elements to significantly predict engineering program expectancy and these two independent variables accounted for 49.2% of the variation in engineering program expectancy. The other three MUSIC elements were excluded from the final model to predict engineering program expectancy.

Table 4.18

Path Coefficients, Standard Errors, and R^2 – Traditional Group

	Empowerment	Usefulness	Success	Interest	Caring	R^2
Engineering Identification	-	-	.261* (.054) 4.951	.128* (.036) 3.525	.161* (.049) 3.323	.270
Engineering Program Utility	-.185* (.066) -2.815	-	.369* (.072) 5.095	-	.285* (.069) 4.134	.132
Engineering Program Belonging	-	-	.114* (.047) 2.452	.213* (.035) 6.074	.449* (.053) 8.512	.534
Engineering Program Expectancy	-.127* (.042) -3.023	-	.728* (.054) 13.563	-	-	.492

Overall, of the five MUSIC elements, success and caring were significant in accounting for variances in engineering identification and three engineering-related motivational factors. Success had the highest effect on engineering identification, engineering program utility, and engineering program expectancy, while caring had the highest influence on engineering program belonging. In the final model, controlling for the other four MUSIC elements, usefulness was not significant in predicting engineering identification and three engineering-related motivational factors. Therefore, usefulness was not a part of any of the structural equations in the final model to predict the endogenous constructs related to engineering. The variance explained for the engineering identification and three engineering-related motivational factors ranged between .132 and .534. Theoretically, the inverse relationships between empowerment and engineering program utility, and empowerment and engineering program expectancy were hard to explain. However, signs of the coefficients could change depending on the variables included in the model and also because of high correlations among the independent variables (Keith, 2006). Multicollinearity could cause problems, such as negative coefficients, standardized regression coefficients greater than 1, and inflated standard errors. (Keith, 2006; Meyers, Gamst, & Guarino, 2006; Pedhazur & Schmelkin, 1991). The discussion of negative coefficients and multicollinearity are applicable to the next sub-section, specifically, the pilot group. The same discussions are also applicable to the two sub-sections under research question three.

Pilot group. The pilot group was used to validate the modified structural model 13. Table 4.19 presents the path coefficients and their standard errors along with the variances explained. In the case of pilot group, success was the only significant predictor of engineering identification and the three independent variables, which accounted for 20.2% of the variance in the dependent variable. Engineering program utility was significantly predicted by empowerment and success, but the three independent variables explained only 5% of the variation in the dependent variable. Interest and caring were the only explanatory variables that significantly predicted engineering program belonging. Taken simultaneously, success, interest, and caring accounted for 37.2% of the variation in engineering program belonging. The coefficients of empowerment and success were significant for engineering program expectancy and the two independent variables together explained 36.6% of the variation in engineering program expectancy.

Not all of the path coefficients were significant in the cross-validation sample. One of the possible reasons could be differences in a sample size. Therefore, the cross-validation of the revised and final model was done again on the pilot group but by increasing *N* to 539 to match the traditional group's sample size. With an increased sample size, two more paths became significant, specifically the associations between engineering program belonging and major intention, and caring and utility. Two of the empowerment coefficients were negative and

Table 4.19

Path Coefficients, Standard Errors, and R^2 – Pilot Group

	Empowerment	Usefulness	Success	Interest	Caring	R^2
Engineering Identification	-	-	.351* (.069) 5.063	.005 (.058) .079	-.029 (.072) -.408	.202
Engineering Program Utility	-.377* (.136) -2.783	-	.276* (.111) 2.488	-	.174 (.124) 1.402	.050
Engineering Program Belonging	-	-	.018 (.056) .326	.158* (.053) 2.987	.414* (.079) 5.193	.372
Engineering Program Expectancy	-.283* (.075) -3.782	-	.566* (.075) 7.497	-	-	.366

significant as they were with the validation sample. Except for a slight difference in the variance explained between the two groups for engineering program utility, the amount of variance explained for the other three variables are similar in the two groups. Like in the case of the traditional group, success and caring were the best predictors of engineering identification, engineering program utility, and engineering program expectancy for the pilot group.

Research Question 3

Research question three pertains to examining the relationships between engineering identification and three engineering-related motivational factors and the two intention variables (major intention and career intention).

Traditional group. Table 4.20 presents the path coefficients and their standard errors along with the variances explained for the final two latent outcome variables. Major intention

Table 4.20

Path Coefficients, Standard Errors, and R^2 – Traditional Group

	Major Intention	Engineering Identification	Engineering Program Utility	Engineering Program Belonging	Engineering Program Expectancy	R^2
Major Intention	-	.529* (.054) 9.886	.187* (.031) 6.006	-.119* (.051) -2.347	.315* (.046) 6.921	.445
Career Intention	.579* (.054) 10.749	.413* (.058) 7.183	079* (.032) 2.472	-	-	.635

was significantly predicted by all of its independent variables. In this equation, engineering identification had the highest coefficient meaning that the value of engineering domain to students' sense of self is a better predictor of major intention and career intention. In the same equation, the coefficient of engineering program belonging was negative which is perhaps due to collinearity. The four independent variables explained 44.5% of the variations in major intention. Career intention, on the other hand, was significantly predicted by all of its independent variables except engineering program belonging and engineering program expectancy. Therefore, these variables were deleted in the final model to predict career intention. The three independent variables accounted for 63.5% of the variance for career intention. In this equation, major intention had the highest coefficient followed by engineering identification.

Pilot group. The pilot group was used as the validation sample. Table 4.21 presents the path coefficients and their standard errors along with the variances explained for the final two latent outcome variables. The coefficients of all the independent variables except for engineering program belonging were statistically significant and the four independent variables together accounted for 50.6% of the variation in major intention. Engineering identification had the highest effect on major intention, controlling for three engineering-related motivational factors.

Table 4.21

Path Coefficients, Standard Errors, and R^2 – Pilot Group

	Major Intention	Engineering Identification	Engineering Program Utility	Engineering Program Belonging	Engineering Program Expectancy	R^2
Major Intention	-	.479* (.073) 6.522	.128* (.039) 3.228	.101 (.073) 1.386	.474* (.075) 6.305	.506
Career Intention	.585* (.070) 8.347	.416* (.075) 5.627	.033 (.035) .948	-	-	.756

Engineering program belonging was not statistically significant in explaining variations in major intention when the effects of the other three variables were statistically controlled. Career intention was significantly predicted by major intention and engineering identification, while the coefficient of engineering program utility was not significant. These three explanatory variables accounted for 75.6% of the variance for career intention. Major intention had the highest influence on career intention followed by engineering identification. Controlling for major intention and engineering identification, engineering program utility did not predict career intention significantly.

