Engineering Educators Bringing the World Together
2025 ASEE Annual Conference & Exposition
Palais des congrès de Montréal, Montréal, QC • June 22–25, 2025
Paper ID #47960

BOARD # 98: WIP: Understanding Patterns of Generative AI Use: A Study of Student Learning Across University Colleges

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Michaela Harper is a doctoral student at Utah State University, pursuing a Ph.D. in Engineering Education. She holds a Bachelor's degree in Environmental Studies, focusing on STEM and non-traditional education approaches, and a Master's degree in Engineering Education, where she explored faculty perspectives on Generative Artificial Intelligence (GAI). Michaela's current research delves deeply into the effects of disruptive technologies on engineering education, driven by her passion for uncovering the foundational nature of phenomena and applying an exploratory and explanatory approach to her studies. Her work aims to illuminate how technological advancements reshape educational landscapes through student and faculty engagement.

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Dr. Cassandra McCall is an Assistant Professor in the Engineering Education Department at Utah State University (USU). Her research focuses on the intersections of disability, identity formation, and culture and uses anti-ableist approaches to enhance universal access for students with disabilities in STEM, particularly in engineering. At USU, she serves as the Co-Director of the Institute for Interdisciplinary

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WIP: Understanding Patterns of Generative AI Use: A Study of Student Learning Across University Colleges

Introduction

Due to the relatively recent introduction of AI to academia, facilitated by the development and release of popular generative AI systems such as ChatGPT, few studies have examined the effects of AI use on student learning and how students view their engagement with course content. However, recent studies have indicated that student use of AI has led to enhanced creativity [1-3], greater comprehension of conceptual material [4], and increased motivation to learn difficult material [2-5]. Further studies have indicated that AI can have a positive effect on students' visualization and simulation of new ideas [2], [6]. A key feature of AI that separates it from other learning resources is its ability to tailor learning materials to the needs of individual students through conversational approaches, smart assessments, and customized feedback, all of which contribute to enhanced learning [2], [7].

While the benefits of AI are numerous, its integration into academia also presents challenges that require careful consideration. One concern consistent throughout the literature is the potential for AI technology to be used for academic dishonesty [7-8]. It is also common for different AI tools to produce inconsistent results, particularly in complex subjects such as engineering which limits their reliability and the trust that students have in them [3-4]. Despite the recent and significant advancements in AI technology, Stübinger found that it is still necessary for the content generated by intelligent computer systems to undergo human review for accuracy [1]. To aid students and teachers in using AI responsibly, a number of AI literacy frameworks have been developed that put forth guidelines on prompt engineering (i.e. developing prompts to maximize output accuracy), evaluation of AI responses, and ethical considerations [9-11].

Due to its versatile nature, AI has the capacity to be used in nearly every academic discipline, similar to the use of the internet. However, AI may be most effective in fields where students are required to complete more ill-defined tasks such as writing lab reports or creative writing [1], [8]. Similarly, AI has been used in marketing and other business fields for content creation, sales optimization, and for customer service chatbots [12-13]. In science education, the use of AI has been shown to can boost students' motivation and participation in learning exercises, but it has limitations regarding complex subjects, and can produce results that vary by an individual's composition of the input prompt [4]. In engineering fields, AI can assist students with design by providing additional perspectives and controlling for constraints [3]. However, in engineering as well as other highly structured fields, scholars are concerned that the overuse of AI tools may lead to diminished critical thinking ability among students [3]. In areas of art education, studies have shown that educators have communicated reservations about the use of AI due to ethical and practical limitations [6].

The acceptance and use of AI across various academic disciplines may be partially explained through the Technology Acceptance Model (TAM) [14]. The TAM framework hypothesizes that adoption of unfamiliar technology is driven by perceived use and perceived ease of use. Perceived usefulness is often more influential in determining the use of technology [14]. Specific to the adoption of AI, Choung, et al. found that trust in AI has a significant effect on the intention to use AI, and that trust was built through perceived usefulness [15]. Furthermore, functionality-related trust played a greater role in AI use than human-like trust [15], and students who use AI more frequently have less anxiety about it [16].

