Work in Progress: A Study of Variations in Motivation and Efficacy for Computational Modeling in First-year Engineering Students

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***Abstract*— Computational modeling skills are critical for the success of both engineering students and practicing engineers and are increasingly included as part of the undergraduate curriculum. However, students' belief in the utility of these skills and their ability to succeed in learning them can vary significantly. This study hypothesizes that the self-efficacy and motivation of engineering students at the outset of their degree program varies significantly 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 materials science and engineering and biomedical engineering). In this pilot study, a survey was used to investigate the motivational and efficacy factors of approximately 70 undergraduate students in their first year of engineering studies at a large public university. Surveys were implemented after students were introduced to MATLAB in their first-year engineering design course. The data was analyzed for variations in baseline motivation based on the students' intended major. The results of this survey will help determine whether efficacy and interest related to computational modeling are indeed lower for certain engineering disciplines and will inform future studies in this area.**

Keywords—first year curriculum, Materials science and engineering, Self-efficacy, computing skills

I. INTRODUCTION

Programming and the use of computational tools have been integral to the curriculum of electrical, software, and computer engineering disciplines for decades. Other engineering disciplines have more recently added computational competencies to the curriculum. Thus, there is a sense that some engineering degrees – and the careers they lead to – do not require a high degree of computational competency. However, instructors and industrial leaders both increasingly agree that computational skills are necessary for success in all engineering fields. As an example, many materials science and engineering (MSE) programs have included significant computational instruction in their curriculum over the past 10 years[1]. Previous experience by the lead author has indicated that a significant proportion of MSE majors may have lower self-efficacy related to using computational tools, specifically MATLAB. These students often reported a belief that they will not need such skills in their career or are fundamentally less capable because they are "not programmers" [2]. More broadly, studies of students taking programming courses have shown that some students find this topic incredibly difficult [3], [4]. To date, little research has identified barriers to learning computational tools such as programming, modeling, or simulation methods specific to different groups of engineering students based on their specialization or sub-discipline. Students often decide to pursue a specific discipline within the field of engineering based on their interests and perceptions of the careers available to them with a certain major [5], and studies have identified differences in some motivational factors for students in traditional engineering majors when compared to those in more interdisciplinary majors [6] [7]. If some engineering disciplines are perceived as being "less computational", then it is likely that students pursuing these will have different – perhaps lower - motivation for learning to use computational tools.

Three motivational factors that are investigated in this study are self-efficacy, expectancy value, and utility value. Self-efficacy is defined as an individual's judgement of his or her ability to execute a task within a specific domain, and it has been applied as a key part of theoretical frameworks in engineering curricula [4], [8]. Expectancy value is an individual's assessment of whether working on a task is likely to lead to the desired outcomes, and utility value is an individual's assessment of how important the task is [9]. Both are closely linked to self-efficacy. In the context of learning computational skills, these aspects of motivation relate to students' perceptions of whether learning these skills is *possible* and *worthwhile*. Some studies have shown that self-efficacy and expectancy value affect student learning, academic success, and career decisions [10].

Studies have shown that a number of factors affect engineering students' self-efficacy and expectancy-value at the outset of their undergraduate studies, and significant variations in prior experience and motivation can exist between students in different majors [8], [11], [12]. If motivational factors for learning computational modeling are indeed lower for certain populations of students – specifically, students in some engineering disciplines compared to others – then interventions aimed at improving self-efficacy and expectancy value could improve learning without requiring major curricular reforms.

This study ultimately seeks to determine whether meaningful differences exist in motivational factors related to computational modeling for first-year engineering students at the time they are exposed to a new computational tool, MATLAB. Specifically, the study hypothesizes that differences might be observed when comparing students in more traditionally computational majors to those in majors that are considered less computer-focused. This paper presents the results of a preliminary study conducted in January 2021.

II. METHODS

A. Rationale and Sample Population

Students taking first-year engineering courses at a large state university in the midwestern United States.were the target population for this study. This university offers 12 different engineering major programs, and students typically apply to their major program in the second year of studies. Until then, they are "engineering pre-majors" [5]. All engineering pre-majors take the same sequence of two first-year design courses. In the first of these courses, students are introduced to the basics of computational thinking, focused on the use of MATLAB. MATLAB is used extensively for the final semester project, and it is expected that students will have spent significant time learning to use the program and to apply this knowledge on assignments by the end of the semester. Approximately 1,400 students take this course in the fall semester.

