EXPLORATION OF LIFELONG LEARNING SKILL AND ENGINEERING

ATTITUDE DEVELOPMENT IN CYBERLEARNING ENVIRONMENTS

A Dissertation

by

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ABSTRACT

This study addressed the following research goals: (1) a reevaluation of Lifelong Learning (LLL) scale's reliability and validity measuring LLL skills, (2) reevaluation of Engineering Attitude Survey's (EAS) reliability and validity of measuring students' attitudes toward STEM fields, (3) effects of an evidence-based pedological (EBP) treatment on students' LLL and engineering attitudes (EA) during a Computer-Aided Design course.

In the first study, I calculated reliability coefficients for the original LLL scale with good internal consistency. The exploratory factor analysis (EFA) yielded two factors (i.e., Learner characteristics and Enjoyment of reading and writing). The confirmatory factor analysis (CFA) measure model fit using five fit indices, initially had poor model fit except for one. After deleting items with low factor loading and low item-factor correlations the model fit was improved, yielding "good fit" for all indices.

In the second study, I calculated original EAS reliability coefficients with good internal consistency. EFA was performed resulting in four factors (i.e., Engineering as a career, Engineer career characteristics, Engineer career personality characteristics, and Engineering is theoretical). CFA model fit using the same five model fit indices did not yield good fit indices. Modifications to the EAS by deleting poor item-factor correlations resulted in improved reliability and construct validity for all of the model fit indices.

In the third study, I used the modified versions of the LLL and EAS and their sub-scales from the first two studies to explore if being educated through an EBP had any statistically significant effect on students' LLL skills and EAs. I found that Factor 1

sub-scale of the EAS named “Engineering as a career” revealed statistically significant results. Students who were female, African American, first-generation college student in their immediate family showed the greater improvements in the “Engineering as career” sub-dimension of the EAS. In all other dimensions of the instruments, students’ mean score differences were improved after the modified versions were considered captured by the effect size differences.

I have identified proven methods, EBP, and improved assessment tools (i.e., modified LLL scale and modified EAS) that can positively impact and monitor vulnerable undergraduate populations and URMs in STEM undergraduate programs.

DEDICATION

There are many people that have earned my gratitude for their contribution to my time in graduate school. More specifically, I would like to thank these people, without whom this dissertation would not have been possible. My husband Dr. Steven Lai Hing, my children Steven Lai Hing II and Divya Lai Hing (and those yet unborn), you are the reason I live. To my siblings, Dr. Robert Hammond and Sierra Hammond, we have struggled, laughed, cried, and succeed in spite of it all, my original crew, I love you to the moon and back. To my parents Dr. Cynthia and Robert Hammond and Dr. Kenneth and Jean Lai Hing, many thanks to you for your sacrifices to ensure that I had every possible advantage and encouraged me to be not only the best student, but most importantly an amazing human being. Last but not least my friends the "girl squad": Jailyn Nicholson, Dorenda Dombokah, Kathy Garcia, Mairelis Jessup, Carolyn Nwankpa, and Sasha Prince, you all have been an integral part of me maintaining my sanity and you all are the best cheerleaders and supporters a friend could ask. My success is a tribute not only to these named friends and family, but my ancestors whose legacy, hopes, and prayers are fulfilled through me and my children.

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NOMENCLATURE

STEM	Science, Technology, Engineering, and Math
CAD	Computer-Aided Design
EFA	Exploratory Factor Analysis
CFA	Confirmatory Factor Analysis
URM	Under Represented Minority
LLL	Lifelong Learning
EA	Engineering Attitudes
EAS	Engineering Attitude Survey
HPL	How People Learn
SPSS	Statistical Package for Social Sciences
HBCU	Historically Black College & University
EBP	Evidence Based Pedagogy
KMO	Kaiser-Meyer-Olkin Measure of Sampling Adequacy
HBCU	Historically Black College and University
MCAR	Missing Completely at Radom
df	Degree of Freedom
RMSEA	Root Mean Square Error of Approximation
CFI	Comparative Fit Index
TLI	Tucker Lewis Index
GFI	Goodness of Fit Index

ML	Maximum Likelihood
SNIP	Source-normalized Impact per Paper
SJR	Scientific Journal Rank

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1. INTRODUCTION

1.1 Background

1.1.1. 21st Century Skills

Around 2009, the U.S. Department of Education along with various organizations, including the National Education Association, the business community, education leaders, and policymakers aimed at identifying skills and a comprehensive strategy to prepare students for the unique local and global challenges of the 21st century. This represents an emerging area of the knowledge base not yet completely developed and has become a movement with a mission to train all students for future success. Partnership for 21st Century Learning (2018), a national and nonprofit organization that advocates for 21st century readiness for every student, has identified skills that are integrated and fundamental for Science, Technology, Engineering and Mathematics (STEM) education. Among the skills required for success as students and as adults in the workforce of the future are flexibility and adaptability, taking initiative, being self-directed and self-disciplined, possessing social and cross-cultural skills, productivity and accountability, leadership, and responsibility. To promote those skills, researchers implemented various interventions. The research synthesized by the National Research Council suggests science instruction should focus on scientific proficiency as a key educational goal for the 21st Century. Students should be able to (a) know, use, and interpret scientific explanations of the natural world; (b) generate and evaluate scientific evidence and explanations; (c) understand the nature and development of scientific knowledge; and (d) participate productively in scientific practices and discourse (Duschl, Schweingruber, & Shouse, 2007; Michaels, Shouse, & Schweingruber, 2008; National Research Council, 2004).

Improving STEM education, plus increasing the participation of underrepresented minorities (URMs), links to the U.S. remaining economically competitive in an increasingly technological world marketplace. STEM education and URM participation are codependent and must be innovative enough to not only attract STEM students, but to encourage them to become working scientists, contributors, and candidates for ever increasing job opportunities in STEM fields (Palmer, Maramba, & Gasman, 2013). Student-centered and learner-oriented environments can be used when instructors' goals include facilitating the development of STEM academic foundations as well as improving students' skills and attitudes towards STEM fields. Cultivating "lifelong learning" skills for underrepresented demographics remains key to the U.S. maintaining and improving our world standing and leadership in science and technology (Galloway, 2004).

1.1.2. Lifelong Learners

Lifelong learners deliberately and voluntarily develop personal characteristics related to acquiring knowledge throughout life by creating and maintaining positive attitudes towards learning for personal and professional development. The National Academy of Sciences supports efforts to increase the participation of URMs in STEM fields. These efforts are essential to sustaining America's research and innovation capacity (Ceci & Williams, 2011). Today's workforce requires knowledge and skills adaptable to the growing technological and global demands. Individuals entering the workforce must be able to continuously update their knowledge base beyond the classroom and even after graduation by learning new techniques and skills in order to keep up with technological developments and innovations. Future STEM practitioners should be lifelong learners.

1.1.3. Reliability and Validity

While the prior research literature contains, many studies utilizing various instructional methods and interventions geared toward measuring lifelong earning (LLL) skills and attitudes, very few of these studies have documented the reliabilities and validities of their analyzed data. Developing ways of obtaining reliable and valid data from assessments, outlining methods to improve existing surveys, and reevaluating existing data sets could prove beneficial for researchers. These improvements allow researcher to have the tools to systematically and effectively modify instructional methods in order to capture the development of LLL skills and attitudes towards STEM fields.

1.1.4. Research Overview

Through the research we conducted while writing this three article dissertation, we addressed the following: (a) a reevaluation of LLL scale reliability and validity of measuring LLL skills, (b) a reevaluation of the Engineering Attitude Survey (EAS) reliability and validity of measuring student attitudes towards STEM fields, and (c) an exploration of the effects of an evidence-based pedagogical treatment on students' LLL skills and Engineering Attitudes (EA) during a Computer-Aided Design (CAD) course offered in a mechanical engineering program at a Historically Black College and University (HBCU) in the Southwest region in the United States (U.S.)

1.1.5. Research Questions

The following research questions guided the research conducted in the three articles:

RQ1: What is the reliability of the modified LLL scale?

RQ2: What is the construct validity and model modification fit of the LLL scale?

RQ3: What underlying constructs and sub-dimensions can be derived from an exploratory factor analysis of the LLL scale?

RQ4: What is the reliability of the modified EAS?

RQ5: What is the construct validity and model modification fit of the EAS?

RQ6: What underlying constructs and sub-dimensions can be derived from an exploratory factor analysis of the EAS?

RQ7: What were the statistically significant relationships among the students' responses to the original versions of the LLL scale and EAS, and their sub-scales, frequency of screen-cast tutorial exercises students completed over the semester, students' ethnicity, gender, first-generation college student status, and type of the treatment (i.e., experimental and comparison) group?

RQ8: What were the statistically significant relationships among the modified versions of the LLL scale, EAS, and their sub-scales, frequency of the screen-cast tutorial exercises students completed over the semester, students' ethnicity, gender, first-generation college status, and the type of treatment group (i.e., experimental and comparison)?

The first two research questions have been addressed in the section 2 titled, "Re-examination of a Lifelong Learning Survey to Improve its Reliability and Validity." This article was submitted for publication to the International Journal of STEM Education. The third and fourth questions have been addressed in section 3 titled, "Re-examination of an Engineering

Attitude Survey to Improve its Reliability and Validity." This article was submitted to the International Journal of Engineering. Within these two sections, we have completed an exploratory factor analysis (EFA) of the survey items alongside the survey responses to elucidate potentially hidden constructs or new factors. During the second phase, we have utilized confirmatory factor analysis (CFA) to verify the relationship between observed variables and the underlying latent constructs. These results are presented in section 4 titled, "Examining the Effect of an Evidence-Based Pedagogy (EBP) on Students' Lifelong Learning Skills and Engineering Attitudes Utilizing the Modified Versions of Lifelong Learning Scale and Engineering Attitude Survey." This section was submitted to the Journal of Engineering Education. The reevaluated LLL scale and EAS were used to investigate the statistically significant differences among the students' gain score means across different treatment groups and students' demographic characteristics. New effect sizes were computed and reported for the group means. A summary of the articles to the submitted journals are outlined in Table 1.

Table 1. Submitted Articles and Journal Summary

Articles	Submitted Journal
Re-examination of a Lifelong Learning Survey to Improve its Reliability and Validity	International Journal of STEM Education Editor- Yeping Li Peer Review Springer Open No word limits
Re-examination of an Engineering Attitude Survey to Improve its Reliability and Validity	International Journal of Engineering Education Editor- Ahmad Ibrahim SJR/SNIP .433/.905 Dublin Institute of Technology Tempus Publications No word limits
Examining the Effect of an Evidence-Based Pedagogy on Students Lifelong Learning Skills and Engineering Attitudes Utilizing the Modified Versions of the Lifelong Learning Scale and Engineering Attitude Survey	Journal of Engineering Education Editor- Lisa C. Benson SJR/SNIP 2.687/8.794 8,000-10,000

1.1.6. Project Summary

The LLL scale and EAS data were collected over four years. A total of 229 students in these four years enrolled in a freshman mechanical engineering course and participated in the CAD screen-cast tutorial, evidence-based pedagogical treatment. The foci of this dissertation research were aimed at (a) utilizing EFA and CFA to improve the LLL scale and EAS, (b) calculating the reliability coefficients of the LLL scale and EAS, (c) calculating the effect sizes of comparison and treatment groups, and (d) the relationships between existing respondent data and the EBP screen-cast activity. The ultimate goal of this research involves an investigation of the construct validity, reliability, and the employment of a factor analysis of the LLL scale and EAS. These surveys are now more effective for researchers to use in investigating participants' development of LLL skills and EA in response to EBP treatments.

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2. RE-EXAMINATION OF A LIFELONG LEARNING SCALE TO IMPROVE ITS RELIABILITY AND VALIDITY

2.1. Introduction

2.1.1. Characteristics of a Lifelong Learner

Edgar Faure coined the term ‘I’ education permanente’ (Faure, 1972), which translates to lifelong learning (LLL). LLL, as described by Faure, represents an inevitable human practice throughout the course of individuals’ lives. Faure argues that human potential, permeation of human rights, and democratic ideals are dependent on the provision of LLL opportunities. When these learning opportunities are limited, learners become deprived of an environment that germinates human rights and democratic ideals. “There are no fixed truths or total definitive knowledge, and because circumstances change, the human condition may be best understood as a continuous effort to negotiate contested meanings” (Mezirow, 2000, p. 3). Because democratic ideals are not fixed nor stable, but are also evolving, learners will develop their own democratic ideals over time. They need to be equipped with learning tools so that they can conceptualize these developing democratic ideals, have the ability to learn new things and continue to learn beyond formal schooling. These LLL skills will prepare them to be productive and responsible workers for the 21st century. A key component these essential skills possess is influencing learners to become autonomous and socially responsible thinkers (Mezirow, 2000).

Researchers have been trying to converge on a unified definition of LLL. Gelpi (1984) an early commentator on LLL, called for more conceptual clarity and a clearer definition of lifelong learning. The characteristics of what defines a lifelong learner is further discussed here in this section.

The identification of the skills and personality traits associated with lifelong learners has been the focus of many studies (Gelpi, 1984; Hojat, Veloski, Nasca, Erdmann, & Gonnella, 2006) Simon, Dedic, Hubbard, and Hall (2015) defined LLL as "a concept that involves a set of self-initiated activities (behavioral) and information seeking skills (capabilities) that are activated in individuals with a sustained motivation to learn and the ability to recognize their own learning needs (cognition)" (pg. 931). LLL represents the development of potential through "continuously supportive process which stimulates and empowers individuals to acquire all the knowledge, values, skills, and understanding they require throughout their lifetimes and to apply them with confidence, creativity and enjoyment in all roles, circumstances and environments" (Watson, 2003, p. 3). Students should also demonstrate an understanding of the importance of LLL and personal flexibility to sustain personal and professional development as the nature of work evolves (Gelpi, 1984; Simon et al., 2015). The lifelong learner characteristics are closely associated with those of the 21st century skills. The required emphasis skills for the lifelong learner and the 21st century workforce both emphasize adaptability, self-direction, responsibility, social and economic priorities, and local and global awareness (Gelpi, 1984).

Educational institutions, colleges, and universities play critical roles in developing students' LLL skills. Many researchers, for example Candy, Crebert, and O'Leary (1994) and Knapper and Cropley (2000) conducted studies on LLL in the context of higher education. Formal education providers are mantled with the responsibility to not only pass on knowledge to their students, but to also incorporate LLL training into the curriculum. Students need to learn strategies for memory, thinking, and ways to motivate themselves (Longworth, 2003). Griffin, MacKewn, Moser and VanVuren (2012) sought to examine what personality characteristics, beliefs, and behaviors contribute most positively to students' academic performance measured by their grade point average (GPA). Griffin et al. (2012) identified students' motivation as the most important determinant of superior academic performance. However, few students will ever directly use the disciplinary knowledge they acquire in universities and will therefore need to be equipped with generic abilities to guide their own learning throughout their lives across diverse situations they encounter after leaving formal education (Partnership for 21st Century Learning, 2018).

Society at large also benefits from citizens being lifelong learners. Dewey's philosophy describes education as the means of social continuity of life (Dewey, 1916, p. 3). Lifelong learners, educated citizens and self-actualization of the citizens represents the foundation of a successful democratic society (Candy, 1991; Candy et al., 1994; Knapper & Cropley, 2000). The triadic nature of lifelong learners includes (a) economic progress and development; (b) personal development and fulfilment; and (c) social inclusiveness, democratic understanding and activity. These three are fundamental to building a more democratic polity and set of social institutions (Hofer & Yu, 2003; Kirby, Knapper, Lamon, & Egnatoff, 2010). The ultimate goal of lifelong learners is to develop the ability to cope with a rapidly changing world, be capable of taking initiative for their own education, and be motivated to continue learning throughout their lives in many different situations (Griffin et al., 2012). The world is changing, fast-moving, and unpredictable and learning throughout a person's lifetime becomes essential to survival. New knowledge is constantly emerging and individuals need to be motivated to evaluate these developments and new technologies to maintain a stable and adaptive society (Kirby et al., 2010).

2.1.2. Lifelong Learning (LLL) Scale

Controlled empirical research on a broad concept such as LLL is difficult, and there are few surveys available to measure LLL skill adoption (Kirby et al., 2010). Some of the available surveys exploring LLL include Crick and Yu's Effective Lifelong Learning Inventory (ELLI). This survey has 72-items, with seven scales (Aspin & Chapman, 2000). This survey targets age group ranges from seven years old to adulthood. ELLI is very extensive and explores socio-emotional issues such as dependence and fragility. According to Kirby et al. (2010), the ELLI has some noted limitations. The scale does not address setting personal and realistic goals, application of existing knowledge and skills, self-evaluation of learning or the location of information from different sources. Kirby et al. (2010) further explained that the ELLI is not a concise measure of cognitive aspects of individual's tendency to engage in LLL. Kirby et al. (2010) developed a more concise, 14-item lifelong learning survey, identified as the LLLS (Knapper & Cropley, 2000). This survey includes five dimensions, including (a) goal setting, (b) application of knowledge and skills, (c) self-direction and self-evaluation, (d) information location, and (e) learning strategy adaption (Longworth, 2003). The reported reliability coefficient, Cronbach's alpha, was 0.71 for the data in hand (Kirby et al., 2010). All 14 items remained in the final survey, as removal of any of the items reduced the alpha coefficient. A one-way analyses of variances (ANOVA) test revealed that LLLS was statistically significant (F-ratio <1.0) with grades or grade average, and gender and age showing no differences. The major criticism of this study has been that the LLLS did not show a positive relationship with the students' GPAs as this is highly inconsistent with the general construct of LLL (Kirby et al., 2010).

Wielkiewicz, Prom, and Loos (2005) developed a LLL scale. Survey items are sourced and combined from the Academic Ethics Items from Rau and Durand (2000), and Leadership and Behavior Scale from Wielkiewicz et al. (2005). Academic ethics focuses on long-term adherence to various ideals such as students' interest in their courses, participation in learning activities outside of class, and reading outside of class requirements. The Leadership Attitudes and Behavior Scale (LABS, Wielkiewicz, 2000), has two subscales, Hierarchical Thinking and Systematic Thinking. These two subscales explore the responses associated with students' ability to be flexible in a rapidly changing world and those in leadership's ability to be effective communicators. The survey items explore the extent to which the person reports positive behaviors and attitudes associated with learning curiosity and critical thinking. Wielkiewicz and Meuwissen (See APPENDIX A) redeveloped the survey, WielkLLL, to broaden the context. The final WielkLLL survey is a 16 item, five-point Likert scale ranging from 1 (*strongly agree*) to 5 (*strongly disagree*). The primary dependent variable is the students' GPAs and a student's WielkLLL score were shown to be the best predictor of GPA. Another important factor for the WielkLLL is the survey can be administered both in and outside an academic context, which is a major goal of capturing information about an individual's LLL skills. For simplicity's sake, the WielkLLL survey will be referred to as the LLL scale for the remainder of this section.

