Effectiveness of Active Learning Methods on Students' Self-efficacy, Learning Motivation and Academic Performance in Numerical Methods in Mechanical Engineering

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Work In Progress:

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Abstract

One of the outcomes of a mechanical engineering degree program is the ability for students to identify, formulate, and solve engineering problems by applying principles of engineering, science, and mathematics. Numerical Methods in Mechanical Engineering (MECHENG 2850) is one of the common core courses that undergraduate mechanical engineering students take in their second year. This course introduces numerical procedures to solve problems that are common to mechanical engineering, and their implementation using MATLAB. One major challenge in this course is that students, especially those without strong programming skills, often view it as a mathematics class, which negatively affects their motivation and performance. Existing literature has extensively verified the anticipating impact of self-efficacy beliefs on students' academic functioning. Although self-efficacy has been well-understood for other domains, it is not well-understood in the context of numerical methods. Self-efficacy has shown to be a task-specific characteristic and thus implementing active learning in numerical methods class could provide more opportunities for students to find tasks that promote feelings of competence and success, which in return would increase their learning motivation and improve their overall performance in the course.

The purpose of this study is to investigate the effectiveness of active learning methods on students' self-efficacy, learning motivation, and academic performance in learning numerical methods. The research will be conducted in large section with 450 students enrolled in the MECHENG 2850 class during the 2024 academic year. We will use a sequential explanatory mixed methods approach to answer our research question. First, we will use a pre- and post-self-efficacy survey to explore the impact of active learning on these two factors. Students' grades, and pre-post knowledge assessment will be used to investigate the effectiveness of active learning on academic performance. Once these data are analyzed, we will purposively sample select participants for a one-on-one semi-structured interview. These qualitative data will enable us to investigate these phenomena in more depth and understand the nuances associated with students' self-efficacy beliefs, learning motivation, and performance in an undergraduate numerical methods course. Findings of this research will help engineering educators design activities that engage students in class, promote their self-efficacy beliefs about numerical methods, and learning motivation, and improve their performance in the course.

1. Introduction

Numerical methods are essential in mechanical engineering for solving complex problems in areas such as fluid dynamics, heat transfer, stress analysis, and optimization [1]. They help approximate solutions to difficult mathematical problems, enhance solution accuracy, support decision-making, and advance knowledge and innovation in the field. Additionally, knowledge of numerical analysis techniques is crucial for designing, analyzing, and optimizing mechanical systems and processes involving mechanics, fluids, heat, and materials. Therefore, learning numerical methods is fundamental for efficiently solving engineering problems and advancing the field's knowledge and innovation [1], [2], [3].

Studying self-efficacy and motivation in the context of numerical methods for Mechanical Engineering is crucial for several reasons. Self-efficacy, denoting an individual's confidence in their capacity to achieve specific tasks, has been identified as a substantial influence on academic performance and learning outcomes within the realm of engineering education [4], [5]. In the field of Mechanical Engineering, where students are required to handle complex numerical analysis and design tasks, understanding, and enhancing self-efficacy can lead to improved problem-solving skills and the ability to transform analytical models into practical solutions [5]. Moreover, motivation, particularly in the form of intrinsic motivation and academic self-regulation, plays a vital role in students' willingness to study engineering and their commitment to completing challenging tasks [4]. This is especially relevant in the context of numerical methods, where sustained effort and engagement are necessary for mastering the subject.

Research has shown that self-efficacy and motivation are strong predictors of academic achievement in engineering education. Existing research provides insights into the impact of self-efficacy and motivation on engineering education, particularly in the context of numerical analysis and design tasks [6], [7]. These studies highlight the significance of these psychological factors in shaping students' academic performance and learning outcomes in the field of mechanical engineering [2][4].

Several strategies could be employed to improve self-efficacy and motivation in Mechanical Engineering students. One effective approach is the implementation of active learning strategies [8], [9]. Active learning methods, such as flipped classroom model, problem-based learning, collaborative projects, and hands-on activities, have been shown to enhance students' self-efficacy and motivation by providing them with opportunities to apply engineering principles in real-world scenarios [10], [11], [12], [13], [14]. These methods not only help students build a deeper understanding of the course material but also contribute to the development of their confidence in tackling engineering challenges, thereby positively impacting their self-efficacy and motivation [10], ultimately resulting in improved academic performance, particularly for underrepresented minority students [15]

In addition to active learning, strategies such as fostering mastery goal orientation [16], incorporating self-regulated learning characteristics into the curriculum [17], providing successful learning experiences , and promoting a supportive and inclusive learning environment [18] are other examples of valuable strategies for improving self-efficacy and motivation in Engineering. By implementing these strategies, educators could support students in overcoming challenges related to numerical methods and enhance their abilities to tackle complex engineering tasks, ultimately leading to improved learning outcomes and better preparation for the demands of the engineering profession. Understanding the impact of active learning methods on students' self-efficacy, learning motivation, and academic performance engineering courses could help educators design and implement active learning strategies that are tailored to the specific needs of mechanical engineering students, ultimately enhancing their self-efficacy, motivation, and academic success.

