Developing the ESLS - Engineering Students Learning Strategies instrument

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1. Introduction

Achieving deep, meaningful learning of engineering concepts is crucial to successfully completing an engineering degree. It is thus important for students to develop more effective learning strategies that result in deep conceptual understanding (Bransford et al., 2000). The first necessary step towards providing students with the support they need to develop effective learning strategies is to understand the typical learning strategies that students are currently employing to support their learning in concept-heavy engineering courses. Once faculty understand the learning strategies students are currently using, they can better develop activities to help students learn content more effectively and become better learnings.   We use the term concept-heavy courses to delineate course such as statics and dynamics that often occur in the middle years of engineering education as opposed cornerstone or capstone engineering courses in which a focus on design processes evokes different approaches to learning. Herein, we describe the development of a survey instrument to measure engineering students' learning strategies (ESLS) in concept-heavy courses, by answering the following research questions:

1. What factors emerge from an Exploratory Factor Analysis used to develop the ESLS survey?
2. What are the validity and reliability measures of the ESLS instrument based on a pilot implementation of the survey?
3. For a pilot implementation of the survey instrument, how do students compare on learning strategy use by gender and grade expectancy?

This effort is part of a larger project exploring the link between motivation and conceptual understanding. Prior qualitative analysis of interviews with students (e.g., (Morelock et al., under review), and to a lesser degree faculty (Soledad et al., 2018), informed the development of this survey. The interview protocols themselves and their analyses were grounded in current literature on learning strategies broadly (e.g., Bransford et al., 2000), the heavy focus on solving problems that is common within concept-heavy engineering courses (e.g., Jonassen, 2014), and existing instruments for measuring learning strategies such as the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich et al., 1993) and the Learning and Study Strategies Inventory (LASSI) (Weinstein et al., 2002). This open-ended approach is important because of the recognized disconnected between the types of classroom settings in which existing instruments were constructed, college classrooms broadly, and concept-heavy engineering classrooms as noted within our work but also that of others (e.g., (Lutz et al., 2018).

2. Perspectives from Literature

Conceptual understanding is important among engineering students as it is a crucial building block for problem solving (Rittle-Johnson et al., 2001) - a skill critical to engineers in the 21st century - and helps students build expertise (Bransford et al., 2000). Developing effective learning strategies is, in turn, key to ensuring that students are able to achieve conceptual understanding. In order to help students, there is a need to understand both the learning strategies that they are currently using and what they should ideally be doing. Recent research that does exist on engineering students' learning strategies tends to focus in the cognitive factors (e.g., (McCord & Matusovich, 2019), Litzinger et al., 2010); or tends to look at perceptions of an beliefs about problems solving (e.g., Kirn & Benson, 2018; McNeill et al., 2016). However, neither approach has yet yielded an instrument that faculty can use to measure student learning in a practical, user-friendly way which is the goal of our research.

2.1 Learning Strategies Employed in Engineering Problem Solving Courses

Within engineering education, researchers have studied learning strategies used by students particularly with regard to problem-solving. From such research, we know that students engage in some but not all of the appropriate strategies needed for successful learning. For example, Litzinger et al showed similarities and differences in how weak and strong problem-solvers where both tended to rely on memory and stronger problem-solvers used more self-explanation. We also know that context can influence student motivations and perceptions of problem-solving (Kirn & Benson, 2018; McNeil et al, 2016). All of these cited works have noted methodological challenges in measuring learning strategies, and all have noted that they have only started parts of the ways students consider problems and how they go about solving them. Clearly more work is needed.

2.2 Existing tools to measure learning strategies

There are existing tools meant to measure learning strategies, such as the LASSI (Weinstein et al., 2002) and the MSLQ (Pintrich et al., 1993). Although work in the field has led to survey development specific to engineering education, such as Pitterson et al. (2016) and Lutz et al. (2018) who developed an instrument to measure students' cognitive engagement focusing on engineering learning environments, these instruments' focus on cognitivist learning approaches indicate an inability to completely measure students' learning strategies in problem solving-centric engineering courses. Thus, information gathered from these instruments, while valuable, may not present a complete picture of how students engage in the learning process of courses that heavily engage in problem solving, information that is crucial towards helping students develop effective learning strategies that promote conceptual understanding.