Comparison of the Structural Paths between the Two Groups

Research question four compares individual structural paths between the two groups. The similarities and differences in the effects of MUSIC constructs (exogenous latent constructs) on the engineering-related motivational factors (first set of endogenous constructs), which are elements of the gamma matrix are presented first followed by the effects of engineering related motivational factors on the intention variables (major and career intentions) which are elements of beta matrix.

Path Coefficients from MUSIC Constructs to Engineering Identification and Engineering-Related Motivational Factors

Engineering identification. The association between success and engineering identification was stronger for the pilot group with a coefficient of .351 and a coefficient of .261 for the traditional group. The relationship between interest and engineering identification was stronger for the traditional group with a coefficient of .128 and the strength of the same relationship for the pilot group was .005, which was not found to be statistically significant. Similarly, the relationship between caring and engineering identification was greater for the traditional group with a coefficient of .161 while the same coefficient was -.029 for the pilot group, which was not found to be statistically significant. Overall, patterns of relationships were similar in the two groups.

Engineering program utility. Empowerment significantly predicted engineering identification for both of the groups. The coefficients were negative in both cases and were greater for the pilot group (-.377) compared to the traditional group (-.185). Success significantly predicted engineering program utility in both of the groups, but the coefficient was greater for the traditional group (.369) compared to the pilot group (.276). The association between caring and engineering program utility was greater for the traditional group with a coefficient of .285 compared to .174 for the pilot group. Overall, the relationships among these constructs were similar in the two groups

Engineering program belonging. Of the five MUSIC elements, success, interest, and caring were retained in the final model to predict engineering program belonging. The influence of the three independent variables were greater in the traditional group as compared to the pilot group. Specifically, the coefficient of success was .114 for the traditional group, while the same coefficient was .018 for the pilot group. Similarly, coefficient of interest was .213 for the traditional group and .158 for the pilot group. Finally, the coefficients of caring was .449 for the traditional group and .414 for the pilot group. Overall, patterns of relationships were similar in the two groups.

Engineering program expectancy. Empowerment and success were the only two MUSIC elements retained in the final model to predict engineering program expectancy. There was an inverse relationship between empowerment and engineering program expectancy for both the groups. The coefficient of empowerment was greater for the pilot group (-.283) compared to the traditional group (-.127). The coefficient of success was .728 for the traditional group and .566 for the pilot group. Overall, the relationships among these constructs were similar in the two groups.

Path Coefficients from Engineering Identification and Three Engineering-Related Motivational Factors to Major and Career Intentions

Major intention. The path coefficients of engineering identification and three engineering-related motivational factors were significant as hypothesized for major intention, but the coefficient of engineering program belonging was negative for the traditional group and the same coefficient was not significant for the pilot group. Comparing coefficients between the two groups, the association between engineering identification and major intention was .529 for the traditional group and .479 for the pilot group. Similarly, the coefficient of engineering program utility was greater for the traditional group (.187) than for the pilot group (.128). The coefficient of engineering program belonging was -.119 for the traditional group and .101 for the pilot group. The influence of engineering program expectancy on major intention was greater for the pilot group with a coefficient of .474 compared to .315 for the traditional group. These differences are small and overall pattern of relationships in the two groups is similar.

Career intention. Engineering program belonging and engineering program expectancy were not retained in the final model to predict career intention. The strength of the relationships between major intention and career intention were similar for the two groups with a coefficient of .579 for the traditional group and .585 for the pilot group. Similarly, the strength of the relationships between engineering identification and career intention were similar for the two groups with a coefficient of .413 for the traditional group and .416 for the pilot group. The coefficient of engineering program utility was .079 for the traditional group and was statistically significant, while the same coefficient was .033 for the pilot group but was not statistically significant.

Summary

This chapter presented descriptive statistics and correlations among the 11 latent variables for the traditional and pilot groups. The analyses of the group differences on the motivational variables and intention variables were presented. No significant differences were found between the two groups on any of the variables both at the beginning and at the end of the semester. Further, discussions of normality of data was included and the univariate statistics showed that the normality assumption was not severely violated. The exploratory factor analyses (EFA) of the estimation sample resulted in deletion of the three negatively worded items from engineering program belonging. The revised factor model was then validated with the validation sample. Based on the results of the factor loadings from the EFA and modification indices, the decision to covary usefulness items one and two was made. The measurement model provided a good fit to the data. This model was then cross-validated with the pilot data and the cross-validation was successful as indicated by the three major fit indices. Next, the structural model was tested with the traditional data. A series of model modifications were made deleting each insignificant path with the lowest z value, one at a time, to obtain a parsimonious model. The final model arrived at was then validated with the pilot data. Some of the path coefficients were not significant in the pilot data, but overall, the final model provided a good fit to the pilot data. Finally, structural paths between the two groups were compared.

Chapter Five: Discussion and Conclusion

Introduction

This final chapter presents a brief overview of the results of the study, specifically its focuses on the group differences explored and the structural model that was tested. Further, discussions and conclusions of the results, implications and limitations of this study, and directions for future research are included in this chapter.

Summary of the Findings

Research Question 1

First year engineering students were assessed on their perceptions of motivation related constructs at the beginning of the semester and at the end of the semester. Differential instructional techniques were used on two groups of students, specifically traditional engineering design (TED) was used on the traditional group and an active learning approach was used on the pilot group. The purpose of the end of the semester survey was to examine the influence of an active learning approach on students' motivation. Results of all the independent sample *t*-tests were statistically insignificant indicating that this study failed to detect effects of an active learning approach on students' motivation. Some studies that showed effectiveness of an active learning approach are presented in the discussion section. Further, a lack of differences between the two groups found in this study and probable causes of these inconsistent findings are discussed in the discussion section.

Structural Model

The domain identification model was tested to predict engineering students' major intention and career intention. The initially hypothesized structural model was presented in Figure 1. There were five exogenous variables and two sets of endogenous constructs. The five MUSIC elements were the exogenous variables. Engineering identification and the three engineering-related motivational factors (engineering program utility, engineering program belonging, and engineering program expectancy) were the first set of endogenous variables. Each of the five exogenous construct was hypothesized to predict each of the first set of endogenous construct. The examination of associations between these two sets of variables formed the second research question of this study.

