SELF-EFFICACY, STUDENT ENGAGEMENT,

AND STUDENT LEARNING IN

INTRODUCTORY STATISTICS

by

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A dissertation submitted in partial fulfillment
of the requirements for the degree

of

Doctor of Education

in

Curriculum & Instruction

MONTANA STATE UNIVERSITY
Bozeman, Montana

April 2017

ACKNOWLEDGEMENTS

I would like to thank all who have aided in the process of completing this degree. First and foremost, I would like to thank my husband and family for supporting me in this endeavor.

Next, I would like to thank my advisor and mentor, Dr. Art Bangert. Completing this degree would not have been possible without your support, guidance, insight, and encouragement. You truly made it possible for me to persist on to graduation and I feel privileged to have spent time under your care and tutelage. I am forever grateful for all you have done in my behalf.

Additionally, I would like to thank Dr. Linda Elliot-Nelson, Light Bryant, Cindy Marchant, and Rita Brown. Dr. Linda Elliot-Nelson gave me great encouragement and help as I navigated the process of IRB approval, comprehensive exam, data analysis, and dissertation writing. Light Bryant supported me in working with the institution to accept my work as a doctoral student. Cindy Marchant was instrumental in helping me with my comprehensive exam. Rita Brown's cooperation was much appreciated in helping me get my research started.

Finally, I would like to thank my students for their work in my classrooms and for their participation in the study. This research was motivated to support their learning and success. Their willingness to share their experiences made this research possible; without their help and participation there would have been no data to study and learn from.

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ABSTRACT

Close to half of undergraduate students in the United States are served by community colleges. Minority, low income, and first-generation postsecondary education students utilize community colleges as a gateway to postsecondary education. Additionally, these institutions provide access to higher education for many nontraditional students, such as adults who work full time while enrolled. This study used partial least squares structural equation modeling (PLS SEM) to investigate and explore the relationship between community college student self-efficacy, engagement, and statistics conceptual understanding in the non-mathematical introductory statistics course and is based on Linninbrink & Pintrich's (2003) model for conceptual understanding. There is much research regarding statistics anxiety, statistics attitude, learning behavior, and statistics achievement where students at four year institutions or graduate students were studied, but few if any studies exist that investigate these same factors with community college students.

Data for this study was collected from $n=161$ student volunteers at three different time points during the semester using all or a subset of the following instruments: Current Statistics Self Efficacy (CSSE) (Finney & Schraw, 2003), Survey of Attitudes Toward Statistics (SATS) (Schau, Steven, Sauphinee, & Del Vecchio, 2995), Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich, Smith, Garcia, & McKeachie, 1993), and Comprehensive Assessment of Outcomes in Statistics (CAOS) (delMas, Garfield, Ooms, & Chance, 2007). Problems with missing data were resolved with multiple imputation methods to preserve power and sample size and prevent introducing bias into the analysis. Overall, the relationships of self-efficacy and engagement explained $R^2=7.6\%$ of the variance in conceptual understanding of statistics. This study found positive relationships between student conceptual understanding of statistics, self-efficacy to learn statistics and student engagement. Behavioral and cognitive engagement did not appear to mediate the influence of self-efficacy but motivational engagement was found to mediate this effect. Additionally, it was found that self-efficacy to learn statistics had a medium effect on statistical understanding at course end. Suggestions for future research are given.

CHAPTER ONE: INTRODUCTION

Background

Statistics plays an important part in our modern world. The accumulation of data, the ability to make sense of data, and the process of making sound decisions based on data are concepts that need to be understood by individuals who live and work in the 21st century. In her book, *Statistical Literacy at School: Growth and Goals*, Watson (2006) posited that all citizens need to be able to provide good evidence-based arguments as well as critically evaluate data-based claims, and therefore, all students should learn these skills as part of their education. Today's students who enroll in institutions of higher education find that many disciplines require one or more statistics courses (Kesici, Baloğlu, & Deniz, 2011).

Over the last century, the statistics student has evolved. In the early 1900s, statistics coursework focused on practicing scientists. Over the next several decades the course changed its focus to prospective scientists who were still completing their degrees. The field of statistics continued to grow through the end of the 20th century into the beginning of the 21st century, changing from being a course taught to a narrow group of future scientists in agriculture and biology to being a collection of courses that are taught to students with very diverse interests and goals from pre-high school to post-baccalaureate (Aliaga, Cobb, Cuff, Garfield, Gould, Lock, Moore, Rossman, Stephenson, Utts, Velleman, & Witmer, 2005). The inclusion of such a wide audience of students has brought with it a wide range of difficulties that researchers, instructors, and institutions have had to address. Among these difficulties are those that influence both cognitive and affective learning outcomes.

Despite the importance statistics plays in our modern world, many adults view statistics in negative light and remember it as their worst course taken in college. Indeed, statistics has a reputation among students as being challenging, irrelevant, dull, and an unwelcome compulsory invasion into their chosen field of study (Ben-Zvi & Garfield, 2008; Croucher, 2006). Harpe, Phipps, & Alowayesh (2012) point out:

> As many students will readily attest, there is a certain amount of stress and anxiety associated with learning statistics-related topics, which may result in students developing negative attitudes toward statistics. These negative attitudes can act as a barrier to learning statistical concepts. Although the evaluation of teaching methods may traditionally focus on learning (or cognitive) outcomes, the study of affective outcomes, such as attitudes, can provide information that is useful in the improvement of teaching processes. (p. 248)

Belief about one's abilities helps manage stress and negative views towards statistics. Self-efficacy, as defined by Bandura (1997), consists of the self-beliefs that students hold about their ability to complete specific tasks or actions successfully. Bandura further states that

> Self-efficacy theory acknowledges the diversity of human capabilities. Thus it treats the efficacy belief system not as an omnibus trait but as a differentiated set of self-beliefs linked to distinct realms of functioning. Moreover, efficacy beliefs are differentiated across major systems of expression within activity domains . . . Efficacy beliefs are concerned not only with the exercise of control over action but also with the self-regulation of thought processes, motivation, and affective and psychological states. (Bandura, 1997, p.l36)

Schunk (2012) defines self-efficacy as perceived capabilities of learning or performing behaviors at designated levels. Self-efficacy is not the same as knowing what to do (Schunk, 2012, p.160). By understanding statistics self-efficacy among community college students in a non-mathematical introductory statistics course, faculty should be able to address the learning needs of students who may be identified as lacking specific levels of self-efficacy.

Onwuegbuzie (2003) states that an important manifestation of student's levels of self-efficacy is found in their expectations of their performance (p. 1023). Onwuegbuzie summarizes Bandura's theory as follows.

> Simply put, self-efficacy theory predicts that an individual's belief system influences behavior choices, effort invested, persistence, and task success. According to this conceptualization, people tend to engage in activities that they believe they can undertake, control their efforts, persevere until this level of performance is accomplished, and then evaluate their performance according to previous expectations (Onwuegbuzie, 2003, p. 1022-1023).

Self-efficacy has been found to serve as a good predictor of course performance, effort, persistence, perseverance, and future enrollment in courses within a domain (Hackett & Betz, 1989; Pajares, 1996; Pajares & Miller, 1995; Zeldin & Pajares, 2000). Pajares (1996) further explains that self-efficacy is task-specific which means that general measures of self-efficacy should be avoided since they decontextualize self-efficacy judgments. Finney & Schraw (2003) responded to self-efficacy research by creating and validating two research instruments that measure levels of students' statistics self-efficacy, namely, the Current Statistics Self-Efficacy (CSSE) and Self-Efficacy to Learn

Statistics (SELS). These two research instruments are task specific within the domain of statistics.

The choices students make in their selection of learning strategies used during their study influences the extent to which students are effective as they cognitively process course content. According to Onwuegbuzie (2000), it is important that students find appropriate learning strategies for statistics in order to reduce anxiety and increase statistics achievement. As such, to increase understanding and decrease negative affective characteristics, certain learning strategies may be employed such as rehearsal, elaboration, organization, critical thinking, metacognitive self-regulation, manipulation of time and study environment, effort regulation, peer learning, and help seeking (Bandalos, Finney, & Geske, 2003; Pintrich, Smith, Garcia, & McKeachie, 1993). According to Pintrich (2000), students who display more self-regulatory strategies demonstrate better learning and higher motivation for learning.

Students of all levels are making choices with regards to self-efficacy and self-regulatory strategies to process their learning experiences. Adult students are faced with a wide range of challenges as they pursue their education. Recent enrollment trends are suggesting that students who pursue higher education are viewing community colleges as a viable path toward obtaining a bachelor's degree (Melguizo, Kienzl, & Alfonso, 2011). Over the last 30 years, the percentage of first-time college students seeking a bachelor's degree has increased steadily from 50% - 63% (Adelman, 2005; Bailey & Alfonso, 2005). During this same period of time, more students started their higher education at a community college and now about half of students in postsecondary education start at a community college (U.S. Department of Education, 2004). Community college advocates are saying that the population of students at four-year colleges and the population of students at community colleges are simply different and the two groups should not be compared directly (Adelman, 2005; Hagedorn, 2009).

Community colleges have also become a source for students to obtain necessary training and certification to qualify for a job. According to the Bureau of Labor Statistics (2013), 70% of all job openings by 2022 will require some type of skilled training or certification. Certification and training that once was provided at the high school level has moved to the community college level because the increasing sophistication of technology requirements are beyond what high schools are prepared to offer (Porchea, Allen, Robbins, & Phelps, 2010). There is a clear financial incentive to seek training or certification from community colleges; in 2015, the median earnings for individuals with an associate's degree is $6400 higher than individuals with only a high school diploma (Bureau of Labor Statistics, 2015). Unfortunately, attrition before degree attainment is more pronounced at the community college level than for four-year institutions. One study found that 45% of students enrolled in a two-year public institution had dropped out three years later and only 16% had completed a degree (Berkner & Choy, 2008). Among two-year institutions, the average first-to-second-year retention rate is 54%; among four-year institutions, the average retention rate is 73% (ACT, 2008).

Improving instruction should be the key goal of any educational research and research into issues that concern statistics education should maintain focus on this goal (Zieffler, Garfield, Alt, Dupuis, Holleque, & Chang, 2008). Broadening our understandings of the learning and teaching of statistics especially at the community college level will ultimately lead to improvements in how instructors are educating students in this field. Zieffler et al. (2008) emphasize the importance of efforts to make the study of statistics a positive one for students. Additionally, teachers need to remain aware that community college students in particular come to statistics courses with a great variation in expectations and perceptions of what statistics is about. Onwuegbuzie (2003) argues that “interventions designed at reducing students’ levels of statistics anxiety, as well as improving their self-perception of their ability to learn statistics may have a direct positive effect on statistics performance. Thus, experimental studies are needed that assess the impact of such strategies on statistics achievement” (p. 1034). Pintrich suggested further research on contextual influences on self-regulation in different content areas (Schunk, 2005). Principles of self-regulation are assumed to generalize across contexts, but self-regulatory processes may vary depending on the content area. Further understanding of these self-regulatory processes may help community college students learn how to modify processes to fit the statistical content area.

Problem Statement

This study will use community college students as the source for the data collection. Community colleges serve a diverse student population. Increases in enrollment for community colleges have exceeded that of four-year institutions in part because of open access and lower tuition costs (AACC, 2015). Close to half of undergraduate students in the United States are served by a community college (AACC, 2015). Minority, low income, and first-generation postsecondary education students utilize community colleges as a gateway to postsecondary education. Additionally, the majority of Black and Hispanic undergraduate students in the United States are enrolled at a community college (AACC, 2015). Nationally, the average age of a community college student is 29 and two-thirds of community college students attend part-time. These institutions provide access to higher education for many nontraditional students, such as adults who are working full time while enrolled. Other nontraditional students served by community colleges include high school students who take courses to get ahead in their studies, students who attend to upgrade their skills for a particular job, and students who attend to pursue a hobby (AACC, 2015).

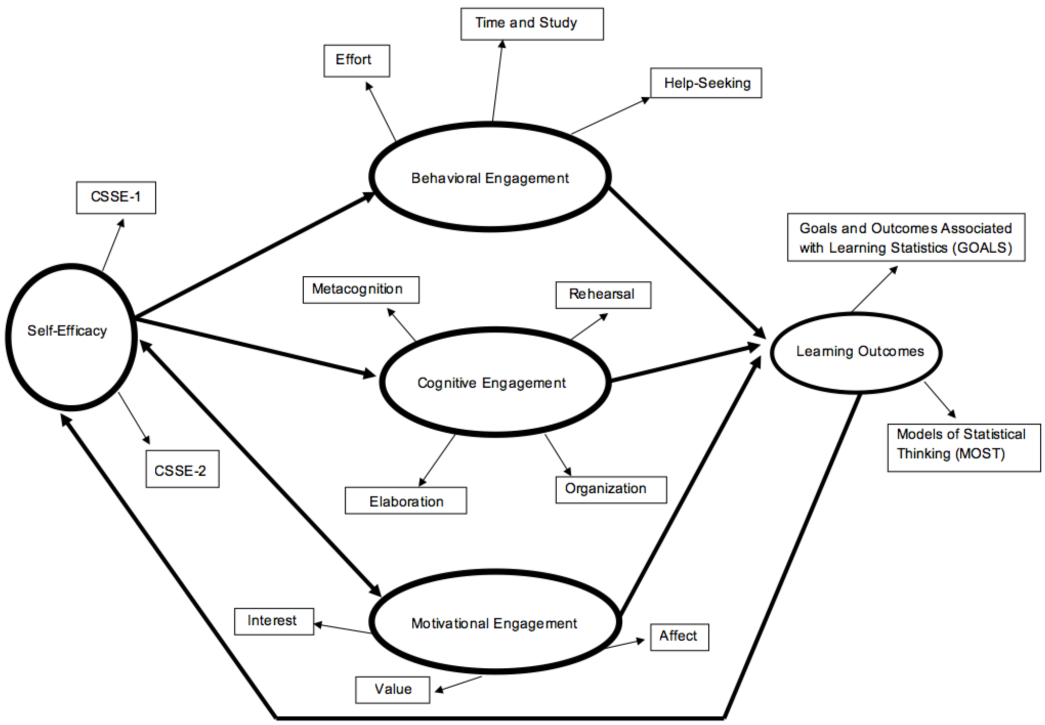
This study is concerned with certain affective factors that might influence the development of important statistics conceptual understandings of students who take the required non-mathematical introductory statistics course at the community college level. Student's self-efficacy toward statistics, attitude toward statistics, and choice of learning strategies employed are thought to influence their conceptual understandings of important statistical ideas upon course completion. It is of interest to understand the relationship among these characteristics so the learning needs of these students can be addressed with the hope of decreasing the number of students who withdraw from/fail the introductory course and are thereby inhibited in their progress toward earning their degree and fulfilling their educational goals.

Traditionally, most post-secondary research has involved four-year institutions (Pascarella, 2006). The field of statistics education reflects this practice as well. Little research, if any, concerning affective factors that might influence the development of important statistical conceptual understandings of students has been conducted with community college students. There is much research regarding statistics anxiety, statistics attitude, learning behavior, and statistics achievement where students at four year institutions or graduate students were studied (Onwuegbuzie 2003; Williams, 2012; Hood, Creed, & Neumann, 2011; Griffith, Adams, Gu, Hart, & Nichols-Whitehead, 2011; Pan & Tang, 2005; Wood & Locke, 1987; Macher, Paechter, Papousek, & Ruggeri, 2011; Chiesi, Primi, & Carmona, 2011; Zeidner, 1991), but few if any studies have investigated these same factors with community college students. delMas, Garfield, Ooms, and Chance (2007, p.50) assert the need to conduct studies that "explore particular activities and sequences of activities in helping to improve students' statistical reasoning as they take introductory statistics courses." This research study seeks to decrease this research gap.

Purpose Statement

The purpose of this study was to investigate affective characteristics and conceptual understanding of community college introductory statistics students by considering the relationships between student conceptual understandings of the non-mathematical introductory statistics curriculum, student self-efficacy toward statistics, student attitude toward statistics, and student self-regulated learning strategies.

The present study examined community college students' characteristics with regards to statistics self-efficacy, attitude, and self-regulated learning strategies, and seeks to understand how these affective characteristics influence conceptual understandings. Thus this study may serve to further our understanding of community college students' experiences and achievement in the introductory statistics course.



Hypothesized model of conceptual understanding. Model is based on Linnenbrink & Pintrich's (2003) general framework for self-efficacy, engagement, and learning.

Figure 1: Hypothesized Model of Conceptual Understanding

Conceptual Framework

It was hypothesized that student conceptual understanding of statistics would be positively influenced by self-efficacy to learn statistics, but that the effect of self-efficacy would be modified through student engagement variables as described by Linnenbrink & Pintrich (2003), namely, behavioral engagement, cognitive engagement, and motivational engagement (see figure 1). These engagement variables are operationalized in terms of self-regulated learning strategies and attitude toward statistics. It was also hypothesized that student engagement variables are positively related to student conceptual understandings. Student characteristics such as gender and race may affect self-efficacy to learn statistics which may be manifested in the selection and use of self-regulated learning strategies as well as student attitude toward statistics which will in turn influence conceptual understanding.

Research Questions

1. Is student conceptual understanding of statistics positively influenced by self-efficacy to learn statistics?

H_0: Student conceptual understanding of statistics is not positively influenced by self-efficacy to learn statistics.

H_a: Student conceptual understanding of statistics is positively influenced by self-efficacy to learn statistics.

2. Is the effect of self-efficacy on student conceptual understanding of statistics mediated by behavioral engagement, cognitive engagement, and motivational engagement?

H_0: The influence of self-efficacy on student conceptual understanding of statistics is not mediated by behavioral engagement.

H_a: The influence of self-efficacy on student conceptual understanding of statistics is mediated by behavioral engagement.

H_0: The influence of self-efficacy on student conceptual understanding of statistics is not mediated by cognitive engagement.

H_a: The influence of self-efficacy on student conceptual understanding of statistics is mediated by cognitive engagement.

H_0: The influence of self-efficacy on student conceptual understanding of statistics is not mediated by motivational engagement.

H_a: The influence of self-efficacy on student conceptual understanding of statistics is mediated by motivational engagement.

Definition of Terms

Community College: In the United States, community colleges are primarily two-year public institutions providing higher education and lower-level tertiary education, granting certificates, diplomas, and associate's degrees ("Community college", 2014).

Conceptual Understanding: Students' understanding of the introductory statistics curriculum with respect to statistical literacy, statistical reasoning, and statistical thinking. (delMas, et al., 2007)

Engagement: In an academic environment, engagement pertains to the quality of effort students make to accomplish their desired scholarly pursuits (Sun & Rueda, 2012).

Face-to-face Course: Course delivered in the traditional on-campus classroom setting.

Introductory Statistics: The introductory statistics course is a one-semester tertiary level course that introduces statistical terms and methodology.

Learning Strategy: "Systematic plan oriented toward regulating academic work and producing successful task performance" (Schunk, 2012, p.495).

Non-mathematical introductory statistics course: An introductory statistics course for non-mathematical majors. The math prerequisite for these courses is set at the college algebra level where the math prerequisite for mathematical introductory statistics courses is set at calculus.

Online Course: Course delivered completely online with no face-to-face contact between instructor and students.

Self-Efficacy: "Self-efficacy refers to perceived capabilities of learning or performing behaviors at designated levels. It is not the same as knowing what to do" (Schunk, 2012, p.160).

Self-Regulation: "Self-regulation refers to processes that learners use and the choices they make to systematically focus their thoughts, feelings, and actions on the attainment of their goals" (Schunk, 2012, p. 441).

Statistical Literacy: Understanding words and symbols; being able to read and interpret graphs and terms (delMas, et al., 2007, p.29).

Statistical Reasoning: Reasoning with statistical information (delMas, et al., 2007, p.29).

Statistical Thinking: Asking questions and making decisions involving statistical information (delMas, et al., 2007, p.29).

Limitations and Delimitations

The participants in this study are students from a small community college in southwestern Arizona who were enrolled in a traditional non-mathematical introductory statistics course with face-to-face or online instructional method of delivery. This community college enrolls 9,000 students annually; 35% are full time students and 65% are part time students. 68% of students are under 25, 32% are ages 25+. Class sizes are small with an average faculty/student ratio of 1:20. The racial composition of students at this institution is American Indian or Alaskan 1%, Asian 1%, Black or African American 4%, Hispanic or Latino 63%, Native Hawaiian or other Polynesian <0.5%, White 22%, race unknown 4%, resident alien 3% and two or more races 1% (National Center for Education Statistics, 2014; Office of Institutional Effectiveness, Research, and Grants, 2014).

The limitations of this study include the use of intact classroom with no random selection or assignment of participants. Students were invited and encouraged to participate, but participation was not compulsory. Face-to-face sections of this course were taught by two different instructors, online sections are taught by both of these instructors, and students self-selected which course section to enroll in. Such choices are influenced by a myriad of factors such as work schedule, preferred instructional delivery mode, a friend's schedule, among others. However, it is assumed that the acquired sample of students will have characteristics that vary little from the population of students who enroll in the traditional non-mathematical introductory statistics course at this community college in southwestern Arizona. In addition, another limitation of this study is the data collection involves self-report. Data of this type are vulnerable to response bias in the form of social desirability. It is possible that responses were modified to give the appearance of positive and desirable outcomes.

Additionally, the author participated in this study as one of the instructors, which could introduce research bias into the results. The author's teaching background is both in traditional teaching as well as student-centered learning. The classes were taught under a traditional instructor-led approach, with an active learning experience at least once each unit. Efforts will be made to hold student interest throughout the course by making use of real data from intriguing and current research to situate the learning of content.

The delimitations of this study include the fact that students in this study may not be representative of students who attend other colleges or universities in Arizona or in other geographical areas due to the unique racial make-up of the student population and its location along the Mexican Border. It may be that results from this study only apply to non-mathematical introductory statistics students at this community college. Additionally, estimates obtained from non-experimental research are limited in terms of their causal inferences. Regardless, this research will inform institutional efforts to improve the conceptual understandings and affective characteristics of these community college students.

Significance of the Study

Several researchers have studied non-cognitive factors such as statistics anxiety; beliefs and feelings about statistics and its utility; the student's perceived ability to successfully complete statistical tasks or solve problems; gender differences; and feelings about the level of difficulty of statistics may be related to university students' understanding and reasoning about statistical concepts (Rodarte-Luna & Sherry, 2008; Virtanen & Nevgi, 2010; Bandalos, Finney, & Geske, 2003; Finney & Schraw, 2003; Kesici, Baloglu, & Deniz, 2011; Baloglu, 2002). "More research is needed to study whether or not these non-cognitive factors are actually related to students' [conceptual] learning" (Zieffler, et al., 2008). In addition, there is a need to conduct studies that explore particular activities and mindsets that might improve students' statistical conceptual understanding as they take non-mathematical introductory statistics courses at both the university and community college levels (delMas, Garfield, Ooms, & Chance, 2003).