For example, the MSLQ (Pintrich et al., 1993) and LASSI (Weinstein et al., 2002) consider course readings as a primary resource and operate within the context that class discussions are preceded by course readings (Pintrich et al., 1993; Weinstein et al., 2002). In the context of problem solving-centric engineering courses, however, course readings are typically used as references to working problems introduced in class (Lee et al., 2013). This indicates certain student learning behaviors and strategies that MSLQ (Pintrich et al., 1993) and LASSI (Pintrich et al., 1993) are unable to capture.

In this study, we used the behaviorist and cognitivist approaches identified by (Morelock et al., under review) to develop an instrument that measures the entire range of learning strategies employed by students in engineering science courses.

3. Methodology

The development of this survey represents a culmination of work on two larger projects (Morelock et al., under review). The research team wanted to study the strategies employed by engineering students and initially used a survey based on existing instruments (such as the MSLQ and LASSI). However, these surveys were found to be inadequate (Morelock et al., under review) which led to a round of exploratory interviews for a deeper dive on learning strategies employed by engineering students that drew on a national sample of participants. These interviews yielded insights into a breadth of strategies used by students but a lack of detail in how such strategies were used. A second round of interviews was then conducted that drew on findings from the first but explored strategy use in more detail and specifically at two case sites- one a large research university and one a small teaching-focused school. The 21 interviews from the second round, yielded over 200 strategies that were then grouped and classified to develop initial survey questions for the ESLS instrument described in this paper. This section details the steps in survey development beginning from after the second round of interviews to pilot testing of the developed instrument, and subsequent psychometric testing for validity and reliability.

3.1 Survey Development

The ESLS instrument was developed in 7 steps following best practice recommendations by Gall, Gall and Borg (2007) as cited in Lee et al. (2014). These 7 steps were distributed over the three phases of this research study. Figure 1 below summarizes these phases and the detail steps.