2.1.3. Reliability and Validity

The literature has documented many treatments and interventions to improve science, technology, engineering and math (STEM) education. However, very few of these studies have reported reliability and validity of analyzed data. This information is vital for educators and researchers to choose effective instructional methods. The research described here reevaluates the survey response data by investigating the reliability and validity of the LLL scale.

2.1.4. Research Summary

In this section, we investigated the LLL scale and its sub-dimensions or latent factors. The survey was administered to 229 undergraduate students. These students were freshman enrolled in a Mechanical Engineering Drawing course being offered by a Mechanical Engineering Department at a Historically Black College and University (HBCU) in the Southwest region in the United States (U.S.). The survey was administered at the beginning and end of each semester over four years. The mechanical engineering students participated in a Computer-aided Design (CAD) screen-cast tutorial, an evidence-based pedagogical treatment. Additionally, a demographic survey was administered. The following research questions are addressed in this section.

RQ1: What underlying data structures can be derived from an exploratory factor analysis of the LLL scale?

RQ2: What is the construct validity and model modification fit of the LLL scale?

RQ3: What is the reliability of the modified LLL scale?

2.2. Methods

229 students completed the LLL scale administered at the beginning and end of each semester of freshman Mechanical Engineering Drawing courses offered in an undergraduate Mechanical Engineering Department. Students also completed a demographic survey. In my research, I measured the data sets and provided: (a) internal consistency or reliability (Cronbach's alpha), (b) underlying data structures or factors that emerge after completing an Exploratory Factor Analysis (EFA), and (c) construct validity derived factors from the LLL scale using Confirmatory Factor Analysis (CFA).

Spearman developed Exploratory Factor analysis (EFA) in the early 1900's (Rau & Durand, 2000). Researchers in the social sciences widely use this statistical method. "The primary purpose of EFA is to arrive at a more parsimonious conceptual understanding of measured variables by determining the number and nature of common factors needed to account for the pattern of correlations among the measured variables" (Fabrigar, Wegener, MacCallum, & Strahan, 1999, p. 275). EFA is based on the common factor model where the measured variables are a linear function of one or more common factors and one unique factor. Fabrigar et al. (1999) further explained that these common factors are unobservable latent variables that influence more than one measured variable. These common factors are presumed to account for the covariances among the measured variables. The common factor model (Thurstone, 1947), the basis of EFA, systematically analyzes the structures of correlations among variables. The model postulates these correlations estimating the pattern of relations between the factors. These relations are then indexed by factor loadings, indicated by eigenvalues greater than one. The overall goal of EFA is to "determine the number and nature of latent variables or factors that account for the variation and covariation among a set of observed measures" (Brown & Moore, 2012, pp. 12,13). These observed measures are interrelated because they share common cause, or influenced by the same underlying construct. The factor analysis represents a more parsimonious explanation of the covariation among the indicators (Brown & Moore, 2012)

We utilized EFA to investigate a large set of student responses to all survey items and groups those statements according to the correlations between the statement responses. This method results in emergent categories and underlying constructs that may not have been readily observed from the original survey questions. We have analyzed the survey responses using EFA to identify separable dimensions or latent factors representing theoretical constructs, within a domain. We have also used the Statistical Package for the Social Science (SPSS) software v.26 to conduct “Dimension Reduction” – Factor Analysis to identify separable dimensions, representing theoretical constructs, within a domain. The analysis scheme included combining the treatment and comparison post-test groups’ respondent data from the LLL scale collected over four years. The goal of this analysis was to develop parsimonious scales of items with clear loading patterns that could be used to eliminate items that fail to load on any factors. Factors retained were determined by using the Scree test. Unrotated eigenvalues were plotted on a coordinate plane and the Scree test examines the slope of the line connecting them. The cutoff for retaining factors was determined by the point in which the slope of the plotted line approaches zero, or the “elbow bend” of the curve. The factors represented after this point indicated factors that if discarded would not have significantly impacted variance accounted for estimates. Following orthogonal rotation extraction, orthogonal (factors kept uncorrelated) Varimax rotation, was performed on retained factors resulting in a smaller number of variables and low factor loadings for the rest. Retained factors which had eigenvalues of more than one (Stephens, 1996) highlighted a small number of important variables.

Complimentary statistical analysis to EFA, confirmatory factor analysis (Joreskog, 1969; Jöreskog, 1971), was used to assess construct validity and model modification fit of the LLL scale. Hypothesized factor structures were tested for fit with the observed covariance structure of the measured variables. This method is most effective when used to assess if the proposed factor structure adequately fits the data and if the structure fits and is parsimonious with other models. CFA relies on the “measurement model,” which describes measured/observed variables reflected in underlying latent/synthetic variables (Thompson, 1998). Because various indices use structural equation modeling based on different assumptions, they often produce contradictory results. There is no single, recognized goodness-of-fit index (Hoyle, 1995). This study utilizes five different model fit indices to evaluate the proposed model derived from the EFA. The indices including Chi-square goodness-of-fit test (Pearson, 1900), Tucker Lewis index (Tucker & Lewis, 1973), Goodness-of-fit test (Joreskog & Sorbom, 1986), Comparative fit index (CFI), and Root Mean Square Error (RMSEA). Chi-square goodness-of-fit test is the most traditional index, assessing overall fit and discrepancy between the sample and fitted covariance matrices. This statistic computation does not aim to reject the null hypothesis; therefore, the model can be taken as fitting the data (Thompson, 1998). Tucker-Lewis index (TLI) measures relative fit that is relatively independent of sample size. Goodness-of fit test (GFI) examines how well sample data fit a distribution from a population with a normal distribution. The test reveals if the sample data represent the data expected to be observed in the actual population. Indices less than zero are treated as zero. GFI with an upper limit of one, represents a perfect model fit. GFI is considered to have acceptable values when values range between .9 and .95 (Thompson, 1998). Comparative fit index-analysis examines discrepancies between the data and the hypothesized model, adjusting for sample size errors present in the chi-squared test model fit (Hu & Bentler, 1999). Root Mean Square Error of Approximation (RMSEA) is a parsimony-adjusted index and the values that range from 0 to 0.08 represents a good fit (Hu & Bentler, 1999). This value is often used as an effect size value to describe a fit for a model in CFA. Schreiber, Nora, Stage, Barlw, and King (2006) provided general rules for acceptable fit values when using RMSEA. In usage of continuous data, they suggested that values ranging between 0.6 and 0.8 indicate a good fit.

2.2.1. Participants

This study comprised 229 participants, 54 (23.6%) females and 175 (76.4%) male students. Over four years, these participants enrolled in various sections of a Mechanical Engineering drawing course offered by a Mechanical Engineering Department at a University in the Southwest region in the U.S. The university was an HBCU and the students were predominantly African American. Specifically, 2 (.9%) of students identified as Caucasian, 9 (3.9%) identified as Mixed Heritage, 14 (6.1%) identifies as Other, 16 (7.0%) identifies as Asian, 23 (10%) identifies as Latino/Hispanic, and 165 (72.1%) identified as African American. Most (98.3%) of the participants were majoring in Mechanical Engineering with the remaining students enrolled in various concentrations of Mechanical Engineering. For example, the concentrations include Aerospace engineering (0.4%), Biology and Mechanical engineering (0.4%), Mechanical engineering and Math (0.4%), and Mechanical engineering and Physics (0.4%). Information about students' first-generation college status was also obtained. For these participants, 83 (36.2%) of students identified as non-first-generation college students and 146 (63.8%) of them identified as first-generation college students. Table 2 contains a summary of all demographic information for the participants.

Table 2. Participants' Demographics

Characteristic	Category	*N*	Percent (%)	Cumulative (%)
Gender				
	Female	54	23.6	23.6
	Male	175	76.4	100.0
	Total	229	100.0	
Ethnicity				
	Caucasian	2	0.9	0.9
	Mixed Heritage	9	3.9	4.8
	Other	14	6.1	10.9
	Asian	16	7.0	17.9
	Latino/Hispanic	23	10.0	27.9
	African American	165	72.1	100
	Total	229	100.0	
Major				
	Aerospace Engineering	1	0.4	0.4
	Biology and Mechanical Engineering	1	0.4	0.8
	Mechanical Engineering and Math	1	0.4	1.2
	Mechanical Engineering and Physics	1	0.4	1.6
	Mechanical Engineering	225	98.3	100.0
	Total	229	100.0	
First-Generation College Status				
	No	83	36.2	36.2
	Yes	146	63.8	100.0
	Total	229	100.0	

2.2.2. Data Organization

In the present study, the data were de-identified and the experimental group categories (comparison and treatment) were numerically coded. The other categories were also numerically coded including students' ethnicity, gender, first-generation college student status, major, and LLL scale responses.

2.2.3. Survey

The LLL scale developed by Wielkiewicz and Meuwissen (2014) is a 16 item, five-point Likert-scale, each item is rated on a scale of 1 to 5 with 1 = Never; 2 = Rarely; 3 = Sometimes; 4 = Often, and 5 = Always or Daily. The LLL survey was administered to 229 students on two different occasions during the semester; specifically, at the beginning and the end of the semester. The goal of the LLL survey was to evaluate the participants' LLL skills. All 16 items in the survey are positive.

2.3. Analysis

To answer the research questions, we performed three distinct analyses, including EFA and effect size (RMSEA) using SPSS software v.26, and CFA using SPSS AMOS v.23. In order to determine whether the data were appropriate for the factor analysis Bartlett's Test of Sampling Adequacy and Kaiser-Meyer-Olkin test (KMO) was applied. Exploratory Factor Analysis (EFA) was used to determine the structure of factor loading. CFA was utilized to verify to what extent the factor structure is appropriate for the factors structure derived from the LLL scale (Thompson, 2004). Effect size was used to investigate the effectiveness of the screen-cast activity and to quantify the differences between the treatment and comparison group (Kelley & Preacher, 2012).

2.3.1. Exploratory Factor Analysis, KMO, Bartlett's Test

EFA was performed with the 16 items of the LLL scale. To determine the suitability of the LLL scale ($N = 229$ with 16 –item survey) in measuring the underlying structure of latent variables, Bartlett's Test of Sampling Adequacy and the KMO of Sampling Adequacy values provided critical information. Acceptable values of Bartlett's Test should be statistically significant at the $p = .05$ level (Williams, Onsman, & Brown, 2010). KMO values between .8 and 1.0 indicate sampling is adequate (Williams et al., 2010). We used SPSS version 26. The results of Bartlett's Test, $\chi^2 = 1493.960$ ($p < .001$) indicated that factors were related and suitable for structure detection. Results from the KMO test, .881, indicated that the proportion of variance in the variables might have accounted for using underlying factors. The results of these two tests are presented in Table 3.

Table 3. LLL Scale Adequacy Testing

KMO and Bartlett's Test

Test	Value	*p*-value
Bartlett's Test of Sampling Adequacy	1493.960 (χ^2)	.000
Kaiser-Meyer-Olkin Factor Adequacy (KMO)	.881	N/A

The 16 items of the LLL scale were subjected to Principle Axis Factoring. Varimax (25) rotation was applied to determine which items belonged to which factor. Factor loading cut-off was set at .30 (Henson & Roberst, 2006). No item was found with factor load values less than .30. After EFA, the LLL scale was found to have a construct with 16 items and two factors. The scree-plot graph of the survey indicated 2 factors with eigenvalues greater than 1 (Figure1). The results of the EFA summarized in Table 4. The table presents 10 of the 16 items loading under the first factor, and the remaining six items loading under the second factor. The first factor was termed as "Learner characteristics" and the second factor was termed "Enjoyment of reading and writing."

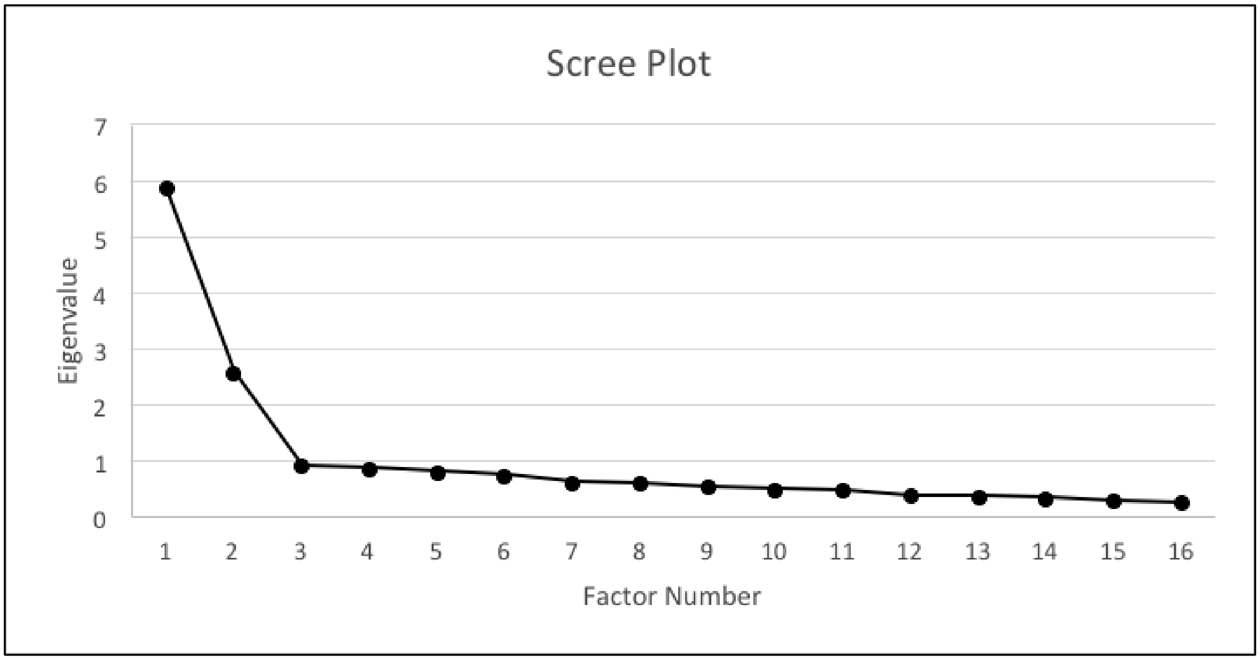

Figure 1. Scree plot for factor analysis of responses to the Life Long Learning Scale

Table 4. EFA Results from Analysis of Responses to LLL Scale

Item number	Item	Factor 1: Learner characteristics	Factor 2: Enjoyment of reading and writing
15	I like to learn new things	.704	
14	I pursue a wide range of learning interest	.687	
11	My activities involve critical thinking	.684	
5	I see myself as a life-long learner	.661	
4	I like to analyze problems and issues in depth	.654	
8	I am a self-motivated learner	.615	
10	I make interesting contributions to discussion in my classes, at work, or with friends	.585	
13	I am curious about many things	.582	
3	I converse with others about new things I learned	.528	
1	I enjoy intellectual challenge	.524	
6	My regular activities involve reading		.784
12	I read for pleasure or entertainment		.759
16	I do a lot of reading that is not required for my classes or job		.731
9	I browse libraries or bookstores for interesting books or magazines		.706
2	I read for the sake of new learning		.702
7	My regular activities involve writing		.523
	Revealed variance (%) Total = 46.3	33.3%	13.0%

The two factors in the LLL scale constituted 46.3% of the total variance. The first factor constituted 33.3% and the second 13.0%. For survey validity, the total variance of factors should account for 41% of the total variance in the participants' responses (Kline, 1994). The total variance for the LLL scale in the present study was 46.3% and therefore were considered applicable with a construct consisting of 16 items and 2 factors.

2.3.2. Cronbach's Alpha Reliability Analysis

Cronbach alpha values of the LLL scale factors were calculated to evaluate internal consistency and reliability of the derived factors. The Cronbach's alpha scores are presented in Table 5.

Table 5. Cronbach's Alpha Values of the LLL Scale

Factor	Number of items	Cronbach Alpha value
Learner Characteristic	10	.873
Enjoyment of reading and writing	6	.861
Total	16	.880

2.3.3. Confirmatory Factor Analysis

CFA was applied to test the LLL scale data compliance of the model obtained using EFA. IBM SPSS AMOS (version 23) statistical software was used for data analysis. The responses included some missing data. Item six had five missing responses, items 11, 12, and 14 each had one missing response. There are 16 items on the LLL scale, with a total of 229 responses which totaled 3,664 potential item responses. The eight missing responses represented 0.03% of the items, or 3.5% of the responses, which was below the acceptable 5% threshold (Schaefer, 1999). The data set was modified by listwise deletions of responses, where missing data were identified (McKnight, McKnight, Sidani, & Gigueredo, 2007; Schaefer & Graham, 2002). Missing data were assumed to be missing completely at random (MCAR). The final sample size of the CFA analysis was reduced from 229 responses down to 221. We considered the 16-items from the survey as first-order factors (indicator variables), and the two conceptual domains (Learner Characteristics and Enjoyment of Reading and Writing) were tested as second-order factors (latent variables). All parameters were freely estimated (derived from the analysis) and indicators were allowed to cross-load (represent multiple latent variables). The factor construct's fit used maximum likelihood (ML) estimations and was examined on the basis of the goodness-of-fit statistics and results of modification index. The fit statistics included RMSEA (Steiger, 2016), Chi square test (Pearson, 1900), comparative fit index (CFI, Bentler, 1990), Tucker-Lewis (TLI, Bentler & Bonnett, 1980; Tucker & Lewis, 1973), and Goodness of Fit index (GFI, Joreskog & Sorbom, 1986). Researchers have suggested that these fit statistics are the most commonly used (Jackson, Gillaspy Jr, & Purc-Stephenson, 2009). The standardized results are summarized in Table 6.