The present study seeks to investigate how the affective characteristics of attitude toward statistics, statistics self-efficacy, and self-regulated learning strategies might be related to statistics conceptual understanding for community college students in a non-mathematical introductory statistics course. Additionally, this study focuses on a student population not traditionally studied and will contribute understanding of how community college students are experiencing the introductory statistics class.

Chapter One Summary

There is a need for further research into the affective characteristics of introductory statistics students to gain a more complete understanding of how affective characteristics influence students' introductory statistics conceptual understandings in a non-mathematical statistics course, especially among the community college student population. Improving our understanding of these student characteristics will lead to curricular interventions designed at improving student attitudes toward statistics and their statistics self-efficacy which might improve self-perception of their ability to learn statistics and is expected to have a direct positive effect on statistics understanding (Onwuegbuzie, 2003). This research study was designed to focus on the experiences of community college students who enroll in a non-mathematical introductory statistics course and seeks improved understanding of the relationship between conceptual understanding and affective characteristics by measuring student statistics attitude, student statistics self-efficacy, self-regulated learning strategies, and student conceptual understandings of the introductory statistics curriculum.

CHAPTER TWO: LITERATURE REVIEW

Introduction

A key goal for educational research should be improving instruction and research into issues such as statistics education should maintain focus on this goal (Zieffler, Garfield, Alt, Dupuis, Holleque, & Chang, 2008). Broadening our understandings of the learning and teaching of statistics will ultimately lead to improvements in how instructors are educating students in this field. Affective factors might influence the development of important statistics conceptual understandings by those who take the required non-mathematical introductory statistics course. Student's self-efficacy toward statistics, attitude toward statistics, and choice of learning strategies employed are thought to influence their conceptual understandings of important statistical ideas upon course completion. It is of interest to understand the relationship among these characteristics so the learning needs of community college students can be addressed with the hope of decreasing the number of students who withdraw from/fail the introductory course and are thereby inhibited in their progress toward earning their degree.

Community College Student

Community colleges serve a diverse student population with a variety of needs. Students who enroll at community colleges for many reasons, and some for more than one reason. These include students pursuing an associate degree (35%), students who intend to transfer to a four-year institution (36%), students who attend to upgrade their skills for a particular job (21%), students pursuing an occupational certificate (13%), students who plan to transfer to another two-year college (15%), and students who attend to pursue a hobby or personal interest (46%) (AACC, 2015; Provasnik & Planty, 2008). This variation in reasons for enrollment point to an "important difference between community colleges and four-year institutions and confounds research on factors relating to community college degree completion" (Porchea, et al., 2010, 682).

Close to half of undergraduate students in the United States are served by a community college. Over the years since the first community college was founded in 1901, community colleges have become an indispensable part of higher education in the United States. Since 1901, over 100 million people have attended a community college (AACC, 2015). In the fall of 2005, more than 6.5 million credit seeking students were enrolled in a community college. Community colleges have become a gateway to higher education for many first generation, low-income, and minority students. Starting in the mid-1980s more than half of community college students have been women. The majority of Black and Hispanic undergraduate students are attending a community college (AACC, 2015).

Nontraditional students, such as adults who are working while enrolled, have access to higher education via community colleges. The average age of community college students is 29 and two-thirds of community college students attend part time (AACC, 2015). In addition to providing access for adults, community colleges are serving an increasing number of traditional aged and high school students who take specific courses to get ahead in their studies. According to the American Association for Community College (2015), half of the students who obtain a baccalaureate degree attended a community college at some point during the course of their undergraduate studies.

However, Adelman (2005) found that among community college students who intend to transfer to a four-year institution to pursue a bachelor's degree, very few of them actually follow a college transfer curriculum. In 2014, among students who started at two-year public institutions in 2008, 26.1% had earned a credential from that institution within the six years of first enrollment, 13% had transferred to a four-year institution and had earned a credential, while 17.9% were still enrolled somewhere (AACC, 2015).

The significant role of the community college to society, the large volume and diversity of students attending a community college, and the low percentage of degree attainment all suggest a great need for understanding the factors that influence the success of a community college student (Porchea, et al., 2010). Attrition before degree attainment is more pronounced at the community college level than for four-year institutions. Among two-year institutions, the average first-to-second-year retention rate is 54%; among four-year institutions, the average retention rate is 73% (ACT, 2008).

Traditionally, most post-secondary research has involved four-year institutions (Pascarella, 2006). The field of statistics education reflects this practice as well. Little research, if any, concerning affective factors that might influence the development of important statistical conceptual understandings of students has been conducted with community college students. This research study seeks to decrease this gap.

Researchers over the past 25 years have provided evidence to suggest that the academic and out-of-class experiences that influence cognitive and affective development during a student's time in college differ along such dimensions as race/ethnicity, first-generation versus non-first-generation status. Additionally, this evidence suggests "community colleges, historically Black colleges, and single-sex colleges each have their own unique impacts on undergraduate students" (Pascarella, 2006, 514). Pascarella (2006) suggests that future inquiry might uncover unique impacts attributable to virtually ignored institutions such as Hispanic serving institutions, among others.

Framework

Linnenbrink & Pintrich (2003) have proposed a general framework for self-efficacy, student engagement, and student learning. Self-efficacy is related to student engagement and learning. Self-efficacy can lead to more engagement and, afterwards, to more learning and higher achievement. The more a student is engaged the more they learn and the higher they achieve, and, subsequently, the more efficacious their self-efficacy becomes (see figure 1).

Self-Efficacy

Most theories of human motivation and behavior include self-beliefs as a key component. Bandura's (1986) social cognitive theory is an example. The central construct of this theory is self-efficacy, which Bandura defines as people's judgments of their capabilities to produce designated levels of performance. According to social cognitive theory, people are more likely to perform tasks they believe they are capable of accomplishing and are less likely to engage in tasks in which they feel less competent. Individual's beliefs about their competencies in a given domain affect the choices they make, the effort they put forth, their inclination to persist at certain tasks, and their resiliency in the face of failure. Self-efficacy concerns people's beliefs that they can complete a domain specific task such as build a deck, read a textbook, ride a bicycle, or complete a statistical analysis and refers to personal judgments of performance abilities in the particular domain of activity.

People form their self-efficacy beliefs by interpreting information from four sources: mastery experiences, vicarious experiences, verbal persuasions, and physical emotional states (Bandura, 1986; Bandura, 1997). The most important source of information comes from the interpreted results of one's past performance, mastery experiences. When one masters a task or skill this creates a strong sense of efficacy to accomplish similar tasks in the future. Alternatively, repeated failure can lower feelings of efficacy toward the task or skill especially if such failures occur early in the course of learning and such failures cannot be attributed to lack of effort or external circumstances. Continued success, on the other hand, supports a sense of self-efficacy that occasional failures cannot weaken.

The second source of self-efficacy information, vicarious experiences, occurs when individuals observe others performing tasks. When others who are perceived as similar in capability are observed succeeding or failing at a task, this information contributes to an individual's belief of their own capabilities. In situations where individuals have little experience with which to form a judgment of their own competence, observing others proves especially informative in terms of self-efficacy.

Beliefs of personal competence are also influenced by the verbal persuasions one receives from others. These take the form of verbal messages and social encouragement about a task and can encourage individuals to exert the extra effort to maintain the persistence required to succeed, resulting in the continued development of skills and of personal efficacy. These verbal messages and social messages can also serve to undermine efficacy beliefs when used to persuade people they lack the ability to succeed.

Individuals also receive information about their competencies from their physical and emotional states. Stress and tension are often interpreted as indications of an inclination to fail, and one's mood can also have a marked effect on self-efficacy beliefs. Typically, optimism and a positive mood enhance self-efficacy beliefs, whereas depression, despair, or hopelessness undermines them (Bandura, 1986; Bandura, 1997; Zeldin & Pajares, 2000).

Information acquired from these four sources does not influence self-efficacy directly; rather, the effect of such information on self-efficacy depends on how the information is evaluated cognitively (Bandura, 1986). The self-efficacy beliefs that people hold influence the choices they make, the amount of effort they expend, their resilience to encountered adversity, their persistence in the face of difficulty, the anxiety they experience, and the level of success they ultimately achieve. Inman and Mayes (1999) observed that community college students were remarkably prone to have lower self-efficacy. Individuals with strong self-efficacy beliefs work harder and persist longer when they encounter challenges than those who doubt their capabilities. Results from research on self-efficacy beliefs indicate that these judgments of personal competence are often stronger predictors of behavior than are prior successes, ability, or knowledge (Bandura, 1986; Pajares, 1996; Schunk, 1991; Zeldin, & Pajares, 2000).

Engagement

Teachers across all levels, from elementary to graduate classrooms, are concerned that some students are involved, engaged, and motivated to learn and others are uninterested, disengaged, and apathetic, even when these students are in the same classroom (Linnenbrink & Pintrich, 2003). Community college students, in particular, struggle with viewing their academic experiences as something they control and can influence with their engagement choices (Luke, Redekop, & Burgin, 2014). Student Engagement is a multifaceted construct. A student is engaged in learning when they display behaviors that demonstrate learning, participate in cognitive learning activities, and express interest and value in what they are learning. Fredricks, Blumenfeld, & Paris (2004) describes engagement as a fusion of behavior, cognition, and emotion. "Defining and examining the components of engagement individually separates students' behavior, emotion, and cognition. To understand learning and achievement, we must understand the affective, behavioral, and cognitive dimensions of student engagement (Parsons, Nuland, & Parsons, 2014). In reality these factors are dynamically interrelated within the individual; they are not isolated processes. (Fredricks, et al., 2004, 61). Linnenbrink and Pintrich model student engagement in terms of behavioral engagement, cognitive engagement, and motivational engagement in their general framework for self-efficacy, engagement, and learning (2003).

Behavioral Engagement. Creating and using self-efficacy is an intuitive process. "Individuals engage in a behavior, interpret the results of their actions, use these interpretations to create and develop beliefs about their capability to engage in subsequent behaviors in similar tasks and activities, and behave in concert with the beliefs created. In school, for example, the beliefs students develop about their academic capabilities help determine what they do with the knowledge and skills they have learned. Consequently, their academic performances are, in part, the result of what they come to believe they have accomplished and can accomplish. This helps explain why students' academic performances may differ markedly when they have similar abilities" (Pajares, 2002, p.116). Saenz, Hatch, Bukoski, Kim, Lee, & Valdez (2011) found that the more engaged community college students were in utilizing college support services, the more likely their overall engagement would increase, which resulted in increased positive outcomes.

Cognitive Engagement. Bandura (1986) first connected self-efficacy and self-regulatory practices when he developed his social cognitive theory. According to his theory, individuals are self-organizing, proactive and self-regulating rather than reactive and shaped by external events. Their developed self-efficacy beliefs are instrumental to the goals they pursue and central to the control they are able to exercise over their environments.

"Self-regulation (self-regulated learning) refers to processes that learners use to systematically focus their thoughts, feelings, and actions on the attainment of their goals" (Schunk, 2012, p. 441). Self-regulation involves learners' choices. "To engage in self-regulation students must have some choices available to them, such as whether to participate, which method they use, what outcomes they will pursue, and which social and physical setting they will work in" (Schunk, 2012, p. 441).

The quality of the self-regulatory skills students employ depends in part on an individual's self-efficacy beliefs in that domain. Regardless of previous achievement or ability, students who believe they are capable of performing academic tasks will use more cognitive and metacognitive strategies, work harder, persist longer, and persevere in the face of adversity. Collins (1982) studied children of low, middle, and high mathematics ability who had, within each ability level, either high or low mathematics self-efficacy. They were tested on a set of mathematical problems. Afterward, all children received the same mathematical instruction and were given a new set of problems to solve along with an opportunity to rework those they had missed from the first set of problems. It was found that level of mathematics ability was related to performance but, regardless of ability level, children with high self-efficacy completed more problems correctly and reworked more of the ones they missed.

Students with high self-efficacy will engage in more effective self-regulatory strategies. Self-assured students will effectively monitor their academic work time, persist when confronted with academic challenges, erroneously reject correct hypothesis prematurely, and solve conceptual problems. As self-efficacy increases, students' self-evaluations about the outcomes of their self-monitoring become more accurate (Bouffard-Bouchard, Parent, & Larivee, 1991).

Academic self-efficacy is related both to cognitive strategy use and to self-regulation through the use of metacognitive strategies, as found in a study by Pintrich & de Groot (1990). Academic self-efficacy also correlated with semester and end-of-year grades, in-class seatwork and homework, exams and quizzes, and essays and reports. Pintrich & de Groot (1990) concluded that self-efficacy served a "facilitative" role in the process of cognitive engagement, that raising self-efficacy might lead to increased use of cognitive strategies and higher performance, and that "students need to have both the 'will' and the 'skill' to be successful in classrooms" (p.38).

Researchers have investigated students' confidence that they possess the self-regulated learning strategies required to succeed in school. They discovered that this self-efficacy for self-regulated learning contributes both to students' motivational beliefs and to the academic success they experience (Zimmerman, 1989; Zimmerman & Bandura, 1994). Other researchers have found that students' self-efficacy for self-regulated learning is related to motivation and achievement in specific academic areas such as language arts, mathematics, and science. Students' confidence in their self-regulated learning strategies is related to their academic self-concept, self-efficacy, value of school, value of particular school subjects, and academic performances. Students' self-efficacy for self-regulated learning is also negatively related with academic and subject-specific anxiety (Pajares, 1996; Pajares & Miller, 1994). In a study with community college students, Liao, Edlin, & Ferdenzi (2014) found that the use of self-regulated learning and extrinsic motivation influenced student persistence/reenrollment. Community college students today are more extrinsically motivated by the future earnings potential of a college degree than to learn for the sake of learning.

Notwithstanding the call from such researchers as Garfield, Hogg, Schau, and Wittinghill (2002), for more researchers to examine models involving cognitive, motivational, and affective predictors of statistics achievement, few can be found among the literature. Bandalos, Finney, and Geske (2003), responded by looking at the role of achievement goals as predictors of self-reported strategy use, self-efficacy, and test anxiety for statistics students. These researchers found that both learning and performance goals positively predicted self-efficacy in the domain of a non-mathematical introductory statistics course.

Motivational Engagement. Few dispute that statistics plays an important role in our modern world, however many adults view statistics in a negative light and remember it as their worst course taken in college. Indeed, statistics has a reputation among students as being challenging, irrelevant, dull, and an unwelcome compulsory invasion into their chosen field of study (Ben-Zvi & Garfield, 2008; Croucher, 2006). Such negative attitudes can act as a barrier to the learning of statistical concepts. Harpe, Phipps, & Alowayesh (2012) point out that researching affective outcomes, such as attitudes, could provide information that is useful in improving the process of teaching and learning statistics.

Bude, Van de Wiel, Imbos, Candel, Broers and Berger (2007) studied motivational constructs and their effect on students' academic achievement within a statistics course. They found a relationship between negative attitudes toward statistics and poor study habits, which led to poor scores on achievement measures. Students' affect and attitudes toward statistics can be researched by considering student beliefs and feelings about statistics and its utility. According to Finney & Schraw (2003), self-efficacy toward statistics has an important role in not only students' attitudes about statistics, but also in influencing their performance in a statistics course. Among the literature there seems to be a lack of evidence to support how non-cognitive factors that are believed to influence the learning of statistics actually relate to students' conceptual understandings of statistics (Zieffler, Garfield, Alt, Dupuis, Holleque, & Chang, 2008).

Garcia and Pintrich (1996) studied a sample of community college students, private 4-year college students, and public 4-year university students and found that increases in positive motivational beliefs are related to higher grades and better performance.

Statistics Conceptual Understanding

What should students know at the end of a non-mathematical introductory statistics course? There is more agreement today among statisticians who answer this question than in the past. Statistical education reformers have collaborated to create an overall Comprehensive Assessment of Outcomes in Statistics (CAOS) that focuses on assessing students' statistical literacy, statistical reasoning, and statistical thinking (delMas, Garfield, Ooms, & Chance, 2007). Statistical literacy refers to the ability to understand words and symbols in addition to being able to read and interpret graphs and statistical terms. Statistical reasoning is the ability to reason with statistical information. Statistical thinking is the disposition for asking questions and making decisions involving statistical information.

The CAOS test provides valuable information on what students supposedly learn and understand after completing a non-mathematical introductory statistics course. All items on the CAOS test were written to require students to think and reason; this is in contrast to many instructor-designed exams that are written to require students to compute, use formulas, or recall definitions. A subset of the CAOS test, Goals and

Outcomes Associated with Learning Statistics (GOALS) Assessment consists of 27 forced-choice items designed to measure students' statistical reasoning. A companion to the GOALS test, the Models of Statistical Thinking (MOST) consists of four real-world contexts with accompanying questions designed to measure students' statistical thinking (R. delMas, R. Isaak, J. Garfield, personal communication, November 11, 2011). These tests were purposefully designed to be different from the traditional test written by course instructors in that their purpose is to get students to think and reason.

Few, if any, researchers have created models that have explored the relationship between statistics self-efficacy, attitude toward statistics, self-regulated learning strategies and student conceptual understandings. Bandalos, Finney, & Geske (2003) created a model of achievement in statistics where achievement was measured by students' midterm and final examination scores on instructor-designed exams. Finney & Schraw (2003) created a model of self-efficacy beliefs where statistics outcomes were measured by multiple-choice items related to self-efficacy belief statements and final course percentage. The present study looked at the relationship between statistics self-efficacy, attitude toward statistics, self-regulated learning strategies, and statistical conceptual understanding as situated in the general framework of self-efficacy, engagement, and learning as discussed by Linnenbrink & Pintrich (2003) and shown in figure 1. By measuring statistics achievement from the perspective of student conceptual understanding instead of from the perspective of instructor-created assignments and tests, such results will reflect the important learning outcomes for students in a non-mathematical introductory statistics course as determined by a collaborative group of statistics educators who are considered experts and leaders in the national statistics education community (delMas, et al., 2007).

Model

Self-Efficacy

Self-efficacy is a motivational construct that is key to promoting students' engagement and learning. Bandura (1986) has defined self-efficacy as "people's judgments of their capabilities to organize and execute courses of action required to attain designated types of performances" (p.391). Student engagement is looked at in terms of behavioral engagement, cognitive engagement, and motivational engagement, see Figure 1. Linnenbrink & Pintrich's (2003) model assumes that all aspects of engagement as well as learning and achievement are reciprocally related in the reality of the classroom. In other words, increased self-efficacy can lead to increased engagement and, subsequently, to more learning and better conceptual understanding; however, the relationships also circle back to self-efficacy over time. That is, the more a student is engaged and the more a student is learning, the better their performance and the higher their self-efficacy.

Behavioral Engagement

Behavioral engagement consists of behavior that can easily be observed while demonstrating student engagement in terms of effort, time and study environment, and help-seeking. According to Linnenbrink & Pintrich's (2003) model, students who put forth more effort, spend more time on tasks, and seek help, are more likely to achieve learning at deeper conceptual levels.

Cognitive Engagement

Cognitive engagement covers cognitive processes of engagement that cannot be observed, i.e., a student may be behaviorally engaged, but not cognitively engaged in a learning activity. A student who is cognitively engaged will think deeply about the content to be learned, think about what they know and do not know, use self-regulated learning strategies that increase their understanding of the material to be learned. Self-regulated learning strategies include rehearsal, organization, elaboration, and metacognition. Students who become more engaged with the material are more likely to understand. Thus, high levels of cognitive engagement reflect the quality of students' efforts in the task as opposed to quantity of effort that reflects behavioral engagement. "Students who are metacognitive are ones who reflect on their own thinking, actions, and behavior and monitor and regulate their own learning" (Linnenbrink & Pintrich, 2003, p.125).

Motivational Engagement

Motivational engagement occurs when students are engaged in the content or tasks in terms of their interest, value, and affect. All of these aspects of motivational engagement can be related to actual learning and achievement; when a student has personal interest in the task, this results in greater learning. Increased levels of motivational engagement result in greater cognitive engagement and enhanced usage of self-regulated learning strategies (Linnenbrink & Pintrich, 2003).

Conceptual Understanding

Conceptual understanding is a student's ability to think statistically, reason statistically, and understand statistical language and representations. What should a student know at the end of a first year statistics course? Expert statistics educators collaborated on this question and established ten topics students should understand conceptually: data collection and design, descriptive statistics, graphical representations, boxplots, normal distributions, bivariate data, probability, sampling variability, confidence intervals, and tests of significance (delMas, Garfield, Ooms, & Chance, 2007). It was hypothesized that student engagement directly influences conceptual understanding while self-efficacy's influence on this component is mediated through the engagement processes.

The three engagement components of this model are likely correlated. As students are cognitively and motivationally engaged, they are more likely to be behaviorally engaged. However, it is possible for students to be behaviorally engaged but not cognitively nor motivationally engaged, as when a student is apparently behaviorally engaged by looking at the teacher but their mind is allowed to wander off topic. Additionally, it is possible for students to be cognitively and behaviorally engaged but not motivationally engaged. This can happen when a student studies and thinks hard about a subject but does not find that subject particularly interesting or useful to them (Linnenbrink & Pintrich, 2003).

Self-efficacy is related to the quantity of effort and the willingness to persist at tasks (Bandura, 1997; Schunk 1989; Schunk 1991). "Individuals with strong efficacy beliefs are more likely to exert effort in the face of difficulty and persist at a task when they have the requisite skills" (Linnenbrink & Pintrich, 2003, p.127). Research indicates a positive relation between self-efficacy and students' behavioral engagements. Students with positive attitudes about their capabilities to do a task are much more likely to put forth effort, persist, and seek help in an adaptive manner. Students who have negative attitudes are much less likely to put forth effort and more likely to give up easily when faced with adversity and difficulties in completing a task.

Students who believe they are capable of completing a task are more likely to be cognitively engaged than those with lower self-efficacy beliefs. High self-efficacy beliefs support students' efforts to understand content and think deeply about it, thus increasing metacognitive processes. Research indicates a positive relation between self-efficacy and student use of cognitive and metacognitive strategies (Linnenbrink & Pintrich, 2003).

Self-efficacy is related to motivational engagement, but motivational engagement is related to self-efficacy. There is both theoretical and empirical evidence to suggest that emotions influence efficacy and efficacy beliefs have an effect on emotions. Students can develop a sense of competence at a task, which then builds a positive attitude toward the task. On the other hand, students may first like some task or topic area and this interest encourages a student to engage in the task. As the student persists in engaging in the task or topic, feelings of self-efficacy will grow (Linnenbrink & Pintrich, 2003).

