

First-Year Engineering Students' Expertise and Trust in GenAI

Campbell R. Bego, PhD
*Dept. of Engineering Fundamentals
J. B. Speed School of Engineering
University of Louisville*
campbell.bego@louisville.edu

Liliana G. Martinez
*Dept. of Bioengineering
J. B. Speed School of Engineering
University of Louisville*
liliana.martinez@louisville.edu

Angela K. Thompson, PhD
*Dept. of Engineering Fundamentals
J. B. Speed School of Engineering
University of Louisville*
angela.thompson@louisville.edu

Cenetria L. Crockett, MS
*Dept. of Anthropology
School of Arts & Sciences
University of Louisville*
cenetria.crockett@louisville.edu

Alwin K. Rajkumar
*Dept. of Computer Engineering and Computer
Science J.B.Speed School of Engineering
University of Louisville*
alwin.rajkumar@louisville.edu

Alvin Tran, MS
*Dept. of Computer Engineering and Computer
Science, J. B. Speed School of Engineering
University of Louisville*
alvin.tran@louisville.edu

Judith H. Danovitch, PhD
*Dept. of Brain and Psychological Sciences
School of Arts & Sciences
University of Louisville*
judith.danovitch@louisville.edu

Elisabeth L. Thomas
*Dept. of Industrial Engineering
J. B. Speed School of Engineering
University of Louisville*
elisabeth.thomas@louisville.edu

Benarji Valavala, MS
*Dept. of Industrial Engineering
J. B. Speed School of Engineering
University of Louisville*
benarji.valavala@louisville.edu

Abstract—This full-length research study investigated first-year engineering students' trust in generative artificial intelligence (GenAI) before and after course instruction. Pre- and post-surveys were conducted with questions on students' experience with GenAI tools as well as trust in GenAI. The trust questions had students evaluate the likelihood of GenAI generating a correct response to various prompts such as “explain the unit circle” (correct response likely) to “solving this system of equations...” (correct response unlikely for tools available in Fall 2023). Within-subjects analyses indicated that lessons in the course significantly increased trust in ChatGPT for correct-response-likely items. In addition, the lessons significantly decreased students' trust in ChatGPT for correct-response-unlikely items. There were no significant interactions between prior experience level and change in trust. These results show that guided exposure to GenAI helped first-year engineering students begin to understand capabilities and limitations of GenAI. These results are promising because student trust in GenAI output will directly impact decisions to engage with it for different tasks. More work is needed to optimize instruction and understand students' use of the tool beyond the classroom integration, including their full ethical decision-making process, but the malleability of trust at this level is an indication that engineering educators can impact student perspectives of GenAI.

Keywords—Generative AI, engineering education, trust.

I. INTRODUCTION

Generative Artificial Intelligence (GenAI) has been increasingly utilized since the public release of ChatGPT by OpenAI® in late 2022 [1]. GenAI chatbots like ChatGPT can respond to prompts with human-like sentences, explanations, summaries, images, and other creative products. This new technology has the potential to improve innovation in many disciplines, including engineering and computing, by facilitating learning and speeding up content production [2]. However,

GenAI sometimes generates incorrect information. Because current GenAI tools produce language that sounds authoritative and knowledgeable, users can be misled by incorrect GenAI responses. The consequences of the misinformation in engineering can be serious, because using an incorrect problem solution may lead to a product that fails. In engineering school, incorrect answers from GenAI may result in an engineering student failing to learn important concepts. Although this may not affect the public immediately, a lack of engineering student understanding of the tool's limitations could be substantially detrimental to our future society, and thus should be addressed immediately.

II. LITERATURE REVIEW

A. GenAI

GenAI refers to a branch of artificial intelligence that utilizes computational techniques to generate new, seemingly original content from existing data. User prompts are broken down into “tokens” (text units with associated properties) by a Generative Pre-trained Transformer (GPT), and responses are generated from the probabilistic assembly of other known tokens [3]. GPTs are developed using both supervised and unsupervised training, and with reinforcement learning from human feedback, which refines model outputs based on user interactions and preferences. The architecture supporting generative AI tools is a deep learning network, which is capable of handling various types of data including text, images, audio, and video [4].