This paper describes a pilot study that seeks to test the hypothesis about differences in students in "computational" majors versus those interested in "less computational" majors. In this context, computational means relating to the use of computers. Specifically, this work seeks to look at engineering subdisciplines that are traditionally considered computational – such as electrical engineering (EE) and computer science and engineering (CSE) – and those that are not – specifically, materials science and engineering (MSE), biomedical engineering (BME), and welding engineering (WE). The specific research question for this pilot study is:

> What are the differences in motivational factors related to computational modeling (specifically for using MATLAB) for students intending to pursue EE or CSE degrees as compared to those intending to pursue MSE, WE, or BME degrees?

B. Survey Description

The survey measures three aspects of motivation: utility value, self-efficacy, and self-regulation. The survey also asked students, "If you had to select your top 3 engineering majors to apply to today, which would they be?" The survey was informed by previous work in self-efficacy [13]. 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 [14], with modifications made to the wording to account for the MATLAB curriculum in the course. The coordinator for the course was consulted in this process to ensure that the questions aligned with course content and correctly encompassed the expected range of skill level for task-specific self-efficacy questions. Before being administered, five engineering students who were not part of the sample population were asked to comment on how clear the survey was, to reflect on what they thought each question meant, and to suggest rewording. The survey was also discussed with the senior advisory committee for the project, whose members provided feedback.

The survey contained a number of questions related to aspects of motivation. Each question asked students to report their level of agreement with statements about the value of computational modeling or their confidence that they could perform a task in MATLAB. The individual questions and four categories are shown in Table 1.

CATEGORY A MEASURES UTILITY VALUE, AND THE OVERALL QUESTION STEM ASKED STUDENTS TO RANK EACH STATEMENT WITH RESPECT TO HOW CERTAIN THEY WERE THAT THE STATEMENT APPLIED TO THEM. RESPONSES WERE CONVERTED TO NUMERICAL MEASURES, WITH 1 = "STRONGLY AGREE" AND 6 = "STRONGLY DISAGREE". CATEGORIES B AND C MEASURE DIFFERENT ASPECTS OF SELF-EFFICACY, AND THE QUESTION STEM ASKED STUDENTS TO INDICATE HOW CONFIDENT THEY ARE THAT THEY COULD DO EACH OF THE TASKS. CATEGORY D RELATES TO SELF-REGULATION AND HAS THE SAME QUESTION STEM AS CATEGORIES B AND C. FOR THIS NUMERICAL CONVERSION, 1 = "EXTREMELY CONFIDENT" AND 6 = "NOT AT ALL CONFIDENT". THE STUDENTS WERE ALSO ASKED THREE QUESTIONS TO PROVIDE AN INDIRECT MEASURE OF THEIR SKILLS IN THE FIRST-YEAR ENGINEERING COURSE. THIS IS LISTED AS CATEGORY E AND IS SHOWN IN

Table 3. In this case, 1 = "Far above average" and 7 = "Far below average", with a middle value of 4 = "average". Thus, for each question a lower value represents greater self-confidence.

Students were taught to use MATLAB in the second half of their first semester, with a final project due in December of 2020. The finalized survey was administered to students at the start of their second semester of engineering design course, in January 2021. In addition to the motivational factors, students were asked to self-report their gender, race, ethnicity, prior programming experience, and math experience. 69 students provided complete responses. Distributions in population with respect to gender and ethnicity were not widely different from those for the institution [15]Demographics for sample population and institution. Some students chose not to report the requested information, and students were not asked to report on their nationality, which resulted in some variations between our demographic numbers and those reported by the institution. The institution also tabulates international students as a separate category.