The purpose of this paper is to identify patterns of AI use in college students across academic disciplines and explore potential factors that may contribute to the adoption of AI in specific fields. Understanding how AI contributes to enhanced learning and its varying acceptance across disciplines may provide valuable insights into its potential for widespread integration.

Methods

Instrumentation

Data for the study was collected through an online survey that was adapted from existing survey instruments focused on technology reuse intention [17], impact of AI on career [18], and learning strategies [19]. The resulting questionnaire was developed to examine how university students perceive and utilize AI systems, such as ChatGPT, as well as to identify motivational factors and learning strategies that impact how students interact with and rely on AI for educational purposes. Demographic information was obtained in the questionnaire for the purpose of exploring how factors such as gender, race, level of education, and disability status influence AI use. The final questionnaire contained 56 items and took approximately 15 to 20 minutes to complete. The findings discussed in this work-in-progress paper are the preliminary findings related to the results of the demographic questions, items related to students' prior AI use in educational contexts, and how many days in a typical week they use AI.

Recruitment and Sampling

Participants were recruited from the graduate and undergraduate student bodies at a large Western University using a voluntary response sampling approach. A recruitment email was sent to the entire student listserv at the beginning of the Fall 2024 semester. This email included information about the study and a link to the online Qualtrics-based survey. To maximize the number of participant responses received, students were encouraged to share the survey with their peers at the same university, following a snowball sampling approach. To further scope the findings from this work-in-progress paper, only the first 977 responses were considered in the analysis. Future work will reflect the entirety of the sample. All respondents who completed the survey were entered into a drawing for a $20 gift card. All recruitment and sampling procedures were approved by the university's IRB office.

Population

All respondents to the questionnaire were students enrolled at a single Western University, with the majority of respondents in the 18 – 23 age range. In total, 977 students responded to the survey. Women represented 54% and men represented 41% of the total respondents, with 3% self-identifying as nonbinary, gender queer, transgender, etc. The majority of the respondents reported their race as White, representing 88% of the total. Other reported races included Asian, Hispanic or Latino, Black or African American, and other self-indicated races. Undergraduate students represented 80% of the sample. A demographic summary of the participants is given in appendix 1.

Participants were asked to identify at least one of the nine colleges associated with their chosen major/program at the university. An option for students not identifying as having a major was also provided. Due to the relatively low number of responses, results from the college of veterinary medicine were omitted from the analysis but demographic data for this group is still presented. A summary of responses from each college is given in table 1.

Table 1. Summary of responses by college.

College	Number of Responses	Percentage of Survey Responses (%)	Enrollment in College	Percent of College Responding to Survey (%)
Agriculture & Applied Sciences	98	12	3509	2.79
Education & Human Services	120	15	5269	2.28
Engineering	149	18	2009	7.42
Humanities & Social Sciences	111	14	2372	4.68
Natural Resources	46	6	665	6.92
Science	125	15	1946	6.42
Arts	23	3	893	2.58
Veterinary Medicine	5	1	71	7.04
None	35	4	8253	0.42
Business	97	12	3913	2.48

Data Analysis

Analysis of the data included descriptive statistics as well as non-parametric tests for group comparisons and tests for independence between categorical variables. Data used in the analysis included categorical variables (i.e., the college associated with the student's chosen major and prior AI use. The number of days in an average week that students reported using AI for school-related activities was analyzed as a continuous variable. Prior to the analysis, normality of the data was assessed using a Kolmogorov-Smirnov test which indicated that the data deviates significantly from a normal distribution ($p<.001$), meaning that non-parametric statistical tests are most suitable for analyzing this data.

