ASEE 2022 ANNUAL CONFERENCE
Excellence Through Diversity
MINNEAPOLIS, MINNESOTA, JUNE 26TH-29TH, 2022 ASEE

Paper ID #38442

A Study of Variations in Motivation Related to Computational Modeling in First-year Engineering Students

Alison K Polasik (Associate Professor of Engineering)

Dr. Alison Polasik joined the Campbell School of Engineering in August 2018. Previously, she was an assistant professor of practice at Ohio State University's Materials Science & Engineering Department. In this position, she designed curriculum for and implemented a number of active learning strategies in large courses on materials engineering, processing, and selection. She was part of the first cohort of instructors to design and implement a new required 3-semester computational lab sequence in the MSE curriculum at OSU in 2013. From 2014 – 2017, she developed and led a program providing materials-science focused professional development to high school science teachers that was funded by the Ohio Department of Education. Much of her work in these areas has been presented at ASEE National Conferences and published in the peer-reviewed proceedings. Polasik has also presented her work at the North American Materials Education Symposium (2014 – 2017) and Materials Science and Technology (2015 and 2017) conferences. At Campbell, Dr. Polasik teaches courses in materials science, statics and mechanical behavior and thermodynamics. She spearheaded the initial development of the Energy Lab in the Engineering Annex. In 2018, Dr. Polasik became an ABET program evaluator for materials engineering programs and joined the TMS Accreditation Committee. She is a member of TMS, ASM, ASEE, and SWE. Dr. Polasik received her bachelor's degree in Materials Science and Engineering from Arizona State University in 2002, followed by MS and PhD degrees in materials science and engineering from Ohio State University in 2015 and 2014, respectively. Her doctoral research focused on understanding microstructural effects on fatigue in titanium alloys, and was funded by the US Air Force and the NSF Graduate Research Fellowship Program.

Work in Progress: A Study of Variations in Motivation Related to Computational Modeling in First-year Engineering Students

Abstract

It is increasingly critical that engineering students develop proficiency with computational modeling tools, and many curricula include some introduction to such tools during their first year. It is clear that student interest and skill can vary significantly based on prior experiences, but it is less clear whether student motivation specifically related to computational modeling varies as well. This study hypothesizes that the self-efficacy and utility value related to computational methods varies significantly in students' first year and that engineering students pursuing some disciplines (such as computer, software, and electrical engineering) will begin with a higher initial self-efficacy than others (such as chemical, materials, and biomedical engineering). A survey was used to investigate the utility value and efficacy of approximately 700 undergraduate students in their first year of engineering studies at both a large public institution and a small private institution. Data is analyzed for variations in baseline motivation based on the students' intended major. This analysis also considers known confounding factors such as gender, race, and prior experience with programming. The results of this survey will help determine whether efficacy and interest related to computational methods vary based on intended major early in an engineering student's academic career. Ultimately, it is hoped that this study can inform future studies related to what types of interventions might benefit students.

Introduction

Learning to use computational tools is often difficult for engineering students. When these computational tools require classic "programming" aspects such as a text-based interface and the use of logic and syntax, assigned tasks can become particularly demanding and frustrating. Even so, the skills associated with using computers to automate, simulate, and model different engineering problems is increasingly critical for students and practicing engineers. For the purposes of this study, "computational tools" are defined as software packages that require specialized training but are at the same time more accessible than those used by programmers and software developers. A deeper understanding of the specific differences in how students [1]think about and motivate themselves to learn computational tools is valuable to improving our teaching in this critical area.

Previous work by the author with 2nd, 3rd, and 4th year students identified a great distribution in student's utility value and interest in using MATLAB within their major-specific courses [2], and that these distributions were unaffected by student's course grades or achievement of learning objectives. Casual conversations with students who perceived MATLAB as not being useful indicated they would not pursue using computational tools in their career. The hypothesis is that engineering students pursuing some majors may develop the belief that using advanced computational tools is not necessary or helpful, and that this could affect (1) whether they choose to learn to use computational tools while at the university and (2) the extent to which they pursue developing these skills as a practicing engineer. These skills have been identified as a critical component of engineering education, and thus students who determine not to acquire or use such skills would be at a handicap in their career.