Chapter Two Summary

Linnenbrink & Pintrich (2003) have proposed a general framework for self-efficacy, student engagement, and student learning that was used to operationalize the investigation of the relationship between self-efficacy toward statistics, attitude toward statistics, use of self-regulated learning strategies, and the development of students' statistical conceptual understandings. Enlarging our understandings of this relationship may lead to improvements in how community college statistics instructors are educating their students. Testing Linnenbrink & Pintrich's (2003) general framework with community college students additionally will serve to lessen the gap that exists among the body of research in statistical education about the experience of these students in this course. Additionally, "More research is needed to study whether or not these non-cognitive factors are actually related to students' [conceptual] learning" (Zieffler, et al., 2008). The present study seeks to investigate how the affective characteristics of attitude toward statistics, statistics self-efficacy, and self-regulated learning strategies might be related to statistics conceptual understanding for community college students in a non-mathematical introductory statistics course.

Research suggests that affective factors influence the development of important statistics conceptual understandings by those who take the required non-mathematical introductory statistics course. Student's self-efficacy toward statistics, attitude toward statistics, and choice of learning strategies employed are thought to influence their conceptual understandings of important statistical ideas upon course completion. It is of interest to understand the relationship among these characteristics so the learning needs of community college students can be addressed. Furthermore, this study focuses on a student population not traditionally studied and will contribute understanding of how community college students are experiencing the introductory statistics class.

CHAPTER THREE: METHODOLOGY

Introduction

The present study was concerned with affective factors that were hypothesized to influence the development of important statistics conceptual understandings by those who take the required non-mathematical introductory statistics course at the community college level. Student's self-efficacy toward statistics and engagement choices were thought to influence their conceptual understandings of important statistical ideas upon course completion. It is of interest to understand the relationship among these characteristics so the learning needs of these students can be addressed with the hope of decreasing the number of students who withdraw from/fail the introductory course and are thereby inhibited in their progress toward earning their degree. Positive improvements in self-efficacy are thought to raise student engagement in terms of behavioral, cognitive, and motivational manifestations with the result of strengthening student conceptual understanding. According to Linnenbrink and Pintrich (2003), students who have positive and relatively high self-efficacy beliefs are more likely to be engaged in the classroom in terms of their behavior, cognition, and motivation.

The purpose of this study was to investigate affective characteristics and conceptual understanding of introductory statistics students by considering the relationships between student conceptual understandings of the non-mathematical introductory statistics curriculum, student self-efficacy toward statistics, student attitude toward statistics, and student self-regulated learning strategies. This research study also seeks to decrease the research gap concerning the experience and achievement of community college students in this course.

The present study examined community college students' characteristics with regards to statistics self-efficacy, attitude, and self-regulated learning strategies, and seeks to understand how these affective characteristics influence conceptual understandings. Thus this study will serve to further our understanding of these students' experiences and achievement in the introductory statistics course by answering the following research questions.

1. Is student conceptual understanding of statistics positively influenced by self-efficacy to learn statistics?

H_0: Student conceptual understanding of statistics is not positively influenced by self-efficacy to learn statistics.

H_a: Student conceptual understanding of statistics is positively influenced by self-efficacy to learn statistics.

2. Is the effect of self-efficacy on student conceptual understanding of statistics mediated by behavioral engagement, cognitive engagement, and motivational engagement?

H_0: The influence of self-efficacy on student conceptual understanding of statistics is not mediated by behavioral engagement.

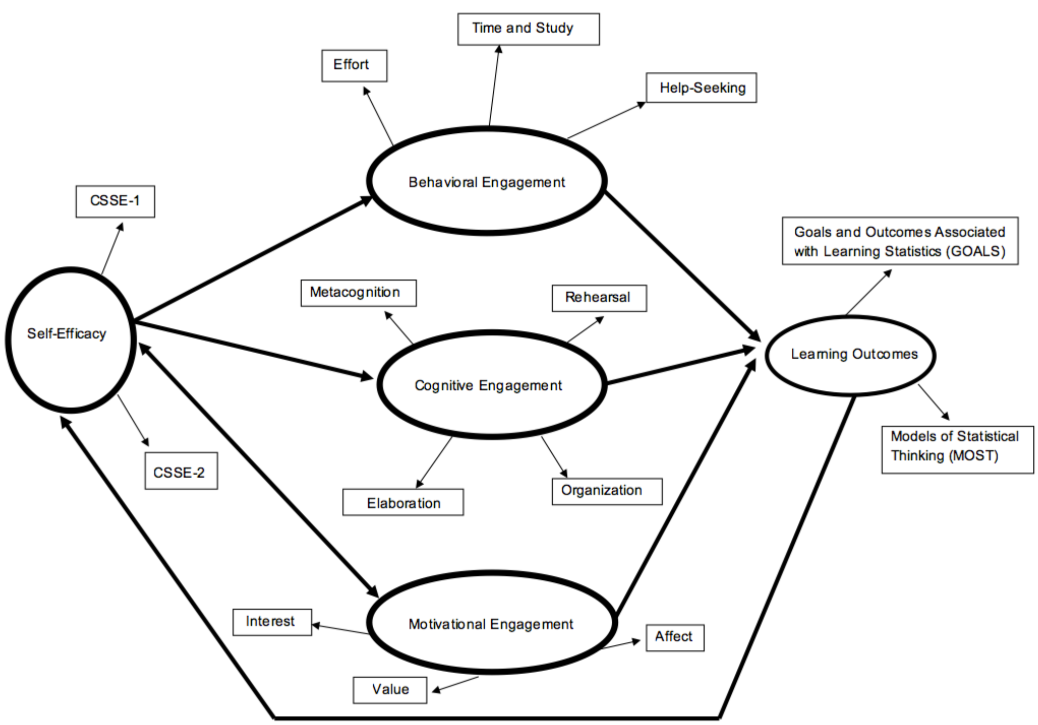
H_a: The influence of self-efficacy on student conceptual understanding of statistics is mediated by behavioral engagement.

H_0: The influence of self-efficacy on student conceptual understanding of statistics is not mediated by cognitive engagement.

H_a: The influence of self-efficacy on student conceptual understanding of statistics is mediated by cognitive engagement.

H_0: The influence of self-efficacy on student conceptual understanding of statistics is not mediated by motivational engagement.

H_a: The influence of self-efficacy on student conceptual understanding of statistics is mediated by motivational engagement.



Hypothesized model of conceptual understanding. Model is based on Linnenbrink & Pintrich's (2003) general framework for self-efficacy, engagement, and learning.

Figure 2: Hypothesized Model of Conceptual Understanding

Research Design

A correlational design using structural equation modeling (SEM) was used to investigate the relationships between community college student self-efficacy, engagement, and statistics learning outcomes in figure 2. Specifically, this study investigates how the affective characteristics of attitude toward statistics (motivational engagement), statistics self-efficacy, and self-regulated learning strategies (behavioral engagement and cognitive engagement) might be related to statistics conceptual understanding for community college students in a non-mathematical introductory statistics course.

It was hypothesized that student learning outcomes are positively influenced by self-efficacy to learn statistics, and that the effect of self-efficacy on student learning was mediated by behavioral engagement, cognitive engagement, and motivational engagement. It was also hypothesized that student engagement variables are positively related to student learning outcomes. The structure analyzed the relationship of self-efficacy on statistical understanding through the mediators of behavioral engagement, cognitive engagement, and motivational engagement. The current study was motivated by Linnenbrink & Pintrich's (2003) model of conceptual understanding.

Participants and Sample Size

Participant volunteers will be sought from students who enroll in the introductory statistics course taught at a small community college along the Mexican Border in southwestern Arizona summer and fall of 2015 and spring 2016. Eleven sections of this class were taught by the author and content was delivered via face-to-face instruction or online instruction. It was projected that there would be approximately 220 students enrolled in the course and it was hoped that at least 200 students would agree to participate. The sample size for conducting structural equation modeling was based on the number of indicator variables used to define latent traits. For this study, the model investigated in figure 2 has five latent variables, three of which are mediator variables, and fourteen indicator variables: self-efficacy's (two indicator variables) effect on learning and achievement is mediated by behavioral engagement, cognitive engagement, and motivational engagement; Behavioral engagement is measured by a subset of items from the Motivated Strategies for Learning Questionnaire (MSLQ) and has three indicator variables consisting of item totals for effort (four items), time and study (eight items), and help-seeking (four items). Cognitive engagement were measured by a subset of MSLQ items to form four indicator variables consisting of rehearsal (four items) and organization (four items), elaboration (six items), and metacognition (twelve items). Motivational engagement was measured using a subset of items from the Survey of Attitudes Toward Statistics (STATS) to form three indicator variables defined as interest (four items), value (nine items), and affect (six items). Learning outcomes were measured using items from the Goals and Outcomes Associated with the Learning of Statistics (GOALS) (27 items) and the Models of Statistical Thinking (MOST) (11 items).

Westland (2010) suggests a 5:1 ratio of sample size per indicator variables in a structural equation analysis. However, Bagozzi (2010) believes a ratio of 5:1 ratio of sample size per indicator variable is too conservative and he suggests that a 2:1 ratio of sample size per indicator variable in a structural equation analysis is sufficient. In their book, A Beginner's Guide to Structural Equation Modeling, Schumacker and Lomax (2004) instruct that a ratio as low as 5 subjects per variable would be sufficient for normal and elliptical distributions when the latent variables have multiple indicators and that a ratio of at least 10 subjects per variable would be sufficient for other distributions. Following Schumacker and Lomax's instruction and making no assumptions on the shape of the distribution, this puts the estimated sample size minimum at 140 subjects. Hair, Hult, Ringle, and Sarstedt (2017) instruct that when the maximum number of independent variables in the measurement and structural models is five, the study needs 122 observations to achieve a statistical power of 80% for detecting R^2 values of at least 0.10 (with a 5% probability error).

The Course

The curriculum taught to students participating in this study is a traditional non-mathematical introductory statistics curriculum and was presented to students from a teacher-centered approach. The course introduces descriptive and inferential statistics such as graphical and quantitative description of data, discrete probability distributions, continuous probability distributions, one- and multi-sample hypothesis tests, confidence intervals, correlation, simple linear regression, and analysis of variance. Students were also taught the basics of running several hypothesis tests in SPSS, including one-sample t-test, independent measures t-test, repeated measures t-test, ANOVA, correlation, and linear regression. The course extended over a 16-week semester followed by a week of final exams with students sitting in class just over four hours each week, on average.

The current textbook takes into account the Guidelines for Assessment and Instruction in Statistics Education (GAISE) (Aliaga, et al., 2005) and focuses on real-world data (Gould & Ryan, 2013). These guidelines/recommendations include (1) emphasize statistical literacy and develop statistical thinking; (2) use real data; (3) stress conceptual understanding, rather than mere knowledge of procedures; (4) foster active learning in the classroom; (5) use technology for developing conceptual understanding and analyzing data; (6) use assessments to improve and evaluate student learning. The Gould & Ryan's' approach is concept-based as opposed to method-based, teaching useful statistical methods while emphasizing that applying the method is secondary to understanding the concept.

Classroom discussions on self-efficacy and student engagement were general in nature off and on throughout the course. Students were encouraged to engage with the course content and form a positive attitude toward statistics, but students were not formally trained in any particular learning/study strategy, i.e. note taking, etc. The instructor demonstrated positive attitudes toward statistics and a strong sense of self-efficacy toward statistics during class meetings; moreover, the instructor was confident that implementing curriculum that adheres to the American Statistical Association's six Guidelines aids students in their work to learn this course's curriculum and build sound conceptual understanding.

Instruments

Demographic Questionnaire

The Demographic Questionnaire was developed by the author to gather information about individual students involved in this study. Items were chosen to obtain a demographic characteristics profile of the participants as a means of describing the sample. The questions gathered information related to type of content delivery format (face-to-face vs. online), semester course is taken, instructor, age, sex, race/ethnicity, citizenship, degree program, expected course grade, and prior statistics experience. Additional questions included the number of prior mathematics courses and grade earned in the prerequisite course for introductory statistics.

Self-Efficacy Toward Statistics

The Current Statistics Self Efficacy (CSSE) (Finney & Schraw, 2003) is a self-report designed to measure statistics self-efficacy that should be given as a pre-test and post-test and can be administered more frequently through a course. This is a one-factor measurement instrument with 14 items on a 6-point Likert-type scale with 1 being "No confidence at all" and 6 being "Complete confidence". Principal component analysis by Finney & Schraw (2003) indicated one factor with 44.53% of the variance in the responses explained. Internal consistency was measured with Cronbach's coefficient alpha at .907 and .935 for the pre- and post-test administrations respectively and all item-total correlations were above .53 for both data collections. Deletion of any of the 14 items from a total composite score decreased the value of Cronbach's coefficient alpha.

Self-Regulated Learning Strategies

The Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich, Smith, Garcia, & McKeachie, 1993) is a self-report designed to measure college students' motivational characteristics and their use of different self-regulated learning strategies for a college course. Pintrich et al. (1993) confirm that the instrument's two sections are independent of each other and may be used in isolation. For this study only selected factors from the self-regulated learning strategies section were used. The self-regulated learning strategies section consists of 50 Likert–type formatted items where answers are placed on a 7-point scale with 1 being "Not at all true of me" and 7 being "Very true of me". The self-regulated learning strategies include elaboration (6 items), rehearsal (4 items), organization (4 items), critical thinking (5 items), metacognition (12 items), effort (4 items), time and study environment (8 items), help-seeking (4 items), and peer learning (3 items). Pintrich et al. (1993) reported their confirmatory factor analysis placed the 50 items across 9 scales with a goodness-of-fit index of .78. Internal reliability coefficients range from a low of .59 to a high of .90. This study utilized the factors of elaboration, rehearsal, organization, metacognition, effort, time and study environment, and help-seeking.

Attitude Toward Statistics

The Survey of Attitudes Toward Statistics (SATS) (Schau, Stevens, Dauphinee, & Del Vecchio, 1995) was designed to measure six factors of attitudes toward statistics: interest (4 items), cognitive competence (6 items), value (9 items), difficulty (7 items), affect (6 items), and effort (4 items). Self-reported responses to these 36 questions are placed on a 7-point Likert-type scale with 1 being “Strongly disagree” and 7 being “Strongly agree”. After confirmatory factor analysis, Schau et al. (1995) reported coefficient alphas ranged from a low of .64 to a high of .85 across the six factors. This study utilized the factors of interest, value, and affect.

Conceptual Understanding

Student conceptual understanding was measured with a subset of the Comprehensive Assessment of Outcomes in Statistics (CAOS) test (delMas, Garfield, Ooms, & Chance, 2007), the Goals and Outcomes Associated with Learning Statistics (GOALS) and the Models of Statistical Thinking (MOST) (R. delMas, R. Isaak, J. Garfield, personal communication, November 11, 2011). The CAOS test was developed over a three-year iterative process in collaboration with statistics education experts. This process began by compiling a list of desired learning outcomes that students completing any introductory statistics course would be expected to understand. Items to assess these desired learning outcomes were obtained, revised, piloted, and vetted in an iterative cycle until there remained 40 items that measure student conceptual understandings with regards to statistical literacy, statistical thinking, and statistical reasoning. Analysis of internal consistency on the 40 items resulted in Cronbach’s alpha coefficient of .82. The 40 items measure student conceptual understandings with regards to data collection and design, descriptive statistics, graphical representations, boxplots, normal distribution, bivariate data, probability, sampling variability, confidence intervals, and tests of significance. The GOALS assessment consists of 27 forced-choice items designed to measure students’ statistical reasoning. The MOST assessment consists of real-world contexts with accompanying questions designed to measure students' statistical thinking; there is a set of items for the first three contexts that consists of an open-ended item followed by two or three forced choice items and there is only a single open-ended item for the last context.

Timeline		
First or Second Week	Eighth or Ninth Week	Sixteenth Week
CSSE – 1	SATS	CSSE – 2
	MSLQ	GOALS & MOST

Table 1: Timeline for Data Collection

Procedures

The data for this study was collected at three different time points, see Table 1. At the beginning of the semester, students were invited to participate and complete the informed consent form. During this same time, participants completed the demographic questions along with the first CSSE. Finney & Schraw (2003) recommend that current statistics self-efficacy be measured both at pre- and post-test time points. Scores for CSSE are a sum total of responses at each measurement. Students' attitude toward statistics, SATS, was measured mid-way through the course and scores are a mean for each of the selected factors. Mid-way through the course students were also measured on their use of self-regulated learning strategies, MSLQ. Scores for MSLQ are a sum total for each factor. At the end of the course students' conceptual understanding were measured by Goals and Outcomes Associated with Learning Statistics (GOALS) and Models of Statistical Thinking (MOST). Scores for the GOALS and MOST were a percentage correct across all items. The second measure of current statistics self-efficacy (CSSE) was measured at the end of the semester at the same time as GOALS and MOST.

The Informed Consent forms were handed out near the beginning of the semester on paper and an electronic copy was posted in Blackboard. Students were informed of the purposes for the study, the lack of risk, and the benefits of the survey before they were invited to participate. The surveys for this study were administered online using Qualtrics. The surveys were created online and links to the questionnaires were posted in Blackboard at each time point of the semester. The data was collected online through Qualtrics' service. Montana State University provides access to Qualtrics for students in support of research activities such as this study.

Research Question	**Data to Collect**
Is student conceptual understanding of statistics positively influenced by self-efficacy to learn statistics? H_0: Student conceptual understanding of statistics is not positively influenced by self-efficacy to learn statistics. H_a: Student conceptual understanding of statistics is positively influenced by self-efficacy to learn statistics	CSSE GOALS MOST
Is the effect of self-efficacy on student conceptual understanding of statistics mediated by behavioral engagement, cognitive engagement, and motivational engagement? H_0: The influence of self-efficacy on student conceptual understanding of statistics is not mediated by behavioral engagement. H_a: The influence of self-efficacy on student conceptual understanding of statistics is mediated by behavioral engagement. H_0: The influence of self-efficacy on student conceptual understanding of statistics is not mediated by cognitive engagement. H_a: The influence of self-efficacy on student conceptual understanding of statistics is mediated by cognitive engagement. H_0: The influence of self-efficacy on student conceptual understanding of statistics is not mediated by motivational engagement. H_a: The influence of self-efficacy on student conceptual understanding of statistics is mediated by motivational engagement.	CSSE MSLQ SATS GOALS MOST

Table 2: Pairing Research Question with Measurement Instrument

It was estimated that the first measurement would require 15 minutes to complete the informed consent, demographic questions, and CSSE-1. The second measurement was estimated to require 20 minutes to complete the MSLQ and SATS. The final measurement was estimated to require 50 minutes to complete CSSE-2, GOALS, and MOST. Students in a face-to-face class completed the instruments during class meetings while students in an online class completed the instruments online. Students who were absent in the face-to-face classes were invited to complete the survey by following the link in Blackboard. Table 2 shows which measurement instruments were intended to answer each research question

Data Analysis

A structural equation model was used to analyze the data gathered in this study. Direct and indirect pathways between the variables were examined to investigate the influence of self-efficacy on student engagement variables as manifested through attitudinal and self-regulation characteristics as well as its influence on students' conceptual understandings. This model is pictured in Figures 1 and 2 and is based on Linnenbrink & Pintrich's (2003) general framework of self-efficacy, engagement, and learning. Student engagement was measured in terms of student attitude toward statistics, SATS (Schau, Stevens, Dauphinee, & Del Vecchio, 1995), and self-regulated learning strategies, MSLQ (Pintrich, Smith, Garcia, & McKeachie, 1993). Self-efficacy was measured directly in the domain of statistics using Finney & Schraw's (2003) CSSE. Student learning was measured by a subset from the comprehensive assessment of outcomes in statistics, CAOS (delMas, Garfield, Ooms, & Chance, 2007).

Direct and indirect effects between the variables was examined to investigate between student self-efficacy, student engagement, and students' conceptual understanding of statistics. Results from this analysis were used to answer the research questions and test the hypotheses posed for this study.

Structural equation modeling is a multivariate analysis method that simultaneously analyzes multiple variables that represent measurements associated with individual, companies, events, etc. SEM is best used to either explore or confirm theory (Hair, et al. 2017). These types of statistical models are used primarily to evaluate whether theoretical models are plausible when compared to observed data. SEMs allow for the representation of complex theory in a single integrated model and enable researchers to incorporate unobservable variables measured indirectly by indicator variables. One of the strengths of this tool is that it facilitates the accounting for measurement error in observed variables. There are two types of SEM: covariance-based SEM (CB-SEM) and partial least squares SEM (PSL-SEM).

Covariance based SEM is primarily used to confirm theories and may determine how well a proposed theoretical model can estimate the covariance matrix for a sample data set. However, CB-SEM requires that all of the covariation between sets of indicators be explained by a common factor. It also requires a large sample size; typically at least 200 observations. In this approach, the constructs are considered as common factors that explain the covariation between its associated indicators (Hair et al., 2017). It is important that the data and residuals be normally distributed so this assumption is met before being able to employ this method.

Partial least squares SEM is primarily used to develop theories in exploratory research where one desires to predict and explain target constructs. A researcher would choose this method when the research objective is theory development and explanation of variance. PLS-SEM focuses on explaining the variance in the dependent variables when examining the model. This approach relaxes the strong assumptions of CB-SEM by making no distributional assumptions and it will work efficiently with small sample sizes and complex models (Hair et al., 2017).

It is important for researchers to understand the difference between these two methods so as to apply the correct method to their research project. To answer the question of when to use CB-SEM versus PLS-SEM, researchers should focus on the characteristic and objectives that distinguish the two methods. CB-SEM is used more widely than PLS-SEM. A researcher who is seeking to confirm theories should choose to use CB-SEM whereas a researcher desiring to study a realm where theory is less developed may use PLS-SEM to develop theory. CB-SEM will consider the constructs as common factors that explain the covariation between its associated indicators. PLS-SEM will use proxies to represent the constructs of interest; these proxies are weighted composites of indicator variables for a particular construct. According to Hair et al., (2017),

> compared to CB-SEM, PLS-SEM emphasizes prediction while simultaneously relaxing the demands regarding the data and specification of relationships. PLS-SEM maximizes the endogenous latent variables' explained variance by estimating partial model relationships in an iterative sequence of OLS (ordinary least squares) regressions. In contrast, CB-SEM estimates model parameters so that the discrepancy between the estimated and sample covariance matrices is minimized (p. 32-33).

Researchers should consider these two approaches as complementary and apply the SEM technique that best suits their research objective, data characteristics, and model setup.

Regardless of statistical method chosen, care should be taken not to assign causation to structural equation models. There are historical concerns over stating causation with SEMs

> A huge logical gap exists between 'establishing causation,' which requires careful manipulative experiments, and 'interpreting parameters as causal effects,' which may be based on firm scientific knowledge or on previously conducted experiments, perhaps by other researches. One can legitimately be in possession of a parameter that stands for a causal effect and still be unable, using statistical means alone, to determine the magnitude of that parameter given nonexperimental data (p. 1).