Major intention and career intention formed the second set of endogenous variables. Each of the first set of endogenous constructs was hypothesized to predict each of the second set of endogenous constructs. The third research question of this study was guided by the examination of association between the two sets of endogenous construct. The initial model was of substantially saturated model. A series of model modifications were made by deleting insignificant paths one at a time to arrive at a parsimonious model using the traditional data. The fit indices (SRMR=.075; RMSEA=.062; and CFI=.971) of the final model with all the significant paths indicated that the proposed revised model provided a good fit to the observed data. The final structural model for the traditional group with standardized path coefficients is presented in Figure 4.1. This revised model was then cross-validated with the pilot data and the fit indices (SRMR=.097; RMSEA=.075; and CFI=.952) suggested that the model was successfully validated on an independent sample. The final structural model for the pilot group with standardized path coefficients are presented in Figure 4.2.

Research Question 2

The second research question addressed the relationship of the dimensions of MUSIC model to engineering related constructs. Of the five MUSIC elements, usefulness was deleted from every structural equation to predict engineering-related constructs because controlling for the other four elements, usefulness did not significantly predict any of the dependent variables. Engineering identification was significantly predicted by success, interest, and caring. Success had the highest impact on engineering identification for both the groups. The variation in engineering identification that the three independent variables accounted for was 27% for the traditional group and 20.2% for the pilot group. The three variables that predicted engineering program utility were empowerment, success, and caring. The coefficients of empowerment was negative for both the traditional and pilot groups. Success had the highest positive effect on engineering program utility for both the groups. Overall, the three variables accounted for 13.2% of variance in engineering program utility for the traditional group and 5% of the variance for the pilot group. Success, interest, and caring were found to have significant relationships with engineering program belonging. Of those three variables, caring had the strongest association with engineering program belonging for both the groups. The amount of variance the three variables explained in engineering program belonging for the traditional and pilot groups were 53.4% and 37.2%, respectively. Finally, empowerment and success were the only two MUSIC elements that had significant effects on engineering program expectancy. The coefficients of empowerment was negative for both the groups. The coefficients of success for the traditional and pilot groups were large at .728 and .566, respectively. Empowerment and success explained 49.2% of variation in engineering program expectancy for the traditional group and 36.6% for the pilot group.

Research Questions 3

The research question three examined the relationship of engineering-related constructs to students' intentions to major in engineering and to enter an engineering career. The engineering identification and three engineering-related constructs predicted major intention significantly. The coefficient of engineering program belonging was negative for the traditional group and it was in an unexpected direction. The same coefficient was not significant in the pilot group. Of the four variables, engineering identification had the highest impact on major intention for both the groups. The engineering identification, engineering program utility, engineering program belonging, and engineering program expectancy accounted for 44.5% of variation in major intention for the traditional group and 50.6% of the variation for the pilot group. Career intention was significantly predicted by major intention, engineering identification, and engineering program utility. Major intention had the strongest association with career intention followed by engineering identification for both the groups. The amount of variance that major intention, engineering identification, and engineering program utility accounted for in career intention for the traditional and pilot groups were 63.5% and 75.6%, respectively. Overall, engineering identification had the highest influence on major intention and career intention compared to the three engineering-related motivational factors. It was found that engineering program belonging and engineering program expectancy did not have significant association with career intention.

Discussion of the Findings

Group Mean Differences

The first research question pertains to the mean differences between students in the traditional and and pilot groups on students' motivation-related beliefs, engineering identification and three engineering-related motivatioal factors, and the two intention variables (major intention and career intention). The difference between the two groups was in the instructional techniques that were used. The instructional techique used for the traditional group was that of traditional engineering design (TED), while the instructional technique used for the pilot group had more features of an active learning approach. For example, lecture and workshop sessions for the pilot group drew on research regarding student motivation (the MUSIC Model), meta-cognition, problem-solving, and problem-based learning. Students in both the groups had opportunities to interact between each other and their instructors. However, students in the pilot group had a greater amount of group work, which resulted in more interactions. Students in the traditional group spent one workshop session on a team activity, while students in the pilot group engaged in team work during several workshop sessions. The results of this study did not support the hypothesis that the pilot group would have higher mean scores on those measures because all the independent samples *t*-tests showed that there were no significant differences between the two groups as demonstrated in Table 4.8.

Students were not randomly assigned to the two groups. In the absence of random assignment, it is difficult to determine that the two groups are equivalent in terms of the variables being investigated. However, with a pretest we can guage whether or not the two groups are similar on the measures collected before administring the intervention to the treatment group (Leedy & Ormrod, 2013). This in turn gives researchers more confidence about any conclusions they would draw from post-treatment results (Pedhazur & Schmelkin, 1991).

Students completed a survey to indicate two intention variables (major and career intentions), engineering identification and three engineering-related motivational factors at the beginning of the semester, which can be described as a pretest. The results of the six inependent sample *t*-tests showed that there were no significant differences in the mean scores between the two groups on those six variables, except in the case of engineering program utility, as demonstrated in Table 4.7. This indicates that the two groups were equivalent, especially on those measures collected at the beginning of the semester, except engineering program utility. Therefore, the lack of differences at the end of semester confirms that this study failed to detect effectiveness of an active learning approach at a statistically significant level.

The result of this study was inconsistent with the findings of other studies. For example, according to Matusovich et al. (2012), students reported higher perceptions of usefulness when the student centered instructional techqnique (PBL) was used compared to students who were taught the class using a traditional engineering design (TED) technique. Usefulness is one of the elements of the MUSIC model of academic motivation. In a similar study, Matusovich et al., (2011) investigated the impact of the two instructional techniques on students' motivation and the results showed that students felt more empowered, yet another MUSIC element, when PBL was used as compared to when TED was used. Jones et al. (2013) found that the use of PBL increased students' motivation and other elements of the MUSIC Model.