This study explores several key motivational factors associated with using computational tools, specifically: utility value, self-efficacy, and self-regulation. Students' scores in these areas are examined using a survey that is given to engineering students taking an introductory engineering course at a large midwestern university. The questions contextualize the broader aspects of computational tools by focusing on MATLAB. MATLAB is a good choice for this study because it combines many of the aspects of computational tools that are most troublesome for novices such as text-based interface, developing automated "scripts", and using correct syntax. It is also a tool that most students will not have seen before (MATLAB is rarely used in secondary schools or degree programs outside of engineering), so that most of the students in the subject pool begin at roughly the same level in this first class.

This work continues a pilot study conducted in Fall 2020. In that analysis, the initial survey looked at motivational factors and analyzed the data by divided into two groups: those who intended to major in computer systems engineering (CSE) or electrical Engineering (EE) – group 1 – and those who intended to major in either biomedical engineering (BME) or materials science and engineering (MSE). These preliminary results indicated that, of the three motivational factors (utility value, self-efficacy, and self-regulation), none showed a significant difference between the two groups and only self-efficacy has a p-value approaching 0.05 on a standard T-test [1]. These results, along with an exploratory factor analysis, helped revise the survey for administration with a similar group of students in Fall 2021.

Methods

A survey was administered to a pool of approximately 700 first-year engineering students at a large midwestern state university. Several questions were modeled after a self-efficacy scale for computer programming primed to the C++ programming language developed by Ramalingam and Wiedenbeck in 1998 [3], with modifications made to the wording to account for the MATLAB curriculum in the course. This survey is used to assess students' motivation for learning to use computational tools like MATLAB in 4 specific areas: utility value, enjoyment, self-efficacy, and self-regulation. Students were also asked to rate their skill in MATLAB tasks relative to peers. Participants were also asked to report on known confounding factors such as prior experiences with programming, gender, race, ethnicity, and first-generation status. The goal of this study is to determine whether there are correlations in students' motivational factors and their intended major.

At this university, all students start as "pre-majors" and apply to a specific major program in their 2nd or 3rd semester. Students can choose from 15 different engineering majors but are not guaranteed admission to their first choice of major. All students were taking the first in a sequence of two introductory courses, and the course curriculum had a large MATLAB component. Surveys were administered during the last week of November and first week of December, after students had finished the MATLAB unit and while they were beginning to work on a significant team project using MATLAB. 80 students responded to the survey request. The survey asked students to identify their 1st, 2nd, and 3rd choice for engineering major. Based on the answers to these questions, students were broken into one of 4 categories. Group A1 students had CSE or EE as a first choice. Group B1 students had MSE or BME as a first choice. Group C1 students identified Chemical Engineering (ChemE) as their first choice. Group D1 students identified Mechanical Engineering (ME) or Aerospace Engineering (AE) as their first choice. Group E1 identified another engineering major as their first choice. Similar nomenclature was used to create group A2, B2, C2, D2, and E2 for students who chose each of the major groups for their second choice. It should be noted that due to the nature of the division there is some overlap between groups. For example, a student could belong to both A1 and C2 based on their identified 1st and 2nd choices. Demographics and population in each group are presented in Table 1. The survey asked students a series of questions designed to gauge their overall motivation for learning to use computational tools. A Likert scale was used for each series of questions, with a higher number indicating a greater degree of motivation in that area. Details on the questions and Likert scales are presented in the Appendix.

Table 1: Participants were divided into groups based on their 1st and second choice major. Key demographic information for each group is presented.