Table 6. CFA Results of LLL Scale

Fit index	Criteria	Intercept points for confirmation	Research finding
df	-	-	103.0
$\chi 2$	P>0.05	-	243.16
RMSEA	0 (excellent fit) 1 (no fit)	≤ 0.06 = excellent fit	0.079
CFI	0 (no fit) 1 (excellent fit)	≥ 0.90 = good fit	0.901
TLI	0 (no fit) 1 (excellent fit)	≥0.92 = good fit	0.885
GFI	0 (no fit) 1 (excellent fit)	≥ 0.90 = good fit	0.881

df: Degree of Freedom

χ^2: Model Chi-Square

RMSEA: Root Mean Square Error of Approximation

CFI: Comparative Fit Index

TLI: Tucker Lewis Index

GFI: Goodness of Fit Index

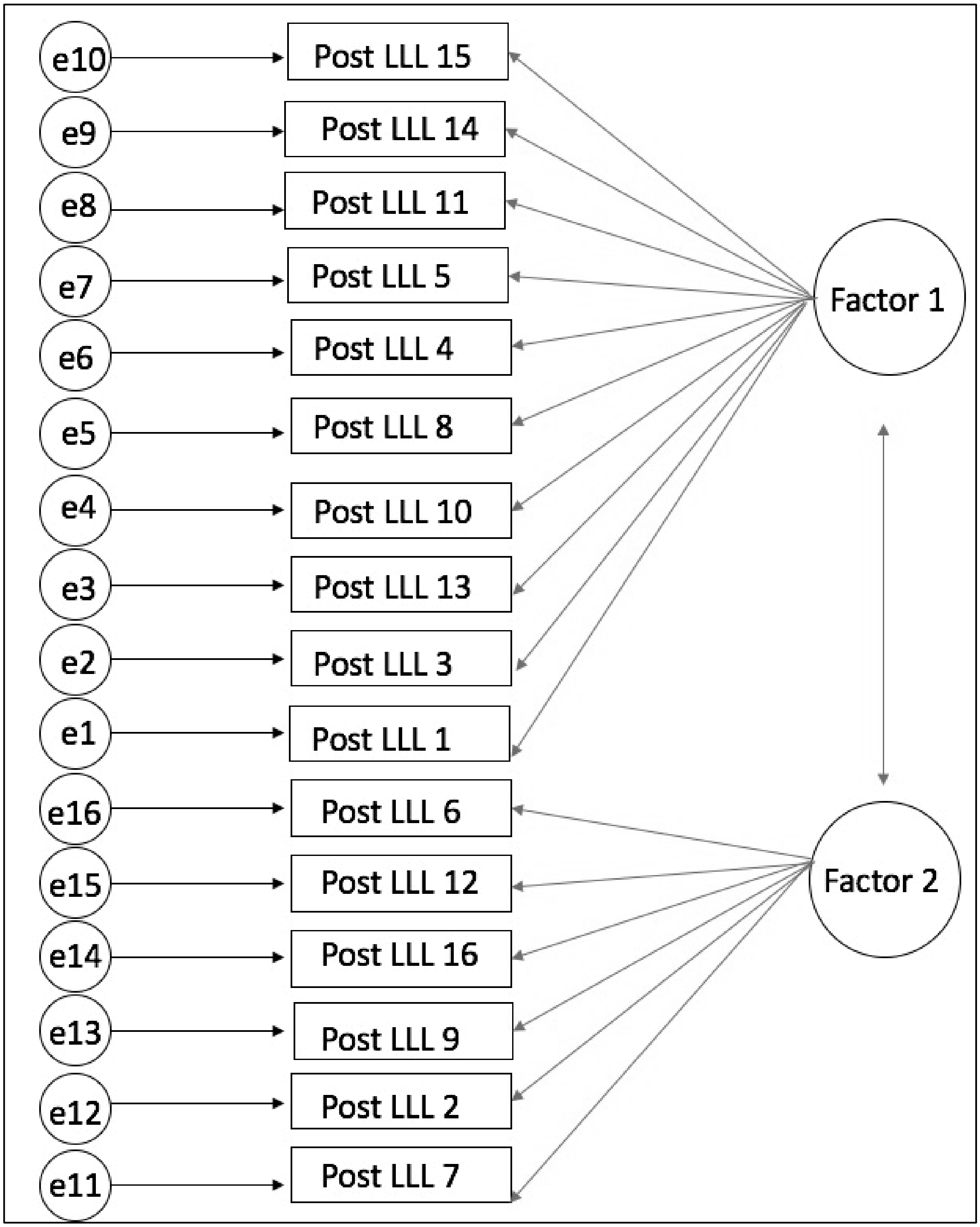

Figure 2. Confirmatory factor analysis model for LLL Scale. (Factor 1 is Learning Characteristics and Factor 2 is Enjoyment of Reading and Writing)

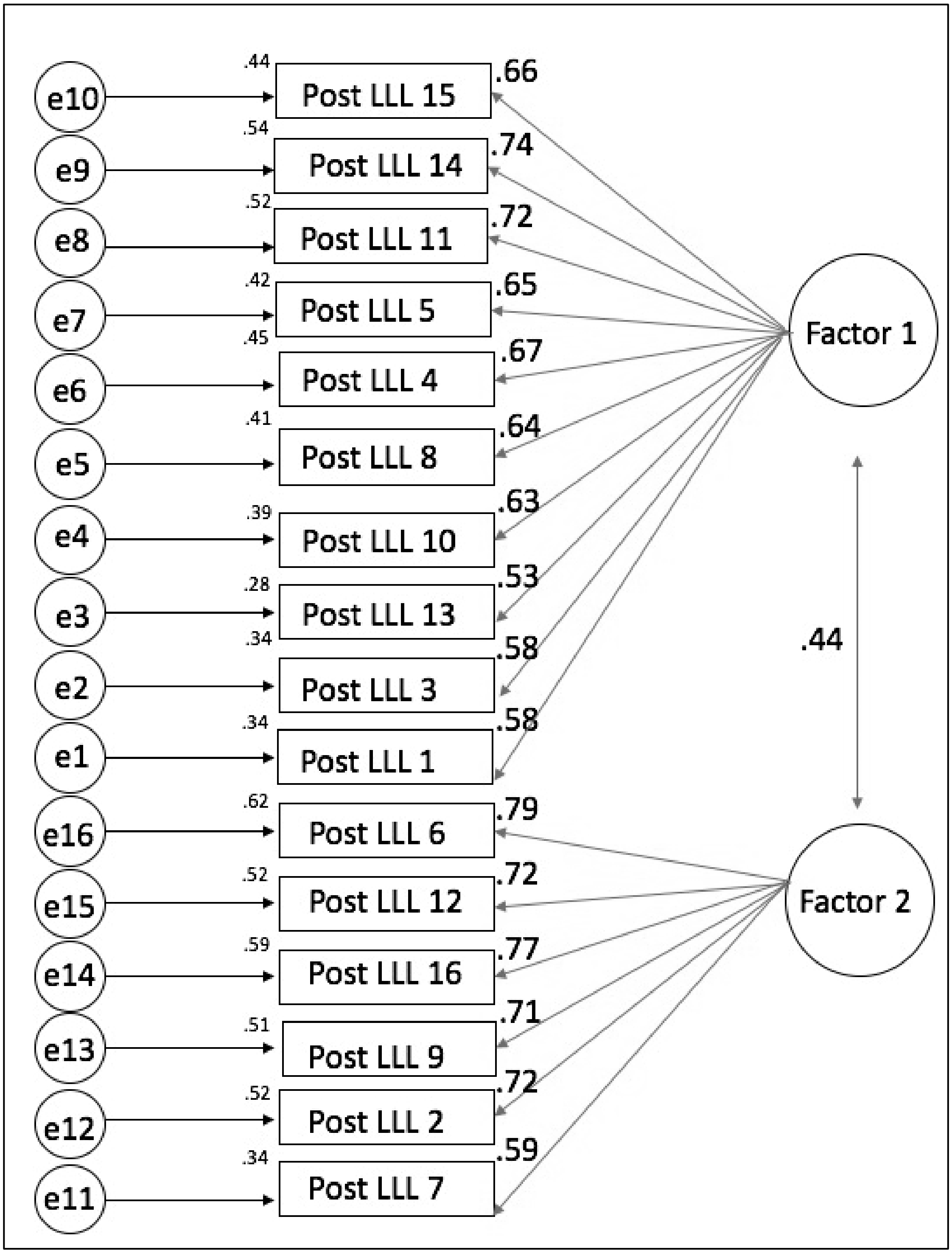

Figure 3. Confirmatory factor analysis measurement model for LLL Scale. (Factor 1 is Learning characteristics and Factor 2 is Enjoyment of reading and writing)

2.4. Conclusions

The research we conducted in this study addresses the reliability of the LLL scale. Both factors elucidated (i.e., Learner characteristics and Enjoyment of reading and writing) were determined to have good internal consistency and the overall LLL scale also has good internal consistency.

The construct validity was also investigated by using CFA. The second-order model did not achieve adequate model fit criteria limits, but the results were approaching acceptable ranges, except for CFI ($df = 103.0$, $\chi^2 = 243.56$, RMSEA=0.079, $p < .000$, CFI = 0.902, TLI = 0.885, GFI = 0.881). The chi-square test is an absolute model fit, therefore if the probability value (p) is less than 0.05, the model is rejected. The model here was rejected as the p value was less than .001. Hu and Bentler (1999) suggested that RMSES values below 0.06 were ideal, the findings here were above this cutoff (RMSEA= .079). Hu and Bentler also suggested that the TLI value should have been above 0.92. In the present study, we reported that the value approached, but did not reach this threshold. CFI compares the fit of a target model to the fit of an independent, or null, model (Perry, 2017). The cut-off for good fit is greater than 0.092, the model fit for this study of 0.902 did meet this criterion. GFI is proportional of the variance accounted for by the estimated population covariance, and the measured values should be within the range of .90 and .95 (Hu & Bentler, 1999). The values reported in this study (GFI = 0.881) were below this cut-off threshold, therefore the proposed model did not fit. The results indicated that modification to the survey would have likely resulted in improvement to the model fit, ultimately improving construct validity of the survey.

Limitations to this study included not having a homogenous and generalizable sample. Because the sample selection was comprised participants from an HBCU, the demographics of the participants were skewed toward participation of ethnic minorities and above average participation of women. The demographics of the present study's sample indicated that the majority of participants identified as African American (72.1%) and most participants were male (76.4%). In the U.S., African American males have been noticeably missing from the population of students enrolled and graduating from Mechanical Engineering programs in the United States (Orr, Lord, Layton, & Ohland, 2014). However, this study reflected a sizable enrollment of minority students, including women, compared to national statistics in the U.S.

Future research can be centered around the exploration of methods to modify the LLL scale. The first suggested survey modification was to delete items with low factor loading. For example, items 10, 13, 3, 1, and 7 had factor loadings less than 0.60. If items 10, 13, 3, 1 were deleted from factor 1, the reliability was reduced to 0.756. However, if only item 7 was deleted from factor 2, the reliability improved to 0.862. Overall, if both sets of items from both factors were deleted, the reliability was reduced to 0.846. If only item 13 and 3 were deleted from factor 1, the reliability was reduced to 0.859. The reliability of the survey overall, if items 13, 3, 1 were deleted, was reduced to 0.850. Another concern was that the first factor had 10 items that loaded on to it, and ideally the number of items per factor could be reduced.

The second suggestion was to remove items that had low item-factor correlations. For example, items 13, 3, and 1 had a low correlation with factor 1 and item

7 had a low correlation with factor 2. Both sets of items had correlation values less than 0.6. If items 13, 3, 1, and 7 were deleted from the CFA, the proposed model fit was improved for each measured fit index, yielding “good fit” criteria thresholds ($df = 53$, $\chi^2 = 84.881$, RMSEA = 0.052, $p = .004$, CFI = 0.969, TLI = 0.961, GFI = 0.939). The model fit improvements could have potentially confirmed item association and latent factors identification as a method to generate a survey tool that instructors could employ alongside EBP to evaluate the development of LLL skills in a variety of classroom environments.

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3. RE-EXAMINATION OF ENGINEERING ATTITUDE SURVEY TO IMPROVE ITS RELIABILITY AND VALIDITY

3.1. Introduction

3.1.1. The STEM Education in 21st Century

3.1.1.1. The STEM Education Problem

Developing science, technology, engineering and math (STEM) education has been regarded as one of the most significant challenges facing educators along with improvement in student performance in the areas of STEM (Han, Capraro, & Capraro, 2015). For example, student enrollment in United States (U.S.) engineering undergraduate programs has increased over the past ten years, but despite this growth, these schools struggle to graduate students of all backgrounds. Historically, a smaller proportion of minority students choose to pursue degrees in science and engineering than do students from groups traditionally well-represented in STEM. There are efforts by the industry sector, public and private educational leaders to boost and produce a competent STEM workforce from diverse backgrounds. However, underrepresented minority (URM) group's participation in the STEM majors is declining (Allen-Ramdial & Campbell, 2014). Increasing recruitment of URMs into STEM fields is a necessary effort, but retaining these students in STEM disciplines must also be a priority (Snyder, Sloane, Dunk, & Wiles, 2016). There are high attrition rates among all students in STEM majors and even higher rates with URMs (Allen-Ramdial & Campbell, 2014; Snyder et al., 2016). With a rapidly changing world and new industries emerging, there is an increase in job opportunities in STEM fields. Thus, STEM education must be an innovative and attractive option for all students.

3.1.1.2. Engineering Education Research

A research trend in engineering education since the 1990s has been devoted to understanding the changes in engineering students' perceptions during the completion of their engineering degrees (Miller, 2014; Xie & Achen, 2009). This focus of engineering education has been to increase student confidence and their ability to achieve in the engineering classroom (Besterfield-Sacre et al., 1996). Personal, environmental, and behavioral factors have different relationships with STEM confidence levels for different groups. Gender differences in STEM are not indifferent to racial and ethnic context. Many elements of student perceptions, including those of professors, ability relative to peers, extent to which the field is rewarding, and the desirability of a chosen major, are all positively associated with student STEM confidence (Besterfield-Sacre, Amaya, Shuman, Atman, & Porter, 1998).

A trend toward education equity incorporates responsibility for STEM educators to ensure that all students have equal access. Social and culturally responsible engineering curriculum should include aspects of social justice components for all students (e.g. Ethical, socio-economic, and political engineering practice) (Litzler, Samuelson, & Lorah, 2014). Educators should be aware of complex factors that include: (a) who students and teachers are, (b) where schools are located, and (c) the types of resources available – along with contextual factors - all contribute to the work of teaching and learning (Hightower et al., 2011; O'Brennan, Bradshaw, & Furlong, 2014).

3.1.2. Engineering Attitudes

Determining the relationship between students' attitudes toward STEM majors and the likelihood they will choose a STEM career has been elusive. An attitude is an organization of beliefs, behavioral tendency toward social significant objects, groups, events or symbols (Argyle, 2005). Attitude is also composed of emotion, cognition and intention (Meyers, 1993). Likert scale can be a direct measurement of attitudes (Likert, 1932). Because attitudes can be measured, monitoring the changes in an individual's attitude can provide information about a person's past or present (Murchison, 1935). A previous study by Osborne, Simon, and Collins (2003) suggested that student's attitude toward enrolling in a course is a strong determinate of a student's choice in pursuing future careers. The old adage, "positive attitudes produce positive results" along with prior research exploring engineering attitudes (Besterfield-Sacre & Altman, 1994; Besterfield-Sacre et al., 1998; Besterfield-Sacre et al., 1996; Besterfield-Sacre, Moreno, Shuman, & Atman, 1999), suggested that positive attitudes towards engineering are associated with the desire to pursue engineering as a career. Assessing engineering attitudes can be used to investigate academic culture and promote change (Hilpert, Stump, Husman, & Kim, 2008).

3.1.2.1. Self-Efficacy, Self-Determination, and Motivation

Educational researchers have developed theories to explain the complex relationship between self-efficacy and motivation. Attitudes toward STEM fields is guided by many factors including self-efficacy, interest, task values, and long-term goals. Parsons et al. (1983) expectancy-value theory is defined by motivation related to an individual's choice, persistence, and performance. In other words, the individual's belief in how they will perform and value the activity is driving motivation to participate in a task. The expectancy-value theory has foundational components similar to Bandura and Wessels' (1997) self-efficacy theory and social cognitive theory (Bandura, 2001). Self-efficacy theory focuses on an individual's belief about their competence and efficacy, expectancies for success or failure and sense of control over outcomes.

Deci and Ryan's (2000) self-determination theory, a theory of motivation, explores students' intrinsic (e.g., doing something because of interest) and extrinsic motivation (e.g., doing something because of a separable outcome). These researchers argued that these motivations are highly complex and must consider context and conditions. Motivations predict student's persistence, interest, and involvement and career trajectories (Wiebe, Unfried, & Faber, 2018). The literature contains many references to domain-specific self-efficacy and academic outcomes. Development of self-efficacy, outcome expectations, and career interests are also associated with demographic factors (e.g., gender, and race/ethnicity) (Granger et al., 2012; Han et al., 2015; Litzler et al., 2014; Schunk, 1991; Simon, Aulls, Dedic, Hubbard, & Hall, 2015). Literature paints a compelling picture that students' STEM attitudes and career interests are in flux during their elementary and secondary school years, though stabilizing and solidifying some during their secondary years (Fouad & Smith, 1996).

Motivation is further explored by Maslow and Lewis (1987), referred to as *Maslow's Hierarchy of Needs*. This motivational theory states that an individual has a series of fundamental needs illustrated as a pyramid. These components include physiological, safety and security, love and belonging, self-esteem, and self-actualization. Learning is highly personal, complex and dependent on intrinsic and extrinsic motivation. The needs outlined by Maslow's hierarchal needs ultimately describe the fundamental environmental conditions that must be met in order for the students to have academic success. Effective learners are described as autonomous and self-motivated managers of their own learning process. These learners are able to identify their learning needs and initiate, monitor, control, and evaluate their learning strategies to address their needs (Lord, Prince, Stefanou, Stolk, & Chen, 2012). When student motivation is directed toward the learning process and they are not distracted with having their basic needs met, then they can cognitively focus on their own learning process. The learning continuum for students includes teacher regulated learning, shared regulation, and ultimately to loosely regulated learning. Students are required to progress in development arriving at loosely regulated learning by satisfying the fundamental needs of human physiology, safety, security, self-esteem, and self-actualization. Once these fundamental needs are met, only then will the individual's learning potential be unlocked allowing the student to reach their full potential (Maslow & Lewis, 1987).