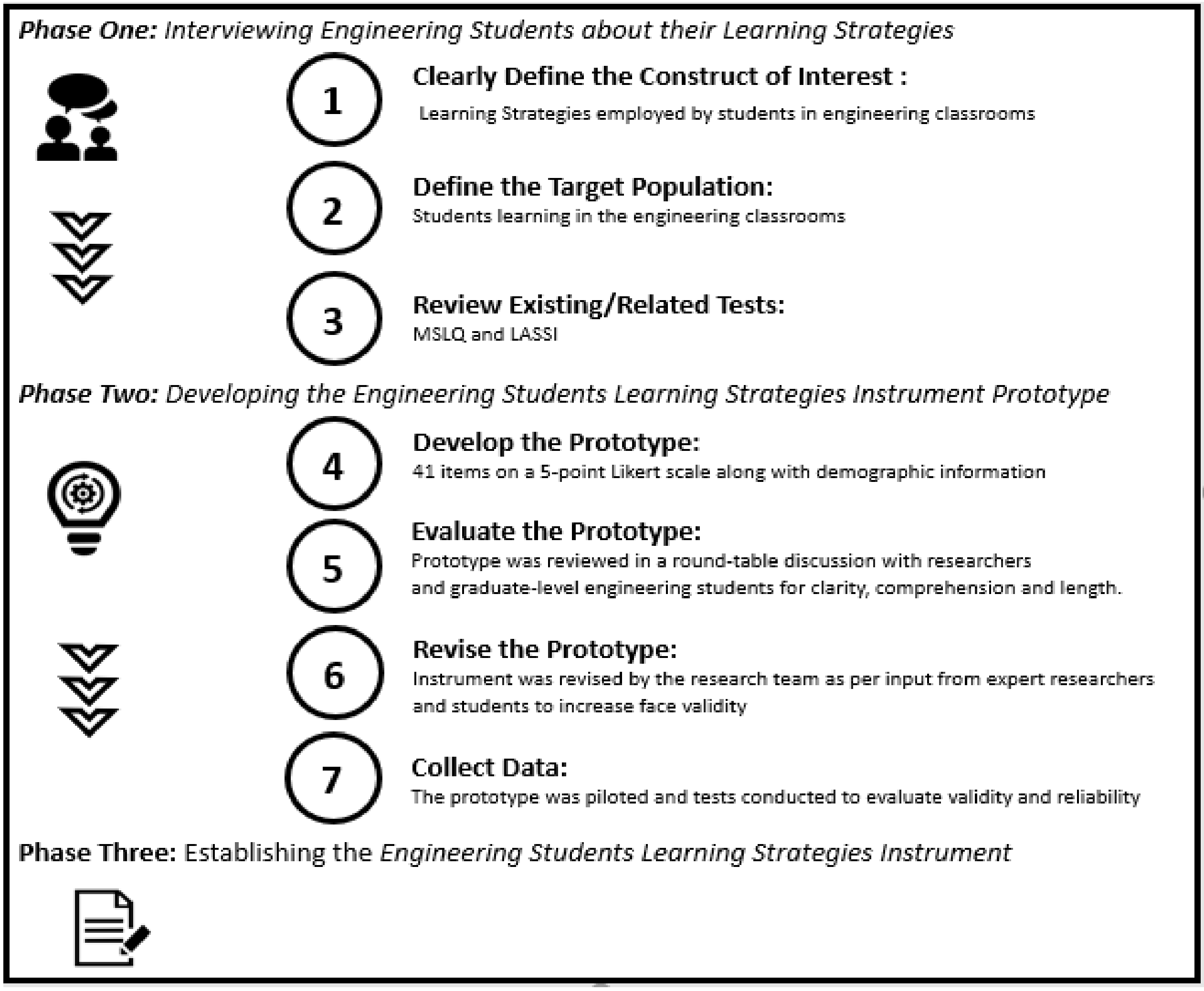

Figure 1: Three Phases of Instrument Development

In the first phase, information about how engineering students talk about the learning strategies they use was collected through hour-long interviews with undergraduate engineering students (Morelock et al., under review). Analyzing the results of these interviews suggested that engineering students had unique learning strategies that were not adequately represented in the strategies covered by other instruments such as the MSLQ (Pintrich et al., 1993) and LASSI (Weinstein et al., 2002). In phase two, we started work on developing a learning strategies instrument prototype specifically for engineering students. A team of four engineering education researchers analyzed all the transcripts from the one-on-one interviews conducted in phase 1, which were then used to formulate statements related to engineering students' learning strategies. These statements were thus grounded in the lexicon of engineering students who had used them to describe learning strategies that they regularly employed. The draft prototype was reviewed by the research team and presented for critique to a research group comprising graduate student researchers and faculty. The research group reviewed the prototype for length, estimated time for completion, language clarity and comprehension. The recommendations from the review were incorporated in the revised version of the ESLS survey. A 41-item pilot-survey was administered to engineering students after each statement had been vetted and checked for face and content validity. Finally, in phase three of survey development the results of the responses to the pilot survey from over a hundred respondents each of whom consented use of their responses for research and development, were used to further establish the ESLS instrument's validity and reliability.