Although some earlier studies have shown that when students are in a more active learning environment, they are likely to be motivated and are likely to identify with the content domain. This study, however, did not find any differences in the two groups in any of the variables of interest. Three probable causes of these inconsistent findings were identified: (1) intensity of treatment, (2) timing of treatment, and (3) length of treatment. The first reason could be the lack of intensity or stregnth of treatment. The instructional technique used for the pilot group had features of an active learning approach, but was not a full-fledged active learning approach and probably not sufficiently different from the other group. Under such circumstances, it may be difficult to detect if the treatment yielded discernable effects or statistically significant benefits. The second reason relates to the timing of treatment. The data for this study were collected from first year engineering students during their first semester. Therefore, it is possible that students were highly motivated when they first began their undergraduate degree in engineering and their initial motivation level were the same when they completed the survey. The inclusion of senior students in such studies may give a clearer picture of the effectiveness of an active learning approach. The third reason could be the length of treatment. It is possible that a period of one semester may not be sufficient for students to form a strong identity and commitment to engineerng. Additionally, a period of one semester may not be sufficient for them to determine whether or not their experiences in engineering are consistent with their initial expectations. The real impact of an active learning approach to emerge may require more than one semester and perhaps a greater intensity of treatment (full-fledged active learning approach).

It is to be noted, however, that the lack of differences between the two groups can be seen as a positive result in the sense that there was no significant decline in the motivational level of students in the pilot group. The pilot program was implemented for the first time. The program was not fully developed then. In other words, the program was still evolving and there was a lot of fluidity. Introduction of any such new programs have the potential to create uncertainty and dissonance in students. Further, it will not be long before students in the two groups exchange information about the way their classes were taught further worsening dissonance in students. Therefore, it can be argued that this result can be seen as a positive outcome because the new program that was implemented for the first time and was still evolving did not led to the decline of motivation of students in the pilot group.

Effects of MUSIC Constructs on Engineering-Related Motivational Constructs

Traditional group. The final proposed model provided a good fit to the observed data as reflected by its fit indices presented in Table 4.16 and 4.17. The variance explained by different combinations of the five MUSIC elements ranged between 13.2% and 53.4% and these are quite substantial. Of the five MUSIC elements, success had significant association with all engineering-related constructs. Similarly, caring was found to have strong associations with all of the dependent variables except engineering program expectancy. Interest significantly predicted engineering identification and engineering program belonging. Overall, success and caring were the best predictors of engineering identification and engineering-related motivational factors. That means, when students feel that they have high probability of success in the coursework and feel cared for in the class, they are likely to have strong identification with engineering fields, perceptions of strong sense of belonging with the engineering fields, and a high sense of commitment to engineering fields.

Some of the path coefficients were not in the expected direction. Specifically, the coefficients of empowerment for engineering program utility and engineering program expectancy were negative. Theoretically, these negative relationshps were hard to explain. That students who have high perceptions of empowerment would have low engineering program expectancy does not make a lot of sense. The same goes for the relationship between empowerment and engineering program utility. Some of the possible statistical and theoretical reasons for these unexpected relationships are presented after the discussion of the associations between MUSIC elements and engineering-related constructs for the pilot group.

Pilot group. The pilot group was used to validate the model that was provisionally accepted as having a good fit to the data. The path coefficients of the pilot group were presented in Table 4.19.

The fit indices, as presented in Table 4.17, suggest that the proposed revised model explained relations in the pilot data reasonably well. However, not all of the path coefficents were significant. Success was the only significant predictor of engineering identificaiton. Controlling for success, interest and caring did not significantly predict engineering identification. Empowerment, success, and caring were hypothesized to predict engineering program utility, but caring was not found to have significant association with engineering program utility. Success did not significantly predict engineering program belonging, but caring and interest did. Success was the only MUSIC element with positive effect on engineering program expectancy. One of the reasons why all of the path coefficients were not significant could be due to the smaller sample size in the case of the pilot group.

Discussion of findings is presented first followed by inverse and unexpected relationships found in this study. Students' perceptions of success could be influenced by their preparation for college during their time in high school. Instructors can also play a role in developing students' motivational beliefs, such as success, interest, and caring through design of the course and support systems. The perception of success fostered in students can have many benefits, including finding the activity they engage in enjoyable and commiting to challenging goals (Schunk & Pajares, 2005). Similarly, instructors can design courses in a way that would get students interested in course materials. Interest has been established to have positive association with, for example, goal setting, learning strategies, and achievement (e.g., Hidi & Renninger, 2006). Caring is an important motivational variable that was found to have positive effect on, for example, self-efficacy, persistence, and performance (e.g., Freeman, Anderman, & Jenson, 2007; Walker & Greene, 2009). The fact that caring had the highest effect on engineering program belonging is consistent with the current literature, as Furrer and Skinner (2003) and Ryan and Patrick (2001) noted that teachers can promote belongingness through building caring relationship with their students. The concept of caring is similar to constructs, such as relatedness, affiliation, and belongingness (e.g., Baumeister & Leary, 1995; Ryan & Deci, 2000).

What are some of the possible statistical and theoretical reasons for the inverse and unexpected relationships found in this study for both the groups. The possible statistical reasons are presented first. There appears to be four possible statistical reasons for the inverse relationship between empowerment and engineering program utility. First, a close examination of inter-item correlations of empowerment and engineering program utility revealed that all of the correlations were weak and most of them were negative. Some of the sample items of empowerment are "I had the freedom to complete the coursework my own way" and "I had control over how I learned the course content.” Some of the sample items of engineering program utility include “Knowing about engineering does not benefit me at all” and “I have little to gain by learning how to do engineering.” Second, correlation between the mean scores of the two variables was .09, as presented in Table 4.6. Third, all the items of engineering program utility were negatively worded. This appears to be problematic because negatively worded items are not considered the exact opposite of postively or directly worded items (Barnette, 2000). Schriesheim and Hill (1981) noted that negatively worded items impair response accuracy. Many authors have (e.g., Barnette, 2000; Schriesheim & Hill, 1981) suggested against using negatively worded items. Robinson, Shaver, and Wrightsman (1991) suggested the use of bidirectional response options. Such an option would have some response options, for example, going from strongly agree to strongly disagree, while some other going from strongly disagree to strongly agree. Fourth, empowerment, which was hypothesized to predict engineering program utility highly correlated with other exogenous variables. Negative coefficients, when unexpected, could be results of multicollinearity or high correlations among the independent variables (Keith, 2006; Meyers, Gamst, & Guarino, 2006; Pedhazur & Schmelkin, 1991).