3.1.2.2. Measuring Engineering Attitudes

Students' attitudes about engineering and their confidence in their abilities to achieve in the engineering classroom have been the targets of engineering education research. Several instruments have been developed to capture student's attitudes of and their impact on student's participation, STEM majors and ultimately careers.

The Pittsburgh Freshman Engineering Attitudes Survey (PFEAS) is a survey designed by Besterfield-Sacre and Altman (1994) to elicit students' attitudes and beliefs. This survey investigates certain variables, which have been associated with persistence. Internal consistency, measured by Cronbach's alpha of 0.8 or better has been reported for each of the 13 factors identified (Burtner, 2005).

Engineering Attitude Survey (EAS) was published by Robinson, Faldi and Maddux (See APPENDIX A). The EAS was a 25 item Likert scale with 5 "positive" attitude questions and 20 "negative" attitude questions. The questions explored attitudes about engineering and what engineers do. The survey was initially implemented in a collaborative study by some professors at the University of Nevada, who specifically designed the assessment. The ideas for questions were sourced by engineering professors, engineers working in industry, and professors in the department of Curriculum and Instruction at University of Nevada. This survey has a 6-point scale that ranges from very strongly agree to very strongly disagree (Very strongly agree =6, Strongly Agree =5, Agree =4, Disagree =3, Strongly Disagree =2, Very Strongly Disagree =1). Most of the items were identified as negative and therefore students' responses were reversed prior to the analyses.

3.2. Research Summary

In this study, we investigated the EAS and its sub-dimensions (in other words, its latent factors). The survey was administered to 229 freshman students who were enrolled in a Mechanical Engineering Drawing course. The course was offered by a Mechanical Engineering Department at a Historically Black College and University (HBCU) in Southwest region in the U.S. The survey was administered at the beginning and end of each semester over the past four years. The Mechanical Engineering students participated in a Computer-aided Design (CAD) screen-cast tutorial, an evidence-based pedagogical treatment. Students also completed a demographic survey. Experimental group students completed an exit survey exploring the experience with the screen-cast tutorials.

The following research questions guided the investigations of the present study.

RQ1: What underlying data structures can be derived from an exploratory factor analysis (EFA) of the Engineering Attitudes Survey (EAS)?

RQ2: What is the reliability of the modified EAS?

RQ3: What is the construct validity and model modification fit of the EAS?

3.3. Methods

3.3.1. Survey

EAS published by Robinson et al. (1999) was used to measure attitudes toward engineering. The survey contained 25 Likert=scale questions exploring attitudes about engineering; what Engineers do, and if an Engineering career is desirable. This survey had a six-point Likert scale, each item is rated on a scale of 1 to 6 with 1= Very Strongly Disagree; 2=Strongly Disagree; 3=Disagree; 4=Agree; 5=Strongly Agree; 6= Very Strongly Agree. The survey items have negative questions and lower scores indicate a positive attitude.

3.3.2. Participants

This study comprised 229 participants, 54 (23.6%) of them were females and 175 (76.4%) were male students. Over four years, these participants were enrolled in various sections of a Mechanical Engineering drawing course. The university is an HBCU and the participants were predominantly African American. Specifically, 2 (0.9%) of the students identified as Caucasian, 9 (3.9%) identified as Mixed Heritage, 14 (6.1%) identify as Other, 16 (7.0%) identified as Asian, 23 (10.0%) identified as Latino/Hispanic, and 165 (72.1%) identified as African American. Most (98.3%) of the participants were majoring in Mechanical Engineering with the remaining students enrolled in various concentrations of Mechanical Engineering (1.7%). Those concentrations included Aerospace Engineering (0.4%), Biology and Mechanical Engineering (0.5%), Mechanical Engineering and Math (0.4%), Mechanical Engineering and Physics (0.4%). Information about first-generation college status was also obtained. For these participants, 84 (36.2%) identified as non-first-generation college students and 146 (63.8%) identified as first-generation college students. Table 7 contains a summary of all demographic information for the participants.

Table 7. Participants' Demographics

Characteristics	Category	*N*	Percent (%)	Cumulative (%)
Gender				
	Female	54	23.6	23.6
	Male	175	76.4	100.0
	Total	229	100.0	
Ethnicity				
	Caucasian	2	0.9	0.9
	Mixed Heritage	9	3.9	4.8
	Other	14	6.1	10.9
	Asian	16	7.0	17.9
	Latino/Hispanic	23	10.0	27.9
	African American	165	72.1	100.0
	Total	229	100.0	
Major				
	Aerospace Engineering	1	0.4	0.4
	Biology and Mechanical Engineering	1	0.4	0.8
	Mechanical Engineering and Math	1	0.4	1.2
	Mechanical Engineering and Physics	1	0.4	1.6
	Mechanical Engineering	225	98.3	100.0
	Total	229	100.0	
First-Generation College Status				
	No	83	36.2	36.2
	Yes	146	63.8	100.0
	Total	229	100.0	

3.3.3. Data Organization

The data provided were de-identified and numerically coded as, ethnicity, gender, first-generation college student status, major, and the EAS responses. The EAS has 5 “positive” attitude questions and 20 “negative” attitude questions. The “negative” response questions were scored in reverse order as the lower scores for these questions indicate a positive attitude. The data were grouped by combining the treatment and comparison post-test groups’ respondent data from the EAS collected over four years.

3.4. Analysis

Three distinct analyses were used to answer the research questions including EFA and effect size (RMSEA) using Statistical Package for the Social Science (SPSS) software v.26, and Confirmatory Factor Analysis (CFA) using SPSS AMOS v.23. Bartlett’s Test of Sampling Adequacy and Kaiser-Meyer-Olkin test (KMO) was applied in order to determine whether the data were appropriate for factor analysis. The EFA analysis identifies separable dimensions, representing theoretical constructs, within a domain and the structure of the factor loading. CFA was used to verify appropriateness of the factor structure for the factors derived from the EAS (Thompson, 2004). The effect size was used to investigate the effectiveness of the screen-cast activity and to quantify the differences between the treatment and the comparison group (Kelley & Preacher, 2012).

The analysis scheme involved the following steps: (a) calculating internal consistency or reliability using Cronbach’s alpha, (b) identifying underlying data factors after completing an EFA, (c) quantifying construct validity of the EAS using CFA, and (e) calculating effect size to investigate the effectiveness of the screen-cast activity.

3.4.1. Exploratory Factor Analysis, KMO, Bartlett's Test

EFA was performed with the 25 items of the EAS. To determine the suitability of the EAS in measuring the underlying structure of latent variables, Bartlett's Test of Sampling Adequacy (Bartlett, 1950) and the KMO of Sampling Adequacy values provided critical information (Kaiser, 1974). Using SPSS version 26, results from the Bartlett's Test, $\chi^2 = 334.299$ ($p < 0.001$) indicate that factors are related and suitable for structure detection. The Bartlett's Test should be significant ($p < .05$) for a factor to be suitable (Williams, Onsman, & Brown, 2010). The results from the KMO test, .904, indicated that the proportion of variance in the variables might be accounted by underlying factors. The KMO index ranging from 0 to 1, with 0.50 was considered suitable for factor analysis (Williams et al., 2010). The results from these two tests are presented in Table 8.

Table 8. EAS Adequacy Testing

KMO and Bartlett's Test

Test	Value	*p*-value
Bartlett's Test of Sampling Adequacy	3343.299 (χ^2)	.000
Kaiser-Meyer-Olkin Factor Adequacy (KMO)	.904	N/A

The 25 items of the EAS were subjected to Principle Axis Factoring. Varimax (25) rotation was applied to determine items belonging to each factor. Factor loading cut-off was set at .30 (Henson & Roberst, 2006). No item was found with factor load values less than .30 that did not also load on another factor. After EFA, the EAS was found to have a construct with 25 items and four factors. The scree-plot graph of the survey indicated four factors with eigenvalues greater than 1 (Figure 4).

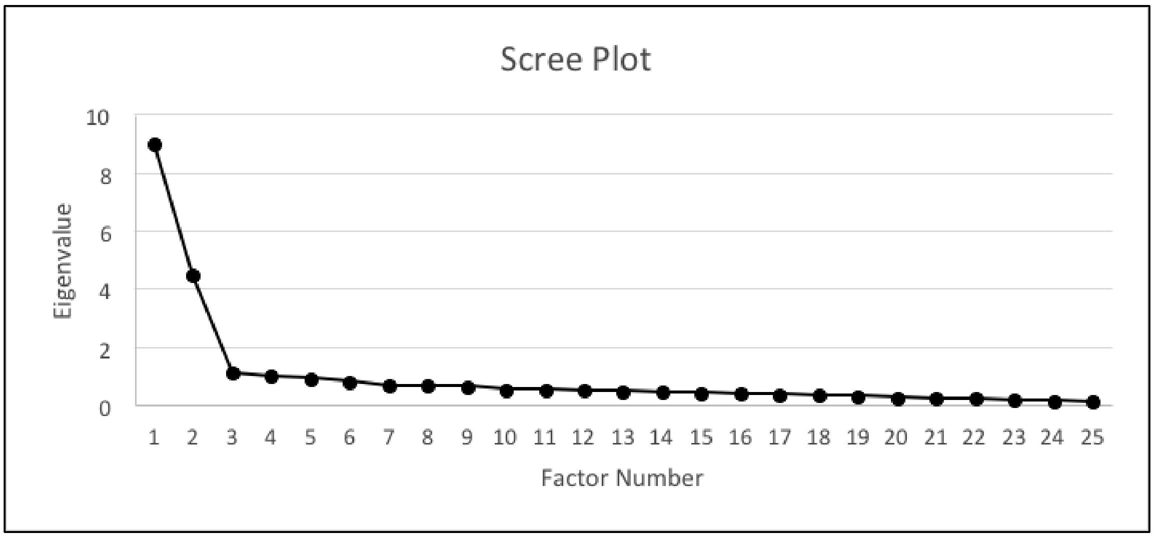

Figure 4. Scree plot for EFA of responses to EAS

Table 9 presents that 8 of the 25 items loaded under the first factor, with item 8 cross-loading on factor 2. The second factor had 6 of the 25 items loaded, with item 10, 13, and 12 cross-loading on factor 3, item 14 cross-loading on factor 4, and item 7 cross-loading on factors 3 and 4. The third factor had 8 of the 25 items loaded with items 6, 15, 17, 19, 22, 23, and 24 cross-loading on factor 2. Item 15 was determined to be more conceptually aligned with factor 2. Factor 4 had three of the 25 items loaded, with item 4 and 9 cross-loading on factor 2, item 5 cross-loading on factor 1. Item 9 was determined to be more conceptually aligned with factor 4. The first factor was termed as "Engineering as a career," second factor was termed "Engineer career characteristics," the third factor is termed "Engineer personality characteristics", and the fourth factor was termed "Engineering is theoretical." The results from the factor loadings are presented in Table 9. The four factors in the EAS constituted 55.7% of the total variance. The first factor constituted 35.9%, the second 17.8%, the third 4.44% and the fourth 4.1%. For survey validity, the total variance of the factors should account for 41.0% of the total variance in the participants' responses (Kline, 1994). The total variance for the EAS in this study was 55.7% and, therefore, could have been considered applicable with a construct consisting of 25 items and four factors. It is important to note that item 15 cross-loaded on factor 2 and 3 and was conceptually more aligned with factor 2. Item 9 cross-loaded on factor 2 and 4 and was conceptually more aligned with factor 4.

Table 9. EFA Results of EAS

Item No.	Item	Factor 1: Engineering as a career	Factor 2: Engineer career characteristics	Factor 3: Engineer personality characteristics	Factor 4: Engineering is theoretical
20	A career in Engineering would be financially rewarding	.891			
3	Engineering would be highly interesting profession for me	.814			
21	Most of the skills learned in Engineering would be useful in everyday life	.806			
25	If I had to do it over again, I would consider a career in Engineering	.810			
18	Engineering is important to future US economic success in the world	.799			
8	Engineers spend most of their time working with computers	-.495			
16	Engineers need a great deal of inborn aptitude for science and mathematics	-.455	.352		
2	Engineers spend most of their time doing complex mathematical calculations	-.532			
Revealed variance (%) Total = 55.7		35.9%			

Table 9. continued

Item No.	Item	Factor 1: Engineering as a career	Factor 2: Engineer career characteristics	Factor 3: Engineer personality characteristics	Factor 4: Engineering is theoretical
11	Engineers have little need for knowledge about economics		.794		
10	Engineers have little need for knowledge about environmental issues		.709	.312	
13	Engineers have little need for knowledge about political matters		.679	.331	
12	Engineers have little need to deal with questions about behavior that is morally right or wrong		.667	.373	
14	To be a good Engineer requires an IQ in the genius range		.446		.320
7	Engineers spend most of their time working in offices		.387	.365	.359
Revealed variance (%) Total = 55.7			17.9%		

Table 9. continued

Item No.	Item	Factor 1: Engineering as a career	Factor 2: Engineer career characteristics	Factor 3: Engineer personality characteristics	Factor 4: Engineering is theoretical
1	Most Engineers have poor social skills			.562	
6	Engineers spend relatively little time dealing with other people		.415	.570	
15	Engineering is a poor career choice because job availability is dependent on defense spending		.399**	.500	
17	Most Engineers have a very narrow outside interest		.451	.555	
19	Engineers typically have very little common sense		.346	.493	
22	Engineers are not typical people who are fun to be around		.333	.758	
23	Engineers do not tend to be appreciative of the arts		.431	.613	
24	Engineers are frequently those individuals who were regarded as "nerds" in high school	-.303	.371	.393	

Table 9. continued

Item No.	Item	Factor 1: Engineering as a career	Factor 2: Engineer career characteristics	Factor 3: Engineer personality characteristics	Factor 4: Engineering is theoretical
4	A problem with Engineering is that Engineers seldom get to do anything practical		.311		.718
5	Engineers deal primarily with theory	-.332			.520
9	Engineers seldom get involved in business decision		.476		.395*
Revealed variance (%) Total = 55.8%				4.4%	4.1%

3.4.2. Cronbach's Alpha Reliability Analysis

Cronbach alpha values of the EAS factors were calculated to evaluate internal consistency and reliability of the derived factors. The overall reliability of the EAS was also calculated. The Cronbach's alpha scores are presented in Table 10.

Table 10. Cronbach's Alpha Values of the EAS Instrument

Factor	Number of items	Cronbach Alpha value
Engineering as a career	8	.448
Engineer career characteristics	6	.866
Engineer career personality characteristics	8	.868
Engineering is theoretical	3	.767
Total	16	.871

3.4.3. Confirmatory Factor Analysis

CFA was applied to test the EAS respondent data for compliance of the model obtained using EFA. IBM SPSS AMOS (version 23) statistical software was used for data analysis. The responses included some missing data. Item 6 and 18 each had two missing responses, item 13 had one missing response. There were 25 items for the EAS instrument, with a total of 229 responses, which totals 5,725 potential item responses. The eight total missing responses represents .09% of the items, or 2.18% of the responses. The missing response data were below the acceptable 5% threshold (Scahefer, 1999). The data set was modified by listwise deletions of responses, where missing data were identified (McKnight, McKnight, Sidani, & Gigueredo, 2007; Schaefer & Graham, 2002). Missing data were assumed to be missing completely at random (MCAR). The final sample size of the CFA analysis was reduced from 229 responses down to 224. We considered the 25-items from the survey as first-order factors (i.e., indicator variables), and the four conceptual domains (i.e., Engineering as a career, Engineer career characteristics, Engineer personality characteristics, and Engineering is theoretical) was tested as second-order factors (i.e., latent variables). All parameters were freely estimated (derived from the analysis) and indicators were allowed to cross-load (represent multiple latent variables). The factor construct's fit used maximum likelihood (ML) estimations and was examined on the basis of the goodness-of-fit statistics and results from the modification index. The fit statistics included RMSEA (Steiger, 2016, Chi square test (Pearson, 1900), comparative fit index (CFI) (Bentler, 1990), Tucker-Lewis (TLI) (Bentler & Bonnett, 1980; Tucker & Lewis, 1973), and Goodness of Fit index (GFI) (Joreskog & Sorbom, 1986). Researchers have suggested that these fit statistics are the most commonly used (Jackson, Gillaspy Jr, & Purc-Stephenson, 2009). The standardized results are summarized in Table 11.