3.2 Research site and participants

We administered the pilot survey at a large research-intensive institution in the United States. The sampling frame consisted of students enrolled in the following concept-heavy engineering courses: Statics, Dynamics, Mechanics of Deformable Bodies, Introduction to Thermal Fluids, Thermodynamics, Heat and Mass Transfer, Fluid Mechanics, System Dynamics, Introduction to Computer Organization, Software Design & Data Structures, and Electric Circuit Analysis during two summer terms and the fall semester in 2017 (Streveler et al., 2008). We sent invitations through the instructors of these courses to an aggregate population of 3,160 students, who were pursuing the following engineering majors: Civil Engineering, Chemical Engineering, Computer Science, Electrical & Computer Engineering, and Mechanical Engineering. To incentivize participation, students who chose to complete the survey had an opportunity to win one of ten $25 Amazon gift cards which were raffled off at the conclusion of data collection.

3.3 Data collection

Besides the demographic information asked (i.e., Gender, Race) and a question about anticipated grade, the students were presented with 41 statements to understand the learning strategies employed by them. The students were asked to respond to these statements using a 5-level Likert-type scale with the key provided in Table 1. From 1 to 5 they were coded as least to most typical for the student.

Code	Statement	Description
1	Not at all typical of me	does not necessarily mean that the statement would never describe you, but it would be true of you only in *rare instances*.
2	Not very typical of me	means that the statement *generally* would not be true of you
3	Somewhat typical of me	means that the statement would be true of you about half the time
4	Fairly typical of me	means that the statement would generally be true of you.
5	Very much typical of me	does not necessarily mean that the statement would always describe you, but that it would be true of you almost all the time

Table 1: Likert-type scale for instrument

A total of 132 students consented to analysis of their responses for research and development purposes. Of these, 40 identified as Female and 89 as Male, while the others chose Other/Custom Answer as their response. The respondents were predominantly White (67.5%) followed by those who identified as Asian (22%) and belonging to Two or more races (7%), with the lowest representation in the categories Other (2.3%) and African American/Black (0.7%).

3.4 Instrument validity and reliability

The pilot survey was developed by our research team and informed primarily by the students' description of the learning strategies they practiced. These strategies as explained previously, were found to be a mix of *both* behavioral and cognitive ones. The statements were further augmented by the researcher team's knowledge and expertise of metacognition frameworks.

A total of 41 statements were included as items part of the pilot run of the ESLS survey. However, we were unsure how the items on the survey would load together as factors and as such did not have a specific beginning hypothesis which we could test. The term *exploratory* describes this condition of having no assumptions or hypotheses about the number of pre-existing constructs, or how items in the survey may statistically relate to each other. We conducted an Exploratory Factor Analysis (EFA) to determine which factors emerged from the instrument developed. EFA is a commonly used technique to examine variables that may exist in the number of items included in a survey (Lee et al., 2014).

The first step for the EFA was to do a pre-check on the adequacy of sample size. Several statisticians have debated on sample size adequacy, with Gorsuch (1997) and Kline, 1994) suggesting 100 subjects, while others like (Cattell, 1978) recommend 3-6 subjects per variable on the survey. In the pilot version of the survey, we had 41 statements and a total of 132 responses. Thus, on average, we met the recommendation of sampling at least 100 subjects, and maintain a sample size to variables ratio greater than 3.

We then used a correlation analysis to remove items which had low correlations (Pearson's correlation coefficient < 0.4) with greater than 80% of the other items. Next, to statistically establish the adequacy of the sample size, we proceeded with Bartlett's test and the Kaiser-Meyer-Olkin (KMO) Measure of Sampling adequacy (results of analysis in Appendix B). The Bartlett's Test of Sphericity establishes whether or not there is scope to find statistically significant factors from the dataset. The KMO measure of sampling adequacy statistically determines if there is adequate data, with scores greater than 0.5 and tending to 1.0 being adequate. For our survey data, the Bartlett Test revealed there to be statistically significant factors. Additionally, the KMO measure for our survey scores was 0.699.

Once the sampling adequacy was established, we proceeded to the next step of factoring the items on the survey. Similar to the rationale provided by Lee et al., (2014) we chose a Principal Axis Factoring since our data was non-normal which necessitated exclusion of use of probabilistic factoring methods such as the Maximum Likelihood Estimation. We also chose an oblimin rotation since we anticipated statistical correlation among the survey items, given that the constructs related to learning strategies would be related to each other. Initial scree plot (Appendix A) revealed the possibility of 6 factors for our analysis.