The negative association between empowerment and engineering program expectancy may be due to high correlations among the independent variables. Some of the sample items of engineering program expectancy are “I think that I will do well in my engineering-related courses this year” and “I am good at math, science, and engineering.” Keith (2006) noted that one of the reasons signs of coefficients change is due to the kind of variables included in the model. Empowerment and success were the two MUSIC elements used to predict engineering program expectancy in the final model. The coefficient of success for engineering program expectancy was .728 for the traditional group and .566 for the pilot group. High coefficients of success for engineering program expectancy, in addition to an issue of multicollinearity, could have played some role in making the coefficents of empowerment for engineering program expectancy negative.

Theoretically, it is hard to explain the inverse relationship between empowerment and engineering program utility. Empowerment is defined as students' perceptions of the amount of control they have over their learning. An example of an empowerment item is "I had options in how to achieve the goals of the course." Jones et al. (2010) defined engineering program utility as "the usefulness of engineering in terms of reaching one's short- and long-term goals" (p. 320). An example of an engineering utility item is "After graduation, an understanding of engineering will be useless to me." Greater autonomy in learning means less structure and a lack of clear guidance in completing coursework. It is, however, possible that students did not have much experience with a greater amount of autonomy during their high school years. Their learning perhaps occurred in a more structured manner with clear guidelines, expectation, and deadlines. Therefore, a plausible theoretical explanation for the inverse relationship between the two variable is that students fail to see the usefulness of engineering to them when students are left to their own device for the most part.

The inverse relationship between empowerment and engineering program expectancy was similarly intriguing. As noted earlier, the data for this study was collected from first-year engineering students during their first semester at a research intensive university. Theoretically, it is possible that many of those students may not have a lot of experiences with a greater level of autonomy over their learning during their high school years. Therefore, a higher level of empowerment leads to a lower level of expectancy belief for them because they probably need a lot of structure in their learning, for example, clear instructions, expectations, and deadlines.

Validating this model with senior students would bring more evidence and clarity to the nature of association between empowerment and engineering program utility, and empowerment and engineering program expectancy in the engineering context, or lack thereof.

Another unexpected result was the insignificant association between usefulness and all of the engineering-related constructs. Statistically, this may have been caused by multicollinearity among the five MUSIC elements. Specifically, the correlation between usefulness and interest was over .8 for both the groups and the correlation between usefulness and empowerment was over .7 for both the groups. Conceptually, the lack of influence of usefulness on any of the engineering-related constructs could be due to the fact that course students were enrolled in was an introductory engineering course. As appendices B through D show, this course covered topics to enhance soft skills, such as team skills, presentation skills, and problem solving skills, in addition to some technical skills. Therefore, it was possible that controlling for other MUSIC constructs, the degree of usefulness reported was not related to perceptions of engineering-related constructs. Tables 4.4 and 4.6 showed that students' reported sense of usefulness did not correlate highly with engineering-related constructs.

Effects of Engineering Identification and Three Engineering-Related Constructs on Major and Career Intentions

Traditional group. The engineering identification, engineering program utility, engineering program beleonging and engineering program expectancy significantly predicted major intention. The coefficient of engineering program belonging for major intention was negative and this was not in the expected direction. The correlation between mean scores of the two variables was .35. The inter-item correlations of the two variables ranged between .14 and .34. The probable causes of inverse relationship between engineering program belonging and major intentions, including measurement and statistical reasons, and theoretical reasons are discussed after the presentation of the relationships between engineering-related construcs and intention variables for the pilot group. Controlling for the other three independent variables, engineering identification had the highest impact on major intention. Engineering program utility and engineering program expectancy also significantly predicted major intention. This result shows that supporting students' engineering identification, engineering program utility, and engineering program expectancy would increase their probability of pursuing engineering majors.

Controlling for engineering identification and engineering program utlity, major intention had the highest influence on career intention followed by engineering identification. The results show that students who strongly intend to pursue engineering majors, who strongly identify with the engineering fields, and who see utility of engineering majors for their short-and long-term goals are more likely to pursue engineering careers. The hypothesized relationships between egnineering program belonging and career intention, and engineering program belonging and engineering program expectancy were not supported. The possible reasons why those hypotheses were not supported are discussed after the presentation of the relationship between engineering-related constructs and the intention variables for the pilot group.

Pilot group. The effects of engineering-related constructs on major intention for the pilot group is quite similar to that of the traditional group, except for engineering program belonging. The examination of the effects of engineering identification and the three engineering-related motivational factors on major and career intentions revealed that the effect of engineering program belonging on major intenion was not signficant. This insignificant path coefficient appears to have been due to a small sample size in the pilot group (*N*=242). When the final structural model was reestimated with the sample size increased to 539 to match that of the traditional group's sample size, engineering program belonging significantly predicted major intention. In other words, if the sample size for the pilot group was closer to the traditional group, the results in the two groups would be more similar.

Similarly, the effects of engineering-related constructs on career intention is quite similar to that of the traditional group. It is to be noted that the coefficients of engineering program utility for career intention for the two groups were not significantly different from each other. However, the same coefficient in the traditional group was statistically significant, while it was not for the pilot group.

Overall, the effect of engineering program belonging on major intention was negative in the traditional group and insignificant in the pilot group. The unexpected relationship between engineering program belonging and major intention is discused first. Next, a lack of relationship between engineering program belonging and career intention, and engineering program expectancy and career intention are presented.

A lack of sense of belonging has been associated with students' intentions to switch to other majors (Marra, Rodgers, Shen, & Bogue, 2012; Wao, Lee, & Borman, 2010). By that logic, higher perceptions of sense of belonging should lead to students' persistence in their majors. However, favorable perceptions of sense of belonging led to decreased major intention for the traidtional group and the same sense of perception did not affect statistically significantly change in the pilot group. What could be the possible reasons for these inconsistent findings? The reasons could possibly be attributed to measurement and statistical issues, and perhaps some theoretical reasons.

Possible measurement and statistical issues are discussed first. For example, engineering program belonging originally had eight indicator variables. Three of them were negatively worded and five of them were positively or directly worded. The EFA suggested two distinct factors because all of the positively worded items loaded together and negatively worded items loaded together. Therefore, the three negatively worded items of engineering program belonging were deleted from the revised factor model. Negatively worded items, when used alone or in conjunction with positively worded items, affect internal consistency, factor structures, and other statistics (Barnette, 2000). When negative and positive items are mixed, it provides lower internal consistency (Schriesheim & Hill, 1981). Further, positively and negatively worded items used to measure a single factor load differently with positively worded items loading together and negatively worded items loading together (Knight, Chisholm, Marsh, & Godfrey, 1988; Pilotte & Gable, 1990). This is consistent with what happened to the factor loadings of engineering program belonging measured with mixed items and researchers' claims that negatively worded items are not the exact opposite of directly worded items. Therefore, the current measures of engineering program belonging may require revision, including avoidance of negatively worded items.

