Engineering Educators Bringing the World Together
2025 ASEE Annual Conference & Exposition
Palais des congrès de Montréal, Montréal, QC • June 22–25, 2025
Paper ID #46019

Work in Progress: Exploring Biomedical Engineering Students' Perceptions of Large Language Models in Academic Settings

Prof. Nathan Hyungsok Choe, The George Washington University

Dr. Hyungsok "Nathan" Choe is an Associate Professor of Practice in the Department of Biomedical Engineering at The George Washington University's School of Engineering and Applied Science. He previously served as a Research Assistant Professor at Ohio State University's Department of Engineering Education.

Dr. Choe holds a Ph.D. in STEM Education (Engineering Education) from the University of Texas at Austin. His research focuses on engineering identity development, career pathways, and integrating computational and AI-based methods in engineering education. He has been actively involved in developing and assessing engineering courses, including project-based learning initiatives.

Chanyee Hong
Hyeyeon Lim

Work in Progress: Exploring Biomedical Engineering Students' Perceptions of Large Language Model in Academic Settings

Introduction

In Work in Progress (WIP) study, we are particularly interested in how engineering students perceive utility value and self-efficacy in using LLM for their engineering studies. Previous research has shown that self-efficacy is closely linked to academic performance, motivation, and persistence in engineering programs [1]. Understanding these perceptions can help educators design more effective curricula that leverage LLM to enhance learning outcomes. Additionally, the utility value of LLM, which refers to the perceived usefulness and practical benefits of these tools, plays a significant role in students' engagement and academic success [2]. By examining these factors, we aim to provide insights into how LLM can be integrated into engineering education to support students' academic and professional development.

Utility value, defined as the perceived usefulness and practical benefits of a tool or task, is a critical factor in students' engagement and motivation in academic settings. Venugopal et al. emphasized that utility value and self-efficacy are essential in shaping the learning outcomes of engineering students, highlighting the importance of integrating practical applications into the curriculum to enhance students' perceived utility value [3]. In the context of using large language model (LLM) like ChatGPT in engineering education, the utility value can significantly influence how students perceive and utilize these tools. Recent studies have explored the impact of LLM on students' perception of utility value in using AI tools. For instance, Rosenzweig et al examined the effectiveness of utility value interventions in online math courses and found that such interventions significantly increased students' perceived utility value and academic performance.[4].

Self-efficacy, defined as an individual's belief in their ability to succeed in specific tasks, plays a crucial role in the academic performance of engineering students [5]. In the context of using large language model (LLM) like ChatGPT in engineering education, self-efficacy can significantly influence how students perceive and utilize these tools. Recent studies have explored the impact of LLM on students' self-efficacy in using AI tools. For instance, Chen et al. reported that using LLM as a teachable agent in programming education improved students' self-regulated learning abilities and self-efficacy in using LLM [6]. These findings indicate that the context and manner in which LLM are integrated into the curriculum can influence its effectiveness in enhancing self-efficacy among engineering students in using LLM.

Research Questions

Given the increasing integration of large language model (LLM) like ChatGPT into academic settings, it is important to understand how these tools are perceived and utilized by students, particularly those in demanding fields such as engineering. This study aims to explore three key research questions specifically within the context of engineering college students.

1. What are the differences in awareness and perception of LLM between users and non-users among students? (RQ1)
2. What are the underlying dimensions of perceived self-efficacy and utility value when engineering college students use LLM for academic purposes? (RQ2)

3. How do perceptions of self-efficacy and utility value in using LLM differ between female and male engineering college students, and between upper-division and lower-division students? (RQ3)

Method

The data was collected from a R1 private university in the Northeast Region in the U.S. For this study, we used two datasets to answer three research questions. First, dataset 1 was used to answer RQ1, and the total number of participants was 60 students from the Biomedical Engineering Department in 2023. Male students were 26 while 34 female students participated in the survey. The distribution of ethnicities includes 30 White, 4 Black, 3 Hispanic, 11 Asian, 2 Mixed (Multi), 1 American Indian, with 9 not provided. In the group of participants, there are 41 students in the upper-division (third and fourth-year level), and 19 students in the lower-division (first and second-year level). Second, dataset 2 was used to answer RQ2 and RQ3. This is a subset of dataset 1, which reminded data of those who have experience of using AL language model. Among a total of 37 students, 21 were male students and 16 were female students. The dataset shows a distribution of ethnicities with 14 White, 4 Black, 1 Hispanic, 8 Asian, and 1 Mixed (Multi), along with 7 responses where ethnicity was not provided. The upper-division, comprising third and fourth-year students, includes 30 individuals, while the lower-division, which consists of first and second-year students, has 7 individuals. This work was determined to be exempt from further review by [Institution] IRB.

Survey Questions & Data Collection: The survey assessed LLM usage for engineering courses and intentions to work in the field, with responses on a binary scale and self-efficacy/utility values on a 5-point Likert scale. Data were collected via the Qualtrics online tool during 10-minute sessions at the start of freshman and senior courses.