This study investigates the impact of active learning methods on self-efficacy, learning motivation, and academic performance in numerical methods within mechanical engineering. Guided by Bandura's Social Cognitive Theory (SCT) [19] and the self-efficacy construct, we employ a sequential explanatory mixed-methods design. The quantitative phase utilizes a non-validated Numerical Methods in Mechanical Engineering self-efficacy scale, followed by a qualitative phase with semi-structured student interviews. Integration of findings in the final phase, analyzed through the lens of SCT, aims to provide a comprehensive understanding of how active learning methods influence the cognitive and motivational aspects of mechanical engineering students, contributing to improved pedagogical practices.

2. Theoretical Framework

Bandura's Social Cognitive Theory (SCT) elucidates human behavior as a system comprising three interacting components: personal, behavioral, and environmental. These three interacting components form what Bandura calls the triadic reciprocity [20]. Self-efficacy is an important component of the personal component of SCT and is based on the foundation that human beings can control their thoughts, feelings, motivation, and actions [19]. According to Bandura, a person's success in completing a certain task may be influenced by their own perception of their abilities to complete that task. Different people may have different self-efficacy beliefs for the same task. Moreover, self-efficacy beliefs may vary from task to task for the same person.
As per Bandura's framework, self-efficacy derives from four primary sources: performance accomplishments, vicarious experiences, verbal persuasion, and emotional arousal [19]. *Performance accomplishments* positively influence a persons' self-efficacy beliefs. The more consistent and frequent successes a person enjoys, the more likely it is for them to develop sustainable expectations of self-efficacy. In addition to performance accomplishments, a lot of information on self-efficacy comes from *vicarious experience*. An individual observing another individual performing well in a stressful and threatening situation will be encouraged to undertake similar challenging tasks. One convenient and easily available source of self-efficacy is *verbal persuasion*. When people are convinced by other people, they tend to believe that they are more capable of performing a task. In this vein, constructive feedback plays a crucial role in developing strong self-efficacy beliefs. The fourth source of self-efficacy beliefs is emotional arousal. *Emotional arousal*, that happens during challenging situations, can also help people inform themselves of their expectations of self-efficacy. High levels of emotional arousal can hamper an individual's performance by increasing anxiety and stress.

3. Research Question(s)

This type of research, called sequential explanatory mixed-methods research, is practical in its approach. The research questions play a crucial role in guiding and shaping the entire process, including choosing the research design, determining the sample size, and selecting data collection methods [21], [22], [23]. In this study, the specific research questions are:

1. The overarching research question is, “What is the effectiveness of active learning methodologies on the students’ self-efficacy and learning outcomes in an introductory undergraduate numerical methods course? “

2. The quantitative research question is, “Do students show variations in self-efficacy and learning outcomes in an introductory numerical methods course after the introduction of active learning methods?”

3. The tentative qualitative question is, “Why do we observe the variations in self-efficacy and learning outcomes in an introductory numerical methods course after the introduction of active learning methods?”

4. Methodology

4.1 Course Introduction

The Numerical Methods in Mechanical Engineering (MECHENG 2850), typically offered to second-year undergraduate mechanical engineering students, provides a comprehensive understanding of the application of numerical techniques in solving complex engineering problems. The course not only covers the theoretical aspects of numerical analysis but also emphasizes the practical implementation of computer programming to address these challenges. Students are exposed to a range of subjects, such as solving nonlinear algebraic equations, systems of linear algebraic equations, interpolation, curve-fitting, ordinary and partial differential equations, and matrix eigenvalue problems. By integrating theoretical knowledge with hands-on programming experience, students develop the proficiency to apply computational tools in simulating and solving problems related to heat transfer, fluid dynamics, structural integrity, and other critical aspects of mechanical systems. The course aims to equip students with the necessary skills to effectively utilize numerical methods and computer programming in the context of mechanical engineering, thereby preparing them for their future courses as well as real-world engineering applications.