Table 11. CFA Results of EAS Instrument

Fit index	Criteria	Intercept points for confirmation	Research finding
df	-	-	269
χ^2	$P>0.05$	-	722.596
RMSEA	0 (excellent fit) 1 (no fit)	≤ 0.06 = excellent fit	0.087
CFI	0 (no fit) 1 (excellent fit)	≥ 0.90 = good fit	0.858
TLI	0 (no fit) 1 (excellent fit)	≥0.92 = good fit	0.841
GFI	0 (no fit) 1 (excellent fit)	≥ 0.90 = good fit	0.802

df: Degree of Freedom

χ^2: Model Chi-Square

RMSEA: Root Mean Square Error of Approximation

CFI: Comparative Fit Index

TLI: Tucker Lewis Index

GFI: Goodness of Fit Index

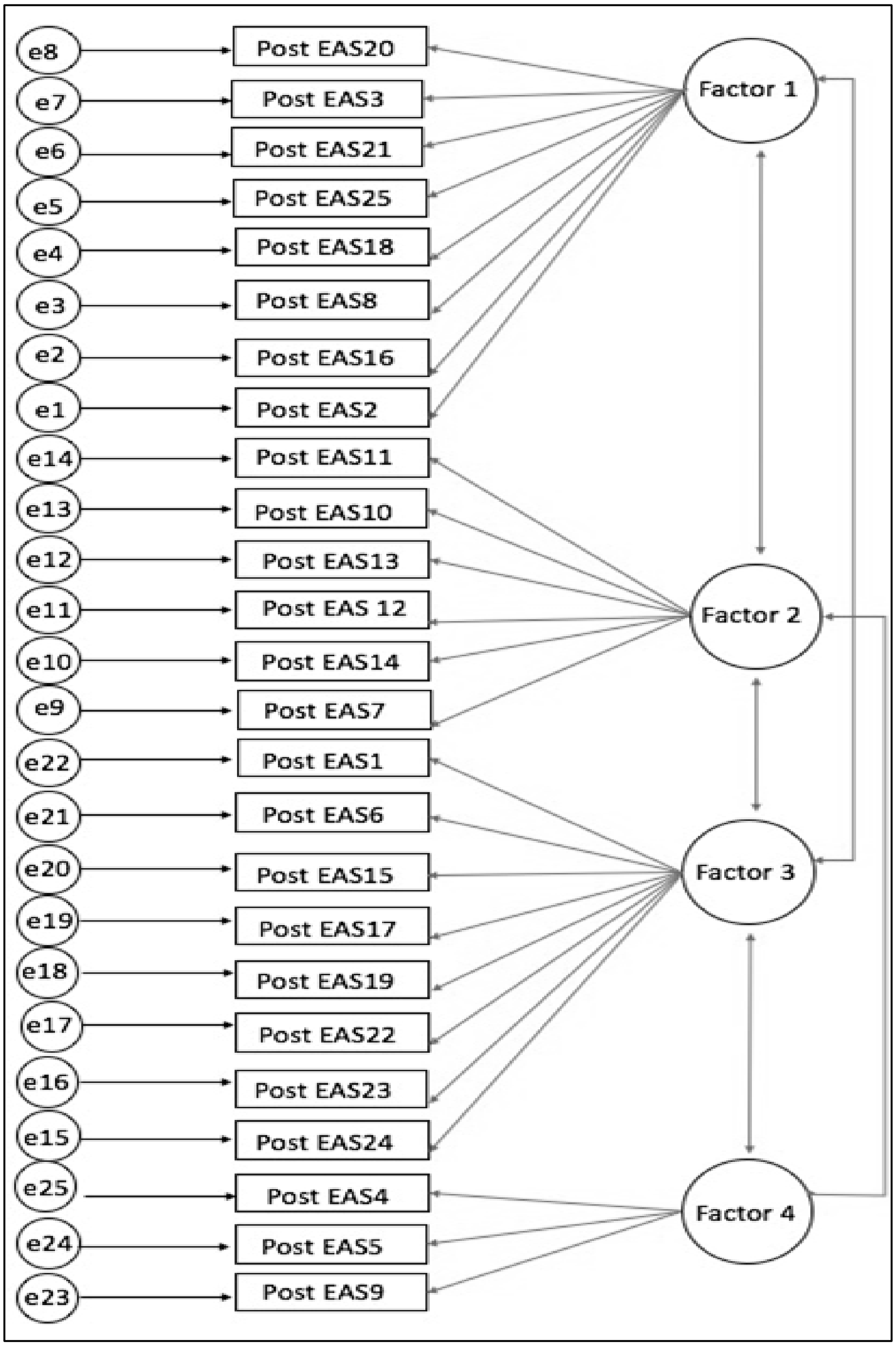

Figure 5. Confirmatory factor analysis model of EAS. (Factor 1 was Engineering as a career, Factor 2 was Engineer characteristics, Factor 3 was Engineer personality characteristics, and Factor 4 was Engineering is theoretical)

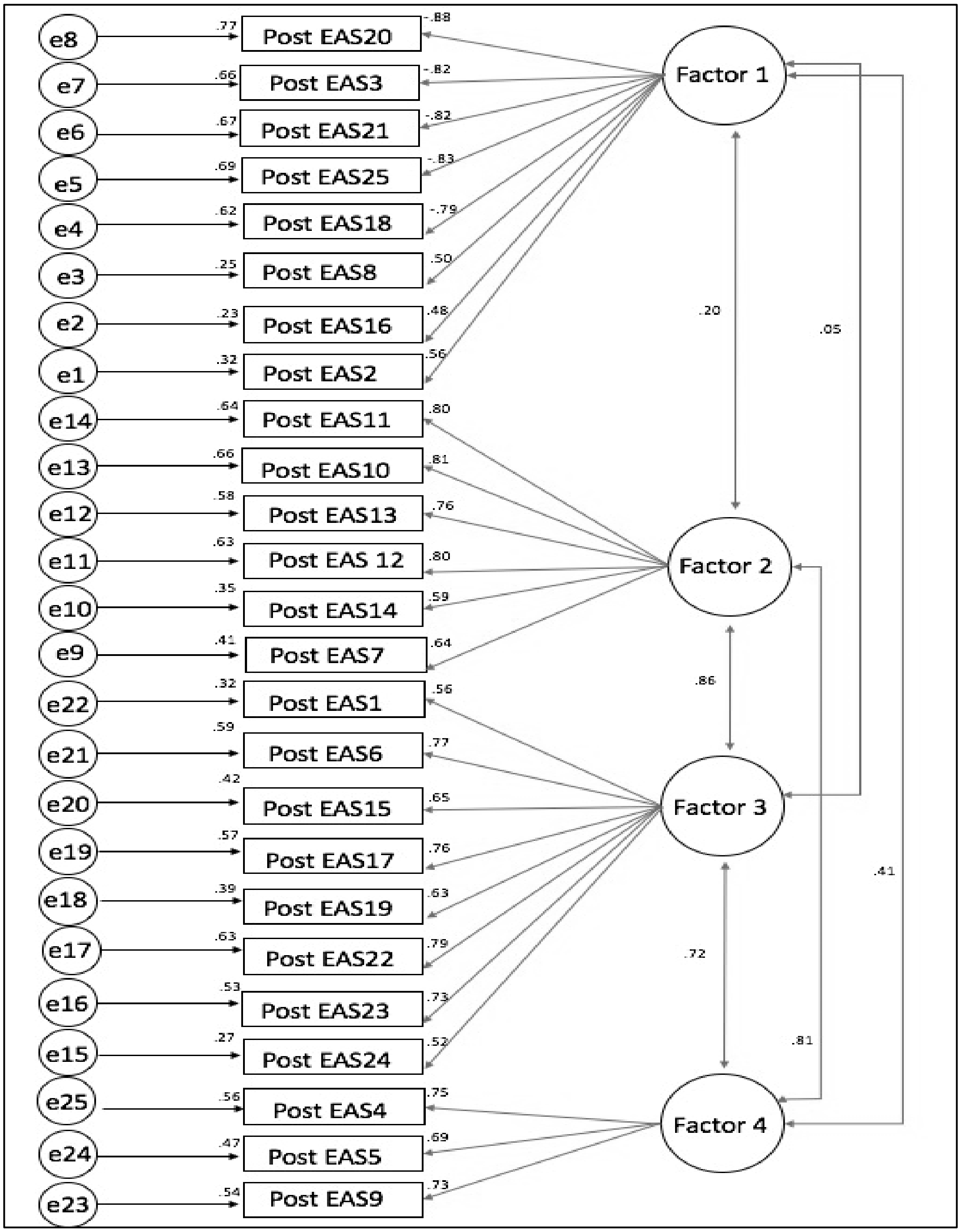

Figure 6. CFA measurement model for EAS. (Factor 1 was Engineering as a career, Factor 2 was Engineer characteristics, Factor 3 was Engineer personality characteristics, and Factor 4 was Engineering is theoretical)

3.5. Conclusions

In this study, we re-evaluated the student data from the EAS resulting in measurement of (a) internal reliability using Cronbach's alpha; (b) identifying factors using EFA; and (c) quantifying construct validity of the EAS using CFA, and (d) calculating effect size to investigate the effectiveness of the screen-cast activity.

The construct validity was also investigated by using CFA. The second-order model did not achieve adequate model fit criteria limits, but the results were approaching to the acceptable ranges ($df = 269$, $\chi^2 = 722.97$, RMSEA = 0.087 $p > .001$, CFI = 0.858, TLI = 0.841, GFI = 0.802). The chi-square test is an absolute model fit, therefore if the probability value (p) is less than .05, then the model is rejected. The model in the present study was rejected as $p < .001$. Hu and Bentler (1999) suggested RMSES values below the range of 0.5 to 0.06 are ideal, the finding here, 0.087, was above this cutoff. Hu and Bentler (1999) also suggested that the TLI value should have been above the range of 0.92-.95. In the present study, we reported the TLI value, 0.841, which approached, but did not reach the threshold. CFI compares the fit of a target model to the fit of and independent, or null, model (Hu & Bentler, 1999; Perry, 2017). The cut-off for good-fit is a value range greater than the range of 0.90-.92, the model fit for this study of 0.858, did meet this criterion. GFI is proportional of the variance accounted for by the estimated population covariance, and the measured values should be within the range of .90 and .95 (Hu & Bentler, 1999). The value reported here of 0.802, was below this cut-off threshold, therefore the proposed model derived from the EFA did not fit.

This study had some limitations. The first limit was related to the Likert-scale options having a majority of negative responses that could have been considered extremes. The literature shows that survey takers do not like selecting extreme options. Respondent's survey selections might not have accurately reflected their true feelings. This subconscious phenomenon could have led to a false impression and skewed results (Hartley & Betts, 2013).

The second limitation was that the present study did not have a homogenous and generalizable sample. The sample selection comprised participants from HBCUs, the demographics of the sample was skewed toward participation of ethnic minorities and above average participation of women. The demographics of the present study's sample indicated that the majority of participants identified as African American (72.1%) and participants were also males (76.4%). African American males have been noticeably missing from the population of students enrolled and graduating from Mechanical Engineering programs in the U.S. (Orr, Lord, Layton, & Ohland, 2014). However, this study reflected a sizable enrollment of minority students, including women, compared to the national statistics in the U.S.

The third limitation was related to the language from items that load on factors 2 and 3, "Engineer career characteristics" and "Engineer career personality characteristics." In the current study, we found difficulty determining if the negatively scored items from the survey were associated with the personality characteristics of people who were engineers (job related characteristics) or characteristics of the individuals who chose engineering as a career (individual personality traits). The items associated with these characteristics cross-loaded on factors 2 and 3.

Future research can focus on investigating methods to modify the EAS. The first suggestion for survey modification was to improve the model fit by deleting items with poor item-factor correlations with the associated factors. For example, factor 1 had a low correlation with items 2, 8 and 16 (.56, .48, .50 respectively). When these three items were deleted from factor 1, the reliability improved dramatically from 0.448 to 0.918. Items 7 and 14 had a low correlation with Factor 2 (.64, .59 respectively). When these two items were deleted from Factor 2, the reliability improved from 0.866 to 0.878. Factor 3 had a low correlation with items 1 and 24 (.56 and .52 respectively). When these items were deleted, the reliability was reduced from 0.868 to 0.864. When items 2, 8, 16, 7, 14,1, and 24 were deleted, the overall survey reliability was reduced from 0.871 to 0.854. When these items were removed from their perspective factors, the proposed CFA model fit meets the "good fit" criteria threshold for only the CFI index. The TLI model fit index approached the threshold but slightly missed the cut-off value ($df = 129$, $\chi^2 = 299.262$, RMSEA = 0.077 $p < .001$, CFI = 0.929, TLI = 0.916, GFI = 0.872).

The results indicated modification to the survey would likely result in improvement to the model fit, ultimately improving construct validity of the survey. However further exploration of survey modification is necessary in order to elucidate a final set of items that would represent good model fit for all indices.

Developing a tool that can be utilized by instructors to accurately assess engineering attitudes in conjunction with evidence-based pedagogies' implementations, are crucial in educating engineers in the U.S. and generating a work force that is representative of the nation's population. We assert that positive engineering attitudes can be used as an early predictor into student's proclivity towards choosing engineering as a desirable career.

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4. EXAMINING THE EFFECT OF AN EVIDENCE-BASED PEDAGOGY ON STUDENTS LIFELONG LEARNING SKILLS AND ENGINEERING ATTITUDES UTILIZING THE MODIFIED VERSIONS OF LIFELONG LEARNING SCALE AND ENGINEERING ATTITUDE SURVEY

4.1. Introduction

Engineering students during their introductory courses as an undergraduate have a high learning curve that includes skills using technology to simulate three-dimensional space through a Computer-aided Design (CAD) software. Traditionally students have been taught these skills passively without requiring any personal input, creativity, or self-reflection. Rote memorization of step-wise procedures and abstract description of the CAD processes have been presented to the students without relevant context and metacognitive thinking. The instructors in traditional CAD learning environments often have provided pre-generated screen-cast tutorials to their students and they expected the students to mimic their designs. This approach represents a knowledge-center and teacher-oriented pedagogy. In the present study, we investigated the use of a student-centered and learner-oriented pedagogy. We asked a group of students to generate CAD tutorials and share them with other students in an electronic repository. The students video-recorded the computer screen of their CAD tutorial and audio-recorded their explanations to the learner simultaneously. This design process required students to employ their creativity, self-reflection, and metacognition. The students took active roles in teaching their peers as well as learning from them and organizing a peer-to-peer learning process.

The theoretical framework for the present study was derived from the "How People Learn" framework developed by Bransford, Brown, and Cocking (2000), Jonassen and Rohrer-Murphy's Activity Theory (1999), and Land and Hannafin's (2000) student-centered learning environments. Bransford et al. (2000) described the learning process as the unity of consciousness and activity, or "Learning is Doing." Bransford et al. (2000) and Johansson and Rohrer-Murphy (1999) noted that students would have more meaningful learning experiences when they were responsible for creating their own learning resources and by completing instructor-guided tasks within an authentic student-centered learning environment. Prior research has shown that students' content learning, motivation, and interest develops more effectively when they learn in a student-centered and learner-oriented environment (Yalvac, Smith, Troy, & Hirsch, 2007). Critics of student-centered learning cite limitations in measuring individual student achievement as many of the activities are in a group setting or are dependent on peer participation. Other limitations include a lack of consideration about how disciplinary knowledge is constructed and what values and norms are required for learning construction (Mckenna, 2013).

Evidence-based pedagogies (EBP) are approaches where they have been proven to be effective based on statistically significant and scientifically reliable evidence (Yalvac et al., 2017). These pedagogies have been identified as the best practice teaching strategies likely to have a positive impact on student achievement, skill-development, and motivation (Besterfield-Sacre, Amaya, Shuman, Atman, & Porter, 1998; Besterfield-Sacre et al., 1996; Besterfield-Sacre, Moreno, Shuman, & Atman, 1999). EBPs aim to apply scientifically derived treatments and incorporate them into educational decision-making. Student-centered teaching approaches and learner-oriented environment designs are pedagogical methods where the student rather than the instructor, is the primary creator of their knowledge base. The instructors utilize specific scaffolded activities, projects, and collaborative learning experiences within the learning environment, which allow students and peer learning groups to generate their own learning resources.

In the present study, we analyzed the data collected through a quasi-experimental pre-test /post-test where the experimental group of students received a student-centered and learner-oriented pedagogy and the comparison group of students received regular instruction (that can be described as knowledge-centered and teacher-oriented). The initial data analysis by Peng et al. (2014) and Zhang et al. (2015) did not provide valid and reliable results for the two surveys utilized in the study. These surveys were a Lifelong Learning (LLL) (See APPENDIX A) scale and an Engineering Attitude Survey (EAS) (See APPENDIX A). The LLL scale and EAS can provide valuable information to researchers and educators about how EBPs impact the development of students' LLL and engineering attitudes. The goal of the present study was to explore and document the relationships among the LLL scale and EAS's sub-dimensions and derived latent factors, demographic characteristics of the respondents, and the type of treatment. The overarching goal was to generate evidence on the significant relationships among the EBPs and the development and/or improvement of LLL skills and engineering attitudes.

4.2. Research Question

The LLL scale and EAS were administered to 229 freshman students who were enrolled in a Mechanical Engineering Drawing course. The course was offered by a Mechanical Engineering Department at a Historically Black College and University (HBCU) in Southwest region in the United States (U.S.). The course was designed to teach students CAD modeling skills using Siemens NX and prepare them for their future careers in design and manufacturing. The LLL scale and EAS were administered at the beginning and end of each semester over four years. Mechanical engineering students in the experimental group participated in a CAD screen-cast tutorial process, which was an evidence-based pedagogical treatment. Students in the comparison group completed a traditional teacher-designed tutorial. Students in both the comparison and experimental groups completed a demographic survey.

We asked the following research questions in the present study:

RQ1: What were the statistically significant relationships among the students' responses to the original versions of the LLL scale and EAS, and their sub-scales, frequency of screen-cast tutorial exercises students completed over the semester, students' ethnicity, gender, first-generation college student status, and type of the treatment (i.e., experimental and comparison) group?

RQ2: What were the statistically significant relationships among the modified versions of the LLL scale, EAS, and their sub-scales, frequency of the screen-cast tutorial exercises students completed over the semester, students' ethnicity, gender, first-generation college status, and the type of treatment group (i.e., experimental and comparison)?

4.3. Methods

4.3.1. Experimental Design

A quasi-experimental pretest-posttest research design (Campbell & Stanley 2015) was implemented over four years with multiple professors teaching various sections over the years. Students were in two different groups; comparison and treatment group. The comparison group received traditional instruction and the treatment group received the treatment that included the student-centered learning and learning oriented environments, utilizing the screen-cast tutorial design activity. All students completed a demographic questionnaire indicating their ethnicity, sex, major, and whether or not they were first-generation college students in their family. Demographic characteristics of the participants are summarized in Table 12.

4.3.2. Study Surveys: LLL Scale and EAS

The LLL scale developed by Wielkiewicz and Meuwissen (1999) was a 16 item, 5-point Likert scale. Each item in the scale was rated on a scale of 1 to 5 ranging from "Never" to "Always or Daily" (Never=1, Rarely=2, Sometimes=4, Often=4, Always or Daily=5). The survey was administered to comparison and treatment groups at the beginning and end of each semester. The goal of the survey was to evaluate participants'

LLL skills. The survey questions and Likert scale key are included in the APPENDIX A.

The EAS published by Robinson et al. (1999) was used to measure students' attitudes toward engineering. The survey contained 25 Likert scale items exploring attitudes about engineering, what engineers do, and exploring if an engineering career was desirable. This survey had a six-point scale that ranged from "very strongly agree" to "very strongly disagree" (Very strongly agree =6, Strongly Agree =5, Agree =4, Disagree =3, Strongly Disagree =2, Very Strongly Disagree =1). The survey items had negative questions and lower scores indicating a positive attitude (See APPENDIX A).