1st Choice Major	Number of Students	Male	Female	Non-Binary	First Generation	Some Experience with Programming
A1 - Comp	28	19	8	1	6 (21%)	15 (54%)
B1 - Mat/Bio	12	7	5	0	2 (17%)	5 (42%)
C1 - Chem	4	2	2	0	1 (25%)	3 (75%)
D1 - Mech	23	19	3	1	2 (9%)	17 (74%)
E1 - Other	13	6	5	2	3 (23%)	10 (77%)
2nd Choice Major	Number of Students	Male	Female	Non-Binary	First Generation	Some Experience with Programming
A2 - Comp	20	14	5	1	4 (20%)	10 (50%)
B2 - Mat/Bio	5	4	1	0	2 (40%)	5 (100%)
C2 - Chem	6	2	4	0	1 (17%)	3 (50%)
D2 - Mech	32	21	10	1	6 (19%)	20 (63%)
E2 - Other	17	12	3	2	1 (6%)	12 (71%)

Results

Average values for each student were calculated in each motivational category (U, SE, SR). Average values were also taken for interest (I) and a self-assessment of relative skill related to computational tools, though each of these included only two questions. This provided a semi-continuous range of values for each motivational category with which to use ANOVA to determine whether there is a statistically significant difference in the means of the values for each motivational category between each of the student groupings (A1-D1 and A2-D2). Overall averages of these averages are shown for each student grouping in Table 2.

A one-way ANOVA was used to determine whether any of the student groups demonstrated a series of means that was significantly different from the others in each motivational category. These tests were done based on students' first choice major picks and second choice picks. Only two motivational factors demonstrated sufficient evidence at a 95% confidence interval that at least one of the means was different from the other – 1st choice groups, for self-efficacy and interest.

Table 2: Demographics of each group based on 1st and 2nd choice of major.

1st choice						
	Count	Utility Value	Enjoyment	Self Efficacy	Self Regulation	Skill
A1 – Comp	28	4.63	4.54	4.93	4.50	5.24
B1 – Mat/Bio	12	5.17	3.67	3.92	4.08	4.39
C1 – Chem	4	5.38	4.63	4.25	4.00	4.42
D1 – Mech	23	4.89	3.64	4.15	3.95	4.56
E1 – Other	13	5.13	3.58	3.83	4.15	4.72
2nd choice						
	Count	Utility Value	Enjoyment	Self Efficacy	Self Regulation	Skill
A2 – Comp	20	4.78	4.63	4.65	4.40	5.08
B2 – Mat/Bio	5	5.25	3.50	3.24	3.20	4.27
C2 – Chem	6	4.88	3.50	4.15	4.50	4.17
D2 – Mech	32	4.98	3.94	4.24	4.25	4.61
E2 – Other	17	4.86	3.71	4.54	4.12	5.10

A Tukey test was then used to determine which major combinations demonstrated a significant difference from the others. For these tests, each of 10 combinations of two major groupings was tested relative to the other. The results of this test are shown in Table 3. Based on these calculations, there is a statistically significant ($\alpha = 0.05$) difference in the average ratings for self-efficacy for students in group A1 as compared to A2, A4, and A5.

Table 3: Results of ANOVA and Tukey tests

Self-Efficacy – based on 1st Choice Majors

<u>ANOVA results:</u> There is sufficient evidence at 95% confidence that at least one of the means is different from the other.

TUKEY – Multiple Comparison of Means

group1	group2	meandiff	p-adj	lower	upper	reject
Chem	Comp	0.6751	0.6677	-0.7733	2.1235	FALSE
Chem	MatBio	-0.3252	0.9	-1.8897	1.2392	FALSE
Chem	Mech	-0.1147	0.9	-1.5827	1.3532	FALSE
Chem	Other	-0.4209	0.9	-1.9703	1.1284	FALSE
Comp	MatBio	-1.0003	0.03	-1.9353	-0.0654	TRUE
Comp	Mech	-0.7898	0.0387	-1.5524	-0.0273	TRUE
Comp	Other	-1.096	0.0102	-2.0055	-0.1866	TRUE
MatBio	Mech	0.2105	0.9	-0.7545	1.1754	FALSE
MatBio	Other	-0.0957	0.9	-1.1805	0.989	FALSE
Mech	Other	-0.3062	0.8874	-1.2464	0.634	FALSE

Discussion and Conclusions

Participation in the survey was much lower than expected, which could be due to various affects that can be tracked back to students' online fatigue and effective communication resulting from the COVID-19 pandemic. Additionally, these results are not controlled for prior exposure to computational tools, though that data was collected in the survey. Ultimately, the sample size was much lower than hope for, and there may be relationships between motivational factors and students' major that the survey was not able to detect.