This three-credit course is traditionally offered in two sections during autumn semesters, with an average enrollment of 100 students in each section, and in one section during spring semesters, with an average enrollment of 250 students. The course comprises two primary modules: lectures, which primarily concentrate on delivering mathematical theory and solving examples using various methods, and recitations, which focus more on hands-on MATLAB programming.

The lectures will be conducted by the instructors, while the recitations will be led by Undergraduate Teaching Assistants (UTAs), with an average ratio of one UTA for every 40 students. In this study, active learning strategies will be implemented in both the lecture and recitation modules.

4.2 Active Learning Strategies

The active learning strategies chosen for the MECHENG 2850 course aim to enhance student engagement and learning outcomes. These strategies include "think pair share", where students are prompted to think about a concept, discuss it with a peer, and then share their thoughts with the class [24], [25]. Additionally, the use of discussion boards provides students with a platform to engage in collaborative and reflective discussions on course topics, thereby promoting deeper understanding and critical thinking [8], [26]. Furthermore, the "muddiest point" technique encourages students to identify and articulate the most challenging or unclear aspects of the material, allowing instructors to address these areas of difficulty directly. By integrating these active learning strategies into the course, students are provided with opportunities for peer interaction, self-reflection, and clarification of complex topics, ultimately contributing to a more dynamic and effective learning experience in the class [9], [27].

4.3 Sequential Mixed-methods Research Design

In this research, we have opted for the mixed-methods sequential explanatory design [21]. This design comprises two distinct phases: an initial quantitative phase succeeded by a qualitative one. The rationale for this selection lies in the comprehensive insights provided by the initial quantitative phase, encompassing data collection and analysis, which establishes an extensive understanding of the problem. The subsequent qualitative analysis then delves deeper, refining the comprehension through a detailed exploration of participants' perspectives [21], [28]. Ultimately, the combined interpretation of both quantitative and qualitative results will be undertaken.

Phase of Study	Procedure	Product
Quantitative Data Collection	- Collect student demographic and background data. - Administer the Numerical Methods in Mechanical Engineering self-efficacy scale (pre and post). - Record midterm and final exam grades.	- Numeric data (n=450) - Participant Demographics
Quantitative Data Analysis	- Clean the data - Conduct a two-tailed paired t-test for Hypotheses testing	- Descriptive and inferential statistics
Connecting Quantitative and Qualitative Phases	- Refine the qualitative research question based on the findings of the qualitative phase. - Utilize maximum variation sampling to determine participant requirements. - Develop quantitative data collection instruments.	- Interview protocol - Recruitment material - Consent forms
Qualitative Data Collection	- Recruit participants using recruitment emails and online forums. - Conduct face-to-face student interviews and record the audio for later reference.	- Transcribed interview and notes (~n=40-50)
Qualitative Data Analysis	- Thematic analysis of the qualitative data	- Conceptual model of emergent themes - Codes and themes - Coding matrix
Integration of Quantitative and Qualitative Findings	- Interpretation and explanation of findings from both the QUANT and equal phase	- Discussion - Implications on practice - Future research -Visual display tying QUANT and equal results

Figure 1: *Phases of the study, procedures used and final product of each step [28]*

4.3.1 Phase 1 - Quantitative study

To gather data from the extensive MECHENG 2850 class, we will employ stratified random sampling [21] with a total enrollment of 450 students over the academic year. The data collection process aims to ensure representation across various demographic factors, including race, gender, and ethnicity. The study requires a targeted sample size of 40-50 students, factoring in a 10%-12.5% response rate. This implies that the survey should be distributed to a minimum of 400 students to achieve the desired sample size while accounting for the anticipated response rate.

In evaluating self-efficacy within the framework of a numerical methods course, we performed an in-depth review of existing literature. This exploration brought to light the absence of a validated scale explicitly tailored for this context. We will adopt a methodology inspired by Adam Carberry's [29]efforts in developing a tool to evaluate self-efficacy in engineering design. This instrument covers various aspects, including confidence, motivation, expectancy for success, and anxiety. Additionally, the Engineering Learning Experiences Scale emphasized the importance of domain-specific instruments for evaluating self-efficacy in the field of engineering [30]. By synthesizing insights from these studies, we aim to develop a comprehensive self-efficacy scale tailored to the unique requirements of learning numerical methods in mechanical engineering. This scale will consider the specific requirements of the field and the fundamental skills necessary for student proficiency. However, as there is a limited sample size, it cannot be considered a validated scale for this study.