In addition to measurement and statistical issues that may be attributable to the inverse relationship between the two variables, there are a few plausible theoretical reasons. First, it is possible that parents of many of those students who participated in this study had made the decisions for them to be in engineering programs. Therefore, students may not be fully decided on completing majors in engineering during their first semester. Under such circumstances, students may not have strong senese of belonging, but if they did, it could very well be artificial. Second, the greatest percentage of attrition from engineering programs occur during the second year of students' undergraduate program. What this could mean is that there exist a large number of students who were inclined to pursue non-engineering majors but were in this introductory engineering class to explore the possibility of earning degrees in engineering. Those students may not be fully committed to pursuing engineering degrees and may be inclined to pursue non-engineering majors. Not all of the students who leave engineering programs are ill-equipped to be successful in engineering.

Controlling for major intention, engineering identification, and engineering program utility, engineering program belonging and engineering program expectancy did not predict career intention significantly. However, such findings are inconsistent with the current literature. For example, engineering program expectancy has been defined as “one’s belief in the possibility of his or her success in engineering” (Jones et. al., 2010, p. 320). The expectancy belief is related to self-efficacy theory (Bandura, 1986). Expectancy for success has been defined as the expectation one has over one’s performance on upcoming tasks in domains, such as mathematics and engineering (Wigfield & Eccles, 2000). Expectancy beliefs have been shown to affect students’ grades, persistence, and career intention (Lent, Brown, & Larkin, 1986; Wright, Jenkins-Guarnieri, Murdock, 2013). However, in this study, the impact of engineering program expectancy and engineering program belonging on career intention was not signficant while controlling for major intention and engineering identification. It is possible that many students earn undergraduate degrees in engineering with a goal to pursue graduate degrees, and ultimately, careers in fields like law, medical, and business. Therefore, this study shows a lack of relationships between engineering program belonging and career intention, and engineering program expectancy and career intention. In other words, this study shows that the value of the domain to students’ sense of self (engineering identification) is a better predictor of students’ career intentions than engineering program belongong and engineeirng program expectancy. Engineering identification was defined as valuing engineering as part of their identity. Some of the sample items of engineering identification are “Being good at engineering is an important part of who I am” and “It matters to me how well I do in engineering school.” However, it is also possible that the effects of engineering program belonging and engineering program expectancy on career intention was indirect through major intention.

Engineering identificaton consistently predicted major and career intentions better than engineering program utility, engineering program belonging, and engineering program expectancy. This is an interesting finding that deserves further investigation and replication. Yet another interesting finding of this study was the significant association between major intention and career intention. It may be common sense to hypothesize that an engineering degree is required for an individual to have an egnineering career. However, there does not appear to be any studies where such an association between major intention and career intention was statistically modeled and tested.

Contributions of the Study

Theoretical Contributions

Many cognitive and non-cognitive factors have been identified that are associated with students’ decisions to commit to engineering majors and careers. However, the problem of the demand-supply gap of STEM professionals has not been resolved. Despite tremendous success in the last six decades in understanding the complexities associated with students’ career decision-making processes, definitive insights are still lacking. This study contributed to better understanding of students’ complex decision-making processes. Therefore, the domain identification model can be a new lens to study students’ commitment to engineering majors and careers. This model adds to the current literature on career theory, such as social cognitive career theory (SCCT).

There does not appear to be clear research on how domain identification is developed and the ways in which it influences other variables. Another contribution of this tudy was the understanding of how domain identification is developed and and how it influences other variables. The domain identification model tested in this study has certain antecedents and consequences. The results show some of the causes and effects of domain identification. Of the five MUSIC elements, success and caring were significant predictors of engineering identification and engineering-related motivational factors. The results of this study suggest that students who felt that they could be successful in an introductory engineering course, who were interested in the course, and who felt cared for in the class will have higher engineering identification. This study brings empirical support for three important components of success, interest, and caring and confirms earlier findings.

The domain identification model tested in this study hypothesized that engineering identification and three engineering-related motivational factors predict major and career intentions. Controlling for engineering-related motivational factors, engineering identification had the highest impact on major intention. Similarly, the influence of engineering identification was greater than the three engineering-related motivational factors on career intention. Such findings show the importance of domain specific identification over other variables, such as engineering program expectancy in accounting for variance in major intention and career intention.

Engineering program expectancy is related to self-efficacy theory. Expectancy belief is related to one's perceived ability to be successful in a specific domain, such as engineering. Engineering program expectancy was found to have significant relationships with major intention, but its relationship with career intention was insignificant. This finding shows that high expectancy beliefs lead to students' pursuing engineering majors, but not necessarily to pursuing engineering career. It is, however, possible that the effect of engineering program expectancy on career intention is indirect through major intention.

Practical Contributions

The findings of this study have some implications for pedagogy. Students' sense of identification can be increased through teaching and suppporting their sense of success, interesting them in the content, and demonstrating care for their success in the course. Focusing on teachers support and caring would also lead to increased sense of perceptions of engineering-related constructs. Students' sense of success in engineering can be fostered in two ways: (1) how prepared they are, and (2) learning environment. Enhancing student perceptions of their ability to succeed in engineering would strengthen their commitment to engineering majors and careers.

Although instructors do not have control over how prepared students were to be successful in engineering programs in terms of their previous math and science achievements, they do have control over creating conducive learning environment and in designing courses in a way that that will boost students' sense of success. For example, providing clear guidelines for all assingments, breaking complex problems into more manageable units, providing timely feedback on their performance, and allowing students to redo their assignments are some of the things that can be done by the instructors to enhance students' sense of success.

Similarly, instructors can demonstrate in a number of ways that they care for how much their students learn and also care for their personal well-being. For example, showing concern for students' success or failure is an important step to help students feel cared for. Such a sense of caring could be instilled in students by following up with them if they are not doing well in the class or missing deadlines to submit assignments. Follow-up can be done through either email communications or one-on-one meetings. Such attention can help students feel cared for. Instructors can also show flexibility, for example, by extending deadlines when their students are faced with situations in their personal lives beyond their control. The instructor can also encourage other students in the class to send students in grief with sympathy and get well soon notes. Such gestures have the potential to help students feel cared for.