This research study was not seeking to establish causal paths between student statistics self-efficacy, engagement constructs, and statistical understanding. Rather, Linnenbrink & Pintrich's model was being explored in the setting of community college students and their experience in a non-mathematical introductory statistics course. As such, PLS-SEM approach was employed to investigate the research questions in this research study. PLS-SEM allows for both exploratory and confirmatory approaches of the model fit by using both the mediating variables and goodness-of-fit during the analysis of the model's relationships.

PLS-SEM provides graphical inspection as part of the analysis by constructing a path model with latent variables. Constructs, variables that are not directly measured, are defined using indicators, or factors. These indicators are the proxy variables that contain the raw data. Hair et al. (2017) explains that the

> Relationships between constructs as well as between constructs and their assigned indicators are shown as arrows. In PSL-SEM, the arrows are always single-headed, thus representing directional relationships. Single-headed arrows are considered predictive relationships and, with strong theoretical support, can be interpreted as causal relationships (p. 11).

There are two elements in a PLS-SEM path model: the structural model or inner model and the measurement model or outer model. The structural model displays the relationships between the constructs while the measurement model displays the relationships between the constructs and the indicator variables. In this study, the structural model outlines the proposed relationship between student statistic self-efficacy, the three facets of engagement, and statistical understanding. The measurement model is manifested in the relationships between the constructs and the indicator variables, or factors (Hair, et al. 2017).

Paths to be Analyzed
Statistics Self-Efficacy, start of semester -> Behavioral Engagement
Statistics Self-Efficacy, start of semester -> Cognitive Engagement
Statistics Self-Efficacy, start of semester -> Motivational Engagement
Behavioral Engagement -> Statistics Self-Efficacy, end of semester
Cognitive Engagement -> Statistics Self-Efficacy, end of semester
Motivational Engagement -> Statistics Self-Efficacy, end of semester
Statistics Self-Efficacy, end of semester -> Statistical Understanding
Statistics Self-Efficacy, start of semester -> Behavioral Engagement -> Statistics Self-Efficacy, end of semester
Statistics Self-Efficacy, start of semester -> Cognitive Engagement -> Statistics Self-Efficacy, end of semester
Statistics Self-Efficacy, start of semester -> Motivational Engagement -> Statistics Self-Efficacy, end of semester
Statistics Self-Efficacy, start of semester -> Behavioral Engagement -> Statistics Self-Efficacy, end of semester -> Statistical Understanding
Statistics Self-Efficacy, start of semester -> Cognitive Engagement -> Statistics Self-Efficacy, end of semester -> Statistical Understanding
Statistics Self-Efficacy, start of semester -> Motivational Engagement -> Statistics Self-Efficacy, end of semester -> Statistical Understanding

Table 3: Paths Analyzed

Path models are developed on two types of theory: measurement theory and structural theory. Measurement theory specifies how the constructs are measured, while structural specifies how the constructs are related to each other in the structural model (Hair, et al., 2017). This study's path model was based on the structural theory proposed by Linnenbrink & Pintrich (2003) and the measurement theory from CSSE (Finney & Schraw, 2003), MSLQ (Pintrich, Smith, Garcia, & McKeachie, 1993), SATS (Schau, Stevens, Dauphinee, & Del Vecchio, 1995), and CAOS (delMas, Garfield, Ooms, & Chance, 2007) instruments. Table 3 outlines the paths that were analyzed in this study.

Study Reliability and Validity

The quality of a study can be judged by validity and validity is assessed in three ways: internal, external, and measurement (Gliner, Morgan, & Leech, 2009). The current study only had one group of subjects and this influences interval validity. This means there is inherent bias because no comparisons are made to another group which means the results should not be interpreted as evidence of causation no matter the strength of the statistical association (Gliner et al., 2009). Even though this study cannot establish causal relationships, it can be mentioned that the constructs were ordered by points of time during each semester. When measurements are ordered on the basis of time, it is possible that one event may impact another event if that event precedes the other event chronologically. This comes into play in the current study by the timing of when each metric was administered: demographics and self-efficacy were measured at the semester's beginning, engagement constructs were measured at the semester's middle, and self-efficacy was measured again along with statistical understanding at the semester's end.

External validity relates to generalizability (Gliner et al., 2009) and there are two criteria to evaluate this: population and ecological. Population external validity assesses how a sample represents the population from whence it comes. Since student participants self-selected which section and semester to sign-up for the introductory statistics class, it can be safely assumed that the sample in this study is representative of students who would enroll in and complete the non-mathematical introductory statistics course at this community college. As for ecological external validity, the participants were measured in a natural setting under normal conditions because student experiences and understanding were measured in their normal environment rather than a lab. Additionally, most higher education students are accustomed to filling out surveys and test forms. So, even though these surveys were unfamiliar to the participants, the process of completing a survey was not unfamiliar to them. Thus participant experiences took place in a natural setting under normal conditions.

The metrics that were used to measure the constructs of self-efficacy toward statistics, student engagement, and statistical conceptual understanding were developed by other researchers. Each group of researchers evaluated the measurement reliability and measurement validity for their particular instrument (Finney & Schraw, 2003; Pintrich, Smith, Garcia, & McKeachie, 1993; Schau, Stevens, Dauphinee, & Del Vecchio, 1995; and delMas, Garfield, Ooms, & Chance, 2007). However, it was not assumed that the behavior of each metric would be as reported in previous research by these respective researchers and so exploratory factor analysis was used to assess the clustering of items in each instrument. Adjustments were made to improve aspects of the design based on the results of exploratory factor analysis.

Chapter Three Summary

Affective factors that might influence the development of important statistical conceptual understandings by those who take the required non-mathematical introductory statistics course at a community college will be investigated with a structural equation model based on Linnenbrink and Pintrich's (2003) general framework of self-efficacy, engagement, and learning. It is of interest to understand the relationship among these characteristics so the learning needs of these students can be addressed with the hope of decreasing the number of students who withdraw from/fail the introductory course and are thereby inhibited in their progress toward earning their degree. This study will also serve to further our understanding of community college students' experiences and achievement in the introductory statistics course.

CHAPTER FOUR: RESULTS

Introduction

This study was concerned with affective factors that were hypothesized to influence the development of important statistics conceptual understandings by those who take the required non-mathematical introductory statistics course at the community college level. Student's self-efficacy toward statistics and engagement choices were thought to influence their conceptual understandings of important statistical ideas upon course completion (Pintrich, 2000; Bandalos, Finney, Geske, 2003); Pintrich, Smith, Garcia, & McKeachie, 1993; Onwuegbuzie, 2000; Hackett & Betz, 1989; Pajares, 1996; Pajares & Miller, 1995; Zeldin & Pajares, 2000). Improving instruction should be the key goal of any educational research and research into issues that concern statistics education should maintain focus on this goal (Zieffler, Garfield, Alt, Dupuis, Holleque, & Chang, 2008). It is of interest to understand the relationship among these characteristics so the learning needs of these students can be addressed with the hope of decreasing the number of students who withdraw from/fail the introductory course and are thereby inhibited in their progress toward earning their degree and fulfilling their educational goals.

This chapter presents demographic information and results from the analysis of data collected to answer the research questions and hypotheses:

1. Is student conceptual understanding of statistics positively influenced by self-efficacy to learn statistics?

H_0: Student conceptual understanding of statistics is not positively influenced by self-efficacy to learn statistics.

H_a: Student conceptual understanding of statistics is positively influenced by self-efficacy to learn statistics.

2. Is the effect of self-efficacy on student conceptual understanding of statistics mediated by behavioral engagement, cognitive engagement, and motivational engagement?

H_0: The influence of self-efficacy on student conceptual understanding of statistics is not mediated by behavioral engagement.

H_a: The influence of self-efficacy on student conceptual understanding of statistics is mediated by behavioral engagement.

H_0: The influence of self-efficacy on student conceptual understanding of statistics is not mediated by cognitive engagement.

H_a: The influence of self-efficacy on student conceptual understanding of statistics is mediated by cognitive engagement.

H_0: The influence of self-efficacy on student conceptual understanding of statistics is not mediated by motivational engagement.

H_a: The influence of self-efficacy on student conceptual understanding of statistics is mediated by motivational engagement.

Preliminary Analysis

Once data collection was complete, the data set was analyzed for missingness. Dong and Peng (2013) recommend that researchers closely examine a data set for missingness and try to determine the missing mechanism, missing rate, and missing pattern before deciding on an appropriate method to deal with missingness. A missing value happens when a participant either does not answer a question in a survey (item nonresponse) or they participate in some but not all of the surveys (wave nonresponse) (Schafer & Graham, 2002). Thus, the recorded responses are not complete for that individual and one should consider whether there is a pattern in the missingness. That is, whether the observations are missing completely at random (MCAR), missing at random (MAR), or missing not at random (MNAR) (Graham, 2009).

The data collected for this study was analyzed for missingness using SPSS. Students who withdrew from the course were removed from the data set prior to analyzing missingness (197 students participated in at least one of the data collection surveys and 36 withdrew from the course before semester's end). It was found that 98.5% of the variables contained missing data, 69.6% of the cases contained missing data, and 29.06% of the values contained missing data. The missingness should next be examined for the pattern of missingness.

If the missing pattern is missing at random (MAR), the probability of missing may depend on the observed data, but not on the unobserved data and missing completely at random (MCAR) is just a special case of MAR (Schafer & Graham, 2002). For MCAR, we think of the missing data as a random sample of all the cases. This means that everything a researcher desires to know about the data set as a whole can be estimated from any of the missing data patterns, including the pattern in which the data exist for all variables (Graham, 2009). For MAR, the probability of a missing value depends on the observed responses and not on the unobserved responses (Dong & Chao-

Ying, 2013). For example, in a study considering the relationship between substance abuse and self-esteem among high school students, frequent substance abuse may be associated with chronic absenteeism and this absenteeism would mean a respondent was not present when the self-esteem questionnaire was administered. This example qualifies as MAR, because the probability of a missing self-esteem value is completely determined by a student's substance use score (Baraldi & Enders, 2010).

In contrast, for missing not at random (MNAR), the probability of missing does depend on the unobserved data (Schafer & Graham, 2002). When the missingness is beyond the control of the researcher, then the distribution of missingness is unknown and one might only assume MAR but there is no way to test this assumption except by obtaining follow-up data from nonrespondents (Graham, 2002). For example, consider a reading test where poor readers fail to respond to certain test items because they do not understand the accompanying vignette. This example is MNAR because the probability of a missing reading score is directly related to reading ability (Baraldi & Enders, 2010).

The consequences for these missingness patterns can mean a loss of statistical power for all three patterns and could possibly yield biased parameter estimates for the MNAR pattern (Graham, 2002). However, Collins, Shaver, and Kam (2001) successfully demonstrated that in many realistic settings, an invalid assumption of MAR may only have a minor effect on estimates and standard errors.

In looking at the pattern of missingness for this data set, it is determined that the pattern of missing is MNAR. If a student is less engaged in the introductory statistics course, then he/she is less likely to choose to participate in this study that is measuring statistics self-efficacy, engagement characteristics, and statistical understanding.

Additionally, a student who has low levels of statistical self-efficacy is less likely to choose to engage in studying and learning for the course and will not gain much in the way of statistical understanding by semester's end. This would imply that the probability for missing values is dependent upon the missing values themselves.

There are techniques that researchers have traditionally used to deal with missingness in data. The most common techniques involve deletion and single imputation approaches. Deletion techniques include listwise deletion (also called complete-case analysis or casewise deletion) and pairwise deletion (also known as available-case analysis). Single imputation techniques are those where the researcher imputes (i.e. fills in) the missing data with seemingly suitable replacements like the mean of the variable or regression imputation (Baraldi & Enders, 2010; Olinsky, Chen, & Harlow, 2003; Graham, 2009; Shafer & Graham, 2002).

Disappointingly, the traditional missing data handling methods produce accurate estimates for the missing values only when the data is MCAR and perform poorly with MNAR data. In fact, these methods introduce bias into the data set and reduce power (Baraldi & Enders, 2010; Shafer & Graham, 2002; Olinsky, Chen, & Harlow, 2003; Graham, 2009). Additionally, these methods decrease the variability in the data and likely reduce the possibility of finding meaningful relationships (Hair, Hult, Ringle, & Sarstedt, 2017).

Modern methods that try to maintain power and decrease bias include model-based methods like maximum likelihood and multiple imputation. According to Baraldi and Enders (2010), "maximum likelihood and multiple imputation tend to fare better than most traditional approaches" in terms of preventing bias and maintaining power. For maximum likelihood estimation, the method estimates the set of parameters for analysis based only on the data that exists. This method creates unbiased parameter estimates when the data are MCAR or MAR but the standard errors (SE) of the parameters are biased downward.

Another modern method is multiple imputation. This method will "fill in" missing data values using a specified regression model. This "fill in" step is repeated *n* times which results in *n* separate data sets. Analyses that follow multiple imputation should be performed on a data set that is the average of all *n* data sets. A disadvantage of this method is there can be room for error when specifying the regression model. An advantage of this method is that the variability and standard errors in the data set are preserved because of the *n* repetitions to "fill in" the missing values (Baraldi & Enders, 2010; Shafer & Graham, 2002; Olinsky, Chen, & Harlow, 2003; Graham, 2009). Multiple imputation also has the advantage of actually replacing the missing data items.

Baraldi and Enders (2010) acknowledge that maximum likelihood and multiple imputation are not a perfect solution to the problem of missing data and they warn that these methods may yield biased parameter estimates when the data are MNAR. They go on to explain that the magnitude of this bias tends to be less than the bias that results from the traditional methods. However, Shafer & Graham (2002) purport that maximum likelihood and multiple imputation are often unbiased with MNAR data even though these methods assume the missing data pattern is MAR. With this information in mind, it was determined that multiple imputation would be used to "fill in" the missing data values for this data set so it could be used for structural equation model analysis, because SEM requires a full set of observations in order to run the analysis (Hair, Hult, Ringle, &

Sarstedt, 2017). One hundred ninety-seven (197) students completed at least one of the surveys. Thirty-six (36) students withdrew from the course, leaving one hundred sixty-one (161) participants for analysis.

Shafer and Graham (2002) explain that Rubin, who proposed multiple imputation, showed the efficiency of an estimate based in *n* imputations, relative to an estimate based on an infinite number of imputations is $(1 + \lambda n)^{-1}$, where λ is the rate of missing information. For this data set, the rate of missing was found to be 29.06%. This formula was used to decide the number of imputations to run: the efficiency for n=5 imputations was .945, the efficiency for n=10 imputations was .972, and the efficiency for n=20 imputations was .986. The gain in efficiency from 10 to 20 imputations was determined to not do much to remove unwanted noise in the estimates, but the gain in efficiency from 5 to 10 was determined to be worth the time and effort (Shafer & Graham, 2002).

Using SPSS, n=10 imputations were ran on the data to "fill in" the missing values for the data set. All of the variables from CSSE-1, CSSE-2, MSQL, SATS, GOALS, and MOST, along with most of the demographics variables and final grade were ran through the imputation analysis. Even though demographic variables were not used as part of the analysis, including as many responses as possible from a participant further informs the imputation process. Shafer & Graham (2002) recommend using all available data for the imputation analysis. "A crucial feature of MI (multiple imputation) is that the missing values for each participant are predicted from his or her own observed values, with random noise added to preserve a correct amount of variability in the imputed data" (Shafer & Graham, 2002). The dependent variable is included in the imputation process so that all relevant parameter estimates are unbiased, while excluding the dependent variable has been shown to produce biased estimates (Graham, 2009). Graham (2009) explains that leaving out the dependent variable will cause the correlations between it and the independent variables to be suppressed (i.e., biased) toward zero. After ten imputations were obtained (i.e., ten separate data sets of complete observations), the average of all data values was obtained for further analysis.

Demographic information was collected on each participant gender, age, race, citizenship, current GPA, number of credits earned toward degree, number of high school math/statistics courses taken, number of college math/statistics courses taken, grade earned in the prerequisite course, and type of degree being pursued. Prior to performing the multiple imputation on the 161 participants, the demographic summaries were obtained on the 197 participants. A summary of the demographic findings is displayed in Table 4.

	n	Percent
Major		
Arts/Humanities	3	2.0
Science and Mathematics	12	7.9
Medicine	39	25.5
Psychology	25	16.3
Sociology/Social Work	20	13.1
Other	54	35.5
Number of high school math courses		
0	2	1.3
1	5	3.3
2	8	5.3
3	38	25.3
4	75	50.0
5	17	11.3
6-12	5	3.4

Table 4: Descriptive Statistics for Demographic Data

Number of college math courses		
0	2	1.3
1	31	20.3
2	72	47.1
3	28	18.3
4	14	9.2
5	2	1.3
6	4	2.6
Grade earned in prerequisite class		
A	50	32.7
B	62	40.5
C	41	26.8
Degree seeking		
Associate	74	48.4
Bachelors	69	45.1
Masters	4	2.6
Doctorate	2	1.3
Certification	2	1.3
Other	2	1.3
Expected Grade from this class		
A	85	55.9
B	58	38.2
C	9	5.9
Type of Class		
Face-to-face	127	83.0
Online	26	17.0
Gender		
Male	31	20.3
Female	122	79.7
Citizenship		
US Citizen	144	94.7
Foreign Student	3	2.0
Other	5	3.3
Age		
17	4	2.6
18	11	7.2
20	32	21.1
21	17	11.2
22	12	7.9
23	11	7.2
24-29	15	9.9
30-39	13	8.6
40-46	8	5.4
Race		
American Indian or Alaskan	2	1.3
Asian	1	.7
African American	5	3.3
Hispanic/Latino	105	69.1
White	28	18.4
Two or more races	11	7.3

Table 4 Continued

The breakdown by major shows 25.5% of participants were studying medicine, 16.3% were studying psychology, 13.1% were studying social work, 7.9% were studying the sciences and math, 2% were studying humanities, and 35.5% were declared other as their major. Fifty percent (50%) of participants reported they had taken four math classes in high school, 25.3% reported taking three high school math classes, and 11.3% reported taking five classes. Forty-seven percent (47.1) reported they had taken two college math classes prior to taking introductory statistics, 18.3% reported taking three college math classes, and 20.3% reported taking one college math class prior to taking introductory statistics. Students must satisfy a prerequisite before taking the course; 32.7% reported earning an A in the prerequisite course, 40.5% reported earning a B, and 26.8% reported earning a C. Eighty-three percent (83%) of participants were enrolled in a face-to-face class while 17.0% were enrolled in an online class. The breakdown of gender showed 20.3% were male and 79.7% were female. The breakdown by citizenship showed 94.7% of participants are U.S. citizens, 2% are foreign students and 3.3% reported their citizenship status was other. The range in ages for the participants is 17 – 46. The majority of students were ages 19 (19.1%), 20 (21.1%) and 21 (11.2%); however, 9.9% were between 24 – 29, 8.6% were between 30 – 39, and 5.4% were between 40 – 46. A high percentage of students are Hispanic/Latino (69.1%), followed by 18.4% white, 6.6% two or more races, 3.3% African American, 1.3% American Indian or Alaskan, and 0.7% Asian.

Prior to conducting exploratory and confirmatory factor analysis the data were analyzed for normality and skewness. Each questionnaire was analyzed separately in SPSS (CSSE, MSQL, and SATS). The GOALS and MOST were not analyzed because these questions were measuring understanding, not student characteristics. According to Leech, Barrett, and Morgan (2011), if the skewness is less than 2.5, then skewness is not significantly different from the normal model and kurtosis does not seem to affect the results of most statistical analyses very much. However, according to Fabrigar, Wenger, MacCallum, and Strahan (1999), when skewness is less than 2.00 and kurtosis is not greater than 7.00, then the variables are not adversely affected when analyzing data using factor analysis.

Factor	Range of Scores for Factor	Mean (M)	Standard Deviation (STDEV)	Skewness	Standard Error (STERR)	Kurtosis	Standard Error (STERR)
CSSE1-A	1 – 54	25.444	.0729	.593	.191	.319	.380
CSSE1-B	1 – 30	10.511	.389	1.271	.191	1.687	.380
CSSE2-A	1 – 42	27.795	.448	-.061	.191	.832	.380
CSSE2-B	1 – 42	22.662	.410	.184	.191	.827	.380
BE1	1 – 35	23.697	.397	-.268	.191	.241	.380
BE2	1 – 21	14.954	.261	-.340	.191	.495	.380
BE3	1 – 14	7.623	/268	-.005	.191	-.599	.380
BE4	1 – 21	16.283	.197	-.298	.191	.501	.206
BE5	1 – 14	7.208	.206	.270	.191	.344	.380
CE1	1 – 35	21.166	.440	-.047	.191	.827	.380
CE2	1 – 42	27.364	.477	.156	.191	.668	.380
CE3	1 – 35	20.053	.397	.389	.191	1.225	.380
CE4	1 – 42	31.321	.380	-.650	.191	3.421	.380
CE5	1 – 21	15.491	.241	-.343	.191	.294	.380
ME1	1 – 7	4.255	.092	-.046	.191	.191	.380
ME2	1 – 7	3.785	.101	.369	.191	.729	.380
ME3	1 – 7	4.509	.094	-.254	.191	.838	.380
ME4	1 – 7	5.347	.090	-.519	.191	.711	.380
GOALS	0 – 100	47.825	.802	-.408	.191	.727	.380
MOST	0 – 100	33.635	1.585	.602	.191	.067	.380
FG	0 – 4	1.93	1.367	-.013	.191	-1.140	.380

Table 4: Means, Standard Deviations, Skewness, and Kurtosis

Normality and Skewness tests were performed on each of the factors for the variables Self Efficacy at start of semester, Self-Efficacy at end of semester, Behavioral Engagement, Cognitive Engagement, Motivational Engagement, and Statistical Understanding. It should be noted that these factors were aligned according to the factor analysis that is discussed in the next section. The summary statistics are given in Table 5. None of the factors were significantly skewed and all of the factors were significantly non-Normal (Table 6).