Table 12. Participants' Demographics

Characteristic	Category	*N*	Percent (%)	Cumulative (%)
Gender	Female	54	23.6	23.6
	Male	175	76.4	100.0
	Total	229	100.0	
Ethnicity	Caucasian	2	0.9	0.9
	Mixed Heritage	9	3.9	4.8
	Other	14	6.1	10.9
	Asian	16	7.0	17.9
	Latino/Hispanic	23	10.0	27.9
	African American	165	72.1	100.0
	Total	229	100.0	
Major	Aerospace Eng.	1	0.4	0.4
	Biology and Mechanical Eng.	1	0.4	0.8
	Mechanical Eng. and Math	1	0.4	1.2
	Mechanical Eng. and Physics	1	0.4	1.6
	Mechanical Eng.	225	98.3	100.0
	Total	229	100.0	
First-Generation College Status	No	83	36.2	36.2
	Yes	146	63.8	100.0
	Total	229	100.0	

4.4. Analysis

4.4.1. Variables

The independent variables included the following: (a) treatment group (i.e., comparison or experimental), (b) screen-cast tutorial exercise frequency (e.g., 1-3 times and more than 3 times), (c) gender (i.e., female or male), (d) ethnicity (e.g., African American or Caucasian), and (e) first-generation college status (i.e., yes or no). The dependent variables including: Original and modified Gain Scores for the LLL scale, including overall responses, factor 1-2 responses; Original and modified Gain Scores for EAS, including overall responses, and factors 1-4. The survey factors include: LLL factor 1 – "Learner characteristic", LLL factor 2- "Enjoyment of reading and writing", EAS factor 1- "Engineering career characteristics", EAS factor 2- "Engineering career characteristics", EAS factor 3- "Engineering personality characteristics", EAS factor 4- "Engineering is theoretical". Items from the LLL scale and EAS were removed to improve the Confirmatory Factor Analysis (CFA) model fit. Items 13, 3 and 1 were removed from LLL factor 1; the new variable name is LLL factor 1 modified. Item 7 was removed from factor 2; the new variable name is LLL factor 2 modified. Items 13, 3, 1 and 7 were removed from the overall survey; the new variable name is LLL overall (modified). Items 2, 8 and 16 were removed from EAS factor 1; the new variable name is EAS factor 1 (modified). Items 7 and 14 were removed from EAS factor 2; the new variable name is EAS factor 2 (modified). Items 1 and 24 were removed from EAS factor 3; the new variable name is EAS factor 3 (modified). There were no modifications made to factor 4. Items 2, 8, 16, 7, 14, 1, and 24 were removed from the overall survey; the new variable name is EAS overall (modified). In Figure 7, the dependent and independent variables of the present study are listed.

Independent Variables		Dependent Variables	
	• Students' ethnicities • Students' gender (2 level) • Students' major • Students' first-generation college student status (2 levels) • Treatment type (2 levels) • Screen-cast exercise frequency (3 levels)		• Original Gain Score LLL scale overall responses • Original Gain Score LLL scale Factor 1 responses • Original Gain Score LLL scale Factor 2 responses • Original Gain Score EAS overall responses • Original Gain Score EAS Factor 1 responses • Original Gain Score EAS Factor 2 responses • Original Gain Score EAS Factor 3 responses • Original Gain Score EAS Factor 4 responses • Modified Gain Score LLL scale overall responses • Modified Gain Score LLL scale Factor 1 resp. • Modified Gain Score LLL scale Factor 2 resp. • Modified Gain Score AES overall responses • Modified Gain Score AES Factor 1 responses • Modified Gain Score AES Factor 2 responses • Modified Gain Score AES Factor 3 responses • Modified Gain Score AES Factor 4 responses

Figure 7. List of dependent and independent variables.

4.4.2. ANOVA

A split one-way Analysis of variance (ANOVA) using first-generation college student status was investigated on each of the variables to evaluate the effect of participation in the CAD screen-cast activity. The between-subject factors were treatment type with two levels (i.e., comparison group and treatment group), screen-cast frequency with three levels (i.e., Less, More, None), gender with two levels (i.e., Male and Female), Ethnicity with six levels (i.e., African American, Asian, Caucasian, Latino/Hispanic, Mixed, Other) and major with five levels (i.e., Aerospace Engineering, Biology and Mechanical Engineering, Mechanical Engineering, Mechanical Engineering and Math, Mechanical Engineering/Physics). The original version of LLL scale and EAS overall and sub-scale gain score means; modified version of the LLL scale and EAS overall and subscale gain score means were analyzed. Tukey HSD post-hoc tests were conducted to evaluate pairwise differences among the means and the significant differences. This is a robust and general post-hoc analysis and is also the "most reasonable balance of power and Type I error comparison among the conventional tests available" (Newsom, 2006). Mostly results that were statistically significant different at the $p < .05$ level were reported.

4.5. Results

4.5.1. Research Question 1

A one-way split ANOVA, first-generation college status, was used to identify whether students' gain scores for the LLL scale, EAS, and their sub-scales resulted in any statistically significant difference among the independent variables. LLL scale and subscales' gain scores did not result in any statistically significant result. We reported in this section the statistically significant differences for first-generation college students' responses in traditional and experimental treatment groups and screen-cast tutorial participation frequencies across three levels. Gain scores were calculated by subtracting pre-score responses from the post-score responses. Gain score means (*M*) and their standard deviations (*SD*) were summarized in Table 13 and Table 14.

Table 13. Original EAS Gain Scores, Treatment, First-generation Status Summary

	Treatment Type	M (SD)	First-Generation Status (N)	Gain Score Means (SD)
EAS Gain Score Factor 1	Comparison (*N* = 79)	-2.556 (5.731)	First-Gen. (*N* = 28)	-2.679* (6.213)
			Non-First-Gen. (*N* = 51)	-2.49 (5.51)
	Experimental (*N* = 147)	-0.946 (5.216)	First-Gen. (*N* = 54)	0.741* (3.919)
			Non-First-Gen. (*N* = 93)	-1.923 (5.628)
EAS Gain Score Factor 2	Comparison (*N* = 74)	-0.297 (5.194)	First-Gen. (*N* = 26)	1.192 (4.089)
			Non-First-Gen. (*N* = 48)	-1.104 (5.578)
	Experimental (*N* = 144)	-0.438 (4.451)	First-Gen. (*N* = 54)	-0.056 (3.259)
			Non-First-Gen. (*N* = 90)	-0.667 (5.037)
EAS Gain Score Factor 3	Comparison (*N* = 76)	-0.842 (6.691)	First-Gen. (*N* = 26)	0.308 (6.589)
			Non-First-Gen. (*N* =50)	-1.440 (6.731)
	Experimental (*N* = 149)	0.591 (6.108)	First-Gen. (*N* = 55)	-0.800 (5.261)
			Non-First-Gen. (*N* = 94)	-0.467 (6.578)
EAS Gain Score Factor 4	Comparison (*N* = 80)	0.163 (1.418)	First-Gen. (*N* = 28)	0.214 (1.371)
			Non-First-Gen. (*N* = 52)	0.135 (1.456)
	Experimental (*N* = 147)	0.013 (2.054)	First-Gen. (*N* = 54)	0.148 (2.252)
			Non-First-Gen. (*N* = 93)	-0.065 (1.938)
EAS Gain Score Overall	Comparison (*N* = 69)	-3.261 (14.382)	First-Gen. (*N* = 23)	0.087 (13.073)
			Non-First-Gen. (*N* =46)	-4.935 (14.847)
	Experimental (*N* = 139)	-2.381 (13.197)	First-Gen. (*N* = 51)	-1.098 (11.011)
			Non-First-Gen. (*N* = 88)	-3.125 (14.319)

Means are statically significantly different at p < .5

Table 14. Original EAS Gain Scores, Screen-Cast Frequency, First-Generation Status Summary

	Screen-Cast Frequency	Gain Score Means (SD)	First-Generation Status (N)	Gain Score Means (SD)
EAS Gain Score Factor 1	Less (*N* = 74)	-1.054 (5.564)	First-Gen. (*N* = 25)	1.280 ** (4.852)
			Non-First-Gen. (*N* = 49)	-2.245 (5.569)
	More (*N*=71)	-0.859 (4.940)	First-Gen. (*N* = 28)	0.286 ** (2.955)
			Non-First-Gen. (*N* = 43)	-1.605 (5.799)
	None (*N*=81)	-2.494 (5.673)	First-Gen. (*N* = 29)	-2.586 (6.121)
			Non-First-Gen. (*N* = 52)	-2.442 (5.468)
EAS Gain Score Factor 2	Less (*N* = 73)	0.507 (3.9480	First-Gen. (*N* = 26)	-0.154 (4.086)
			Non-First-Gen. (*N* = 47)	0.872 *** (3.865)
	More (*N* = 69)	-1.391 (4.806)	First Gen. (*N* = 27)	0.037 (2.361)
			Non-First-Gen. (*N* = 42)	-2.301 *** (5.706)
	None (*N*=76)	-0.342 (5.142)	First-Gen. (*N* = 27)	1.148 (4.016)
			Non-First-Gen. (*N* = 49)	-1.163 (5.535)
EAS Gain Score Factor 3	Less (*N* = 76)	0.289 (5.101)	First-Gen. (*N* = 26)	-0.885 (5.450)
			Non-First-Gen. (*N* = 50)	0.900 (4.853)
	More (*N* = 71)	-1.409 (6.995)	First-Gen. (*N* =28)	-0.571 (5.209)
			Non-First-Gen. (*N* = 43)	-1.953 (7.959)
	None (*N* = 78)	-0.949 (6.637)	First-Gen. (*N* = 27)	0.111 (6.542)
			Non-First-Gen. (*N* =51)	-1.509 (6.682)

Means are statically significantly different at p < .5

Table 14. *Continued*

	Screen-Cast Frequency	Gain Score Means (SD)	First-Generation Status (N)	Gain Score Means (SD)
EAS Gain Score Factor 4	Less (*N* = 74)	0.041 (1.739)	First-Gen. (*N* = 25)	-0.040 (1.670)
			Non-First-Gen. (*N* = 49)	0.082 (1.789)
	More (*N* = 71)	-0.014 (2.369)	First-Gen. (*N* = 28)	0.357 (2.711)
			Non-First-Gen. (*N* = 43)	-0.256 (2.117)
	None (*N* = 82)	0.159 (1.409)	First-Gen. (*N* = 29)	0.172 (1.365)
			Non-First-Gen. (*N* = 53)	0.151 (1.446)
EAS Gain Score Overall	Less (*N* = 70)	-0.100 (10.874)	First-Gen. (*N* = 24)	-0.417 (13.777)
			Non-First-Gen. (*N* = 46)	0.065 (9.176)
	More (*N* = 67)	-4.672 (15.139)	First-Gen. (*N* = 26)	-1.654 (8.182)
			Non-First-Gen. (*N* = 41)	-6.585 (18.083)
	None (*N* = 71)	-3.324 (14.186)	First-Gen. (*N* = 24)	-0.417 (12.801)
			Non-First-Gen. -(*N* = 47)	-5.000 14.691

Means are statically significantly different at p < .5

4.5.1.1. Original Gain Scores LLL Scale, Factor 1, Factor 2, Overall

We did not find any statistically significant result when we ran ANOVA to explore the relations among the LLL scale, its sub-dimensions, treatment type, screen-cast frequency, and students' demographics including first-generation college student status, gender, ethnicity, and major.

4.5.1.2. Original Gain Scores EAS Factor for First-generation College Student

4.5.1.2.1. EAS Gain Scores Factor 1 and Screen-cast Frequency

A one-way split ANOVA, first-generation college student status, was used to identify whether there was a statistically significant relationship among the students' EAS Factor 1 sub-scale with original items, gain scores across three different screen-cast exercise frequency groups (*Less, Experimental Group 1 with one to three screen-cast exercise*: $M = 1.280$, $SD = 4.852$, $N = 25$; *More, Experimental Group 2 withfour4 or more screen-cast exercise* $M = .286$, $SD = 2.955$, $N = 28$; *None, Traditional group with no screen-cast exercise*: $M = -2.586$, $SD = 6.121$, $N = 29$). The result showed a statistically significant difference for the first-generation college students' EAS factor 1 sub-scale with original items, gain scores and screen-cast exercise frequency groups (F $(2,79) = 4.746$, $p = .011$) (Table 15). The Tukey HSD post-hoc indicated that 'None' screen-cast activity participation was statistically significantly different from 'Less' screen-cast activity participation ($p = .012$) (Table 16). Further, Partial Eta Squared, effect size, suggested a large practical significance ($\eta p^2 = 0.107$). Cohen's *d* for the 'Less' and 'None' groups had a medium effect size ($d = 0.064$).

Table 15. ANOVA EAS Gain Scores Factor 1 & Screen-Cast Frequency

	Groups	*df*	Sum of Squares	Mean of Squares	*F*	*p*	Partial Eta Squared
Screen-cast Frequency							
	Between Groups	2	222.272	111.136	4.746	.011*	.107
	Within Groups	79	1849.789	25.415			
	Total	81	2072.061				

*Significant at *p*<.05
(First-generation College Student= Yes)

Table 16. ANOVA EAS Gain Scores Factor 1 & Screen-cast Frequency Post-hoc

Screen-cast Frequency	Screen-cast Frequency	*p*	Cohen's *d*
Less	None	.012*	0.064
	More	.736	
More	None	.071	

*Significant at *p*<.05

4.5.1.2.2. EAS Gain Scores Factor 1 and Treatment

A one-way ANOVA was used to identify whether there was a statistically significant relationship between students' EAS factor 1 gain scores and treatment type, specifically in the experimental and the comparison group for first-generation college students. First generation college students' EAS Factor 1 gain scores in the experimental group (N = 54, M = 0.741, SD = 3.919) were statistically significantly better (F (1,80) = 9.29 , p = .003) than first-generation college students' EAS factor 1 gain scores in the comparison group (N = 28, M = -2.679, SD = 6.213) at $p < .05$ **(Table 17).** Cohen's *d,* effect size, suggested a large difference between the group means (d = 0.658). We did not find any statistically significant differences for non-first-generation college students in the same sub-dimension.

Table 17. ANOVA EAS Gain Scores Factor 1 & Treatment Type

	Groups	*df*	Sum of Squares	Mean of Squares	*F*	*p*	Cohen's *d*
Treatment							
	Between Groups	1	215.58	215.583	9.290	.003	0.658
	Within Groups	80	1856.478	23.206			
	Total	81	2072.061				

*Significant at p<.05
(First-generation College Student= Yes)

4.5.2. Research Question 2

A one-way split ANOVA, first-generation college status, gender and ethnicity was used to identify whether students' gain scores for the modified LLL scale, modified EAS, and their sub-scales resulted in a statistically significant differences between the independent variables. Gain scores were calculated by subtracting pre-score responses from the post-score responses. The statistically significant relationships are summarized and the numbers and results of the second research questions are described in this section.

We found a statistically significant difference when we split the first-generation college students and ran an ANOVA to compare the experimental group first-generation college students' EAS factor 1 gain scores and comparison group first-generation college students' EAS factor 1 gain scores and the three different screen-cast frequencies.

We also found statistically significant results when we split the survey responses by ethnicity and gender. African American students and female students' responses had a statistically significant results in association with the EAS factor 1 sub-scale with original items, gain score means across the two treatments and three different screen-cast exercise groups showed differences.

4.5.2.1. Modified Gain Scores LLL Scale Factor 1, Factor 2, Overall

There was no statistically significant result to report for the modified LLL scale and subscale. We investigated the LLL scale and sub-scales using a split-file ANOVA, first-generation college student status in relationship to gender, ethnicity, major, screen-cast frequency, or treatment type.

4.5.2.2. Original and Modified Gain Scores EAS Factor 1

4.5.2.2.1. EAS Gain Score Factor 1 (Original and Modified), Gender and Treatment

When we analyzed the female students' responses to the two surveys, their sub-scales, and their modified versions, we found that female students in the experimental group ($N = 39$, $M1 = -0.436$, $SD1 = 5.139$, $M2 = -1.179$, $SD2 = 5.871$) at $p = .05$ level decreased their attitudes towards engineering as career (EAS Factor 1) statistically significantly less than female students in the comparison group ($N = 14$, $M1 = -4.286$, $SD1 = 5.209$, $M2 = -6.286$, $SD2 = 8.407$) for the original sub-scale ($F(1, 51) = 5.74$, $p = .02$, $\eta p^2 = 0.101$) and modified sub-scale ($F(1, 51) = 6.147$, $p = .017$, $\eta p^2 = 0.108$) (Table 8). In the control group, female students' EAS Factor 1 responses dramatically lowered where in the experimental group, female students' EAS Factor 1 responses lowered statistically significantly less than the control group.

Table 18. ANOVA EAS Gain Scores Factor 1 Original and Modified, Gender, Treatment

Gender		Groups	*df*	Sum of Squares	Mean of Squares	*F*	*p*	Partial Eta Squared
Female	EAS Gain Score Factor 1	Between Groups	1	152.6585	152.685	5.741	.020*	.101
		Within Groups	51	1356.447	26.597			
		Total	52	1509.132				
Female	EAS Gain Score Factor 1 (Modification)	Between Groups	1	268.607	268.607	6.147	.017*	.108
		Within Groups	51	2228.601	43.698			
		Total	52	2497.208				
Male	EAS Gain Score Factor 1	Between Groups	1	45.163	45.163	1.511	.221	.009
		Within Groups	171	5111.970	29.895			
		Total	172	5157.133				
Male	EAS Gain Score Factor 1 (Modification)	Between Groups	1	48.163	48.163	1.281	.259	.007
		Within Groups	171	6430.92	37.605			
		Total		6478.555				
			172					

*Significant at $p<.05$

4.5.2.2.2. EAS Gain Scores Factor 1 (Original and Modified), Gender and Screen-cast Frequency

We found statistically significant differences when we run ANOVA to compare female students' EAS factor 1 gain scores across different screen-cast exercise groups for the original set (F (2, 50) = 3.356, $p = .043$, $\eta p^2 = 0.118$) of items and for the modified items (F (2, 50) = 3.554, $p = .036$, $\eta p^2 = 0.124$). Table 19 represents female and male students' EAS factor 1 gain score means across the three screen-cast exercise groups. When we run the Tukey HSD post-hoc analyses to explore which group is different from another group, we found that female students who completed four or more (more) screen-cast exercises over the semester ($N = 18$, $M1 = 0.444$, $SD1 = 4.435$) improved their attitudes towards engineering as career (EAS factor 1) statistically significantly different from the female students who did not complete any screen-cast exercises over the semester ($N = 14$, $M1 = -4.286$, $SD1 = 5.209$). The modified set of items for EAS Factor 1 sub-dimension showed an increased difference between the two groups. The Tukey HSD post-hoc analyses with the modified set of items for EAS Factor 1 sub-dimension revealed that female students who completed four or more (more) screen-cast exercises over the semester ($N = 18$, $M2 = -0.056$, $SD2 = 4.151$) reduced their attitudes towards engineering as career (EAS factor 1) statistically significantly less than the female students who did not complete any screen-cast exercises over the semester ($N = 14$, $M2 = -6.286$, $SD2 = 8.407$). In other words, in the none screen-cast exercise group, female students' engineering as career attitudes were dramatically reduced. In contrast, in the four or more screen-cast exercise group, female students' engineering as career attitudes slightly increase or very slights decreased that could almost be considered as no change. Table 20 represents the post-hoc analyses for the female students' groups. The effect sizes between the more screen-cast exercise group and no screen-cast exercise group indicated a very large difference (d = 1.26) for the original set of items and a large difference (d = .98) for the modified set of items for the EAS factor 1 sub-scale.