Data Analyses

For the dataset in question, we tackled the issue of missing data by excluding one entry where the participant failed to complete the necessary inquiries regarding their LLM experience. All data analyses for this study were conducted using STATA 17. We omitted students' intention to work in the engineering field due to statistical dominance of affirmative responses.

Descriptive statistics summarized the data characteristics, including total responses and calculation of means and standard deviations to understand data distribution. Chi-squared Test of Independence tests analyzed differences in AI language model usage across gender and class standing. An exploratory factor analysis (EFA) using the principal factor method was conducted on eight items to identify underlying factors of utility and self-efficacy in using LLMs for academic purposes. The KMO measure of 0.8511 and Bartlett's test confirmed the data's suitability for EFA, followed by a varimax rotation to enhance interpretability. Independent t-tests compared self-efficacy and utility value perceptions across genders and student levels. All tests, including chi-squared, t-tests, and correlations, required a p-value below 0.05 to be considered significant.

Result

The results section explores the differences in LLM awareness and perception among students. Appendix A shows that 21 out of 26 male students use LLM, compared to 16 out of 34 female students, indicating a gender disparity in adoption. Chi-squared results ($\chi^2(1, N=60) = 7.0828$, $p < .001$) confirm significant differences in LLM usage between male and female students. Appendix B indicates that 30 out of 41 upper-division students use LLM, versus 7 out of 19 lower-division students, with significant chi-squared results ($\chi^2(1, N=60) = 7.2486$, $p = .007$) indicating usage differences based on academic standing. These findings suggest the need for targeted strategies to enhance engagement with LLM across different demographic groups.

RQ2 utilized Dataset 2 and Exploratory Factor Analysis to extract two key factors—self-efficacy and utility value—from responses about engineering students' use of LLM for academic purposes. Factor 1, self-efficacy, which emerged from three items, had a Cronbach's alpha of 0.82, indicating strong internal consistency. One representative item from this factor is: "I feel more confident in my ability to succeed in engineering with the help of LLM." Factor 2, utility value, assessed by two items, had a Cronbach's alpha of 0.73, highlighting the perceived practical benefits of LLM. One representative item from this factor is: "LLM is a useful tool for solving engineering problems."

RQ3 examined differences in self-efficacy and utility value perceptions between genders and academic standings shown Appendix C. Independent samples t-tests showed no significant differences in self-efficacy or utility value perceptions across the groups, suggesting similar levels of perceived effectiveness and utility of LLM among engineering students regardless of gender or academic level.

Discussion and Future Work

Study Limitations: This study's limitations include its data source from a single institution, potentially affecting generalizability to other regions or universities. The survey, conducted in 2023, may not fully capture current LLM perceptions due to rapid advancements in technology. A disproportionate number of female biomedical engineering students in the sample could also bias results. Future studies should broaden the sample across various engineering disciplines to improve findings' applicability.

Future Work: Future research should broaden the participant pool to include diverse institutions and fields of engineering. Longitudinal studies are recommended to track changes in LLM perceptions over time. Combining quantitative data with qualitative methods like interviews could offer deeper insights into student attitudes. Research should also evaluate educational interventions that promote AI literacy and ethical LLM use, alongside developing reliable tools for measuring utility value and self-efficacy. Examining LLM's long-term impact on academic and career outcomes could inform educational strategies and policy [7,8].

Conclusion

The study highlighted significant gender and academic level disparities in LLM usage among biomedical engineering students, indicating a need to consider these factors in LLM adoption in education. Despite no found differences in perceived efficacy and utility, the study underscores the role of demographic factors in LLM integration into curricula. Addressing these issues through targeted interventions could enhance AI literacy and prepare students for an AI-driven professional landscape [8].

References

[1] J. R. Power, D. Tanner, and J. Buckley, “Self-efficacy development in undergraduate engineering education,” *European Journal of Engineering Education*, pp. 1–25, Jul. 2024. doi:10.1080/03043797.2024.2368149

[2] F. Wu, W. Fan, C. Arbona, and D. de la Rosa-Pohl, “Self-efficacy and subjective task values in relation to choice, effort, persistence, and continuation in engineering: An expectancy-value theory perspective,” *European Journal of Engineering Education*, vol. 45, no. 1, pp. 151–163, Aug. 2019. doi:10.1080/03043797.2019.1659231

[3] A. Venugopal, R. Singh, and Devika, “Role of self-efficacy in the learning output of Engineering Education,” *Sustainable Production, Life Cycle Engineering and Management*, pp. 233–242, 2020. doi:10.1007/978-3-030-44248-4_23

[4] E. Q. Rosenzweig *et al.*, “Promises and pitfalls of adapting utility value interventions for online math courses,” *The Journal of Experimental Education*, vol. 87, no. 2, pp. 332–352, Feb. 2019. doi:10.1080/00220973.2018.1496059