	Kolmogorov-Smirnov			Shapiro-Wilks		
Factor	Statistic	df	P-Value	Statistic	df	P-Value
CSSE1-A	.101	161	.000	.968	161	.001
CSSE1-B	.183	161	.000	.877	161	.000
CSSE2-A	.141	161	.000	.945	161	.000
CSSE2-B	.163	161	.000	.955	161	.000
BE1	.094	161	.002	.974	161	.004
BE2	.110	161	.000	.969	161	.001
BE3	.134	161	.000	.942	161	.000
BE4	.118	161	.000	.959	161	.000
BE5	.123	161	.000	.965	161	.000
CE1	.129	161	.000	.967	161	.001
CE2	.120	161	.000	.965	161	.000
CE3	.137	161	.000	.959	161	.000
CE4	.126	161	.000	.938	161	.000
CE5	.133	161	.000	.957	161	.000
ME1	.135	161	.000	.961	161	.000
ME2	.145	161	.000	.943	161	.000
ME3	.137	161	.000	.954	161	.000
ME4	.108	161	.000	.938	161	.000
GOALS	.134	161	.000	.969	161	.001
MOST	.089	161	.004	.965	161	.000
FG	.161	.161	.000	.892	161	.000

Table 5: Tests of Normality

Exploratory Factor Analysis

Each instrument was analyzed with factor analysis to ensure that the data from the respective survey measures the construct they were intended to measure. This analysis was necessary in order to determine the proper course of action for the SEM process. It should be noted that this data set is unique to the setting in which it was collected: a small community college along the southwest Arizona border, close to Mexico with a high percentage of Hispanic students. Accordingly, it should not be unexpected that the factor loadings were unique to this data set and different from previous research.

The factor analysis found that the items clustered differently, forming somewhat different factors than reported in previous research. Principal components analysis with promax rotation was conducted to assess how the variables in each instrument clustered. There are two basic types of rotation: orthogonal and oblique. Orthogonal rotation methods assume that the factors in the analysis are uncorrelated while oblique rotation methods assume that the factors are correlated. Factors in psychological research are rarely uncorrelated and independent. According to Maurice (1957), "On a priori grounds it is plausible to expect that the underlying dimensions in this domain [psychological] would be correlated." She goes on to say that simple structure is best obtained by oblique rotation methods without the restrictive assumptions for orthoganality and the researcher will find a considerably better fit of the data to the model. Linnenbrink & Pintrich (2003), believe that all three components of engagement are correlated both among the three components and between the three components. Brown (2009) demonstrated that when "identification of the basic structuring of variables into theoretically meaningful subdimensions is the primary concern of the researcher," then any method of rotation would be successful in finding said structure. As such, promax rotation was selected to allow for the factors to be correlated (Brown, 2009; Maurice, 29576; IBM, 2017).

Item	Component Loading		
	1	2	Communality
Explain the difference between a sampling distribution and a population distribution	.91		.65
Interpret the results of a statistical procedure in terms of the research question	.87		.71
Identify if a distribution is skewed when given values of three measures of central tendency	.96		.61
Identify the scale of measurement for a variable	.78		.56
Select the correct statistical procedure to be used to answer a research question	.72		.71
Identify the factors that influence power	.60		.62
Identify when the mean, median, and mode should be used as a measure of central tendency	.50		.61
Distinguish between a population parameter and a sample statistic	.47		.64
Explain what the value of the standard deviation means in terms of the variable being measured	.45		.64
Distinguish between a Type I error and a Type II error n hypothesis testing		1.09	.88
Distinguish between the information given by the three measures of central tendency		.94	.87
Explain what the numeric value of the standard error is measuring		.89	.78
Distinguish between the objectives of descriptive versus inferential statistical procedures		.87	.82
Interpret the probability value (p-value) from a statistical procedure		.45	.61
Eigenvalues	6.26	4.24	
% of variance	60.12	9.20	

Table 6: Component Loadings for Rotated Components of CSSEpre

<u>The Current Statistics Self-Efficacy (CSSE)</u>

This instrument consisted of fourteen questions that originally loaded as a single factor for statistics self-efficacy. For the CSSE administered at the beginning of the semester, two factors were rotated, based on the eigenvalues over 1 criterion and the scree plot. After rotation, the first factor consisting of 9 questions (statistics self-efficacy with regards to theory) accounted for 60.2% of the variance and the second factor consisting of the remaining 5 questions (statistics self-efficacy with regards to interpretation) accounted for 9.2% of the variance. Table 7 displays the items and component loadings for the rotated components, with loadings less than .30 omitted to improve clarity. To assess whether the data form two reliable scales, Cronbach's alpha was computed for each scale. The theory scale had an alpha of .92 and the interpretation scale had an alpha of .93 indicating good internal consistency.

Item	Component Loading		
	1	2	Communality
Identify when the mean, median, and mode should be used as a measure of central tendency	1.00		.71
Distinguish between a population parameter and a sample statistic	.81		.68
Explain the difference between a sampling distribution and a population distribution	.81		.70
Explain what the value of the standard deviation means in terms of the variable being measured	.76		.62
Identify if a distribution is skewed when given values of three measures of central tendency	.69		.54
Interpret the probability value (p-value) from a statistical procedure	.67		.64
Select the correct statistical procedure to be used to answer a research question	.43		.50
Distinguish between the objectives of descriptive versus inferential statistical procedures		1.01	.70
Distinguish between the information given by the three measures of central tendency		.81	.67
Identify the factors that influence power		.73	.65
Distinguish between a Type I error and a Type II error n hypothesis testing		.61	.44
Explain what the numeric value of the standard error is measuring		.59	.68
Identify the scale of measurement for a variable		.52	.49
Interpret the results of a statistical procedure in terms of the research question		.45	.66
Eigenvalues	5.17	4.72	
% of variance	53.97	7.98	

Table 7: Component Loadings for Rotated Components of CSSEpost

The data from administration of CSSE at the end of the semester with the same 14 questions also showed two factors, but these were different than the first administration. After rotation, the first factor consisting of 7 questions (statistics self-efficacy with regards to descriptive skills) accounted for 54.0% of the variance and the second factor consisting of the remaining 7 questions (statistics self-efficacy with regards to inference skills) accounted for 8.0% of the variance. Table 8 displays the items and component loadings for the rotated components, with loadings less than .30 removed. Table 22, in

Chapter Five, shows a comparison of how the fourteen questions clustered for the two measurements of self-efficacy to learn statistics. To assess whether the data form two reliable scales, Cronbach's alpha was computed for each scale. The descriptive scale had an alpha of .89 and the inference scale had an alpha of .88 indicating good internal consistency.

The Motivated Strategies for Learning Questionnaire (MSLQ)

This instrument consisted of forty-two questions designed to measure three factors related to Behavioral Engagement and four factors related to Cognitive Engagement. The MSLQ was administered mid-semester to measure student choices with regards to Behavioral Engagement (BE) and Cognitive Engagement (CE). Ten factors were rotated based on the eigenvalues over 1 criterion and the scree plot. After rotation, the first factor (CE rehearsal) accounted for 22.82% of the variance, the second factor (CE elaboration) accounted for 8.33%, the third factor (CE organization) accounted for 5.92%, the fourth factor (BE effort) accounted for 5.14%, the fifth factor (CE metacognition) accounted for 4.43%, the sixth factor (CE critical thinking) accounted for 3.97%, the seventh factor (BE study environment) accounted for 3.66%, the eighth factor (BE help seeking) accounted for 3.12%, the ninth factor (BE persistence) accounted for 2.96% and the tenth factor (BE time management) accounted for 2.75%, accumulating to account for 63.10% of the variance. Two questions loaded solo as factors eleven and twelve. These questions were "Even if I have trouble learning the material in this class, I try to do the work on my own, without help from anyone" and

Item	Component Loadings									
	1	2	3	4	5	6	7	8	9	10
I make lists of important items for this course and memorize the lists	.74									
I make sure that I keep up with the weekly readings and assignments for this course	.69									
When I study for this course, I write brief summaries of the main ideas from the readings and my class notes	.66									
When I study the readings for this course, I outline the material to help me organize my thoughts	.65									
When I study for this course, I go over my class notes and make an outline of important concepts	.63									
I try to relate ideas in this subject to those in other courses whenever possible		.99								
When I study for this class, I practice saying the material to myself over and over		.66								
I try to apply ideas from course readings in other class activities such as lecture and discussion		.56								
I try to understand the material in this class by making connections between the readings and the concepts from the lectures		.54								
When reading for this class, I try to relate the material to what I already know		.43								
If course readings are difficult to understand, I change the way I read the material		.43								
If I get confused taking notes in class, I make sure I sort it out afterwards			.78							
When reading for this course, I make up questions to help focus my reading			.63							
I ask myself questions to make sure I understand the material I have been studying in this class			.60							
When I study for this class I set goals for myself in order to direct my activities in each study period			.52							
I make simple charts, diagrams, or tables to help me organize course material			.42							

Table 8: Component Loadings for Rotated Components of MSLQ

	1	2	3	4	5	6	7	8	9	10
I often find that I have been reading for this class but don't know what it was all about				.81						
I rarely find time to review my notes or readings before an exam				.58						
During class time I often miss important points because I'm thinking of other things				.55						
When course work is difficult, I either give up or only study the easy parts				.48						
I often feel so lazy or bored when I study for this class that I quit before I finish what I planned to do				.45						
When studying for this course I try to determine which concepts I don't understand well					.78					
When I become confused about something I'm reading for this class, I go back and try to figure it out					.64					
When I study for this class, I pull together information from different sources, such as lectures, readings, and discussions					.62					
I try to think through a topic and decide what I am supposed to learn from it rather than just reading it over when studying for this course					.50					
I work hard to do well in this class even if I don't like what we are doing					.45					
I memorize key words to remind me of important concepts in this class					.44					
When studying for this course, I read my class notes and the course readings over and over again						.87				
When I study for this course, I go through the readings and my class notes to try to find the most important ideas						.63				
Before I study new course material thoroughly, I often skim it to see how it is organized						.54				
I usually study in a place where I can concentrate on my course work							.88			
I have a regular place set aside for studying							.85			
I make good use of my study time for this course							.43			

Table 9 Continued

	1	2	3	4	5	6	7	8	9	10
I try to identify students in this class whom I can ask for help if necessary								.89		
When I can't understand the material in this course, I ask another student in this class for help								.87		
I attend this class regularly									1.06	
Even when course materials are dull and uninteresting, I manage to keep working until I finish									.61	
I try to change the way I study in order to fit the course requirements and the instructor's style									.43	
I find it hard to stick to a study schedule										.84
I often find that I don't spend very much time on this course because of other activities										.53
Eigenvalues	3.37	3.61	2.95	2.87	3.43	2.04	2.16	1.76	2.10	1.37
% of variance	22.8	8.33	5.92	5.14	4.43	3.97	3.66	3.12	2.96	2.75

Table 9 Continued

"I ask the instructor to clarify concepts I don't understand well". Consequently, these two questions were eliminated from the analysis.

Table 9 displays the items and component loadings for the rotated components, with loadings less than .30 removed. To assess whether the data form ten reliable scales, Cronbach's alpha was computed for each Scale. These alphas range from .52 to .80; three scales were below .70, but the rest were above .70 indicating good internal consistency for seven scales and minimally adequate reliability for three scales.

The Survey of Attitudes Toward Statistics (SATS)

This instrument consists of eighteen questions designed to measure three factors with regards to Motivational Engagement. The SATS was administered to measure student choices with regards to Motivational Engagement (ME). Four factors were rotated based on the eigenvalues over 1 criterion and the scree plot. After rotation, the first factor (ME interest) accounted for 36.75% of the variance, the second factor (ME affect) accounted for 13.12%, the third factor (ME value) accounted for 7.34%, and the fourth factor (ME application) accounted for 6.12%, accumulating to account for 63.37% of the variance. One question loaded solo as factor five. This question was "Statistical skills will make me more employable". Consequently, this question was eliminated from the analysis.

Table 10 displays the items and component loadings for the rotated components, with loadings less than .30 removed. To assess whether the data form two reliable scales, Cronbach's alpha was computed for each scale. These alphas range from .54 to .90; one scale was below .70, but the rest were above .70 indicating good internal consistency for three scales and minimally adequate reliability for one scale.

Item	Component Loading				
	1	2	3	4	Communality
I am interested in learning statistics	.88				.74
I like statistics	.87				.84
I enjoy statistics courses	.84				.74
I am interested in using statistics	.82				.83
I am interested in being able to communicate statistical information to others	.71				.68
I am interested in understanding statistical information	.70				.69
I use statistics in my everyday life	.56				.61
Statistical thinking is not applicable in my life outside of my job	.38				.53
I get frustrated going over statistics tests in class		.81			.61
I feel insecure when I have to do statistics problems		.80			.64
I am scared by statistics		.72			.63
I am under stress during statistics class		.66			.81
Statistics should be a required part of my professional training			.79		.75
Statistical skills will make me more employable			.69		.74
I will have no application for statistics in my profession			.66		.61
Statistics is irrelevant in my own life				.81	.66
Statistics is worthless				.70	.57
Eigenvalues	5.77	2.99	2.14	1.51	
% of variance	36.75	13.16	7.34	6.12	

Table 9: Component Loadings for Rotated Components of Motivational Engagement

Structural Equation Model

In response to the exploratory factor analysis indicating that factors clustered differently than reported in previous research thus forming somewhat different factors, the model for the current study was adjusted from what Linnenbrink & Pintrich (2003) proposed, see Figure 3. Self-efficacy was split into two variables to reflect the two different time periods when it was measured: start of semester (CSSE1) and end of semester (CSSE2). Each of these variables had two factors to reflect student self-efficacy to learn statistics at the particular time point. The first measure of self-efficacy was kept at the start of the path model and the second measure of self-efficacy placed to the right of the engagement variables with their paths flowing through it to reach statistical conceptual understanding where the paths ended. Because it is proposed that self-efficacy influenced statistical understanding, this ordering of variables preserved the proposed relationship.

After completing exploratory factor analysis, the next step is to investigate the relationship of statistics self-efficacy, behavioral engagement, cognitive engagement, motivational engagement, and statistical conceptual understanding. This study was exploring the relationship between statistics self-efficacy, engagement variables, and statistical understanding for community college students taking an introductory statistics course.

As such, this study sought to evaluate whether the model inspired by Linnenbrink and Pintrich's model from Figure 1 represents (or fits) the relationship of these variables in relation to community college students taking an introductory statistics course.

Testing Linnenbrink & Pintrich's (2003) general framework with community college students will serve to lessen the gap that exists among the body of research in statistical education about the experience of these students in this course. Additionally, this study would like to determine if statistical self-efficacy, behavioral engagement, cognitive engagement, and motivational engagement can predict and explain the variance in statistical understanding.

Structural equation modeling (SEM) is a multivariate analysis method that simultaneously analyzes multiple variables that represent measurements associated with individual, companies, events, etc. SEM is best used to either explore or confirm theory (Hair, et al. 2017). These types of statistical models are used primarily to evaluate whether theoretical models are plausible when compared to observed data. SEMS allow for the representation of complex theory in a single integrated model and enable researchers to incorporate unobservable variables measured indirectly by indicator variables. One of the strengths of this tool is that it facilitates the accounting for measurement error in observed variables.

There are two types of SEM: covariance-based SEM (CB-SEM) and partial least squares SEM (PSL-SEM). A researcher who is seeking to confirm theories should choose to use CB-SEM whereas a researcher desiring to study a realm where theory is less developed may use PLS-SEM to develop theory. A researcher would choose Partial Least Squares SEM (PLS-SEM) when the research objective is theory development and explanation of variance. PLS-SEM focuses on explaining the variance in the dependent variables when examining the model. In the words of Hair, Hult, Ringle, and Sarstedt (2017), through PLS-SEM "we can determine how well the theory fits the data" (p.105).

Coded Name	Variable
Latent Trait	
SEpre	Current Statistics Self Efficacy, start of semester
Indicators	
CSSE1-A	Statistical self-efficacy with regards to theory
CSSE1-B	Statistical self-efficacy with regards to interpretation
Latent Trait	
BE	Behavioral Engagement
Indicators	
Table 11 Continued	
BE1	Effort
BE2	Environment
BE4	Persistence
BE5	Time management
Latent Trait	
CE	Cognitive Engagement
Indicators	
CE1	Rehearsal
CE2	Elaboration
CE3	Organization
CE4	Metacognition
CE5	Critical Thinking
Latent Trait	
ME	Motivational Engagement
Indicators	
SATS_1	Interest
SATS_2	Affect
SATS_3	Value
SATS_4	Application
Latent Trait	
SEpost	Current Statistics Self Efficacy, end of semester
Indicators	
CSSE2-A	Statistical self-efficacy with regards to descriptive skills
CSSE2-B	Statistical self-efficacy with regards to inference skills
Latent Trait	
SU	Statistical Understanding
Indicators	
GOALS_percent	Percent correct on the GOALS question subset of CAOS
MOST_percent	Percent correct on the MOST question subset of CAOS
FG	Final grade for the course

Table 10: Description of Labels

The goal of PLS-SEM is to maximize the amount of explained variance (i.e., the value of R^2) "of the endogenous latent variables in the PLS path model" (Hair, et al., 2017, p.105). To accomplish this goal, the evaluation of the quality of the PLS-SEM measurement and structural models focuses on ways to measure the model's predictive capabilities. Hair et al., (2017), explain, "as with CB-SEM, the most important measurement model metrics for PLS-SEM are reliability, convergent validity, and discriminant validity. For the structural model, the most important evaluation metrics are R^2 (explained variance), f^2 (effect size), and the size and statistical significance of the structural path coefficients" (p.105). Table 11 gives a description for the latent traits and their indicators in SmartPLS.

Measurement Model Analysis

The outer loadings of the indicators are shown in Table 12. It is preferred, as a rule of thumb, for the outer loading to be 0.70 or higher. However, Hulland (1999) explained that researchers frequently obtain weaker outer loadings in studies such as this that seek to explore theory, in which case, outer loadings between 0.40 and 0.70 are acceptable. Factor loadings that are less than 0.40 are marked with an asterisk (*). Three items loaded below the acceptable level and they are all indicators on the Behavioral Construct. Two of these indicators were just below 0.4, but BE3 was considerably below the 0.4 level. However, because of the nature of this study being exploratory, these indicators were not removed from the analysis.

The reliability and validity statistics are presented in Table 13. Average Variance Extracted (AVE) is a common measure to establish convergent validity on the construct level. An AVE value of 0.5 or higher indicates that the construct, on average, explains more than half of the variance of its indicators (Bagozzi & Yi, 1988). On the other hand, when AVE is less than 0.5, this indicates that, on average, more variance remains in the error of the items than in the variance explained by the construct (Hair, et al., 2017). As denoted with an asterisk, the BE construct falls considerably below 0.5 and the ME construct falls just below 0.5, but again, since the nature of this study is exploratory, these constructs were not removed from the analysis.

Indicators	Construct	Outer Loadings
CSSE1-A	SEpre	0.937
CSSE1-B	SEpre	0.945
BE1	BE	0.925
BE2	BE	0.395*
BE3	BE	0.191*
BE4	BE	0.362*
BE5	BE	0.723
CE1	CE	0.713
CE2	CE	0.844
CE3	CE	0.772
CE4	CE	0.780
CE5	CE	0.726
SATS_1	ME	0.732
SATS_2	ME	0.831
SATS_3	ME	0.495
SATS_4	ME	0.570
CSSE2-A	SU	0.950
CSSE2-B	SU	0.937
GOALS_percent	SEpost	0.517
MOST_percent	SEpost	0.860
FG	SEpost	0.762

Table 11: Outer Loadings

Bagozzi and Yi (1988) have stated that the internal consistency reliability measures, composite reliability and Cronbach's alpha, should be 0.7 or higher. However, Hair et al. (2017) state these should be between 0.60 and 0.90. As shown in Table 13, all composite reliability measures are within the recommended range, but BE's and SU's Cronbach's alpha are below 0.60, denoted with an asterisk. Early research investigating internal consistency reliability suggested that coefficients in the range of .60 were considered acceptable for exploratory work (Nunnally, 1967).

Construct	AVE	Sqrt(AVE)	Composite Reliability	Cronbach's Alpha
SEpre	0.886	0.941	0.939	0.871
BE	0.340*	0.583	0.671	0.547*
CE	0.591	0.769	0.878	0.833
ME	0.449*	0.670	0.758	0.678
SEpost	0.890	0.943	0.942	0.877
SU	0.529	0.727	0.764	0.551*

Table 12: Reliability and Validity

The extent to which a construct is strictly distinct from other constructs by empirical standards is discriminant validity (Hair et al., 2017). Hair et al. describe two methods for measuring discriminant validity: cross loadings and the Fornell-Larcker criterion.

Indicator	SEpre	BE	CE	ME	SEpost	SU
CSSE1-A	**0.937**	0.105	0.150	0.091	0.253	0.102
CSSE1-B	**0.945**	-0.035	0.200	-0.058	0.087	-0.032
BE1	0.005	**0.925**	0.165	0.612	0.337	0.332
BE2	0.090	**0.395***	0.558	0.211	0.066	0.000
BE3	0.059	**0.191***	0.262	0.060	0.057	-0.131
BE4	0.094	**0.362***	0.508	0.148	0.037	-0.041
BE5	-0.006	**0.723**	0.249	0.391	0.129	0.146
CE1	0.076	0.216	**0.713**	0.089	0.118	-0.140
CE2	0.192	0.247	**0.844**	0.390	0.275	0.002
CE3	0.197	0.323	**0.772**	0.280	0.129	0.024
CE4	0.096	0.389	**0.780**	0.218	0.179	0.102
CE5	0.103	0.261	**0.726**	0.095	0.125	-0.092
SATS_1	0.089	0.408	0.419	**0.732**	0.222	0.155
SATS_2	-0.005	0.561	0.150	**0.831**	0.463	0.380
SATS_3	-0.040	0.231	0.269	**0.495**	0.106	0.084
SATS_4	-0.024	0.292	0.185	**0.570**	0.152	0.091
CSSE2-A	0.157	0.299	0.209	0.430	**0.950**	0.286
CSSE2-B	0.180	0.272	0.233	0.386	**0.937**	0.230
GOALS_percent	0.006	0.033	-0.037	0.094	0.119	**0.517**
MOST_percent	0.103	0.184	0.068	0.266	0.249	**0.860**
FG	-0.054	0.302	-0.080	0.336	0.208	**0.762**

Table 13: Cross-loadings

Table 14 displays the cross-loadings and Table 15 displays the Fornell-Larcker criterion. The cross –loadings should be lower than an indicator's outer loading on the associated construct. As denoted in the table with an asterisk, three of the BE indicators did not meet this criteria. However, because the nature of this study is exploratory, these were not removed from the analysis. Other than these three indicators, discriminant validity was maintained.

The Fornell-Larker criterion compares the square root of the AVE values with the latent variable correlations (Hair et al., 2017). "Specifically, the square root of each construct's AVE should be greater than its highest correlation with any other construct" (Hair et al, 2017, p.116). This method's logic is based on the idea that a construct should share more variance with its associated indicator than it does with any other construct. In Table 15, the number at the top of each column is the square root of that construct's AVE while the numbers below are the correlations with other constructs. As denoted with an asterisk, BE does not meet the criteria for discriminant validity. This construct was not removed from the analysis because the nature of this study is exploratory. All other constructs met the criteria for discriminant validity. However, recent research by Henseler, Ringle, & Sarstedt (2015) has found that neither the Fornell-Larcker criterion nor the performance of cross-loadings reliably detects discriminant validity issues. Apparently, cross-loadings fail to indicate a lack of discriminant validity when two constructs are perfectly correlated, which renders this criterion ineffective for empirical research. Additionally, the Fornell-Larcker criterion performs especially poorly when indicator loadings of the constructs under consideration differ only slightly.