B. Advantages and Limitations of GenAI in Education

GenAI offers several affordances that could enhance student learning at the undergraduate level. For example, GenAI tools can summarize text or ideas on-demand, reducing wait time for individualized feedback. GenAI tools can even write summaries and explanations in different tones, creating responses that

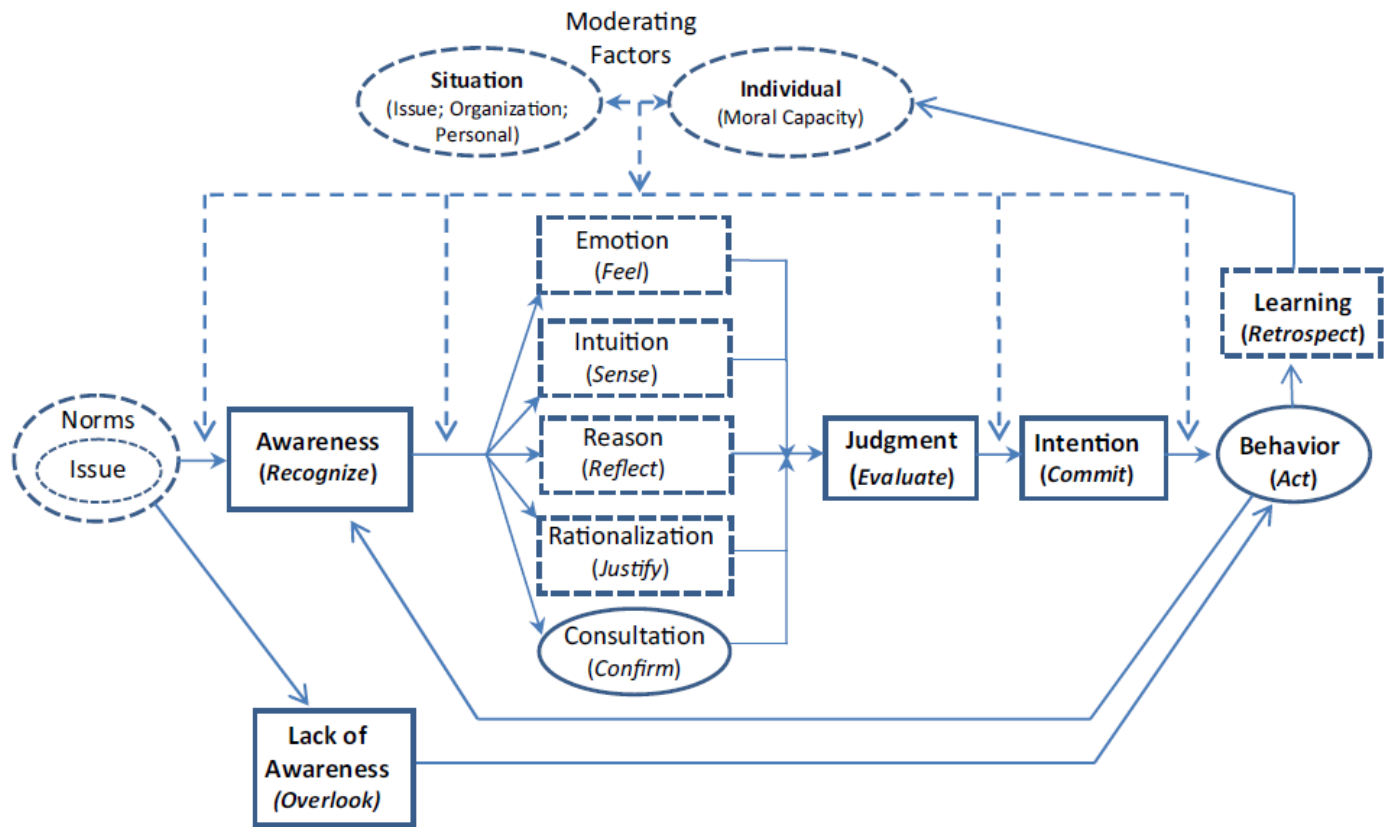


Figure 1: Schwartz's (2016) Integrated Ethical Decision-Making Framework [10].

sound more creative, balanced, or technical, and rewriting a response in different words can improve understanding [5], [6]. GenAI tools can be used to revise students' writing, helping with grammar or making suggestions regarding tone, punctuation, or diction. GenAI tools can also write computer code in multiple languages including C++, Swift, Java, and others [7].