TABLE 1: DEMOGRAPHICS FOR SAMPLE POPULATION AND INSTITUTION

Descriptor	Number. in Sample	% of Sample	% at Institution (population)
Female	21	30%	23.9%
Male	48	70%	76.1%
Hispanic or Latino	4	6%	3.7%
Asian	8	12%	8.4%
Black or African American	2	3%	3.5%
White	56	81%	61.4%

C. Initial Data Analysis

DATA COLLECTION WAS HAMPERED BY ISSUES ASSOCIATED WITH THE COVID-19 PANDEMIC, AND THE STUDY WILL BE REPEATED IN THE FALL OF 2021. THIS PRELIMINARY ANALYSIS THEREFORE DEALS WITH A SUBSET OF SURVEY QUESTIONS SHOWN IN

TABLE 22 AND

Table 33. The 69 responses were separated by intended major such that two groups were created: those who had either CSE or EE listed as their first or second choice for intended major (Group I, n=25), and those who listed MSE, BME, or WE as their first or second choice for intended major (Group II, n=16). Including multiple potential majors in the grouping accounted for the possibility that students' intentions are still somewhat fluid during their first year and provided data groups that were large enough to analyze. Previous studies demonstrated that students who change majors during the first year will often transfer within these groups [5]. Students who did not have a preferred major in any of the five targeted areas (n=25) and students who planned majors in both Group I and Group II specialties (n=3) were also not included in this analysis. The average score for

III. RESULTS AND DISCUSSION

The categorical responses on the questions listed in each category A – E were combined into an average value for each category for each student to give a roughly continuous set of values for each category for the population as a whole. In this way, each student has a numerical value corresponding to their motivation levels. to the questions in categories A – E. It is important to note that a higher number in this case denotes a *lower* utility value, self-efficacy, or self-regulation. These averages for groups I and II for each category can be seen in **Error! Reference source not found.**.

An independent-samples t-test was used to test whether the means of Groups I and II for each category were significantly different. The results of these calculations are presented in **Error! Reference source not found.**. If we use the conventional α=0.05 or 95% confidence, category C demonstrates a significant difference. However, this category only had two questions; averaging only two questions resulted in a less continuous range of values. Thus, the application of a t-test is less reliable. Group I and Group II are not significantly different in their measures for Categories A, B, D, and E. The p-value for categories B, C, and E are much lower than for A and D, which could indicate that significant statistical differences might be detectable with a larger data set.

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TABLE 2: SURVEY INFORMATION FOR QUESTIONS ADDRESSING MOTIVATIONAL FACTORS.

	Motivation Factors – Survey Categories and Questions		
	Question Stems	***1***	***6***
A – Expectancy and Utility Value	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 Agree	Strongly Disagree
B - Self Efficacy 1	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.	Extremely Confident	Not at all Confident
C – Self-Efficacy 2	10 – complete a MATLAB project if I only had the built-in help menu for help (in other words, I could not google for the answer) 11 – Find ways of overcoming problems in completing a MATLAB assignment if I got stuck at a point while working on the project.	Extremely Confident	Not at all Confident
D – Self Regulation	12 – Manage my time efficiently if I had a pressing deadline on a MATLAB project. 13 – Find a way to concentrate on my program, even when there were many distractions around me. 14 – Find ways of motivating myself tow ork on a MATLAB assignment, even if the problem area was of no interest to me.	Extremely Confident	Not at all Confident

TABLE 3: SURVEY INFORMATION FOR QUESTIONS RELATED TO PERFORMANCE. PARTICIPANTS WERE ASKED TO RATE THEMSELVES ON 3 METRICS RELATIVE TO THEIR PEERS.

	Self-Evaluation of Performance		
	Question Stems	***1***	***7***
E - Performance	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	Far above average	Far below average

TABLE 4: COMPARISON OF MOTIVATION CATEGORIES A-E FOR GROUPS I AND II. GROUP I IS STUDENTS INTERESTED IN ELECTRICAL OR COMPUTER SYSTEMS ENGINEERING, AND GROUP II IS STUDENTS INTERESTED IN MATERIALS SICENCE, BIOMEDICAL, OR WELDING ENGINEERING MAJORS.

Category	Group	Average	P-value for t-test
A – Utility Value	Group I	2.14	0.671
	Group II	2.28	
B - Self-Efficacy	Group I	2.28	**0.053**
	Group II	2.86	
C - Self-Efficacy	Group I	2.68	**0.019**
	Group II	3.44	
D - Self-Regulation	Group I	2.58	0.605
	Group II	2.77	
E - Performance	Group I	2.78	0.125
	Group II	3.28	

IV. CONCLUSIONS

The results of this study are still inconclusive. There may be differences in some motivation factors between engineering pre-majors interested in computationally focused degrees and those who are pursuing majors that seem to be less so. The p-value for the t-tests that look at the self-efficacy sub score means (categories B and C) between groups 1 and 2 are much lower than for the other categories. The results of this pilot will inform the study conducted in Fall 2021. Interviews with study participants are being conducted in the Summer of 2021. These interviews address students' beliefs about computational modeling and their motivation related to learning to use MATLAB in particular and computational tools and programming in general. The results of these interviews will inform minor changes to the survey. The finalized survey will be administered in the fall of 2021, with an anticipated participation of at least 200 students. With many potential participants, it will be possible to investigate whether there is a significant difference in motivation by surveying these students about their intended major and asking questions about motivation related to computational modeling in general and MATLAB tasks in particular.