Limitations

There are several limitations in this study. First, it is a cross-sectional study. Cross-sectional data is not the most appropriate for causal inferences because it violates one of the assumptions of causality, which is a temporal sequence, among others. The cause and effect inferences can be drawn only tentatively. Furthermore, it can be used to understand plausible relationships between variables of interest and see if the data is consistent with the hypothesized causal model.

The second limitation is the exploratory nature of this study. The initial hypothesized model was highly saturated. The model modification process was based on post hoc revisions. Therefore, there is a need to replicate this study and validate this model on more diverse student populations. The cross-sectional nature of the data and the exploratory nature of this study make the relationships among the latent variables more tentative and less confirmatory.

Third, in this quantitative study, the data collected was self-reported by research participants. Self-reported data has numerous disadvantages, one of which is response bias. Reponse biases, such as acquiescence, deviant responding, and social desirability can compromise the validity of the scales (Paulhus, 1991).

Fourth, students were not randomly assigned to two groups. Randomization is a key component of any experimental study and for making strong causal statements. Therefore, the non-experimental design of this study restricts drawing cause and effect relationships between latent variables in the domain identficiation model.

Fifth, there is not a sufficient number of participants from minority groups; for instance, women and people of color. The model data fit could perhaps be different in a sample that consisted of a greater number of participants from minority and underrepresented groups. However, the size of the minority groups did not permit estimation of factorial and strutural models. The data for this study was collected from a comprehensive research university with a predominantly white student population. Therefore, this model may be generalizable only to students attending similar institutions. Therefore, this study should be replicated with more diverse student populations.

Sixth, some of the measures of the latent variables were not satisfactory, specifically engineering program utility and engineering program belonging. Engineering program utility was measured with six indicator variables but all of them were negatively worded items. Engineering program belonging was measured with eight indicator variables and three of them were negatively worded items. Negatively worded items, when used alone or in conjunction with positively worded items, affect internal consistency, factor structure, and other statistics (Barnette, 2000). Further, there were some issues of multicollinearity. Despite these limitations, the findings of this study made some significant contributions as discussed in the previous section.

Future Research

This study made some contributions to the current literature on students' decision-making processes to commit to engineering majors and engineering careers. At the same time, it raised some questions as well. For example, the model used in this study was tested on data collected from first year engineering students, specifically during their first semester at a research intensive university. Therefore, students may not have a lot to reflect on their engineering experiences. If they had, the relationships between variables could be different and stronger. This model should, therefore, be tested on senior students in a longitudinal study to confirm or examine the hypothesized association between the latent variables in the domain identification model. Longitudinal data will provide a strong evidence for causal inferences and growth and change in students' intentions to stay in engineering.

The domain identification model tested in this study should be replicated with more diverse samples. For example, factors that affect women's decisions may be different than men's. In addition, this study should be replicated with a similar study design and similar samples. Makel and Plucker (2014) noted "if education research is to be relied upon to develop sound policy and practice, then conducting replications on important findings is essential to moving towards a more reliable and trustworthy understanding of educational environments" (p. 313). Longitudinal and replication studies would bring more evidence and clarity to the findings of the study.

The instructional technique used for the pilot group had more features of an active learning approach, but that was not a full-fledged active learning approach. Therefore, it cannot be concluded that the active learning approach did not produce the intended results. This could very well be an issue of duration and length of treatment because of which we failed to detect effectiveness of an active learning approach. Therefore, increasing the intensity of the active learning approach and the duration of this treatment may bring more clarity to the impact of an active learning approach on students' academic motivation and commitment to engineering, or lack thereof.

Conclusion

This study explored mean differences between the traditional and pilot groups on five elements of the MUSIC Model of Academic Motivation, engineering identification and three engineering-related motivational factors, and two intention variables (major intention and career intention). The purpose of exploring the group mean difference was to investigate the impact of an active learning approach on students' academic motivation. This study failed to show the expected impact of an active learning approach. Next, this study examined the tenability of the domain identification model. The revised model provided a good fit to the data. This model adds to the current literature on understanding students' decision-making processes to commit to engineering majors and engineering careers. The findings of this study showed that success, interest, and caring are important for forming engineering identification, and that success and caring are important predictors of engineering program utility and engineering program expectancy. Furthermore, it showed that engineering identification is a strong predictor of major intention and career intention.

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Appendix A (151)

A comparison of FYE and Classic Fall 2013

Course Objectives (FYE)

At the conclusion of this course a student will be able to

- Compare and contrast the contributions of different types of engineers in the development of a product or process.
- Develop a plan of study for his/her undergraduate career
- Synthesize information from several sources in addressing an issue
- Communicate information effectively
- Solve problems using a variety of strategies
- Articulate holistic issues that impact engineering
- Model an engineering system
- Contribute to team efforts

Course Objectives (Classic)

Course Objectives: Having successfully completed this course, the student will be able to:

- Demonstrate a basic understanding of the engineering design process;
- Demonstrate basic facility with hands-on design and design evaluation, accomplished by working in teams;
- Demonstrate a knowledge of the disciplines of the Virginia Tech College of Engineering;
- Demonstrate an understanding of professional ethics and application to real-life situations;
- Apply the scientific method to problem solving including use of software where applicable;
- Graph numeric data and derive simple empirical functions;
- Develop and implement algorithms and demonstrate understanding of basic programming concepts;
- Demonstrate a basic awareness of contemporary global issues and emerging technologies, and their impact on engineering practice.