Descriptive statistics consisted of calculating the percentage of students in each college who responded "yes" to an item asking if they had previously used AI for educational purposes as well as average and standard deviation values for the number of days in a week that students typical AI use for educational purposes. Independence between variables of students' college and their reported AI use was assessed using a Chi-squared test. A group comparison between students' college and the frequency of AI use was conducted using the Kruskal-Wallis test. Comparisons between colleges were made using Dwass-Steel-Critchlow-Fligner pairwise comparisons. All analyses were performed using Microsoft Excel or Jamovi version 2.3.28 [20].

Results

Results reveal that students in the school of business have the highest percentage of AI use measured both by prior AI use and the frequency of their AI use. Students in the college of the arts have the lowest rate of having used AI for their education as well as the lowest frequency of AI use. Table 2 presents a heat map of the results.

Table 2. Heat map of AI use by college.

College	Percent That Have Used AI	Average Days of AI Use per Week
School of Business	76%	3.36
College of Science	70%	2.16
College of Agriculture and Applied Sciences	66%	2.98
College of Natural Resources	61%	2.25
College of Education and Human Services	60%	2.60
College of Engineering	60%	2.39
College of Humanities and Social Sciences	52%	2.46
None	51%	2.33
College of the Arts	43%	2.00

Results of a Chi-squared test of independence revealed that there is a statistically significant association between students' college and if they have used AI for educational purposes, χ^2 (8, N = 728) = 22, p = 0.005. Likewise, a group comparison between students' college and the number of days in a week they use AI for educational purposes using the Kruskal-Wallis test revealed that the relationship is statistically significant χ^2 (8, N = 728) = 22.9, p = 0.004.

Table 3. Results of statistical tests of association.

Statistical Test	Dependent Variable	χ^2	Degrees of Freedom	p-value	Interpretation
Chi-squared	Have used AI or not	22	8	0.005	There is a significant association between students' college and if they have used AI
Kruskal-Wallis	Days per Week of AI Use	22.9	8	0.004	There is a significant association between students' college and the frequency of their AI use

The Dwass-Steel-Critchlow-Fligner pairwise comparisons revealed statistically significant differences in weekly AI use between students in the school of business and both the college of engineering and the college of science. The remainder of this paper focuses primarily on the relationship between AI use in each of these three colleges. The full pairwise comparison results are presented in Appendix 2.

Table 4. Statistically significant Dwass-Steel-Critchlow-Fligner pairwise comparisons.

Comparison	W	p-value
Engineering – Business	4.5089	0.038
Science – Business	5.6784	0.002

Discussion and Implications

Results of the analysis indicate that business students use AI significantly more than students in technical fields such as science and engineering. These findings are mostly consistent with trends reported about AI use in business and technical fields [12]. Likewise, results from this study align with reservations about AI use in art fields [5-6]. Differences in AI use may stem from the types of problems typical in these fields. Business problems often involve organizational performance [21], financial decisions [22], market strategies, customer needs [23], and resource management [24], with a shared focus on delivering information to decision-makers. Engineering/Science problems usually focus on solving technical or theoretical challenges requiring a deep level of understanding of science and technology for precise solutions [25-27]. Solutions often arise after physical modeling, simulations, and experiments. Further research employing the instrument to explore professionals' AI use in these areas would be valuable for refining the hypothesis.

Additionally, and at the undergraduate level in this particular institution, differences in faculty coaching and use of AI may significantly change the results of this study. It is also likely that a professional acumen requirement in the school of business that include data analytics taught by pro-AI faculty may be driving up business students' use of AI where this is not as big of a driving motivation in the science and engineering undergraduate curriculum.

One possible explanation for these findings through the lens of the TAM model [14] is that students in the school of business may have higher perceived usefulness of AI systems than students in engineering or science. Because business students use AI for functions such as advertising content and customer engagement [12], it may be easier for students to see immediate results. On the other hand, AI systems can have issues understanding or communicating complex technical subjects that are common in science and engineering [4]. This may dissuade some students from using AI due to their perception of its capabilities.