Reduction in the number of items from 41 to 20 was achieved in one of three ways: (a) through correlation analysis by deleting items that did not correlate with any of the other items (i.e., less than 0.4 Pearson's coefficient for correlation with 80% or more items), (b) by deleting items that loaded onto multiple factors, and (c) deleting items that loaded onto a factor with a weak factor loading (less than 0.5). This convention is in keeping with statisticians (e.g., Thompson (2004), Costello and Osborne (2005) and Pallant (2010)) who recommend that loadings less than 0.5 need not be considered, nor items that load onto multiple factors so as to ensure sparse loading and a clean structure. Finally, once the factors were identified through the exploratory factor analysis, we wanted to compare across groups of students' responses to see if the differences in certain factors versus others were statistically significant. We used an independent samples t-test and an Anova for these comparisons across groups. Results of the analysis are elaborated in the next section.

4. Results and Discussions

The aim of this exploratory research study is to develop and gather validity evidence for a survey instrument that can be used to measure engineering students' learning strategies. As elaborated previously, development of such an instrument is important because: (a) it will allow educators to facilitate enhanced conceptual understanding among students in the engineering classrooms and (b) existing surveys to measure learning strategies do not cater to the *wide* range of strategies that students in the engineering classrooms may be employing.

To answer the RQs driving this study we used an Exploratory Factor Analysis to reveal 6 factors which emerged from a pilot administration of the ESLS survey to 132 engineering students who consented that their responses be used for research and dissemination purpose. We then compared the aggregate scores for the factors, across gender, race/ethnicity and self-reported grade expected.

4.1 RQ1: What factors emerge from an Exploratory Factor Analysis used to develop the ESLS survey?

At the end of our factor analysis we were left with 17 statements which loaded onto 6 factors. These factors explained approximately 64% of the total variability in the data, and all had eigen-values greater than 1 (Appendix A). The six factors revealed through EFA were:(1) Working the Problems, (2) Associations with the Real World, (3) Seeking Help to Improve Conceptual Understanding, (4) Planning, (5) Utilizing Resources, and (6) Interactions. These six factors are triangulated by some of the main themes that emerged from a deeper qualitative analysis (Morelock, et al. (under review)) of students describing their learning strategies. The Working the Problems factor – primarily one targeting behavioristic strategies, may be the most important factor of this instrument, and one which sets it apart from other instruments like the MSLQ (Pintrich et al., 1993) and LASSI (Pintrich et al., 1993). As elaborated in previous sections, students in engineering classrooms described how they employ a wide range of learning strategies which may include certain behaviorist ones such as working and re-working similar problems to increase conceptual understanding (Morelock, et al., (under review).

4.2 RQ2: What are the validity and reliability measures of the ESLS instrument based on the pilot implementation of the survey?

Validity and reliability are critical to establishing a questionnaire as an instrument of high quality. While validity is the 'extent to which an instrument measures what it claims to measure, rather than something else', reliability is the extent to which an instrument can be expected to give the same measured outcome when measurements are repeated' (Taber, 2013). The instrument development described in this paper followed several best practices (e.g., Bolarinwa (2015), Taber (2018) an Netemeyer,et al. (2003)) to establish both validity and reliability. Face and content validity of this instrument were ensured by having experts review the items for readability, clarity and comprehension. Exploratory Factor Analysis is a statistical method that is useful as it: a)increases the reliability of a scale by identifying inappropriate items that can be removed Yu and Richardson (2015), and b) identifies the dimensionality of constructs when this information is limited (Netemeyer, Beaden and Sharma, 2003). The previous section transparently describes the process followed for extracting factors using EFA. Following the EFA, we additionally wanted to ensure that there was internal consistency among the items themselves. Cronbach's alpha is a measure of internal consistency reliability for an instrument (Tavakol and Dennick, 2011). Several authors (e.g., Bolarinwa (2015), Taber (2017)) caution against blindly stating the Cronbach’s alpha value, reminding researchers that while higher values (>0.7) are desired, values that are too high may be equally indicative of problems with the instrument as lower values (<0.5). We found all six factors to individually have values greater than 0.6 for Cronbach’s alpha. Factors 5 and 6 have values for Cronbach’s alpha at less than 0.65, and while these values may have just about made the cut-off, the lower number may be a result of shorter length of the sub-scale (Tavakol and Dennick, 2011). Overall, the survey has a high value of Cronbach’s alpha which indicates a reliable and stable instrument.