Construct	BE	CE	ME	SEpost	SEpre	SU
BE	0.583*					
CE	0.369	0.769				
ME	0.611	0.320	0.670			
SEpost	0.303	0.234	0.434	0.944		
SEpre	0.034	0.187	0.015	0.177	0.941	
SU	0.259	-0.010	0.339	0.275	0.035	0.727

Table 14: Fornell-Larker Criterion

Hair et al. (2017) discuss Henseler's et al. (2015) remedy to the problems of assessing discriminant validity. They propose assessing the heterotrait-monotrait ratio (HTMT) of the correlations. This ratio is an estimate of what the true correlation between two constructs would be, if they were perfectly measured. Table 16 shows the Heterotrait-monotrait ratio (HTMT). If a HTMT value is close to 1, this indicates a lack of discriminant validity. According to this method proposed by Henseler et al. (2015), it appears that discriminant validity was maintained.

Construct	BE	CE	ME	SEpost	SEpre	SU
BE						
CE	0.857					
ME	0.714	0.421				
SEpost	0.298	0.251	0.428			
SEpre	0.177	0.200	0.110	0.207		
SU	0.450	0.208	0.388	0.378	0.121	

Table 15: Heterotrait-Monotrait Ratio (HTMT)

<u>Structural Model Analysis</u>

Once the construct measures have been reviewed for reliability and validity, the next step is to assess the structural model results. It is important to note that PLS-SEM estimates the parameters so as to maximize the explained variance of the endogenous latent variables. On the other hand, CB-SEM estimates the parameters so that the difference between the sample covariances and those predicted by the theoretical/conceptual model are minimized. This characteristic of CB-SEM lends to measures of model fit such as the chi-square goodness-of-fit statistic, which are based on the difference between the two covariance matrices (Hair et al., 2017). PLS-SEM does not have a comparable way to measure model fit. The inability to measure model fit has been viewed by many as a flaw (Henseler & Sarstedt, 2013).

Even though PLS-SEM was originally designed for prediction purposes, recent research has proposed methods to measure model fit for PLS-SEM and many of which are in early stages of development (Hair et al, 2017). Model fit indices allow researchers to judge how well a hypothesized model structure fits the empirical data and, thus will help to identify model misspecifications. Henseler et al. (2013) identified the standardized root mean square residual (SRMR), which is a model fit index well known from CB-SEM, as a way to measure model fit for PLS-SEM. Prior to their work, SRMR was not applied to PLS-SEM. The SRMR is defined as “the root mean square discrepancy between the observed correlations and the model-implied correlations” (Hair et al., 2017, p.193). SRMR is an absolute measure of fit so a value of zero indicates perfect fit. When measuring model fit for CB-SEM, Hu & Bentler (1998) suggest that a value less than 0.08 is considered a good fit. The current study’s standardized root mean residual (SRMR) is 0.118 and falls above the 0.08 threshold, which may indicate this model does not fit the empirical data.

However, Hair et al. (2017) believe that the threshold of 0.08 is too low for PLS-SEM because the error between the observed correlations and the model-implied correlations plays different roles in CB-SEM and PLS-SEM. On the one hand, CB-SEM aims at minimizing the difference between the two correlations whereas PLS-SEM aims at maximizing the explained variance of the endogenous construct(s). The two approaches to SEM have different goals, so using the same metric to measure model fit may be contradictory. Hair et al. (2017) state that currently it is unknown whether fit measures add any value to PLS-SEM analyses. “PLS-SEM focuses on prediction rather than on explanatory modeling and therefore requires a different type of validation. More precisely, validation of PLS-SEM results is concerned with generalization which is the ability to predict sample data, or preferably, out-of-sample data” (Hair et al., 2017, p.194). Hair et al. (2017) advise against the routine use of model fit indices in the context of PLS-SEM because researchers may be tempted to sacrifice predictive power in order to achieve better model fit.

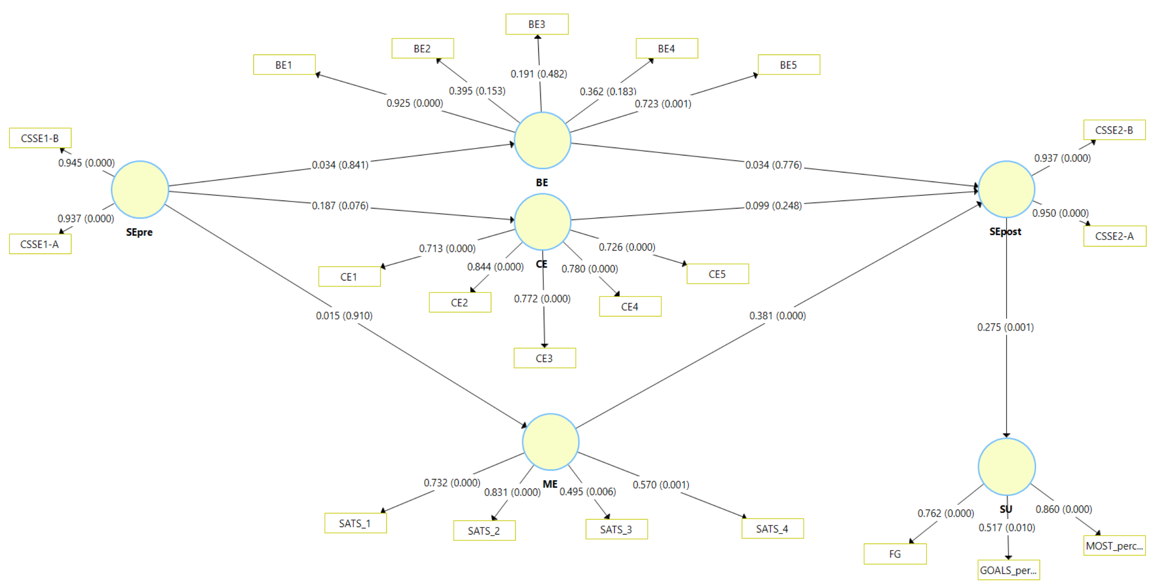


Figure 3: Path Analysis. Note: numbers in parentheses are p-values for the path coefficients

Figure 3 displays the path analysis for the current model. This figure includes the path coefficients with p-values given in parenthesis.

The bootstrap statistical output, containing the correlation coefficients, p-values, and t-statistics associated with each relationship are displayed in Table 17. When a study is exploratory in nature, researchers generally set significance level at 10% (Hair et al., 2017). The relationships of SEpre on CE, ME on SEpost, and SEpost on SU were significant at the 10% significance level; however, none of the other relationships yielded significance.

Causal Relationship	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	Standard Error (STERR)	T-Statistic	P-Value
SEpre ->BE	0.034	0.047	0.172	0.172	0.201	0.841
SEpre ->CE	0.187	0.207	0.105	0.105	1.774	0.076*
SEpre ->ME	0.015	0.013	0.129	0.129	0.113	0.910
BE->SEpost	0.034	0.072	0.120	0.120	0.285	0.776
CE->SEpost	0.125	0.086	0.086	1.154	0.248	0.125
ME->SEpost	0.381	0.366	0.090	0.090	4.222	0.000*
SEpost->SU	0.275	0.289	0.085	0.085	3.224	0.001*

Table 16: Bootstrap Statistical Output. Note: *p<.10

The path coefficients of the structural model can be interpreted relative to one another (direct effect). If one path coefficient is larger than another, then its effect on the endogenous latent variable is greater. One can interpret the individual path coefficients of the path model in similar fashion as the standardized beta coefficients in an ordinary least squares regression analysis. That is, “a one-unit change of the exogenous construct changes the endogenous construct by the size of the path coefficient when everything else (i.e., all other constructs and their path coefficients) remains constant” (Hair et al., 2017, p.197). Table 18 shows the indirect effects.

Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	Standard Error (STERR)	T Statistics (|O/STDEV|)	P Values
BE -> SEpost						
BE -> SU	0.009	0.020	0.036	0.036	0.264	0.792
CE -> SEpost						
CE -> SU	0.027	0.036	0.027	0.027	1.002	0.316
ME -> SEpost						
ME -> SU	0.105	0.108	0.045	0.045	2.314	0.021*
SEpost -> SU						
SEpre -> BE						
SEpre -> CE						
SEpre -> ME						
SEpre -> SEpost	0.025	0.035	0.068	0.068	0.372	0.710
SEpre -> SU	0.007	0.010	0.021	0.021	0.323	0.747

Table 17: Indirect Effects. Note: *p<.10

Indirect effects can also be measured and assess one construct's effect on another via one or more mediating constructs. The sum of the direct and indirect effects is referred to as the total effect. To compute an indirect effect, find the product of the effects along the path between the constructs and sum each of the indirect paths. Table 19 presents the total effects of the structural model. As denoted with an asterisk, four of the total effects had significant effects at the 10% significance level: ME -> SEpost, ME-> SU, SEpost ->SU and SEpre->CE.

The most common metrics used to evaluate the structural model is the coefficient of determination (R^2 value) and the adjusted coefficient of determination. The coefficient of determination measures the model's predictive power and is calculated as the squared correlation between a specific endogenous construct's actual and predicted values. The coefficient represents the percent of variance in the endogenous constructs explained by all of the exogenous constructs linked to it (Hair et al., 2017). The coefficient of determination also represents a measure of in-sample predictive power (Sarstedt, Ringle, Henseler &Hair, 2014).

Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	Standard Error (STERR)	T Statistics (|O/STDEV|)	P Values
BE -> SEpost	0.034	0.072	0.120	0.120	0.285	0.776
BE -> SU	0.009	0.020	0.036	0.036	0.264	0.792
CE -> SEpost	0.099	0.125	0.086	0.086	1.154	0.248
CE -> SU	0.027	0.036	0.027	0.027	1.002	0.316
ME -> SEpost	0.381	0.366	0.090	0.090	4.222	0.000*
ME -> SU	0.105	0.108	0.045	0.045	2.314	0.021*
SEpost -> SU	0.275	0.289	0.085	0.085	3.224	0.001*
SEpre -> BE	0.034	0.047	0.172	0.172	0.201	0.841
SEpre -> CE	0.187	0.207	0.105	0.105	1.774	0.076*
SEpre -> ME	0.015	0.013	0.129	0.129	0.113	0.910
SEpre -> SEpost	0.025	0.035	0.068	0.068	0.372	0.710
SEpre -> SU	0.007	0.010	0.021	0.021	0.323	0.747

Table 18: Total Effects. Note: *p<.10

It is difficult to provide rules of thumb for acceptable R^2 and adjusted R^2 values as it depends on the model complexity and the research discipline, but Cohen's (1988) suggestion of effect sizes for R^2 values can be interpreted according to the following criteria: .02 = small, .13 = moderate, and .25 = large effects. The R^2 values reported in Table 20 show effect sizes. According to Cohen's (1988) criteria, BE has practically no effect, CE has a small effect, ME has no effect, SEpost has a large effect, and SU has a moderate effect. Some might claim these effects are instead moderate and small; since the purpose of this study is exploratory in nature, these two effects are interpreted as large and moderate respectively.

Construct	Correlation (R)	R^2	Adjusted R^2
BE	0.034	0.001	-0.005
CE	0.187	0.035	0.029
ME	0.015	0.000	-0.006
SEpost	0.446	0.199	0.183
SU	0.275	0.076	0.070

Table 19: Correlations, R^2, and Adjusted R^2 Results

It is common practice of late to report the effect size for an analysis and PLS-SEM is no exception. In context of PLS-SEM, effect size measures the change in R^2 when a specified exogenous construct is omitted from the model and so can be used to evaluate whether the omitted construct has a substantive impact on the endogenous construct(s) (Hair, et al., 2017). Table 21 reports the f^2 effect size. Hair et al. (2017) provide the following criteria for interpreting the size of effect: small (0.02), medium (0.15), and large (0.35). As shown in the table, SEpre shows no effect on BE, SEpre has a small effect on CE, SEpre has no effect on ME, BE has no effect on SEpost, CE has a small effect on SEpost, ME has a medium effect on SEpost, and SEpost has a medium effect on SU.

Causal Relationship	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	Standard Error (STERR)	T-Statistic	P-Value
SEpre ->BE	0.001	0.034	0.038	0.038	0.031	0.975
SEpre ->CE	0.036	0.059	0.046	0.046	0.787	0.432
SEpre ->ME	0.000	0.018	0.023	0.023	0.009	0.993
BE->SEpost	0.001	0.016	0.023	0.023	0.037	0.970
CE->SEpost	0.010	0.023	0.024	0.024	0.427	0.670
ME->SEpost	0.112	0.122	0.062	0.062	1.809	0.071
SEpost->SU	0.082	0.103	0.062	0.062	1.330	0.184

Table 20: Effect Size

Summary of Results

The analysis showed that student conceptual understanding of statistics (SU) was positively influenced by self-efficacy to learn statistics (SEpre and SEpost). This was made evident because all pathways in the model were positive. Additionally, the analysis showed that self-efficacy to learn statistics measured at the beginning of the semester (SEpre) had no effect on student behavioral engagement (BE), explaining only 0.1% of the variance of behavioral engagement; had a small effect on student cognitive engagement (CE), explaining only 3.5% of the variance of cognitive engagement; and had no effect on student motivational engagement (ME), explaining 0.0% of the variance of motivational engagement. But as the path continued beyond these engagement variables to self-efficacy to learn statistics measured at the end of the semester (SEpost) some effect became evident. The behavioral engagement (BE) showed no effect on end-of-semester self-efficacy (SEpost), cognitive engagement (CE) showed a small effect on end-of-semester self-efficacy (SEpost), and motivational engagement (ME) showed a medium effect on end-of-semester self-efficacy (SEpost), explaining 19.9% of the variance of self-efficacy measured at the end of the semester. Finally, as the path continued through the second self-efficacy measure on to student conceptual understanding of statistics, (SU) this last association in the model had a medium effect and the model explains 7.6% of the variance in student conceptual understanding of statistics (SU).

Chapter Four Summary

Initial explorations of the data found that 98.5% of the variables contained missing data, 69.6% of the cases contained missing data, and 29.06% of the values contained missing data and it was determined the missing pattern was missing not at random (MNAR). Problems with MNAR missingness were addressed by employing the modern missing data handling method multiple imputation. This method was chosen because it preserves power and decreases bias better than traditional methods and it fills in the missing data values to preserve sample size.

Generally, the model showed significantly non-normal factors and exploratory factor analysis indicated a clustering of factors different than that reported in previous research. As such, the path model was adjusted to reflect the self-efficacy construct being measured at two time points and the new clustering of factors on the engagement constructs. The model exhibited indicator reliability issues with behavioral engagement (BE) and motivational engagement (ME), not issues with composite reliability, and issues with Cronbach's alpha for behavioral engagement (BE) and statistical understanding (SU). Discriminant validity was maintained for all except three behavioral engagement indicators but behavioral engagement construct (BE) was found to meet the HTMT criteria for discriminant validity. It is important to remember the current study is exploratory in nature with the purpose to evaluate whether the model inspired by Linnenbrink and Pintrich (2003) represents the relationship of these variables in relation to community college students taking an introductory statistics course.

Overall, the relationships of SEpre on CE, ME on SEpost, and SEpost on SU were significant while none of the other relationships were found to be significant at the 0.10 significance level. Of these significant relationships ME on SEpost and SEpost on SU had a medium effect while SEpre on CE had a small effect. On a final point, the model explains 19.9% of the variance of self-efficacy measured at the end of the semester (SEpost) and 7.6% of the variance in student conceptual understanding of statistics (SU).

CHAPTER FIVE: DISCUSSION

Introduction

This study was designed to investigate the relationship between affective characteristics and conceptual understanding of introductory statistics students by considering the influences of student self-efficacy toward statistics, student attitude toward statistics, and student self-regulated learning strategies on student conceptual understandings of the non-mathematical introductory statistics curriculum. This research study also seeks to decrease the research gap concerning the experience and achievement of community college students in this course.

This chapter presents a summary and interpretation of the results of the investigation. It provides an overview of the study design and analysis of the data. Finally, this chapter describes the study's contributions to literature, its implications for professional practice, and suggests topics for further study.

Summary and Interpretation of the Findings

Relationship Between Student Conceptual Understanding of Statistics and Self-Efficacy to Learn Statistics

The results of this study supported the hypothesis that student conceptual understanding of statistics is positively influenced by self-efficacy to learn statistics. In the model analysis, all pathways were found to be positive thus indicating a positive relationship between these two constructs. This outcome is in line with previous research (Onwuegbuzie, 2003; Linnenbrink & Pintrich, 2003; Pintrich, Smith, Garcia, &

McKeachie, 1993; Fredricks, Blumenfeld, & Paris, 2004; Pike, Smart & Ethington, 2011). In research looking at self-efficacy for study skills among community college students, Silver, Smith, & Greene (2001) reported a link between self-efficacy and achievement. In a study linking self-efficacy and performance in grammar, Collins & Bissell (2004) found a positive correlation between self-efficacy and performance.

The current study also found that the path from self-efficacy to learn statistics measured at the end of the semester (SEpost) to student conceptual understanding of statistics (SU) was significant with a medium effect size. The measures of self-efficacy to learn statistics measures at the beginning of the semester (SEpre) combined with the three engagement variables (BE, CE, and ME) to explain 19.9% of the variance in student's reported self-efficacy to learn statistics measured at the end of the semester (SEpost). According to Cohen's (1988) scale, this indicates a large effect. Additionally, all paths in the model combined to explain 7.6% of the variance in student's measured conceptual understanding of statistics (SU). Cohen's (1988) scale indicates this is a small effect. However, one should not discount an effect on the basis of it being judged small. Prentice & Miller (1992) have said that small effects may have "enormous implications" in terms of practical context because it may be an effect that is "so pervasive it holds even under the most inauspicious circumstances" (p.163).

Research results on the effect of self-efficacy on educational goal attainment are mixed. Pintrich and Schunk (1996) found when self-efficacy beliefs were high, students would persist on tasks to further develop their skills and promote their capabilities. However, when self-efficacy beliefs were low, students would avoid new tasks that may assist them in learning a new skill. Pintrich and Garcia (1991) found that students who were high in self-efficacy for academic performance were more likely to demonstrate self-regulated learning behavior. In a meta-analytic study, Multon, Brown, & Lent (1991) reported that self-efficacy's influence on the performance of lower achieving students was greater than that of the students at a higher level of academic achievement on the same grade level. On the other hand, other studies report a less robust relationship between self-efficacy and achievement. Robins & Beer (2001) indicate that there is often a lack of achievement calibration between students' beliefs about their competency and their actual performance. Additionally, Young & Ley's (2002) research revealed that developmental college students tend to have a high sense of self-efficacy that is incongruous with their academic skills and in fact student perceptions often exaggerate what he or she is capable of doing.

It is an interesting result that the items in the CSSE instrument factored differently for the administration at the start of the semester than it did at the administration at the end of the semester. This difference is evidence that student's conceptual understandings of statistics did change over the course of the semester. Table 22 compares how the fourteen items on the CSSE instrument loaded into two different sets of two factors from each administration. For SEpre (CSSE1), the two factors could represent self-efficacy with regards to statistical theory and self-efficacy with regards to interpretation. For SEpost (CSSE2), the two factors could represent self-efficacy with regards to descriptive skills and self-efficacy with regards to inference skills. This change in self-efficacy perceptions reflects what Finney & Schraw (2003) report from their research; that is an improvement in self-efficacy over the course of a semester. Perhaps students' prior experiences and knowledge of statistics influenced their perceptions of self-efficacy toward statistics. However, after completing the course they were much better equipped to self-report on their self-beliefs toward statistics which led the factors to align with the two main themes of statistics, that is descriptive skills and inference skills.

Item	CSSE1-A	CSSE1-B	CSSE2-A	CSSE2-B
Explain the difference between a sampling distribution and a population distribution	X		X	
Interpret the results of a statistical procedure in terms of the research question	X			X
Identify if a distribution is skewed when given values of three measures of central tendency	X		X	
Identify the scale of measurement for a variable	X			X
Select the correct statistical procedure to be used to answer a research question	X		X	
Identify the factors that influence power	X			X
Identify when the mean, median, and mode should be used as a measure of central tendency	X		X	
Distinguish between a population parameter and a sample statistic	X		X	
Explain what the value of the standard deviation means in terms of the variable being measured	X		X	
Distinguish between a Type I error and a Type II error n hypothesis testing		X		X
Distinguish between the information given by the three measures of central tendency		X		X
Explain what the numeric value of the standard error is measuring		X		X
Distinguish between the objectives of descriptive versus inferential statistical procedures		X		X
Interpret the probability value (p-value) from a statistical procedure		X	X	

Table 21: Comparison of Factor Loadings for SEpre and SEpost

Relationship Between Self-Efficacy, Behavioral Engagement, and Student Conceptual Understanding of Statistics

The results of this study did not support the hypothesis that the influence of self-efficacy on student conceptual understanding of statistics is mediated by behavioral engagement. The current study found that all paths in the relationship between self-efficacy to learn statistics, behavioral engagement, and student conceptual understanding of statistics to be non-significant with no effect. Self-efficacy to learn statistics measured at the beginning of the semester (SEpre) was reported to explain 0.1% of the variation in behavioral engagement (BE). Pintrich, Smith, Garcia & McKeachie, (1993) acknowledge that in their MSLQ instrument, peer learning and help-seeking were generally weakly correlated with the factors elaboration, organization, metacognition, time and study, effort, critical thinking, rehearsal, and task value. The current study used the factors elaboration, organization, metacognition, time and study, help-seeking, and effort to measure behavioral engagement and cognitive engagement. Pintrich, Smith, Garcia & McKeachie, (1993) were also surprised that the use of peer learning and help-seeking were not significantly related to grades. Perhaps these weaknesses in their MSLQ instrument contributed to the non-significant result from the analysis of the present study despite the fact that there is a growing body of research that supports the positive effect student engagement has on desired outcomes in college (Chickering & Gamson, 1987; Pascarella & Terenzini, 2005; Greene, Marti, & McClenney, 2015; Pintrich, Smith, Garcia & McKeachie, 1993). Linnenbrink & Pintrich (2003) consider help-seeking and peer learning to be important indicators of behavioral engagement, but the current study did not support this. Individuals with strong self-efficacy beliefs were found to be more likely to "exert effort in the face of difficulty and persist at a task when they have the requisite skills" to do so (Linnenbrink & Pintrich, 2003, p.127). On the other hand, studies by Schunk (1989, 1991) provide evidence that there are students who know the material and have the requisite skills but they are not confident that they can use their knowledge or make good use of their skills.