Table 19. ANOVA EAS Gain Scores Factor 1 Original and Modified, Gender, Screen-cast Frequency

Gender		Groups	*df*	Sum of Squares	Mean of Squares	*F*	*p*	Partial Eta Squared
Female	EAS Gain Score Factor 1	Between Groups	2	178.592	89.296	3.356	.043*	.118
		Within Groups	50	1330.540	26.611			
		Total	52	1509.132				
Female	EAS Gain Score Factor 1 (Modification)	Between Groups	2	310.835	155.417	3.554	0.036*	.124
		Within Groups	50	2186.373	43.727			
		Total	52	2497.208				
Male	EAS Gain Score Factor 1	Between Groups	2	40.918	20.459	.680	.508	.008
		Within Groups	17 0	5116.215	30.095			
		Total	17 2	5157.133				
Male	EAS Gain Score Factor 1 (Modification)	Between Groups	2	61.520	30.760	.815	.444	.009
		Within Groups	17 0	6417.035	37.747			
		Total	17 2	6478.555				

*Significant at $p<.05$

Table 20. Post-hoc results for the female students' gain scores of the original and modified versions of the EAS Factor 1 sub-scale across three different screen-cast frequency groups.

Gender		Screen-cast Frequency	Screen-cast Frequency	*p*	Cohen's *d*
Female	EAS Gain Score Factor 1	Less	More	.589	
			None	.201	
		More	None	.034*	1.26
	EAS Gain Score Factor 1 (Modification)	Less	More	.591	
			None	.175	
		More	None	.029*	0.98

*Significant at $p<.05$

4.5.2.2.3. EAS Gain Scores Factor 1 (Original and Modified), Ethnicity, and Treatment

When we grouped students based on their reported ethnicities and run the similar analyses, we found differences for African Americans. African American students who were in the experimental group ($N=111$, $M1 = -0.829$, $SD1 = 4.941$, $M2 = -1.658$, and $SD2 = 5.672$) reduced their attitudes towards engineering as career option statistically significantly less than the African Americans who were in the comparison group ($N = 53$, $M1 = -3.736$, $SD1 = 6.029$, $M2 = -4.925$, and $SD2 = 7.925$), $F(1, 161) = 10.732$, $p = .001$, $\eta p^2 = 0.062$ for the original sub-scale and $F(1, 161) = 9.114$, p = .003, $\eta p^2 = 0.053$ for the modified sub-scale).

Table 21. ANOVA EAS Gain Scores Factor 1 Original and Modified, Ethnicity, Treatment

Ethnicity		Groups	*df*	Sum of Squares	Mean of Squares	*F*	*p*	Partial Eta Squared
African American	EAS Gain Score Factor 1 (With Original Items)	Between Groups	1	303.145	303.145	10.732	.001*	.062
		Within Groups	162	4576.050	28.247			
		Total	163	4879.195				
	EAS Gain Score Factor 1 (With Modified Items)	Between Groups	1	382.841	382.841	9.114	.003*	.053
		Within Groups	162	6804.689	42.004			
		Total	163	7187.530				

*Significant at $p<.05$

4.5.2.2.4. EAS Gain Scores Factor 1 (Original and Modified), Ethnicity and Screen-cast Frequency

When we analyzed the students' responses to the two surveys, their sub-scales, and their modified versions, separated by the students' self-identified ethnicity, we found statistically significant differences across the three screen-cast exercise groups for the African American students only. The gain score means for the Hispanic/Latino students and other ethnicities did not show any statistically significant difference for the three screen-cast exercise groups.

We found statistically significant differences when we run ANOVA to compare African American students' EAS Factor 1 gain scores across different screen-cast exercise groups for the original set of items (F (2,161) = 4.864, p = .009, $\eta p^{2} = 0.057$) and for the modified set of items (F (2, 161) = 4.903, p = .009, $\eta p^{2} = 0.057$). Table 22 represents African American students' EAS Factor 1 gain score means across the three screen-cast exercise groups. When we ran the Tukey HSD post-hoc analyses to explore which group was different from another group, we found that African American students who completed four or more (more) screen-cast exercises over the semester (N = 51, $M1$ = -0.784 , $SD1$ = 4.323, $M2$ = -0.922, $SD2$ = 3.659) reduced their attitudes towards engineering as career (EAS Factor 1) statistically significantly less than the African American students who did not complete any screen-cast exercises over the semester (N = 55, $M1$ = -3.60, SD = 5.959; $M2$ = -4.80, $SD2$ = 7.809). Table 23 represents the post-hoc analyses for the African American students' groups. The effect sizes between the less screen-cast exercise group and no screen-cast exercise group indicated a medium difference (d = .469); and more screen-cast exercise group and no screen-cast exercise group indicated a medium difference (d = .541) for the original items EAS factor 1 sub-scale. In the post-hoc analyses, we observed only one statistically significant difference that was between more screen-cast exercise group and no screen-cast exercise group. The effect size was (d = .636) which represented a medium group difference for the modified set of items for the EAS factor 1 sub-scale.

Table 22. ANOVA EAS Gain Scores Factor 1 Original and Modified, Ethnicity, Screen-cast Frequency

Ethnicity		Groups	*df*	Sum of Squares	Mean of Squares	*F*	*p*	Partial Eta Squared
African American	EAS Gain Score Factor 1 (With Original Items)	Between Groups	2	277.988	138.994	4.864	.009*	.057
		Within Groups	161	4601.207	28.579			
		Total	163	4879.195				
	EAS Gain Score Factor 1 (With Modified Items)	Between Groups	2	41	206.315	4.903	.009*	.057
		Within Groups	161	6804.689	42.080			
		Total	163	7187.530				

*Significant at $p<.05$

Table 23. Post-hoc results for African American students' gain scores of the original and modified version of the EAS Factor 1 sub-scale across three different Screen-cast Frequency groups

	Screen-cast Frequency	Screen-cast Frequency	*p*	Cohen's *d*
EAS Gain Score Factor 1	Less	More	.993	
		None	.022*	0.469
	More	None	.020*	0.541
EAS Gain Score Factor 1 (Modification)	Less	More	.506	
		None	.106	
	More	None	.007*	0.636

*Significant at $p<.05$

4.5.2.2.5. EAS Gain Scores Factor 1 (Modified) and Screen-cast Frequency

A one-way split ANOVA, first-generation college student status, was used to identify whether there was a statistically significant relationship between the EAS Factor 1 (modified) gain scores screen-cast frequency (*Less, Experimental Group 1 with 1 to 3 screen-cast activity*: $M = 0.800$, $SD = 3.851$, $N = 25$; *More, Experimental Group 2 with 4 or more screen-cast activity*: $M = -0.071$, $SD = 2.308$, $N = 28$; *None, Traditional group with no screen-cast activity*: $M = -3.759$, $SD = 8.06$, $N = 29$). The results for EAS Factor 1 gain scores and screen-cast frequency ($F\,(2,79) = 5.533$, $p = .006$) show a statistically significant difference among the three groups (Table 24).

The Tukey HSD post-hoc indicated that 'None' screen-cast activity participation was statistically significantly different from 'Less' screen-cast activity participation ($p = .008$) and "More" was statistically significantly different from "None" ($p = .032$). (Table 25). Partial Eta Squared, effect size, suggested a large practical significance (ηp^2

= .123) between the three screen-cast frequency groups. Further, Cohen's *d*, effect sizes between the less screen-cast exercise group and no screen-cast exercise group indicated a medium difference (*d* = .722); and more screen-cast exercise group and no screen-cast exercise group indicated a medium difference (*d* = .622) for the modified items EAS Factor 1 sub-scale.

Table 24. ANOVA EAS Gain Scores Factor 1 Modified and Screen-Cast Frequency

	Groups	*df*	Sum of Squares	Mean of Squares	*F*	*p*	Partial Eta Squared
Screen-cast Frequency							
	Between Groups	2	324.845	162.422	5.533	.006*	.123
	Within Groups	79	2319.167	29.357			
	Total	81	2644/012				

*Significant at $p<.05$
(First-generation College Student= Yes)

Table 25. ANOVA EAS Gain Scores Factor 1 Modified and Screen-Cast Frequency Post-hoc

Screen-cast Frequency	Screen-cast Frequency	*p*	Cohen's *d*
Less	More	.829	
	None	.008*	0.722
More	None	.032*	0.622

*Significant at $p<.05$

4.6. Conclusion

The research questions addressed in this study include analysis of the respondent data from the original and modified LLL scale and EAS response data, two factors derived from the LLL scale and four factors derived from the EAS, used as dependent variables for analysis. The LLL factor scores were elucidated using EFA and CFA in an earlier study using EFA and CFA in Section 2 and four EAS factors derived using the same method in another study (Section 3). In a previous study, modifications (e.g., item deletion) to the LLL scale and EAS were identified that could improve the Cronbach's alpha, reliability, and/or improve the construct validity using CFA, model fit (i.e., Model Chi-Square, Root Mean Square Error of Approximation, Comparative Fit Index, Tucker Lewis Index, Goodness of Fit Index). We used the modified LLL and EAS and in Scores from items associated with the derived factors as additional dependent variables. In this study, we investigated the relationships between the following independent variables: first-generation college status, treatment/comparison groups, and screen-cast tutorial frequency, ethnicity, gender and major.

4.6.1. EAS Gain Scores & Treatment

4.6.1.1. EAS Factor 1: Engineering as a Career & First- Generation College Student

A one-way split ANOVA, for first-generation college student status results indicated that the EAS factor 1 gain score, "Engineering as a career," had a statistically significant relationship with treatment for the original EAS (p = .003) and the modified

EAS (p = .001). The original EAS students' respondent data for the comparison group had a negative mean gain score (M = -1.22) and the experimental treatment group had a positive mean gain score M = 0.741 in association with EAS Factor 1. The modified EAS factor 1 had complimentary results. Students in the comparison group had a negative mean gain score (M = -3.893) and the experimental group had positive mean gain scores (M = 0.333). We expect students in the comparison group to have negative attitude toward engineering as a career. Conversely, students who have participated in the screen-cast tutorial should have a more positive attitude association with engineering as a career option. These are promising results with large practical significance for both the original EAS factor 1 (d = 0.658) and the modified EAS factor 1 (d = 0.683). The EAS factor 1 and the modified EAS factor 1 had similar results, however modification to the EAS provided stronger evidence that the treatment group students' attitudes toward engineering, career improved where comparison group students' attitudes towards engineering career decreased after the semesters were completed.

4.6.1.2. EAS Factor 1: Engineering as a Career & Gender

A one-way split ANOVA, for gender, specifically female, results indicated that the EAS factor 1 gain score, "Engineering as a career," had a statistically significant relationship with treatment for the original EAS (p = .020) and the modified EAS (p = .017). The male respondent data did not indicate any statistically significant difference. The original EAS female students' respondent data for the comparison group had a very large negative mean gain score for the original EAS Factor 1 (M = -4.4286) and modified EAS factor 1 (M = -6.286). The females in the experimental treatment group, while still negative, had a near neutral mean gain score (M = -0.436) for the original EAS factor 1 and a slightly negative mean gain score (M = -1.179) for the modified EAS factor 1. Students in the comparison treatment group are expected to have negative attitude toward engineering as a career. Conversely, students who have participated in the screen-cast tutorial should have a more positive attitude association with engineering as a career option. The modifications we performed on the surveys and their sub-scales showed a slight improvement in the p value we found (p = .017). Original EAS factor 1 items generated a .05 p value difference where the modified EAS Factor 1 items generated a .02 p value difference. This indicated that modifications made on the EAS factor 1 items had improved the evidence that female students in the experimental group reduced their engineering attitudes statistically significantly less than the female students in the comparison group. Table 18 represented the ANOVA results from both original EAS factor 1 items and modified EAS factor 1 items for the female students across the treatment types. When we ran the same test for the male students, we did not find any statistically significant difference across the treatment types.

4.6.1.3. EAS Factor 1: Engineering as a Career & Ethnicity

A one-way split ANOVA, for ethnicity, specifically African American, results indicated that the EAS factor 1 sub-scale with original items, gain score, “Engineering as a career,” had a statistically significant relationship with treatment. The original and modified EAS Factor 1 was statistically significantly different for students who identified as African American (p = .001 and p = .003 respectively. The other respondent data separated by ethnicity did not indicate a statistically significant difference. These results suggested that African American students in the study, compared to other ethnicities, were more responsive to the EBPs, which impacted significantly less decrease in their engineering attitudes after the completion of the semester.

4.6.2. EAS Gain Scores & Screen-cast Tutorial Frequency

4.6.2.1. EAS Factor 1: Engineering as a Career

A one-way split ANOVA, for first-generation college student status results indicated that the EAS factor 1 gain score, "Engineering as a career," had a statistically significant relationship with screen-cast tutorial exercise frequency for the original EAS factor 1 items (p = .011) and the modified EAS factor 1 items (p = .006). The original EAS factor 1 sub-scale students' respondent data for the group who participated "Less" (i.e., one to three screen-cast activities) had a positive mean gain score (M = 1.280); the students who participated "More" (i.e., four or more screen-cast activities) also had a positive mean gain score (M = .286); the students in the comparison group who did not participate in any screen-cast tutorial had a negative mean gain score (M = -2.586). The modified EAS students' respondent data had similar results. The group who participated "Less" (i.e., one to three screen-cast activities) had a positive mean gain score (M = 0.800); the students who participated "More" (i.e., four or more screen-cast activities) also had a slightly negative mean gain score, but approaching neutral (M = -0.071); the students in the comparison group who did not participate in any screen-cast tutorials had a negative mean gain score (*M* = -3.759). The EAS factor 1 and the modified EAS factor 1 had similar results, however modification to the EAS did have a slightly negative mean gain score for "More" screen-cast tutorial frequency. However, the modified EAS factor 1 was more statistically significant. The Tukey HSD post-hoc for the original EAS factor 1 indicated that "None" was statistically significantly different from "Less" ($p = .012$). The Tukey HSD post-hoc for the modified EAS factor 1 indicated that "None" was statistically significantly different from "Less" ($p = .008$) and "None" was statistically significantly different from "More" ($p = .008$), providing increased statistical significance when modified versions of the EAS Factor 1 item sets were used. These have been promising results as there was a large practical significance for both of the original EAS factor 1 ($\eta p^{2} = 0.107$) and the EAS factor 2 ($\eta p^{2} = .123$) results. We expected, and results reflected, that students in the experimental treatment group, who had increasing participation with the screen-cast tutorial would also have had an improved attitude with engineering as a career.

A one-way split ANOVA, for gender results indicated that EAS factor 1 gain score had a statistically significant relationship with screen-cast tutorial exercise frequency for original EAS factor 1 ($p = .043$) and the modified EAS factor 1items ($p = .036$) .The original EAS factor 1 sub-scale female students' respondent data for the group who participated "Less" (i.e.,1 to 3 screen-cast activities) had a negative mean gain score ($M = -1.191$); the students who participated "More" (i.e., 4 or more screen-cast activities) had a positive mean gain score ($M = 0.444$); the students in the comparison group who did not participate in any screen-cast tutorials had a negative mean gain score (*M* = -4.286). The modified EAS female students' respondent data had similar results. The group who participated "Less" (i.e.,1 to 3 screen-cast activities) had a negative mean gain score (*M* = -2.143); the students who participated "More" (i.e., 4 or more screen-cast activities) also had a slightly negative mean gain score, but approaching neutral (*M* = -0.056); the students in the comparison group who did not participate in any screen-cast tutorials had a very negative mean gain score (*M* = -*6.286*). The EAS factor 1 and the modified EAS factor 1 had similar results, however modification to the EAS did have a slightly negative mean gain score for "More" screen-cast tutorial frequency. However, the modified EAS factor 1 was more statistically significant. The Tukey HSD post-hoc for the original EAS factor 1 indicated that "More" was statistically significantly different from "None" (*p* = .034). The Tukey HSD post-hoc for the modified EAS factor 1 indicated that "None" was statistically significantly different from "More" (*p* = .029). These have been promising results as there was a large practical significance for both of the original EAS factor 1 (ηp^{2} = 0.118) and the EAS factor 2 (ηp^{2} = .124) results. These results, similar to the previous results highlighted that female students with increasing participation with the screen-cast tutorial would have had an improved attitude with engineering as a career or would have had less decrease in their attitudes.