Appendix B (152-153)

Explicit Similarities and Differences Between the Two Classes

	Classic	FYE
Linear/Power/Exponential functions	Plotting by hand Finding and reporting equations	Plotting in Matlab Finding and reporting equations
Least Squares regression	By hand and in excel	In Matlab (but no coverage of theory)
Sketching	Multiview and Isometric (1 week) [redacted] text pp 253 – 309	No formal instruction
Ethics	In class discussion, Incident at Morales, [redacted] text pp 157-183	No formal instruction
Design	Sustainable Energy Project – Engineering Design Reading	Problem Solving Project – Problem solving instruction rather than Design Process instruction.
Teamwork	1 class – Forming, Storming, Norming, ….	Parts of several classes – Roles, dealing with conflict,
Programming	Flowcharting LABVIEW Loops Decisions (Case) Vectors Summing	Flowcharting MATLAB Loops Decisions Vectors Max and min
Sensors	Ultrasonic sensor (with Labview) B	Ultrasonic Sensor/Arduino/ Matlab Infrared sensor/Arduino/Matlab

General problems	Some trig/geometry/logic problems	Open ended ill structured problems – amount of trig/geometry etc needed varied with problem. Groups chose from 7 problems – 1. Assembly Plant 2. Bass Boost 3. Traffic control at PF and UCB. 4. Water Rocket Launch 5. Data Acq on Football helmet 6. Obstacle avoidance robot 7. Hanging the SEB engine

Appendix C (p. 154-155)

Course Outline – Fall 2013 – FYE (Pilot Group)

W	Dates	Workshop	Class
1	Aug 26-30	Product Archeology – Preparation (cell phone) /Course Introduction Investigate Global, Social, Environmental, and Economic factors around the design a cell phone (student choice of cell phone). What impacted design, what impact did phone have.	Information Sources - College librarian presented on using the library, finding and evaluating sources, citing sources.
2	Sept 2*–6	Product Archeology: Artificial Hip (Preparation phase) and Cell Phone (a simple text and talk phone) (Excavation Phase). Look into GSEE factors affecting form and manufacture.	Product Archeology: Follow up on Artifical Hip – investigating GSEE factors in class. Product Archeology = Engineering
3	Sept 9-13	Engineering Careers – Job Skills and competencies, Discuss similarities across all fields, discuss common skills. Common Book discussion - opportunities.	Guest Speaker – Career Services – what can career services do for students
4	Sept 16-20	Data Analysis and Representation Introduction to graphing – linear, exponential, and power. Graphing Basics, using data and graphing to estimate the value of parameter Matlab: Introduction to vectors, Graphing	Professional Engineering/ABET Data Acquisition/LEWAS LAB
September xx – October xx Departmental Information Sessions			
5	Sept 23-27	Acquiring data – design an experiment to determine constant g. Available measurement system can measure distance and time. Can use pendulum eqns or eqns of motion. Mathematical Models Matlab: Script files	Algorithm Development and programming Loops and Decisions – translation of problem to flowchart to code
6	Sept 30-Oct 4	Data Acquisition Arduinos and ultrasonic sensor Gravity Experiment – measure dist and time Analyzing data – parsing (using part of a vector)	Programming Max and Min Nested and stacked ifs .mat files
Test 1 October 3 (Thursday) 7pm			
7	Oct 7-11	Line Following Robot – Getting to know the robot Communicating with the Robot	Programming Logic, decisions, logical operators Robot Algorithm Testing
8	Oct 14-18	Robot Testing	Line Following Robot algorithm recap

			Review of Test 1
9	Oct 21-25	Problem Solving: Introduction	Teamwork Feedback Contracts
10	Oct 28-Nov 1	Problem Solving: Problem Definition Common Book	TeamRoles Teamwork Goals
11	Nov 4-8	Problem Solving: Representations	Pathways Planner
12	Nov 11-15	Problem Solving: Questioning – Claims/arguments Pathways Planner Exercise	No Lecture
Test 2 November 14 (Thursday) 7pm			
13	Nov 18-22	Problem Solving: Documentation – supporting/justifying Assertion Evidence Form	Technical Presentations Project Deliverables
Thanksgiving Break November 25-29			
14	Dec 2 -6	Problem Solving: Evaluation Presentation Expectations	Project Presentations Review of Test 2 /Exam notes
15	129-11	Presentations	No class
Final Exam December 13, 2013 (Friday) 7:00pm-9:00pm			

Appendix D (p. 156-157)

Course Outline - Classic Fall 2013 (Traditional Group)

Week	Dates	Lecture	Workshop
1	Aug 26-30	Course Introduction	Workshop introduction Problem solving (hands-on)
Friday, August 30, 2013 Last day to add classes			
2	Sept 2-6	Introduction to design Engineering as a profession	Teamwork Team building design activity (hands-on)
3	Sept 9-13	Problem solving Sketching	Sketching activity (hands-on)
Departmental Information Sessions (see course website for exact dates and times; you are required to attend four as part of the course)			
4	Sept 16-20	Graphing	Design Project introduction Graphing (hands-on)
5	Sept 23-27	Graphing Linear Regression	Design Project discussion Graphing/least squares linear regression activity (hands-on)
6	Sept 30 – Oct 4	Problem Solving Mechantronics	Mechatronics I (hands-on)
TEST 1 October 3 (Thursday) 7:00 PM			
Friday, October 4, 2013 Last day to drop classes without grade penalty			
7	Oct 7-11	Sustainability Flowcharting	Flowcharting (hands-on)
8	Oct 14-18	Problem Solving Ethics	No workshops this week
Friday, October 18, 2013 Fall Break			
9	Oct 21-25	LabVIEW programming	LabVIEW (hands-on) Ethics
Monday, October 21, 2013 Last day to resign without grade penalty			
Tuesday, October 22 – Tuesday, October 29, 2013 Course Request for Spring 2014			
10	Oct 28 – Nov 1	LabVIEW Programming	LabVIEW (hands-on)
11	Nov 4 – 8	Intro to LabVIEW DAQ LabVIEW programming	LabVIEW (hands-on) LabVIEW DAQ (hands-on)
12	Nov 11-15	LabVIEW Programming	LabVIEW programming
TEST 2 November 14 (Thursday) 7:00 PM			
13	Nov 18-22	LabVIEW programming	Design Project demonstration, Design Project: report, presentation slides, and peer evaluation are due 11:59 PM the day before your workshop
November 22, 2013 Deadline to request rescheduling of final exams that conflict or constitute a third exam within 24 hours			

<table>
<tr><td colspan="4">Saturday, November 30, 2013   Web Drop/Add begins for Spring Semester 2014</td></tr>
<tr><td colspan="4">November 23– December 1, 2013   Thanksgiving Break</td></tr>
<tr><td>14</td><td>Dec 2-6</td><td>Globalization of engineering
Practice & Study Abroad</td><td>Mechatronics II (hands-on)
Workshop Wrap up</td></tr>
<tr><td colspan="4">Friday, December 6, 2013   Last day to apply for Course Withdrawal</td></tr>
<tr><td>15</td><td>Dec 9-11</td><td>Course wrap up</td><td>No workshop</td></tr>
<tr><td colspan="4">Thursday, December 12, 2013   Reading Day (no classes)</td></tr>
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