Relationship Between Self-Efficacy, Cognitive Engagement, and Student Conceptual Understanding of Statistics

The results of this study did not support the hypothesis that the influence of self-efficacy on student conceptual understanding of statistics is mediated by cognitive engagement. This study found the relationship between self-efficacy to learn statistics, cognitive engagement, and student conceptual understanding of statistics to be non-significant. It was found that self-efficacy to learn statistics measured at the start of a semester (SEpre) was significantly related with cognitive engagement (CE) with a small effect size, which is in line with previous research (Silver, Smith, & Greene, 2001). Self-efficacy to learn statistics measured at the beginning of the semester (SEpre) explained 3.5% of the variance in cognitive engagement (CE) which is a small effect according to Cohen (1988). On the other hand, the relationship of cognitive engagement (CE) with self-efficacy to learn statistics at the end of a semester (SEpost) was not significant and the relationship of cognitive engagement (CE) and student conceptual understanding of statistics (SU) was also non-significant. Both of these paths were positive, but non-significant. Self-efficacy theory predicts that student self-efficacy should be positively related to their cognitive engagement (Bandura, 1986; Schunk, 1991). Theory also indicates a link between level of cognitive engagement and successful learning (Silver, Smith, & Greene, 2001; Zimmerman, 1989) yet such a link was not found in this current study.

Pintrich, Smith, Garcia & McKeachie, (1993) acknowledged that rehearsal strategies were not correlated significantly with final grade in their MSLQ instrument. They explain that this might suggest reliance by students on more surface processing strategies, which are not helpful for academic performance. Pintrich, Smith, Garcia & McKeachie, (1993) continue by explaining that "students who successfully manage their own time and study environment, as well as their own efforts (persistence at difficult tasks) were more likely to perform better in their courses" (p.811). Linnenbrink & Pintrich (2003) also state that students who use more surface processing strategies, like rehearsal, learn the material but the learning is not meaningful or deep learning. In contrast, students who paraphrase or summarize the material or organize it in some way often display deeper, more conceptual learning. Pintrich, et al., (1993) found that students who relied on deeper processing strategies like elaboration and/or organization were more likely to receive higher grades in a course.

Linnenbrink & Pintrich (2003) acknowledge that there are two issues that need to be resolved with their model via future research regarding self-efficacy and cognitive engagement. The first issue is that there may be occasions where students are very confident in what they think they already understand about a subject and this confidence interferes with their learning. This strong self-efficacy belief that they already know the content to be learned may lead such students to be less engaged in learning new ideas and so would not achieve as much as they are capable of achieving. Students with this characteristic are prone to cling to their misconceptions about the content and believe their misconceptions are appropriate and so their efficacy beliefs would inhibit their cognitive engagement in the material, thus limiting change in their conceptual learning (Linnenbrink & Pintrich, 2003).

The second issue with Linnenbrink & Pintrich's (2003) model is related to the first issue and they call it a problem of calibration. "Calibration refers to the idea that individuals' self-efficacy judgments should be matched or calibrated to reflect their actual performances and accomplishments . . . [T]he problems of calibration include both overestimation and underestimation of expertise" with the subject (p.131). These issues are in line with Douzenis' research (1997) wherein it was found that quality of effort in academic tasks was related to community college students' estimates of knowledge gained. Douzenis explains that this makes sense because a history of academic struggles is a common reason why students choose to attend community colleges as opposed to a university. In the classroom, it is a detrimental problem if a student thinks they can read or perform other content related tasks when in fact their skill level is too low to be successful (Linnenbrink & Pintrich, 2003).

Relationship Between Self-Efficacy, Motivational Engagement, and Student Conceptual Understanding of Statistics

The results of this study did support the hypothesis that the influence of self-efficacy on student conceptual understanding of statistics is mediated by motivational engagement. The results of this study found the relationship between motivation (ME) and self-efficacy to learn statistics at the end of a semester (SEpost) was significant with a medium effect size. Additionally, the relationship between motivational engagement (ME) and student conceptual understanding of statistics (SU) was also significant. This is in agreement with research by Liao, Edlin, & Ferdenzi (2014) wherein they found that self-efficacy correlated well with motivational measures. Additionally, a meta-analysis by Emmioglu & Capa-Aydin, (2012) clearly suggest that attitudes and achievement in statistics are related.

However, in the current analysis the path from self-efficacy to learn statistics at the start of the semester (SEpre) was not significantly related with motivational engagement (ME) and SEpre explained 0.000% of the variance in ME. This finding is in line with Finney and Schraw's (2003) report that the self-efficacy to learn statistics measure completed near the beginning of a semester showed a weak relationship with attitudes towards statistics measures. Finney & Schraw (2003) explain further that they did not expect a strong relationship between these variables because most students had low current self-efficacy at the start of the course, but later had a higher level of self-efficacy (nearly a two standard deviation increase) at the end of the course. However, in their study of the SATS instrument, Vanhoof, Kuppens, Sotos, Verschaffel, & Onghena (2011) reported a rather high association between the interest and value factors. Perhaps this characteristic contributed to the current study's non-significant path from self-efficacy to learn statistics at the start of the semester (SEpre) to motivational engagement (ME).

On the other hand, Pintrich, et al., (1993) found motivational factors to be significantly correlated with final grade. They further explain that "students who approached their course work with an intrinsic goal for learning, who believed that the material was interesting and important, who had high self-efficacy beliefs for accomplishing the tasks, and who rated themselves as in control of their leaning were more likely to do well in terms of course grade" (p.810). Linnenbrink & Pintrich (2003) also report that self-efficacy is positively related to adaptive motivational beliefs, such as interest, value, and utility, while also being negatively related to negative emotions such as anxiety.

Model Adjustment

The model analyzed in this current study was based on Linnenbrink & Pintrich's (2003) general framework for self-efficacy, engagement, and learning. Exploratory factor analysis indicated that the factors clustered differently than reported in previous research thus forming somewhat different factors. This new clustering guided model adjustment from that shown in Figure 1 to that shown in Figure 3. Self-efficacy was split into two variables to reflect the two different time periods when it was measured: start of semester (SEpre) and end of semester (SEpost). The first measure of self-efficacy (SEpre) was kept at the start of the path model while the second measure of self-efficacy (SEpost) was placed to the right of the engagement variables. The paths from the three engagement variables flowed to end of semester self-efficacy (SEpost) and on to statistical conceptual understanding (SU) to complete the model.

Implications for Practice and Theory

In research investigating the mediating effects of student engagement on the relationship between academic disciplines, Pike, Smart, & Ethington (2011) did not find evidence of a mediating effect for engagement. These researchers caution that it may be premature "to conclude that student engagement does not mediate the relationships between academic disciplines and learning outcomes" (568) because their measurement instruments may have failed to include appropriate types of engagement measures that would explain their constructs. In light of poor performance of behavioral engagement and cognitive engagement in the model and weaknesses in the metrics chosen to measure them, this research study may have experienced a similar failure to appropriately measure the engagement constructs with the chosen measurement instruments. Perhaps a mediating effect would be evident in a study similar to the current study if different metrics are chosen to define the constructs in the model.

Collins & Bissell (2004) found that students tend to overestimate their own abilities at the beginning of the semester and believe they know more about the class' subject than they actually do. It appears that the subjects in this study overestimated their ability to learn introductory statistics and this overestimation influenced the level of skill with which they employed the various engagement strategies. Instructors of introductory statistics at the community college level would be wise to think about the ways in which they teach each concept and how they might influence student self-efficacy and how their students might engage in the course. To understand achievement, instructors need to understand student engagement (Parsons, Nuland, & Parsons, 2014).

It is important for students to understand their weaknesses in understanding the content but it is difficult to get students to acknowledge these weaknesses and engage more meaningfully with the content. Trawick & Corno (1995) posit that self-regulatory training is an essential component to the success of community college students. Engstrom and Tinto (2008) warn that the success of institutions of higher education depends on community colleges' successful implantation of effective strategies for training students in engagement strategies and academic support.

Underprepared students might desire a college degree but might not realize the level of work or academic preparedness involved in successfully obtaining that degree. As a result, it is even more important for community colleges to put into place an effective support system to help students reach their educational goals (Liao, Edlin, & Ferdenzi, 2014). Additionally, Bowen, Chingos, and McPherson (2009) caution that the existence of ambitions does not mean that all ambitious students know how to translate these ambitions into realities.

Linnenbrink & Pintrich (2003) suggest if students are given tasks that are challenging but not too difficult and they experience success upon completion of these tasks that self-efficacy to learn may increase. As self-efficacy to learn increases, so will interest, value, and utility. A strategy such as this one would be very useful for teachers to implement. Teachers can design and organize their instruction to have a positive impact on student self-efficacy to learn which would lead to improved student engagement and improved learning.

While engagement strategies can be easily taught, Pressley (1995) found that use of such strategies may not transfer to new settings even if the teaching of said strategies attempted to foster transfer of strategy use. Pressley (1995) suggests a plausible explanation for this is that a student's self-efficacy for learning in a domain is too low to warrant the extra effort required by the strategy, or it could be that self-efficacy for effective strategy use is itself too low. Since a student's self-efficacy is related to level of cognitive engagement, perhaps problems with self-efficacy may explain why some students do not use strategies that they seem to possess (Silver, Smith, & Greene, 2001). Horn & Nevill, (2006) have reported that community college students possess greater academic risk than their four-year peers. Some strategies community colleges could implement might include putting into place effective student support mechanisms to ensure that students do have the skills to succeed in their college program, especially in regards to engagement factors. Another strategy would be to train their instructors in the importance of teaching students how to use various engagement strategies along with learning content. The current study suggests the subjects in this study are weak in their use of behavioral engagement and cognitive engagement strategies. These students could benefit from efforts by the community college to help them improve the effectiveness of engagement strategies they employ as they study during the non-mathematics introductory statistics class. The community college institution plays a pivotal role in providing students a first line of defense against them failing and leaving college without realizing their goal of earning the desired degree. These efforts can come from the institution itself or from instructors of this class, or both.

While it was not a purpose of this study to research racial disparities for Hispanic students, the majority of participants reported being Hispanic (69.1%). This study contributes to furthering the understanding of engagement variables and their relationship with learning outcomes for Hispanic community college students who are enrolled in a nonmathematical introductory statistics course. Educational leaders and policy experts concerned with eliminating the racial disparities in educational attainment may add this study's findings to help guide their development and implementation of strategies to help these students succeed (Green, Marti, & McClenney, 2008).

Recommendations for Further Research

The variance in statistical understanding that can be explained by the specified path model is 7.6% and shows that statistical understanding at the completion of a nonmathematical introductory statistics course at a community college is a complicated process and may involve many other factors in addition to self-efficacy toward statistics and engagement variables. It is of interest that additional studies be designed to assess factors that may affect statistical understanding in combination with self-efficacy to learn statistics and engagement factors.

Further studies are needed to examine whether community college students in other settings exhibit positive relationships in a similar path model and result in a comparably small amount of explained variance on statistical understanding. Since the current study involved subjects who self-selected to participate and the data collected is self-reported data, the results may or may not extend to other community colleges in Arizona or across the United States. However, if this study were to be replicated in another setting at another institution it could be determined whether students in similar situations exhibit a comparably small amount of explained variance on statistical understanding. It would also be of interest to research what methods for teaching effective usage of various engagement strategies accomplishes improvement in student understanding of statistical concepts at course completion.

Further research could look at particular misconceptions about nonmathematical introductory statistics community college students are prone to cling to as well as look at the problem of calibration. Once common misconceptions and calibration issues are identified via research, instructors of this course could address student misconceptions at relevant points during the semester in an effort to encourage students to discard their misconceptions and use their cognitive engagement skills to facilitate change in their conceptual learning. Research along this line would address both issues in Linnenbrink & Pintrich’s (2003) model.

Perhaps new metrics need to be developed to measure student engagement variables. Are students today profiting from the same self-regulated learning strategies as students from yesteryear? The current study begs an answer to this question. The MSLQ instrument was developed in 1991; the CSSE instrument was developed in 1995; the SATS was developed in 2003; and the CAOS instrument was developed in 2007. The development of new instrument(s) will help researchers learn what strategies today's students are using in their studies and determine which strategies are more effective in promoting deep learning and understanding at course completion.

Conclusion

This research study was designed to focus on the experiences of community college students in a non-mathematical introductory statistics course with the purpose to improve understanding of the relationship between conceptual understanding and student engagement. Improving our understanding of these student characteristics will lead to interventions designed at improving student conceptual understanding (Onwuegbuzie, 2003). Furthermore, this study focused on a student population not traditionally studied and improves understanding of how community college students are experiencing the introductory statistics class.

Linnenbrink & Pintrich's (2003) proposed general framework for self-efficacy, student engagement, and student learning served as a model to operationalize the investigation of the relationship between self-efficacy toward statistics, attitude toward statistics, use of self-regulated learning strategies, and the development of students' statistical conceptual understandings. Enlarging our understandings of this relationship helps instructors of community college non-mathematical introductory statistics courses better understand the experiences of their students with regards to these important constructs.

Results from the literature on the relationship between self-efficacy and academic performance among community college students are mixed and some are inconclusive (Liao, Edlin, & Ferdenzi, 2014; Nakajima, 2009; Silver, Smith, & Greene, 2001; Welsh, 2008; Randall, 2009). The current study found a positive relationship between student conceptual understanding of statistics and self-efficacy to learn statistics. It was not found that behavioral engagement and cognitive engagement mediated the influence of self-efficacy to learn statistics measured at the beginning of the semester on statistical understanding at course end. However, motivational engagement was found to mediate the effect of self-efficacy to learn statistics measured at the beginning of the semester. Additionally, it was found that self-efficacy to learn statistics measured at the end of the semester had a medium effect on statistical understanding at course end.

REFERENCES CITED

Adelman, C. (2005). *Moving into town-and moving on: The community college in the lives of traditional-age students*. Washington, DC: U.S. Department of Education.

ACT, Inc. (2008). *National collegiate retention and persistence to degree rates.* Iowa City, IA: Author.

Aliaga, M., Cobb, G., Cuff, C., Garfield, J., Gould, R., Lock, R., Moore, T., Rossman, A. Stephenson, R., Utts, J., Velleman, P., & Witmer, J. (2005). Guidelines for assessment and instruction in statistics education: College report. Retrieved from http://www.amstat.org/education/gaise/GaiseCollege_Full.pdf

American Association of Community Colleges. (2015). Students at community colleges. Retrieved April 18, 2015 from http://www.aacc.nche.edu/AboutCC/Trends/Pages/studentsatcommunitycolleges.aspx

Bailey, T., & Alfonso, M. (2005). Paths to persistence: An analysis of research on program effectiveness at community colleges. *Lumina foundation for education new agenda series, 6*(1).

Baloglu, M. (2003). Individual differences in statistics anxiety among college students. *Personality and individual differences*, 34, 855-865.

Bandalos, D. L, Finney, S. J., & Geske, J. A. (2003). A model of statistics performance based on achievement goal theory. *Journal of educational psychology, 95*(3). 604-607. doi: 10.1037/0022-0663.95.3.604

Bandalos, D. L, Yates, K, & Thorndike-Christ, T. (1995). Effects of math self-concept, perceived self-efficacy, and attributions for failure and success on test anxiety. *Journal of educational psychology, 87*(4), 611-623.

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory.* Englewood Cliffs, NJ: Prentice-Hall.

Bandura, A. (1997). *Self-efficacy: The exercise of control.* New York, NY: W. H. Freeman.

Bagozzi, R. P. (2010). Structural equation models are modeling tools with many ambiguities: Comments acknowledging the need for caution and humility in their use. *Journal of consumer psychology, 20(*2010*)*, 208-214.

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the academy of marketing and science*, *16*(1), 74-94.

Baraldi, A. N., & Enders, C. K. (2009). An introduction to modern missing data analyses. *Journal of school psychology 48*(2010), 5-37.

Benson, J. (1989). Structural components of statistical test anxiety in adults: an exploratory model. *The journal of experimental education, 57*(3), 247-261.

Ben-Zvi, D. & Garfield, J. B. (2004). *The challenge of developing statistical literacy, reasoning, and thinking*. Dordrecht; Boston: Kluwer Academic.

Ben-Zvi, D. & Garfield, J. B. (2008). Introducing the emerging discipline of statistics education. *School science and mathematics, 108*, 355-361.

Berkner, L, & Choy, S. (2008). *Descriptive summary of 2003-2004 beginning postsecondary students: Three years later.* Washington, DC: National Center for Education Statistics.

Bouffard-Bouchard, T., Parent, S., & Larivee, S. (1991). Influence of self-efficacy no self-regulation and performance among junior and senior high-school aged students. *International journal of behavioral development, 14*, 153-164.

Bowen, W. G., Chingos, M. M., & McPherson, M. S. (2009). *Crossing the finish line: Completing college at America's public universities.* Princeton, NJ: Princeton University Press.

Brown, J. D. (2009). Choosing the right type of rotation in PCA and EFA. *Shiken: JALT testing & evaluation SIG newsletter, 13*(3) November 2009, 20-25. Retrieved from https://jalt.org/test/PDF/Brown31.pdf

Bude, L., Van De Wiel, M. W. J., Imbos, T., Candel, M. J. J. M., Broers, N. J., & Berger, M. P. F. (2007). Students' achievements in a statistics course in relation to motivational aspects and study behavior. *Statistics education research journal, 6*(1), 5-21. Retrieved from: http://www.stat.auckland.ac.nz/~iase/serj/SERJ6(1)_Bude.pdf

Bureau of Labor Statistics. (2013). Employment projections program. U.S. department of labor, U.S. Bureau of Labor Statistics. Retrieved April 24, 2015 from http://www.bls.gov/emp/ep_table_education_summary.htm

Bureau of Labor Statistics. (2015). Earnings and unemployment by educational attainment. U.S. department of labor, U.S. Bureau of Labor Statistics. Retrieved April 24, 2015 from http://www.bls.gov/emp/ep_chart_001.htm

Cheema, J. R. (2014). A review of missing data handling methods in education research. *Review of educational research, 84*(4), 487-508.

Chickering, A. W., & Gamson, Z. F. (1987). Seven principles for good practice in undergraduate education. *AAHE bulletin, 39*(7), 3-7.

Chiesi, F., Primi, C., & Carmona, J. (2011). Measuring statistics anxiety: Cross-country validity of the statistical anxiety scale. *Journal of psychoeducational assessment, 29*(6), 559-569.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences.* Mahwah, NJ: Lawrence Erlbaum.

Collins, J. L. (1982, March). *Self-efficacy and ability in achievement behavior.* Paper presented at the annual meeting of the American Educational Research Association, New York.

Collins, L. M., Schafer, J. L., & Kam, C. M. (2001). A comparison of inclusive and restrictive strategies in modern missing-data procedures. *Psychological methods,* 6, 330-351.

Community College. June 11, 2014. In Wikipedia. Retrieved from http://en.wikipedia.org/wiki/Community_college

Croucher, J. (2006). Teach statistics? You bet! *Significance*, March, 46-48.

Cruise, R. J., Cash, R. W., & Bolton, D. L. (1985). Development and validation of an instrument to measure statistical anxiety. In *Paper presented at the proceedings of the American Statistical Association.*

delMas, R., Garfield, J., Ooms, A., & Chance, B. (2007). Assessing students' conceptual understanding after a first course in statistics. *Statistics education research journal, 6*(2), 28-58.

Dong, Y., & Peng, C. J. (2013). Principled missing data methods for researchers. *Springer Plus, 2013* **2**:222. doi: 10.1186/2193-1801-2-222

Douzenis, C. (1997). The relationship of quality of effort and estimate of knowledge gain among community college students. *Community college review, 24*(3), 27-35.

Emmioglu, E., & Capa-Aydin, Y. (2012). Attitudes and achievement in statistics: A meta-analysis study. *Statistics education research journal, 11*(2), 95-102.

Engstrom, C., & Tinto, V. (2008). Access without support is not opportunity. *Change, 40*(1), 46-50.

Fabrigar, L. R., Wenger, D. T., MacCallum, R. C., & Strahan, El J. (1999). Evaluating the use of exploratory factor analysis in psychological research. *Psychological methods, 4*(3). 272-299.

Faul, F., Erdfelder, E., Buchner, A., & Lang, A. G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods, 41*, 1149-1160.

Finney, S. J., & Schraw, G. (2003). Self-efficacy beliefs in college statistics courses. *Contemporary educational psychology*, 28, 161-186.

Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. *Review of educational research, 74*(1), 59-109.

Garcia, T. & Pintrich, P. R. (1996). The effects of autonomy on motivation and performance in the college classroom. *Contemporary educational psychology 21*, 477-486.

Garfield, J., Hoss, B., Schau, D., & Wittinghill, D. (2002). First courses in statistical science: The status of educational reform efforts. *Journal of statistics education, 10*(2). Retrieved November 28, 2014, from http://www.amstat.org/publications/jse/v10n2/garfield.html

Gliner, J. A., Morgan, G. A., & Leech, N. L. (2009). Research methods in applied settings: An integrated approach to design and analysis (2nd ed.). New York, NY: Taylor & Francis.

Gould, R., & Ryan, C. (2013). *Introductory statistics: Exploring the world through data.* Boston, MA: Pearson.

Graham, J. W. (2009). Missing data analysis: Making it work in the real world. *Annual Review,* 60. 549-576. doi: 10.1146/annurev.psych.52.110405.085530

Green, T. G., Marti, C. N., & McClenney, K. (2008). The effort-outcome gap: Differences for African American and Hispanic community college students in student engagement and academic achievement. *The journal of higher education 79*(5), 513-539.

Griffith, J. D., Adams, L. T., Gu, L. L., Hart, C. L., & Nichols-Whitehead, P. (2011). Students' attitudes toward statistics across the disciplines: A mixed-methods approach. *Statistics education research journal, 11*(2), 45-56.

Hagedorn, L. S. (2009, April). *Remedial education: Findings and interpretations of America's growing problem.* American education research association, San Diego, CA.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Los Angeles: Sage.

Hanna, D., Shevlin, M., & Dempster, M. (2008). The structure of the statistics anxiety rating scale: A confirmatory factor analysis using UK psychology students. *Personality and individual differences 45*, 68-74.

Harpe, S., Phipps, L. B., & Alowayesh, M. S. (2012). Effects of a learning-centered approach to assessment on students' attitudes towards and knowledge of statistics. *Pharmacy teaching and learning 4*(2012), 247-255.

Hackett, G., & Betz, N. E. (1989). An exploration of the mathematics self-efficacy/mathematics performance correspondence. *Journal of research in mathematics education, 20*, 261-273.