4.3 RQ3: For a pilot implementation of the survey instrument, how do students compare on learning strategy use by gender and grade expectancy?

We used an independent sample t-test to compare the scores for the six factors, across groups for gender (i.e., male versus female) and race/ethnicity (i.e, white versus others - grouped due to lack of adequate sample size per each race/ethnicity category). No statistically significant differences across these two groups were observed at a significance level of alpha = 0.05. Thus, we failed to reject the null hypothesis that the means across the groups are equal. Table 2 tabulates the means and standard deviations for the responses to the six factors across the groups for gender and race/ethnicity.

Factor	Gender	N	Mean	Std. Deviation
Working the Problems	Male	89	4.35	0.54
	Female	40	4.33	0.57
Associations with Real World	Male	89	3.66	0.89
	Female	40	3.47	0.96
Improving Conceptual Understanding	Male	89	2.60	1.06
	Female	40	2.36	0.83
Planning	Male	89	3.30	0.88
	Female	40	3.15	1.03
Utilizing Resources	Male	89	3.27	0.93
	Female	40	3.30	0.94
Interaction	Male	89	4.03	0.69
	Female	40	4.00	0.92

Factor	Race/Ethnicity	N	Mean	Std. Deviation
Working the Problems	White	89	4.37	0.56
	Other	43	4.23	0.58
Associations with Real World	White	89	3.56	0.94
	Other	43	3.68	0.86
Improving Conceptual Understanding	White	89	2.48	1.00
	Other	43	2.59	0.99
Planning	White	89	3.25	0.93
	Other	43	3.25	0.90
Utilizing Resources	White	89	3.32	1.00
	Other	43	3.19	0.75
Interaction	White	89	3.97	0.80
	Other	43	4.06	0.70

Table 2: Comparison of scores on the six factors across (a) gender and (b) race/ethnicity groups.

However, when we used ANOVA to compare whether there were differences in the responses based on whether or not the student anticipated a high(A), medium(B) or low(C and lower) grade in the course, and their scores for the six factors, we found there to be statistical significant differences for factors related to (1) Working The Problems, (3) Seeking Help to Improve Conceptual Understanding, and (4) Planning. No differences in means were observed across the anticipated grade levels for factors related to (2) Associations with the Real World (5) Utilizing Resources, and (6) Interactions. This indicates that there is a possibility that students who reported anticipation of higher grades have differences in learning strategies. Specifically, these students who reported anticipating higher grades rated themselves higher at statements indicating working through the problems, seeking help to improve their conceptual understanding, and planning for learning. This result draws attention to the wide range of learning strategies – both behaviorist and cognitivist, needed to attain enhanced conceptual understanding in engineering courses. While existing surveys are unable to capture this wide range of strategies, the ESLS instrument described in this paper will be able to help instructors learn more about how students in their classrooms are strategizing their learning.

4.4 Summary

This paper addresses the gap in literature presented by existing surveys which do not adequately cater to engineering contexts. Engineering students differ from other majors since they reported employing a wide range of strategies ranging from cognitivist to behaviorist in order to gain a deeper conceptual understanding. There are several critiques of employing behaviorist learning strategies. However, since it was observed that engineering students may indeed be using them to gain conceptual understanding, measuring these engineering student specific learning strategies can be very helpful for engineering educators. This research study presented an overview of the steps in the development of the ESLS instrument (Appendix B) intended to measure engineering students' learning strategies. It is hoped that this work finds its intended value among educators to help them understand and measure how students in the engineering classrooms are employing learning strategies.