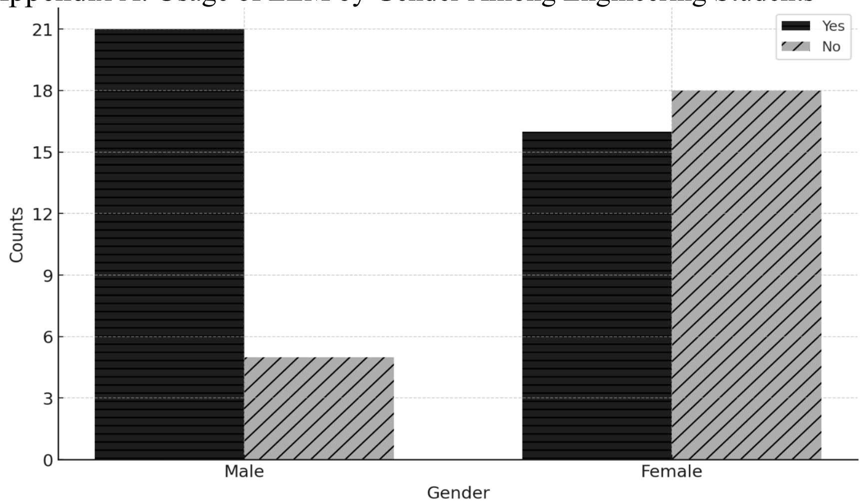
[5] M. A. Hutchison, D. K. Follman, M. Sumpter, and G. M. Bodner, “Factors influencing the self-efficacy beliefs of first-year engineering students,” *Journal of Engineering Education*, vol. 95, no. 1, pp. 39–47, Jan. 2006. doi:10.1002/j.2168-9830.2006.tb00876.x

[6] A. Chen, Y. Wei, H. Le, and Y. Zhang, "Learning-by-teaching with ChatGPT: The effect of teachable ChatGPT agent on programming education," *arXiv preprint arXiv:2412.15226*, 2024.

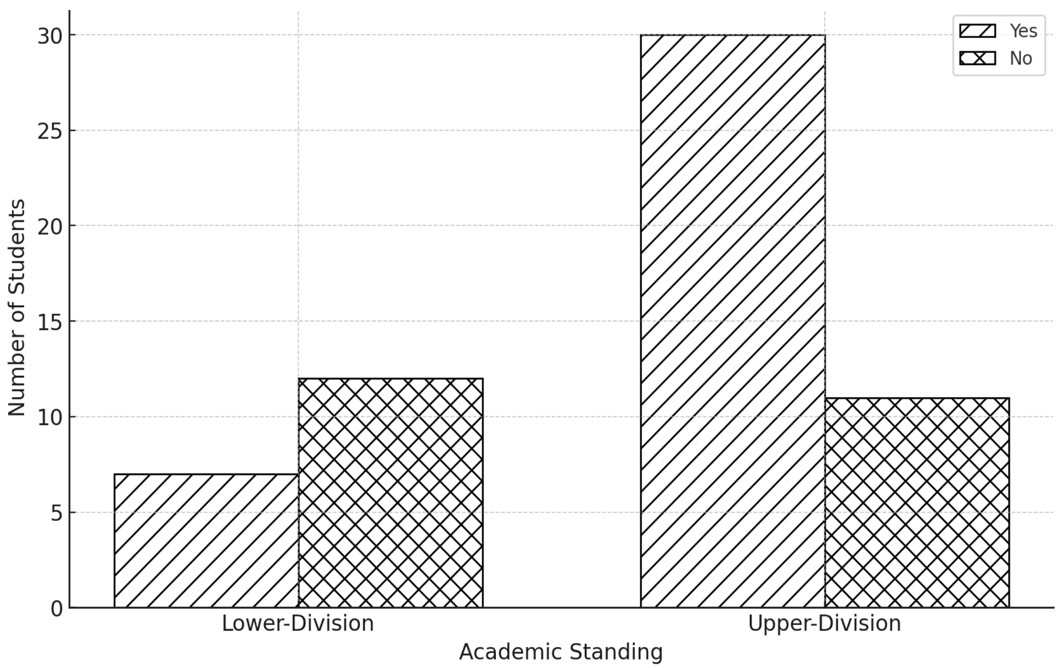
[7] D. Reeping and A. Shah, *"Board 50: Work in Progress: A Systematic Review of Embedding Large Language Model in Engineering and Computing Education,"* Paper presented at the 2024 ASEE Annual Conference & Exposition, Portland, Oregon, June 2024. [Online]. Available: https://doi.org/10.18260/1-2--47047

[8] D. Reeping and A. Shah, *"Board 50: Work in Progress: A Systematic Review of Embedding Large Language Model in Engineering and Computing Education,"* Paper presented at the 2024 ASEE Annual Conference & Exposition, Portland, Oregon, June 2024. [Online]. Available: https://doi.org/10.18260/1-2--47047

Appendix A: Usage of LLM by Gender Among Engineering Students



Appendix B: Usage of LLM by Academic Upper/Lower division Among Engineering Students



Appendix C Comparison of LLM *self-efficacy* and *utility values* Across Gender and Division Groups

Group	**N**	**Self-Efficacy (Mean)**	**Self-Efficacy (SD)**	**Utility Value (Mean)**	**Utility Value (SD)**
Female	16	3.19	0.87	3.90	0.66
Male	21	3.02	0.75	3.50	0.61
Upper-Division	30	3.17	0.83	3.77	0.68
Lower-Division	7	2.76	0.53	3.29	0.39