Hailikari, T., Nevgi, A., & Komulainen, E. (2008). Academic self-beliefs and prior knowledge as predictors of student achievement in mathematics: A structural model. *Educational psychology, 28*(1), 59-71.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the academy of marketing science, 43*, 225-135.

Henseler, J., & Sarstedt, M. (2013). Goodness-of-fit indices for partial least squares path modeling. *Comput stat,* 28, 565-580.

Hood, M., Creed, P. A., & Neumann, D. L. (2011). To understand the relationship between student attitudes and achievement in statistics. *Statistics education research journal, 11*(2), 72-85.

Horn, L. J., & Nevill, S. (2006). *Profile of undergraduates in U.S. postsecondary education institutions: 2003-04, with a special analysis of community college students* (NCES Publication No. 2006-184). U.S. Department of Education. Washington, DC: National Center for Education Statistics.

Hu, L. T, & Bentler, P. M. (1998). Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification. *Psychological methods, 3*, 424-453.

Hulland, J. (1999). Use of partial least squares (PLS) in strategic management research: A review of four recent studies. *Strategic management journal, 20*, 1951-204.

IBM. (2017). *Factor Analysis Rotation.* Retrieved from https://www.ibm.com/support/knowledgecenter/en/SSLVMB_23.0.0/spss/base/idh_fact_rt.html

IBM. (2011). *IBM SPSS Missing Values 20*. Retrieved from http://www.math.uni-leipzig.de/pool/tuts/SPSS/IBM%20SPSS%20Missing%20Values.pdf

Inman, W., & Mayes, L. (1999). The importance of being first: Unique characteristics of first generation community college students. *Community college review, 26*(4), 3-22.

Kesici, S. Baloğlu, M., & Deniz, M. E. (2011) Self-regulated learning strategies in relation with statistics anxiety. *Learning and individual differences, 21*(2011), 462-477.

Lavasani, M. G. & Ejei, M. W. J. (2011). The role of achievement goals, academic motivation, and learning strategies in statistics anxiety: Testing a causal model. *Procedia social and behavioral sciences, 15*, 1881-1886.

Leech, N. L., Barrett, K. C., & Morgan, G. A. (2011). *IBM SPSS for intermediate statistics: Use and interpretation* (4th ed.). New York, NY: Routledge

Liao, H., Edlin, M., & Ferdenzi, A. C. (2014). Persistence at an urban community college: The implications of self-efficacy and motivation. *Journal of research and practice, 38*(7), 595-611.

Linnenbrink, E. A. & Pintrich, P. R. (2003). The role of self-efficacy beliefs in student engagement and learning in the classroom. *Reading & writing quarterly, 19*, 119-137.

Lopez, E. J., Nandagopal, K., Shavelson, R. J., Szu, E., & Penn, J. (2013). Self-regulated learning study strategies and academic performance in undergraduate organic chemistry: An investigation examining ethnically diverse students. *Journal of research in science teaching, 50(*6). 660-676.

Luke, C., Redekop F., & Burgin, C. (2014). Psychological factors in community college student retention. *Community college journal of research and practice,* 39, 222-234.

Macher, D., Paechter, M., Papousek, I., & Ruggeri, K. Statistics anxiety, trait anxiety, learning behavior, and academic performance. *Eur j psychol educ (2012), 27*, 483-498.

Maurice, L. (1957). Orthogonal Versus Oblique Rotations. *Journal of consulting psychology, 21*(6), 448-449.

Melguizo, T., Kienzl, G. S., & Alfonso, M. (2011). Comparing the educational attainment of community college transfer students and four-year college rising juniors using propensity score matching methods. *The journal of higher education, 82(3), 265-291).*

Multon, K. D., Brown, S. D., & Lent, R. W. (1991). Relation of self efficacy beliefs to academic outcomes: A meta-analytic investigation. *Journal of counseling psychology, 38*(1), 30-38.

Nakajima, M. A. (2009). *What factors influence student persistence in the community college setting?* (Unpublished doctoral dissertation). University of Southern California, Los Angeles, CA.

National Center for Educational Statistics. (2014). *Arizona Western College*. Retrieved from http://nces.ed.gov/collegenavigator/

Nunnally, J. C. (1967). *Psychometric theory.* McGraw-Hill: University of Michigan.

Olinsky, A., Chen, S., & Harlow, L. (2003). The comparative efficacy of imputation methods for missing data in structural equation modeling. *European journal of operational research 151*(2003), 53-79.

Office of Institutional Effectiveness, Research, and Grants. (2014). [A resource guide designed in support of the Yuma/La Paz Community College District planning process]. Arizona Western College Fact Book. Retrieved from https://www.azwestern.edu/Institutional_Research/downloads/2013-2014%20FACT%20BOOK.pdf

Onwuegbuzie, A. J. (2000). Attitudes toward statistics assessments. *Assessment & evaluation in higher education, 25*(4), 321-339.

Onwuegbuzie, A. J. (2003). Modeling statistics achievement among Graduate Students. *Educational and psychological measurement*, 63(6), 1020-1038. doi: 10.1177/0013164402250989.

Onwuegbuzie, A. J. & Wilson, V. A. (2003). Statistics anxiety: Nature, etiology, antecedent, effects, and treatments—A comprehensive review of the literature. *Teaching in higher education, 8*(2), 195-209.

Pajares, F. (1996). Self-efficacy beliefs in academic settings. *Review of educational research, 66*, 543-578.

Pajares, F. (2002). Gender and perceived self-efficacy in self-regulated learning. *Theory into practice, 41*(2), 116-125. doi: 10.1207/s15430421tip4102_8

Pajares, F., & Miller M. D. (1994). Role of self-efficacy and self-concept beliefs in mathematical problem-solving: A path analysis. *Journal of educational psychology, 86*, 193-203.

Pan, W. & Tang, M. (2005). Students' perceptions on factors of statistics anxiety and instructional strategies. *Journal of instructional psychology, 32*(3), 205-214.

Parsons, S. A., Nuland, L. R., & Parsons, A. W. (2014). The ABCs of student engagement: Teachers can increase all-important student engagement by being aware of its affective, behavioral, and cognitive dimensions. *Phi delta kappan,* *95*(8), 23.

Pascarella, E. T. (2006). How college affects students: Ten directions for future research. *Journal of college students development, 47*, 508-520.

Pascarella, E. T., & Terenzini, P. T. (1978). Student-faculty informal relationships and freshman year educational outcomes. *Journal of educational research, 71*, 183-189.

Pearl, J. (2012). The causal foundation of structural equation modeling. *California University Las Angeles Department of Computer Science*, 370, 1-36.

Pike, G. R., Smart, J. C., 7 Ethington, C. A. (2011). The mediating effects of student engagement on the relationships between academic disciplines and learning outcomes: An extension of Holland's theory. *Res High Educ 53*, 550-575. Doi: 10.1007/s11162-011-9239-y

Pintrich, P. R. (2000). Multiple goals, multiple pathways: The role of goal orientation in learning and achievement. *Journal of educational psychology, 92*, 544-555.

Pintrich, P. R., & de Groot, E. V. (1990). Motivational and self-regulated learning components of classroom academic performance. *Journal of educational psychology, 82*, 33-40.

Pintrich, P. R., & Garcia, T. (1991). Student goal orientation and self-regulated learning components of classroom academic performance. *Journal of educational psychology, 82*(1), 33-40.

Pintrich, P. R., & Schunk, D. H. (2002). *Motivation in education: Theory, research, and applications* (2nd ed.). Upper Saddle River, NJ: Merrill-Prentice-Hall.

Pintrich, P. R., Smith, D. A. F., Garcia, T., & McKeachie, W. J. (1993). Reliability and predictive validity of the motivated strategies for learning questionnaire (MSLQ). *Educational and psychological measurement*, 53, 801-813. doi: 10.1177/0013164493053003024

Porchea, S. F., Allen, J., Robbins, S., & Phelps, R. P. (2010). Predictors of long-term enrollment and degree outcomes for community college students: Integrating academic, psychosocial, socio-demographic, and situational factors. *The journal of higher education, 81*(6), 680-708.

Prentice, D. A., & Miller, D. T. (1992). When small effects are impressive. *Psychological bulletin, 112*(1), 160-164.

Pressley M. (1995). More about the development of self-regulation: Complex, long-term and thoroughly social. *Educational psychologist, 30*, 207-212.

Provasnik, S., & Planty, M. (2008). *Community colleges: Special supplement to the condition of education 2008.* Washington, DC: National Center for Education Statistics.

Randal L (2009). *The effect of reading self-efficacy, expectancy-value, and metacognitive self-regulation on the achievement and persistence of community college students enrolled in basic skills reading courses.* (Unpublished doctoral dissertation). University of Southern California, Los Angeles, CA.

Ringle, C. M., Wende, S., & Becker, J. –M. 2015. "SmartPLS 3." Boenningstedt: SmartPLS GmbH, http://www.smartpls.com.

Robins, R. W., & Beer, J. S. (2001). Positive illusions about the self: Short-term benefits and long-term costs. *Journal of personality and social psychology, 80*(2), 348-352.

Rodarte-Luna, B., & Sherry, A. (2007). Sex differences in the relation between statistics anxiety and cognitive/learning strategies. *Contemporary educational psychology, 33*(2008), 327-344. doi: 10.1016/j.cedpsych.2007.03.002

Rosario, P., Nunez, J. C., Valle, A., Gonzalez-Pienda, J., & Lourenco, A. (2013). Grade level, study time, and grade retention and their effects on motivation, self-regulated learning strategies, and mathematics achievement: A structural equation model. *Eur j psychol educ, 28*, 1311-1331. doi: 10.1007/s10212-012-0167-9

Saenz, V. B., Hatch, D., Bukoski, B. E., Kim, S., Lee, K., & Valdez, P. (2011). Community college student engagement patterns: A typology revealed through exploratory cluster analysis. *Community college review, 39*(3), 235-267.

Sarstedt, M., Ringle, C. M., Henseler, J., & Hair, J. F. (2014). On the emancipation of PLS-SEM: A commentary on Rigdon (2012). *Long range planning, 47*, 154-160.

Schafer, J. L., & Graham, J. W. (2002). Missing data: Our view of the state of the art. *Psychological Methods, 7*(2), 147-177. doi: 10.1037//1082-989X.7.1.147

Schau, C., Stevens, J., Dauphinee, T. L., & Del Vecchio A. (1995) The development and validation of the survey of attitudes toward statistics. *Educational and psychological measurement, 55*(5), 868-875.

Schumacker, R. E., & Lomax, R. G. (2004). *A beginner's guide to structural equation modeling* (2nd edition). Mahwah, NJ: Lawrence Earlbaum Associates, Publishers.

Schunk, D. H. (1985). Self-efficacy and classroom learning. *Psychology in the schools, 22(2)*, 208-223.

Schunk, D. H. (1986). Vicarious influences on self-efficacy for cognitive skill learning. *Journal of social and clinical psychology, 4*(3), 316-327.

Schunk, D. H. (1989). Self-efficacy and achievement behaviors. *Educational psychology review, 1*(3), 173-208.

Schunk, D. H. (1991). Self-efficacy and academic motivation. *Educational psychologist, 26*(3-4), 207-231. doi: 10.1080/00461520.1991.9653133

Schunk, D. H. (2005). Self-regulated learning: The educational legacy of Paul R. Pintrich. *Educational psychologist, 40*(2), 85-94.

Schunk, D. H. (2012). *Learning theories: An educational perspective* (6th ed.). Boston, MA: Pearson.

Silver, B. B., Smith, E. V., & Greene, B. A. (2001). A study strategies self-efficacy instrument for use with community college students. *Educational and psychological measurement*, 61, 849-865. doi: 10.1177/00131640121971563

Sun, J. C. & Rueda, R. (2012). Situational interest, computer self-efficacy and self-regulation: Their impact on student engagement in distance education. *British journal of educational technology, 43*(2), 191-204.

Trawick, L., & Corno, L. (1995). Expanding the volitional resources of urban community college students. In P.R. Pintrich (Ed.), *Understanding self-regulated learning* (pp. 57-70). San Francisco, CA: Jossey-Bass.

U.S. Department of Education, National Center for Education Statistics. (2004). *Digest of education statistics, 2004*. Washington, DC: U.S. Government Printing Office.

Vanhoof, S., Kuppens, S., Sotos, A. E. C., Verschaffel, L., & Onghena, P. (2011). Measuring statistics attitudes; Structure of the survey of attitudes toward statistics (SATS-36). *Statistics education research journal, 10*(1), 35-51.

Virtanen, P. & Nevgi, A. (2010). Disciplinary and gender differences among higher education students in self-regulated learning strategies. *Educational psychology, 30*(3), 323-347. doi: 10.1080/01443411003606391

Watson, J. M. (2006). *Statistical literacy at school: Growth and goals.* Manwah, NJ; Erlbaum.

Welsh, J. B. (2008). *Identifying factors that predict student success in a community college online distance learning course*. (Unpublished doctoral dissertation). University of North Texas, Denton, TX.

Williams, A. S. (2012). Worry, intolerance of uncertainty, and statistics anxiety. *Statistics education research journal, 12*(1), 48-59.

Wong, K. K. (2013). Partial least squares structural equation modeling (PLS-SEM) techniques using SmartPLS. *Marketing bulletin, 24*, Technical Note 1.

Wood, R. E. & Locke, E. A. (1987). The relation of self-efficacy and grade goals to academic performance. *Educational and psychological measurement 1987, 47*, 1013-1024.

Young, D. B., & Ley, K. (2002). Brief report: Self-efficacy of developmental college students. *Journal of college reading and learning, 33*(1), 21-29.

Zeidner, M. Statistics and mathematics anxiety in social science students: some interesting parallels. *Br. J. educ. psychol. 61*, 319-328.

Zeldin, A. L., & Pajares, F. (2000). Against the odds: Self-efficacy beliefs of women in mathematical, scientific, and technical careers. *American educational research journal, 37*(1), 215-246.

Zieffler, A., Garfield, J., Alt, S., Dupuis, D., Holleque, K., & Chang, B. (2008). What does research suggest about the teaching and learning of introductory statistics at the college level? A review of the literature. *Journal of statistics education, 16*(2). Retrieved from: www.amstat.org/publications/jse/v16n2/zieffler.html

Zimmerman, B. J. (1989). A social cognitive view of self-regulated academic learning. *Journal of educational psychology, 81,* 329-339.

Zimmerman, B. J., & Bandura, A. (1994). Impact of self-regulatory influences on writing course attainment. *American educational research journal, 31*, 845-862.

Zimmerman, B. J., & Schunk, D. H. (2001). Self-regulated learning and academic achievement—Theoretical perspectives, 2nd ed. Mahwah, New Jersey: Lawrence Erlbaum Associates.

APPENDICES

APPENDIX A

DEMOGRAPHIC QUESTIONS

DIRECTIONS: For each of the following statements mark the one best response. Notice that the response scale changes on each item.

What is your major? If you have a double major, pick the one that bests represents your interests.

1. Arts/Humanities
2. Biology
3. Business
4. Chemistry
5. Economics
6. Education
7. Engineering
8. Mathematics
9. Medicine/Pre-Medicine
10. Psychology
11. Sociology/Social Work
12. Statistics
13. Other

Current grade point average (please estimate if you don't know; give only one single numeric response: e.g., 3.52). If you do not yet have a grade point average, please enter 99: _____

For each of the following three items, give one single numeric response (e.g., 26). Please estimate if you don't know exactly.

Number of credit hours earned toward the degree you are currently seeking (don't count this semester): _____

Number of high school mathematics and/or statistics courses completed: _____

Number of college mathematics and/or statistics courses completed (don't count this semester): _____

MAT 142 or higher is the prerequisite for this course. What grade did you earn in the course you used to satisfy the prerequisite? _____

1. A 2. B 3. C

Degree you are currently seeking: _____

1. Associate
2. Bachelors
3. Masters
4. Doctorate
5. Certification
6. Post-bachelor's Licensure
7. Specialist
8. Other

What grade do you expect to receive in this course? _____

1. A 2. B 3. C 4. D 5. F

In order to describe the characteristics of your class as a whole, we need your responses to the following items.

Which instructional format for this course are you taking?
1. Face-to-face 2. Online _____

Which semester are you taking this course?
1. Summer 2015 2. Fall 2015 3. Spring 2016 _____

Section number you are enrolled in (for example, 003; if you do not know which section you are enrolled in, then please ask): _____

Your sex: 1. Male 2. Female _____

Your citizenship: 1. US citizen 2. Foreign student 3. Other _____

Your age (in years): _____

Your race: _____

1. American Indian or Alaskan	5. Polynesian
2. Asian	6. White
3. African American	7. Two or more races
4. Hispanic/Latino	8. Other

APPENDIX B

CURRENT STATISTICS SELF-EFFICACY (CSSE)

Current Statistics Self-Efficacy (CSSE)

Please rate your confidence in your ***current ability*** to successfully complete the following tasks. The item scale has six possible responses: (1) no confidence at all, (2) a little confidence, (3) a fair amount of confidence, (4) much confidence, (5) very much confidence, (6) complete confidence. For each task, please mark the one response that represents your confidence in your ***current ability*** to successfully complete the task.

	No confidence at all					Complete confidence
1. Identify the scale of measurement for a variable	1	2	3	4	5	6
2. Interpret the probability value (p-value) from a statistical procedure	1	2	3	4	5	6
3. Identify if a distribution is skewed when given values of three measures of central tendency	1	2	3	4	5	6
4. Select the correct statistical procedure to be used to answer a research question	1	2	3	4	5	6
5. Interpret the results of a statistical procedure in terms of the research question	1	2	3	4	5	6
6. Identify the factors that influence power	1	2	3	4	5	6
7. Explain what the value of the standard deviation means in terms of the variable being measured	1	2	3	4	5	6
8. Distinguish between a Type I error and a Type II error in hypothesis testing	1	2	3	4	5	6
9. Explain what the numeric value of the standard error is measuring	1	2	3	4	5	6
10. Distinguish between the objectives of descriptive versus inferential statistical procedures	1	2	3	4	5	6
11. Distinguish between the information given by the three measures of central tendency	1	2	3	4	5	6
12. Distinguish between a population parameter and a sample statistic	1	2	3	4	5	6
13. Identify when the mean, median, and mode should be used as a measure of central tendency	1	2	3	4	5	6
14. Explain the difference between a sampling distribution and a population distribution	1	2	3	4	5	6

APPENDIX C

MOTIVATED STRATEGIES FOR LEARNING QUESTIONNAIRE (MSQL)

Learning Strategies

DIRECTIONS: The following questions ask about your learning strategies and study skills for this class. **There are no right or wrong answers. Answer the questions about how you study in this class as accurately as possible**. Use the same scale to answer all of the questions below. If you think the statement is very true of you, circle 7; if a statement is not at all true of you, circle 1. If the statement is more or less true of you, find the number between 1 and 7 that best describes you.

Not at all true of me						Very True of me
1	2	3	4	5	6	7

	Not at all true of me						Very true of me
When I study the readings for this course, I outline the material to help me organize my thoughts	1	2	3	4	5	6	7
During class time I often miss important points because I'm thinking of other things	1	2	3	4	5	6	7
I usually study in a place where I can concentrate on my course work	1	2	3	4	5	6	7
When reading for this course, I make up questions to help focus my reading	1	2	3	4	5	6	7
I often feel so lazy or bored when I study for this class that I quit before I finish what I planned to do	1	2	3	4	5	6	7
When I study for this class, I practice saying the material to myself over and over	1	2	3	4	5	6	7
Even if I have trouble learning the material in this class, I try to do the work on my own, without help from anyone	1	2	3	4	5	6	7
When I become confused about something I'm reading for this class, I go back and try to figure it out	1	2	3	4	5	6	7
When I study for this course, I go through the readings and my class notes to try to find the most important ideas	1	2	3	4	5	6	7
I make good use of my study time for this course	1	2	3	4	5	6	7
If course readings are difficult to understand, I change the way I read the material	1	2	3	4	5	6	7
When studying for this course, I read my class notes and the course readings over and over again	1	2	3	4	5	6	7

I work hard to do well in this class even if I don't like what we are doing	1	2	3	4	5	6	7
I make simple charts, diagrams, or tables to help me organize course material	1	2	3	4	5	6	7
I find it hard to stick to a study schedule	1	2	3	4	5	6	7
When I study for this class, I pull together information from different sources, such as lectures, readings, and discussions	1	2	3	4	5	6	7
Before I study new course material thoroughly, I often skim it to see how it is organized	1	2	3	4	5	6	7
I ask myself questions to make sure I understand the material I have been studying in this class	1	2	3	4	5	6	7
I try to change the way I study in order to fit the course requirements and the instructor's style	1	2	3	4	5	6	7
I often find that I have been reading for this class but don't know what it was all about	1	2	3	4	5	6	7
I ask the instructor to clarify concepts I don't understand well	1	2	3	4	5	6	7
I memorize key words to remind me of important concepts in this class	1	2	3	4	5	6	7
When course work is difficult, I either give up or only study the easy parts	1	2	3	4	5	6	7
I try to think through a topic and decide what I am supposed to learn from it rather than just reading it over when studying for this course	1	2	3	4	5	6	7
I try to relate ideas in this subject to those in other courses whenever possible	1	2	3	4	5	6	7
When I study for this course, I go over my class notes and make an outline of important concepts	1	2	3	4	5	6	7
When reading for this class, I try to relate the material to what I already know	1	2	3	4	5	6	7
I have a regular place set aside for studying	1	2	3	4	5	6	7
When I study for this course, I write brief summaries of the main ideas from the readings and my class notes	1	2	3	4	5	6	7

When I can't understand the material in this course, I ask another student in this class for help	1	2	3	4	5	6	7
I try to understand the material in this class by making connections between the readings and the concepts from the lectures	1	2	3	4	5	6	7
I make sure that I keep up with the weekly readings and assignments for this course	1	2	3	4	5	6	7
I make lists of important items for this course and memorize the lists	1	2	3	4	5	6	7
I attend this class regularly	1	2	3	4	5	6	7
Even when course materials are dull and uninteresting, I manage to keep working until I finish	1	2	3	4	5	6	7
I try to identify students in this class whom I can ask for help if necessary	1	2	3	4	5	6	7
When studying for this course I try to determine which concepts I don't understand well	1	2	3	4	5	6	7
I often find that I don't spend very much time on this course because of other activities	1	2	3	4	5	6	7
When I study for this class, I set goals for myself in order to direct my activities in each study period	1	2	3	4	5	6	7
If I get confused taking notes in class, I make sure I sort it out afterwards	1	2	3	4	5	6	7
I rarely find time to review my notes or readings before an exam	1	2	3	4	5	6	7
I try to apply ideas from course readings in other class activities such as lecture and discussion	1	2	3	4	5	6	7