4.5 Limitations and Future Work

This study has several limitations. The first being that of inadequate racial representation for the pilot implementation. For example, we had only one respondent out of 132 who self-identified as African American/Black. This poses a threat of marginalizing voices of already under-represented minority groups. The instrument will need to be administered at multiple engineering schools for a wider demographic to gain insights that will truly be generalizable and inclusive by being representative of measuring learning strategies of different demographic groups of engineering students. Second limitation is that the learning strategies were considered in isolation, hence nuances in situational factors that may be motivating adoption of certain strategy have not been explored. The third limitation is that of the self-reported grade expectancy which may be inflated or may vary depending on the time in the semester that the survey was administered. Future work related to this project include gaining deeper understanding of critical nuances that have not yet been studied such as understanding the intention behind the learning strategy, i.e., pattern-matching in practicing problems vs striving for conceptual understanding.

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Appendix A: Exploratory Factor Analysis

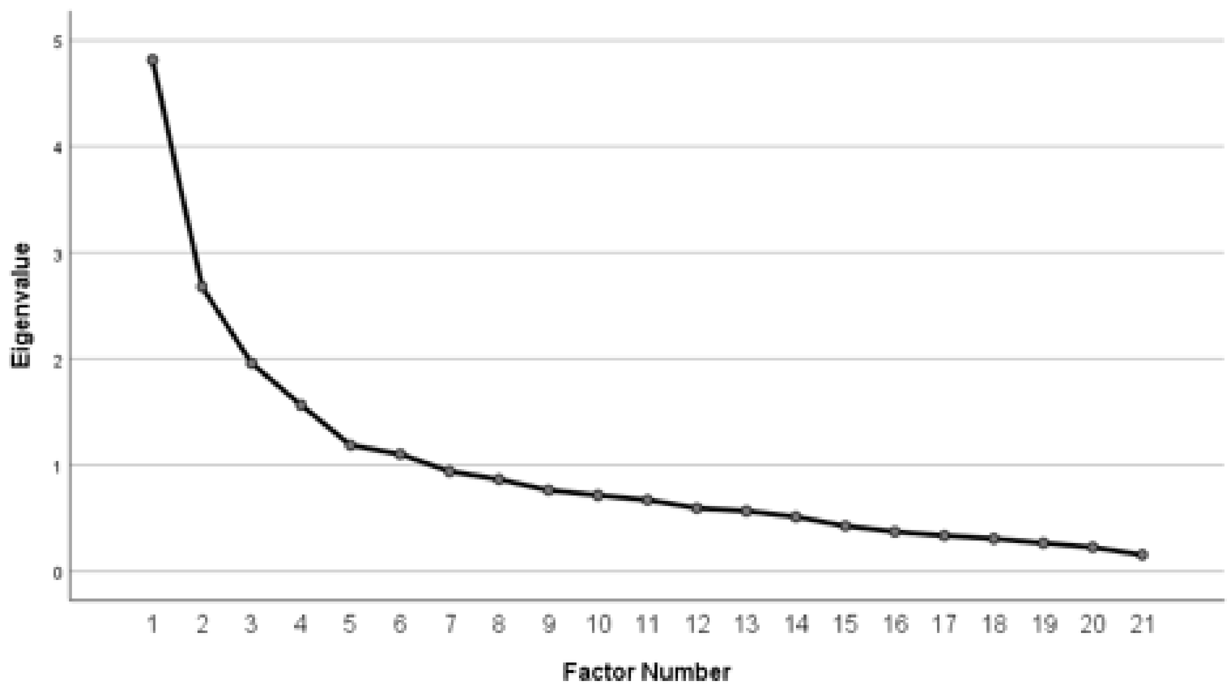
KMO

Kaiser-Meyer Olkin Measure of Sampling Adequacy	0.70

Bartlett's Test of Sphericity

Approx. Chi Square	969.84
df	210
Sig.	.000

Scree Plot



Factor Loadings						
Item	**Factor 1**	**Factor 2**	**Factor 3**	**Factor 4**	**Factor 5**	**Factor 6**
Working Out Problems (alpha = 0.78)						
1. When I am studying a topic, working out the problems helps me understand the important concepts related to the topic.	0.77					
7. Solving problems helps me test myself to see what I understand.	0.68					
4. Practicing problems before a test help me prepare for the test.	0.66					
26. Working a problem helps me understand details of a concept.	0.56					
12. I know I understand a concept if I can work out a problem from scratch without looking at anything else.	0.42					
Associations with the Real World (alpha = 0.78)						
38. When learning I attempt to make connections to aspects of my life.		0.90				
39. When learning I attempt to make connections to the “real world”.		0.89				
40. When learning I attempt to make connections to related materials or prior knowledge.		0.50				
Improving Conceptual Understanding (alpha = 0.70)						
31. I regularly seek help from the instructor in class to help understand the concepts taught.			0.48			
15. I regularly seek help of the instructor during office hours to help understand the concepts taught.			0.47			
Planning (alpha =0.65)						
36. I seek information about (and prepare for) future course events.				0.74		