Educational implications include training students in AI applications relevant to their field and integrating AI into the curriculum for maximum benefit. With many students unfamiliar with modern tools like ChatGPT, a gap likely exists in understanding AI's discipline-specific uses.

Limitations

This preliminary study only assesses the frequency of AI use in students without exploring the depth or quality of engagement with AI tools. The measurement of AI use is also limited to how many days in a week the student used the technology rather than the number of hours of AI use. It is also limited to students at a single university which may limit generalizability due to differences in institutional or regional culture or other factors impacting students' exposure to AI that are not yet known.

Conclusion

This study reveals significant differences in AI use across academic disciplines, with business students showing the highest adoption, likely due to the practical applications of AI in their field and the differences in problems solving that may be involved. In contrast, students in technical fields like engineering and science use AI less frequently, likely due to perceived limitations in the ability of AI to handle complex subjects. These findings highlight the importance of perceived usefulness in AI adoption, suggesting that AI training and integration strategies are needed to address the specific applications of AI in different disciplines.

Acknowledgements

This material is based upon work supported by the National Science Foundation through Award No. 2346881. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

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Appendix 1

Demographics of students participating in the study.

		Number	Percentage (%)
Gender	Women	443	54
	Men	330	40
	Self-Indicated	22	3
	Do not want to disclose	20	2
Race	White	718	88
	Asian	34	4
	Hispanic or Latino	31	4
	Black or African American	8	1
	Other	24	3
Degree Program	Doctoral	64	8
	Master's and Doctoral Concurrent	5	1
	Master's	89	11
	Undergraduate	654	80

Appendix 2

Pairwise comparisons - Weekly Use

		W	p
Art	Agriculture and Applied Science	1.6884	0.958
Art	Engineering	0.4825	1.000
Art	Humanities and Social Sciences	0.0765	1.000
Art	Science	-0.2774	1.000
Art	Education	0.7995	1.000
Art	Business	2.6133	0.650
Art	None	0.0458	1.000
Art	Natural Resources	0.1463	1.000
Agriculture and Applied Science	Engineering	-2.5411	0.685
Agriculture and Applied Science	Humanities and Social Sciences	-2.5013	0.703
Agriculture and Applied Science	Science	-3.7216	0.173
Agriculture and Applied Science	Education	-1.5156	0.978
Agriculture and Applied Science	Business	1.6618	0.962
Agriculture and Applied Science	None	-1.9535	0.905
Agriculture and Applied Science	Natural Resources	-2.0759	0.871
Engineering	Humanities and Social Sciences	-0.5171	1.000
Engineering	Science	-1.4583	0.983
Engineering	Education	0.8539	1.000
Engineering	**Business**	**4.5089**	**0.038**
Engineering	None	-0.4842	1.000
Engineering	Natural Resources	-0.3693	1.000
Humanities and Social Sciences	Science	-0.6668	1.000
Humanities and Social Sciences	Education	1.2776	0.993
Humanities and Social Sciences	Business	4.1353	0.083
Humanities and Social Sciences	None	-0.0409	1.000
Humanities and Social Sciences	Natural Resources	0.1025	1.000
Science	Education	2.2291	0.818
Science	**Business**	**5.6784**	**0.002**
Science	None	0.3982	1.000
Science	Natural Resources	0.6839	1.000
Education	Business	3.3349	0.308
Education	None	-0.9223	0.999
Education	Natural Resources	-0.9708	0.999
Business	None	-3.0801	0.420
Business	Natural Resources	-3.4679	0.256
None	Natural Resources	0.1125	1.000

Appendix 3

Contingency Table

	Have Used AI		
College	**No**	**Yes**	**Total**
Art	10	10	20
Agriculture and Applied Science	26	65	91
Engineering	48	89	137
Humanities and Social Sciences	37	58	95
Science	25	88	113
Education	38	72	110
Business	15	74	89
None	12	18	30
Natural Resources	15	28	43
Total	226	502	728