The self-efficacy survey will be conducted both at the start and conclusion of the semester to evaluate students' self-efficacy in learning MECHENG 2850. This approach aims to minimize the impact of response recall by spacing the surveys apart. In addition to the self-efficacy scale, demographic and background information, midterm grades, and final grades will be collected. The data analysis will involve two-tailed paired t-tests to examine the significance of any observed changes in self-efficacy beliefs. This approach facilitates a thorough assessment of how effectively the research question concerning the development of students' self-efficacy in learning MECHENG 2850 is answered by the outcomes. Additionally, the results can be evaluated for criterion-related validity [21] by connecting them to Bandura's Social Cognitive Theory (SCT) self-efficacy construct [19]. This involves examining the correlation between the findings and the self-efficacy construct detailed in Bandura's SCT to ascertain the degree to which the results align with established validity criteria.

4.3.2 Phase 2 - Integration of Quantitative and Qualitative Data

In this stage, the synthesis of the quantitative and qualitative components of the study will occur. The insights gained from the previous quantitative phase will guide the qualitative aspect [21], [28]. The initial step in this integration phase is to revise the qualitative research question in light of the outcomes from the quantitative data analysis. Subsequently, the second step involves formulating and testing the data collection protocol [31], which, in this instance, will be a semi-structured interview protocol. This protocol stands as a crucial outcome of integrating the quantitative and qualitative aspects of the study. In accordance with the findings of the quantitative phase and utilizing Bandura’s Social Cognitive Theory (SCT), the interview protocol will be crafted. A pilot test will be conducted to identify any shortcomings and limitations in the interview protocol, and necessary adjustments will be implemented based on the pilot results. Furthermore, for communicative validity [32], the interview protocol will be deliberated with peers and refined based on their input [33].

4.3.3 Phase 3 - Qualitative study

In this phase, students from the same group who have participated in both the pre-survey and post-survey, providing demographic and grade information, will be invited to partake in interviews. Utilizing maximum variation sampling [34], we aim to select interview participants with diverse perspectives, capturing common patterns across this diversity. Those chosen will be sent email invitations for the interviews and will be requested to sign consent forms. Anticipating that qualitative research does not require large sample sizes [21], [34], we expect around 40-50 students to volunteer for the interviews. Conducted face-to-face, the interviews will be audio-recorded [21]. The transcripts will be verbatim transcribed to facilitate subsequent data analysis. Before commencing the analysis of interview transcripts, participants will be asked to review them to ensure communicative validity [34]. Once member checking is completed, thematic analysis procedures [35], [36] will be employed to analyze the transcripts. Grounded in Bandura's Social Cognitive Theory (SCT), this framework will guide the data analysis procedures. To uphold reliability in the qualitative research, two different researchers will independently code the transcripts to ensure consistency in data collection and interpretation [37].

4.3.4 Phase 4 - Integrating Quantitative and Qualitative Findings.

The final stage of this mixed-methods study encompasses the merging of both quantitative and qualitative components. In designs aimed at explanation, this integration phase raises inquiries into how the qualitative data elucidate the quantitative results and vice versa [21], [34]. Since we are collecting multiple sources of data, we will also conduct thorough triangulation of various sources of data at this stage [34]. For instance, we could use demographic information to disaggregate our survey data to see how self-efficacy of different groups change. We could also incorporate the insights gathered from the interview data to provide deeper context and explanation for the quantitative findings, aligning with the methods suitable for an explanatory sequential mixed-methods study. The Social Cognitive Theory (SCT) can be effectively utilized to interpret the integrated findings. Additionally, constructing a visual representation that connects qualitative themes with quantitative results can improve understanding and contribute to addressing the overarching question in mixed-methods research [21].

5. Immediate Future Directions

The next steps for this study involve collecting data in both the spring and fall of 2024, with data analysis scheduled for the spring of 2025. We are currently in the process of establishing the interview protocols and applying for Institutional Review Board (IRB) approval from the institution.

6. Conclusions

This paper introduces a proposed mixed-methods study with an explanatory sequential design, aiming to investigate shifts in self-efficacy and learning outcomes in an introductory numerical methods course following the incorporation of active learning approaches. The study will initiate with the collection of quantitative data, utilizing a computer programming self-efficacy scale that has been expanded based on existing literature, though not yet validated. The insights gained from the quantitative data will then inform the structure of the subsequent qualitative phase of the research. In this qualitative phase, data will be collected and analyzed. The integration of both quantitative and qualitative findings will be utilized to address the primary research question, and the analysis will be conducted through the framework of Bandura's Social Cognitive Theory (SCT).

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