34. I create and maintain a study schedule.				0.56		
35. When choosing a course, I make my decision by selecting reputable professors.				0.53		
Utilizing Resources (alpha =0.62)						
23. I use the textbook to get a deeper understanding of concepts I have learned in class.					-0.68	
24. Solving problems from the textbook which are similar to those solved in class, help me understand concepts better.					-0.59	
Interactions (alpha =0.63)						
13. Talking about concepts or equations with a classmate or a friend help me understand the topic better.						0.79
11. Explaining a concept to another person helps me test myself if I know the concept well.						0.51

Appendix B: Engineering Students' Learning Strategies Instrument

Part A: Learning Strategies Employed

1. **Working Out Problems**
    a. When I am studying a topic, working out the problems helps me understand the important concepts related to the topic.
    b. Solving problems helps me test myself to see what I understand.
    c. Practicing problems before a test helps me prepare for the test.
    d. Working a problem helps me understand details of a concept.
    e. I know I understand a concept if I can work out a problem from scratch without looking at anything else.
2. **Associations with the Real World**
    a. When learning I attempt to make connections to aspects of my life.
    b. When learning I attempt to make connections to the "real world."
    c. When learning I attempt to make connections to related material or prior knowledge.
3. **Improving Conceptual Understanding**
    a. I regularly seek help from the instructor in class to help understand the concepts taught.
    b. I regularly seek the help of the instructor during office hours to help understand the concepts taught.
4. **Planning**
    a. I seek information about (and prepare for) future course events.
    b. I create and maintain a study schedule.
    c. When choosing a course, I make my decision by selecting reputable professors.
5. **Utilizing Resources**
    a. I use the textbook to get a deeper understanding of concepts I have learned in class.
    b. Solving problems from the textbook which are similar to those solved in class, help me understand concepts better.
6. **Interactions**
    a. Talking about concepts or equations with a classmate or a friend helps me understand the topic better.
    b. Explaining a concept to another person helps me test myself if I know the concept well.

Part B: Demographic Information

1. **Indicate your preferred gender:**
    a. Male
    b. Female
    c. Custom
    d. Prefer not to answer

2. **Indicate your race/ethnicity:**
    a. White
    b. African-American
    c. Hispanic, Latino or Spanish origin
    d. Asian-Pacific Islander
    e. American Indian or Alaska Native
    f. Other
    g. Prefer not to answer

3. **List the course you are enrolled in**
4. **List your anticipated grade in this course**