With these caveats, it is interesting that the self-efficacy of students whose first choice for engineering major is either CSE or EE (A1) is higher than those in the groups for any other major (B1, D1, and E1). The exception to this is when comparing them to students' whose first choice is chemical engineering (C1). This relationship does not hold when comparing self-efficacy scores for students based on their second choice of major. While it would make sense for students' prior exposure to programming to confound the self-efficacy, the survey results show that the percentage of students who have prior coding experience is not higher for group A1.

Based on these results, interviews being conducted in the Spring of 2022 will seek to validate the survey results and determine the strength of any link between students' self-efficacy and their choice of major.

Acknowledgements

The author thanks Dr. Rachel Kajfez, Dr. Alejandra Magana, Dr. Julie Martin, and Dr. Raeal Moore for their mentorship and advising on this project.

This material is based upon work supported by the National Science Foundation under Grant No. 2025093 and the PFE: RIEF program. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author and do not necessarily reflect the views of the National Science Foundation.

References

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Appendix

	Motivation Factors – Survey Categories and Questions		
	Question Stems	***1***	***6***
Utility Value	**How much do you agree with the following statement?** *Note: a 7th option, "I have no opinion", was also offered. These responses were not included in the averages* 1 - In order to successfully complete my engeineering degree, I will need to develop the skills to use computational programs such as MATLAB. 2 - In order to successfully complete my engineering degree, it is important hat I learn how to write/code programs similar to those used in MATLAB. 3 - To be a successful engineer, I will need to develop the skill to use copmutational programs (such as MATLAB) to solve problems. 4 - Developing computational skills will offer me a wider range of employment options	Strongly Disagree	Strongly Agree
Interest	5 – I ejoyed learning to work with MATLAB 6 – I would like to have a career that requires me to use programming and computational skills frequently		
Self Efficacy	**How confident are you that you could do the following tasks?** 1 – Write Syntactically correct lines in MATLAB (without errors in spelling or order of commands). 2 – Understand the structure of a MATLAB script if appropriate comments were included by the writer (comments are the notes preceded by % that give information about the next section of code). 3 – Understand the structure of a MATLAB script if it were NOT commented. 4 – Write logically correct sections of a MATLAB script (where all of th commands are in the correct order to do the task). 5 – Write a small MATLAB script (5 – 25 lines) to solve a simple problem that is familiar to me. 6 –Write a medium sized MATLAB sript (40 – 100 lines) to solve a problem that is familiar to me. 7 – Write a long MATLAB script (more than 120 lines) with nested commands (for example, calculations within a loop) to solve a problem that is familiar to me. 8 – Make use of a pre-written MATLAB script, making minor modifications as necessary. 9 – Debug (correct all the errors) as I write my program.	Not at all Confident	Extremely Confident

<table>
<tr><td rowspan="2"></td><td colspan="3">Motivation Factors – Survey Categories and Questions</td></tr>
<tr><td>Question Stems</td><td>1</td><td>6</td></tr>
<tr><td>Self-Regulation</td><td>10 – Manage my time efficiently if I had a pressing deadline on a MATLAB project.
11 – Come up with a suitable strategy for a given programming project in a short time.
12 – Find a way to concentrate on my program, even when there were many distractions around me.
13 – Find ways of motivating myself tow ork on a MATLAB assignment, even if the problem area was of no interest to me.</td><td></td><td></td></tr>
<tr><td rowspan="2">Indirect Skill Assessment</td><td rowspan="2">Compared to other first year engineering students, how would you rate your skill at the following tasks?
1 – Writing scripts in MATLAB
2 – MATLAB tasks in ENGR 1181
3 – Overall performance in engineering classes</td><td>1</td><td>7</td></tr>
<tr><td>Far Below Average</td><td>Far Above Average</td></tr>
</table>