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REFERENCES

[1] R. A. Enrique, M. Asta and K. Thornton, "Computational materials science and engineering education: An updated survey of trends and needs," *Jom,* vol. 70, *(9),* pp. 1644-1651, 2018.

[2] A. K. Polasik and D. Riegner, "Successes and lessons learned in an undergraduate computational lab sequence for materials science and engineering," in *Proceedings of the 2017 ASEE Annual Conference & Exposition,* 2017, .

[3] Y. Qian and J. Lehman, "Students' misconceptions and other difficulties in introductory programming: A literature review," *ACM Transactions on Computing Education (TOCE),* vol. 18, *(1),* pp. 1-24, 2017.

[4] V. G. Renumol, D. Janakiram and S. Jayaprakash, "Identification of cognitive processes of effective and ineffective students during computer programming," *ACM Transactions on Computing Education (TOCE),* vol. 10, *(3),* pp. 1-21, 2010.

[5] A. Theiss *et al*, "Engineering major selection: An examination of initial choice and switching throughout the first year," in *2016 ASEE Annual Conference & Exposition,* 2016/06/26, Available: https://peer.asee.org/engineering-major-selection-an-examination-of-initial-choice-and-switching-throughout-the-first-year.

[6] Lisa Benson, Adam Kirn and Courtney June Faber, "CAREER: Student motivation and learning in engineering," in Jun 15, 2014, Available: https://search.proquest.com/docview/2317704820.

[7] A. Kirn and L. Benson, "Engineering Students' Perceptions of Problem Solving and Their Future," *Journal of Engineering Education (Washington, D.C.),* vol. 107, *(1),* pp. 87-112, 2018. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/jee.20190. DOI: 10.1002/jee.20190.

[8] J. P. Concannon and L. H. Barrow, "A reanalysis of engineering majors' self-efficacy beliefs," *Journal of Science Education and Technology,* vol. 21, *(6),* pp. 742-753, 2012.

[9] M. Bong, "Role of self-efficacy and task-value in predicting college students' course performance and future enrollment intentions," *Contemp. Educ. Psychol.,* vol. 26, *(4),* pp. 553-570, 2001.

[10] R. W. Lent, F. G. Lopez and K. J. Bieschke, "Mathematics self-efficacy: Sources and relation to science-based career choice." *Journal of Counseling Psychology,* vol. 38, *(4),* pp. 424, 1991.

[11] M. A. Hutchison *et al*, "Factors influencing the self-efficacy beliefs of first-year engineering students," *J Eng Educ,* vol. 95, *(1),* pp. 39-47, 2006.

[12] B. D. Jones *et al*, "An analysis of motivation constructs with first-year engineering students: Relationships among expectancies, values, achievement, and career plans," *J Eng Educ,* vol. 99, *(4),* pp. 319-336, 2010.

[13] A. Bandura, "Self-efficacy: Toward a unifying theory of behavioral change," *Psychological Review,* vol. 84, *(2),* pp. 191-215, 1977. Available: https://www.ncbi.nlm.nih.gov/pubmed/847061. DOI: 10.1037/0033-295X.84.2.191.

[14] V. Ramalingam and S. Wiedenbeck, "Development and Validation of Scores on a Computer Programming Self-Efficacy Scale and Group Analyses of Novice Programmer Self-Efficacy," *Journal of Educational Computing Research,* vol. 19, *(4),* pp. 367-381, 1998. Available: https://journals.sagepub.com/doi/full/10.2190/C670-Y3C8-LTJ1-CT3P. DOI: 10.2190/C670-Y3C8-LTJ1-CT3P.

[15] The Ohio State University "The college of engineering annual statistical report," 2020. https://engineering.osu.edu/about/annual-statistical-report