Finally, A one-way split ANOVA, for ethnicity results indicated that EAS factor 1 gain score had a statistically significant relationship with screen-cast tutorial exercise frequency for African American for the EAS factor1 original and modified EAS factor 1

(p = .009) and the modified EAS factor 1 items (p = .009). The original EAS factor 1 sub-scale African American students' respondent data for the group who participated "Less" (i.e., 1 to 3 screen-cast activities) had a slightly negative mean gain score (M = -0.897); the students who participated "More" (i.e., 4 or more screen-cast activities) had a slightly negative mean gain score (M = -0.784); the students in the comparison group who did not participate in any screen-cast tutorials had a very negative mean gain score (M = -3.600). The modified EAS African American students' respondent data had similar results. The group who participated "Less" (i.e.,1 to 3 screen-cast activities) had a negative mean gain score (M = -2.310); the students who participated "More" (i.e., 4 or more screen-cast activities) also had a slightly negative mean gain score, but approaching neutral (M = -0.922); the African American students in the comparison group who did not participate in any screen-cast tutorials had a very negative mean gain score (M = -4.800). The EAS factor 1 and the modified EAS factor 1 had similar results, however modification to the EAS did have a slightly negative mean gain score for "More" screen-cast tutorial frequency. The Tukey HSD post-hoc for the original EAS factor 1 indicated that "Less" was statistically significantly different from "None" (p = .022, d =.469); and "More" was statistically significantly different from "None" (p = .020, d = .541) at p=.05 level. The Tukey HSD post-hoc for the modified EAS factor 1 indicated that "More" was statistically significantly different from "None" (p = .007, d = *.636*). These results along with Cohen's d effect sizes emphasized a medium practical significance. African American students who participated in the screen-cast tutorial exercises reduced their engineering attitudes concerning engineering as a career less than the African American students who did not participate in the screen-cast tutorial exercises. The effect of the screen-cast tutorial exercise participation was more visible with or impactful for the African American students when compared to students belonging to other ethnic groups in this study.

4.6.3. LLL & EAS Summary

In this study, we investigated the relationship between the original and modified LLL scale and EAS respondent data with respect to first-generation college student status. The results indicated that the EAS factor 1 revealed crucial information about the relationships among the use of the EBP, screen-cast tutorial activity, and the development of engineering attitudes as career. Students' positive attitudes towards engineering as career were either improved or did not decrease much when they participated in a student-centered and learner-oriented instruction.

4.7. Discussions and Implications for Future Research

Female, first-generation, and African American students' EAS factor 1 gain scores were statistically significantly better in the groups that received EBPs. It is sine qua non to teach student-centered and learner-oriented to help improve equity in education in the short term and social justice in the long term. Retaining female, first-generation, and African American students in the STEM pipeline is paramount for the U.S.'s economic future and engineering workforce. Considering that many students in the U.S. find the STEM fields uninteresting and irrelevant, teaching through EBPs and attracting students' interest in engineering careers are recommended. Future research can investigate student populations who have been traditionally underrepresented in STEM fields and how their interest, motivation, and attitude can be improved through the use of EBPs. Additional empirical evidence will help convey the importance of EBPs and teaching undergraduate courses through student-centered and learner-oriented instructional strategies.

4.8. References

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5. CONCLUSIONS

5.1. Purposes of the Lifelong Learning (LLL) Scale & Engineering Attitude (EAS) Investigations

In the first study, my purpose was to investigate the LLL scale and its sub-dimensions or latent factors. In the second study, my purpose was to re-evaluate the EAS. The LLL scale was designed to measure LLL skills. The EAS was designed to explore undergraduate college students' engineering attitudes. The surveys were administered in a mechanical engineering course. To answer the research questions, we performed two distinct analyses described in Section 2 and 3, including completion of exploratory (EFA) and confirmatory factor analysis (CFA) in order to identify latent variables/factors, and explore the construct validity of the LLL scale and the EAS. Section 4 evaluated the combined data set containing from the LLL scale and the EAS to calculate reliability and effect size in order to quantify the effectiveness of the evidence-based pedagogy EBP (i.e., screen-cast tutorial activity). Students' responses were analyzed by selecting for first-generation college student status, ethnicity and gender.

5.2. LLL Scale Investigation Results Review

EFA of the LLL scale respondent data, produced a two-factor model that included latent factors termed, "Learner Characteristics" and "Enjoyment of Reading and Writing." The factor loadings are distinct with no items cross-loading. The first factor named, "Learner Characteristic" contained ten items and the second factor named, "Enjoyment of Reading and Writing" contained six items. The Cronbach's alpha values suggested the factors elucidated, contained adequate reliability and internal consistency (Burtner, 2005). CFA generated a model evaluating “goodness-of-fit” and evaluated construct validity associated with the derived factors (Schreiber, Nora, Stage, Barlow & King, 2006). One of the fit indices, Comparative Fit Index (CFI), met model fit criteria, indicating a good model fit for the identified factors. The other model fit for the other four indices did not achieve adequate model fit. However, the model fit values approached acceptable ranges. To improve the LLL scale, some modifications were presented. For example, removing items with (1) low factor loadings (i.e., items 10, 13, 3, 1, 7); and (2) items with low item-factor correlation (i.e., factor 1 removed items 13, 3, 1 and factor 2: removed item 7) were discussed. These modifications were being predicted to improve the model fit. Ultimately the proposed modifications improved both the reliability and construct validity, yielding “good fit” criteria thresholds of factors derived from the LLL scale. In Section 4, we used the original and modified set of items for the LLL scale to explore the impact of an instructional treatment on students’ LLL and engineering attitudes.

5.3. EAS Investigation Results Review

EFA produced a four-factor model including latent factors termed (“Engineering as a Career,” “Engineering Career Characteristics,” “Engineering Personality Characteristics,” and “Engineering as Theoretical”). The first factor had distinct loading patterns with only one item, 16, cross-loading on the second factor. Factors 2, 3, and 4 had many low and cross-loadings items. The Cronbach’s alpha values reported have good reliability and internal consistency, except for the first factor. The CFA investigates the goodness-of-fit and determines if there is construct validity associated with the derived factors. The model fit indices did not reach adequate model fit criteria limits, but the values approached acceptable ranges. One of the major problems we observed with the items and the derived factors, was difficult for the student respondents to distinguish between negative aspects of engineering careers and negative characteristics of individuals who happen to have a career in engineering. We believe that this was why items exhibited low and cross factor loadings. This implication of a construct validity problem rooted in muddled language leads to the suggestion that these items either need to be removed, or the survey items needed to be rewritten to enhance clarity. Additionally, removing items with low factor loadings, cross-loading factors, and items with low item-factor correlation (i.e., Factor 1 removed items 2, 8, 16; factor 2 removed items 7 and 14; factor 3 removed items 1 and 24; factor 4 did not have any modifications) were predicted to improve both the model fit and ultimately the reliability and construct validity of the EAS instrument.

Section 2 and Section 3 both provided foundational analysis for the development of two instruments that had factors with strong reliability and meet “good-fit” criteria for construct validity. The results described here provided researchers a plan-of-action in continuous development and modification of LLL scale and EAS as assessment tools. These tools, employed alongside EBP, can reliably assess the effectiveness of developing LLL skills and the improvement of engineering attitudes.

In the third study, my purpose was to explore the effects of the evidence-based pedagogical treatment on the undergraduate mechanical engineering students' development of LLL skills and improvement of engineering attitudes during a computer aided design course. The LLL scale and EAS from Section 2 and Section 3 were used to further explore the relationships among the demographic data of the students enrolled in the Computer-aided Design (CAD) course and the impact of different instructional treatments on their LLL and engineering attitudes. We split the data based on student demographics and ran the f-tests to explore if the means of the gain scores of the students to the original and modified LLL scale and EAS were more statistically significant across the different treatment types.

We split the data based on students' demographic characteristics and investigated their gain score means across different treatment types and screen cast exercise tutorial frequencies. We found and reported statistically significant relationships for the EAS Factor 1 items, both original and modified set of items. There was no statistically significant result identified for the original or modified LLL scale and its sub-scales. Gain scores were calculated by subtracting pre-score responses from the post-score responses. First-generation college students in the experimental treatment group improved attitudes about engineering as a career (EAS factor 1). The students in the treatment group with increased participation with the screen-cast tutorial performed statistically significantly different from the students who were in the comparison group with no participation in the screen-cast tutorials. Some of those results indicated that students in the treatment group reduced their attitudes about engineering as a career statistically significantly less than those in the comparison group as captured through EAS Factor 1 items.

We also investigated the students' gain scores of the original LLL scale and EAS, separating male and female participants and running the analysis to explore the impact of the treatment on female students' gain scores means. There was statistically significant relationship among the female students' responses to the original and modified versions of the EAS factor 1 in relationship to screen-cast frequency and experimental treatment groups. Female students in the experimental treatment group who increased their participation with the screen-cast tutorial had less reduced attitudes toward engineering as a career compared to the comparison group. These results are important because they highlight EBP that can aid in retaining female student in the science, technology, engineering and math (STEM) pipeline.

Selecting for African American students, we found a statistically significant relationship between original and modified EAS factor 1 and the treatment groups. These ethnic groups in the treatment group demonstrated improved attitudes toward engineering as a career. Selecting for only African American students, there was a statistically significant difference in the relationship between EAS factor 1 and screen-cast tutorial frequency. African American students, who had increased participation with the screen-cast exercise tutorials had improved their attitudes toward engineering as a career. These results reiterated the importance of utilizing EBP in STEM education with the goal of improving attitudes toward STEM, which in turn could aid in retention and recruitment of underrepresented minority (URM) groups participating in STEM major and ultimately choosing STEM as a career.

Overall, the goal of the third study evaluated the survey tools used to measure the impact of EBP on developing LLL skills and engineering attitudes, and therefore improving STEM education. Continued modification of the surveys will identify additional, statistically significant results alongside results that show increased effect size associations. Additional empirical evidence can draw attention to the importance of student-centered, learner-oriented instruction, and EBPs in STEM undergraduate education.

5.4. Implications

5.4.1. The STEM Problem

There is an increase in the number of jobs in the 21st century economic climate that demands experience and skills that a STEM education can afford (Granger et al., 2012; Han et al., 2015; Land & Hannafin, 2000; Litzler et al., 2014; Lord et al., 2012; Peng et al., 2014). STEM occupations are steadily increasing and most education systems have not kept up with the workforce demands. The STEM pipeline is a term used to describe the pathway that students journey along from formal education to careers in STEM fields. This pipeline is often described as "leaky" because of a lack of recruitment, retention and persistence of URMs in STEM education and ultimately STEM careers (*The STEM Pipeline*, 2015). To compound the issue further, the number of students who intend to pursue a career in the STEM fields is consistently reduced between primary, secondary, and postsecondary education. There is an even greater reduction in the number of students who ultimately graduate in a STEM focused field (Zhang et al., 2015).

5.4.2. Solution

A possible solution to the problem is a change in the focus of STEM education. Students today face unique local and global challenges that are presented in the 21st century. Traditionally education has centered solely around teaching students specific content. There has been a shift in methodology where STEM education not only includes science content matter but also aims at developing readiness for 21st century skills. It is important that students cultivate 21st century skills and continue to develop those skills in the classroom and throughout their lifetime. Lifelong learning and 21st century skills both emphasize adaptability, self-direction, responsibility, social and economic priorities, and local and global awareness (Wielkiewicz & Meuwissen, 2014).

5.4.3. Study Contributions & Future Impact

This study has contributed to the efforts to promote the STEM pipeline by refining instruments that could aid in measuring EBP methods in undergraduate STEM courses. The LLL scale and EAS can equip STEM instructors and researchers alike with assessment tools to analyze the effects of student-centered and learner-oriented instructional strategies integrated into STEM education. Utilization of surveys, for example, the LLL scale, assesses endeavors to measure development of LLL skills. The modified EAS is a useful tool to measure improved attitudes toward engineers and engineering careers as a desirable profession. Both surveys can be used in coordinated effort to identify relational and demographic characteristics of the learners. These characteristics can also be used to explore the impact and development of LLL skills and engineering attitudes.

We identified that student-centered and learner-oriented collectively known as EBPs, for example, screen-cast tutorial, is effective in improving attitudes toward engineering as a career. First-generation college students over non-first-generation college students, females over male students, and African Americans students over other ethnic groups students were identified as having improved attitudes to engineering as a career. First-generation college students have been identified as a vulnerable college population as they encounter a multitude of unique obstacles. These students often have a lack of college readiness (i.e., practical knowledge to be successful, lower SAT/ACT scores, unfamiliar with college rigor), deficient familial support, financial instability; they may experience racial disparity, low academic self-esteem, culture shock and cultural isolation (Falcon 2015). Traditional lecture style curriculum has not encouraged students to be an active architect and developer of their own learning resources. Conversely, courses that embrace a more active learning, EBP strategy has encouraged students to take inventory of their learning styles/preferences, identification of learning strengths or weakness, develop or adapt their own learning strategies, time management and organization skills. The development of the screen-cast tutorials created a cyberlearning environment in which students took ownership and responsibility of their own learning process, where they could feel empowered in generating new knowledge and making tangible connections with otherwise abstract engineering concepts. The impact of the screen-cast tutorial resulted in first-generation college student participants having a more significant response to developing positive engineering attitudes changes from before and after the semester. Non-first-generation college students do not share the same college experience obstacles as first-generation college students. The results outlined in this study reflected that non-first-generation college students were not as receptive to student-centered instruction, as they did not show significant and positive changes in their attitudes toward engineering as a career choice. Non-first-generation college students might have been resistant to the non-traditional learning environments as they have had succeeded in the traditional, lecture style instruction. Non-first-generation college students might also have been motivated to pursue engineering as a career regardless of the instructional strategies employed in the classroom.

With a rapidly changing world that is dependent on technology, STEM education must be an innovative and attractive option for students, especially those who have historically been excluded. URMs such as, ethnic minority students and women are not well represented in the pursuit and obtainment of STEM degrees, which in turn leaves a stark absence of URM in the STEM workforce. Recruitment, retention, persistence are major factors in URMs participation in STEM. It is common knowledge that there are more men than women in STEM fields. The reasons for the gender disparity have been well documented. STEM is plagued by a “A masculinized culture [of STEM fields] consist[ing] of explicit and implicit beliefs, behaviors, policies, practices, and procedures that tout men's interests, abilities and skills as superior to women's (Cheryan, Ziegler, Montoya, & Jiang, 2017). A recent study by Riegle-Crumb, King and Irizarry (2019) found that African American and Latino students have the same interest levels in STEM majors as their white counterparts, however African American and Latinos are highly unlikely to graduate from these programs. The reason why the ethnic URM students have such high attrition rates remains elusive. Our study utilizing the CAD screen-cast tutorial incorporates key EBPs, such as student-centered and learner-oriented instruction. We found statistically significant difference between the female and male students, and African American and Latino students compared to other ethnic groups. Members of the treatment group who had increased participation with the screen-cast tutorial, had improved attitudes toward engineering as a career. Education researchers and STEM instructors have been exploring ways to make STEM education inclusive and engaging for all students and this study provides support that EBP is a tool to continue to improve STEM education for the most underrepresented population. One of the limitations of our study is that the data included mostly African American students as they attended a Historically Black College and University (HBCU). We only found statistically significant differences after we separated the data set into individual ethnic groups. Future research is needed that includes all ethnicities in more equitable ratios in order to obtain investigations with generalizable results.

In Section 2, we identified two latent factors (i.e., Learning Characteristics, Enjoyment of reading and writing) and proposed modifications (e.g., deletions) to the original LLL scale which has improved reliability and construct validity. In Section 3, we identified 4 latent factors (i.e., Engineering as a career, Engineer characteristics, Engineer career personality characteristics, engineering is theoretical) and also proposed item modification (e.g., item deletions) to the original EAS which also resulted in improved reliability and construct validity. The factors identified can be incorporated into learning objectives of STEM curriculum and implemented using EBP. In Section 4, we identified statistically significant relationships between the scale and sub-scale of the EAS. We identified first-generation college student status, gender and ethnicity as student demographics that were positively influenced by EBP teaching strategy and had improved attitudes toward STEM careers. The modified LLL scale and EAS, improved reliability and construct validity are novel contributions these studies provide to the literature in regards to instrument development and implementation for STEM education. In the three studies reported in this document, we have identified proven methods, EBP, and improved assessment tools (i.e., modified LLL scale and modified EAS) that can positively impact and monitor vulnerable undergraduate populations and URMs in STEM undergraduate programs.

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APPENDIX A

Lifelong Learning Scale*

The scale items measure the extent to which the person's behavior reflects' positive attitude toward learning, curiosity, and critical thinking.

1. I enjoy intellectual challenges.
2. I read for the sake of new learning.
3. I converse with others about new things I have learned.
4. I like to analyze problems and issues in depth.
5. I see myself as a lifelong learner.
6. My regular activities involve reading.
7. My regular activities involve writing.
8. I am a self-motivated learner.
9. I browse libraries or bookstores for interesting books or magazines.
10. I make interesting contributions to discussions in my classes, at work, or with friends.
11. My activities involve critical thinking.
12. I read for pleasure or entertainment.
13. I am curious about many things.
14. I pursue a wide range of learning interests.
15. I like to learn new things.
16. I do a lot of reading that is not required for my classes or job.

Each item is rated on a scale of 1 to 5 with 1 = Never; 2 = Rarely; 3 = Sometimes; 4 = Often, and 5 = Always or Daily.

All items are positive—there is no item to reverse.

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Engineering Attitude Scale**

*1. Most engineers have poor social skills.
*2. Engineers spend most of their time doing complex mathematical calculations.
3. Engineering would be a highly interesting profession for me.
*4. A problem with engineering is that engineers seldom get to do anything practical.
*5. Engineers deal primarily with theory.
*6. Engineers spend relatively little time dealing with other people.
*7. Engineers spend most of their time working in offices.
*8. Engineers spend most of their time working with computers.
*9. Engineers seldom get involved in business decisions.
*10. Engineers have little need for knowledge about environmental issues.
*11. Engineers have little need for knowledge about economics.
*12. Engineers have little need to deal with questions about behavior that is morally right or wrong.
*13. Engineers have little need for knowledge about political matters.
*14. To be a good engineer requires an IQ in the genius range.
*15. Engineering is a poor career choice because job availability is dependent on defense spending.
*16. Engineers need a great deal of inborn aptitude for science and mathematics.
*17. Most engineers have very narrow outside interest.
18. Engineering is important to future US economic success in the world.
*19. Engineers typically have very little common sense.
20. A career in engineering would be financially rewarding.
21. Most of the skills learned in engineering would be useful in everyday life.
*22. Engineers are not typically people who are fun to be around.
*23. Engineers do not tend to be appreciative of the arts.
*24. Engineers are frequently those individuals who were regarded as “nerds” in high school.
25. If I had to do it over again, I would consider a career in engineering.

KEY:
6=Very Strongly Agree; 5=Strongly Agree; 4=Agree; 3=Disagree;
2=Strongly Disagree; 1=Very Strongly Disagree
****Negative questions—lower scores indicate a positive attitude***

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