In addition to helping students, there are potential affordances for instructors like automatic essay grading and text translation. This type of assistance could allow teachers to focus on educational design and responding to students, as well as help translate lessons to reach a wider audience [8].

However, GenAI tools are limited in several ways. Although they can describe the steps of problem-solving in mathematics, current GenAI tools cannot yet perform calculations or computations [3]. This limitation is particularly significant in engineering education, where students may try to ask for help on specific mathematical problems. An overlapping limitation is that GenAI tools can produce inaccurate information, sometimes called "hallucinations" [9]. Due to the carefully cultivated authoritative and knowledgeable tone, students may obtain false information and take it at face value, which could result in an insufficient understanding of the topic. It is currently not possible to identify the sources that helped to generate the responses of GenAI, so it can be difficult to verify the information within the responses.

There are additional ethical issues around GenAI tools in education. This technology is built on specific training data, which intrinsically has limitations, biases, as well as ownership claims. Plagiarism can be indirect or hidden and is more difficult to detect. Because GenAI is easily accessible, students may be tempted to use these tools to accomplish tasks instead of engaging with course topics more deeply.

The speed, wide knowledgebase, and accessibility of novel tools may allow students to use GenAI to improve their learning. However, the tools may also be used by students in an academically dishonest way which might reduce their learning.

C. Uses of GenAI, and Ethical Decision-Making

Whether GenAI is beneficial for or detrimental to learning depends on how students use it. Students may prompt a GenAI tool to complete an entire assignment, for example, which would circumvent the learning or practice opportunity. This type of use is a form of academic dishonesty, as students would be submitting work that is not their own. A good way to use GenAI, on the other hand, would be to ask for clarification on a topic. This use would support learning (if the correct information is given) and would not present an academic integrity issue.

Thus, deciding how to engage with GenAI tools is an ethical issue. According to theoretical frameworks (e.g., the Integrated Ethical Decision-Making Framework, Figure 1, [10]), ethical decision-making involves both rational and non-rational (i.e.,

emotional) cognitive processes that are activated and strengthened by contextual factors. Individual factors such as moral character disposition and integrity capacity also impact student decision-making. Procedurally, ethical decision-making begins with a student becoming aware of an ethical dilemma, such as whether and how to engage with GenAI to complete an assignment. In the next stage of decision-making, students judge or evaluate the scenario, drawing upon five different internal and interacting factors: emotion, intuition, reason, rationalization, and consultation. For example, students have emotions in and around the ethical scenario, and these feelings (e.g., excitement or anxiety about GenAI) affect decision-making even without students recognizing them cognitively. Rationalization, as another example, may appear as thoughts such as “it’s not that bad”, “technically it’s within bounds”, or “it’s just the one time.” Fundamentally, judgment and intention are both emotionally and rationally driven [10].

The final part of the decision-making model is the feedback loop. After performing an ethical or unethical action, consequences and retrospection affect future ethical decisions. For example, after deciding to use GenAI on one portion of a paper, a teacher could encourage or punish the action, which would impact how the student feels about the GenAI in future assignments.

D. Digital Literacy

Improving awareness, knowledge, and framing around GenAI is therefore likely to help students with ethical decision-making, and this fits into the concept of literacy. Digital literacy is “the constantly changing practices through which people make traceable meanings using digital technologies” [11]. Digital literacy has become increasingly more important with the emergence of internet technologies and information sources such as Google and Wikipedia. Without the understanding of how search engines and/or other online sources operate, students could often confuse trustworthy and untrustworthy sources, trusting incorrect information and mistrusting information from a reputable source [11]. Passively intaking knowledge, and complacency or ignorance around epistemic value can create inconspicuous gaps of knowledge as well as misconceptions.

This dangerous concept of epistemic ignorance is very relevant for students with respect to GenAI platforms. Although GenAI tools have many capabilities, trust in the output without critical analysis or understanding of the process and origins of the generated information can lead to misconceptions and gaps in knowledge. It is important that students do not passively absorb information from these sources without a general understanding of functionality and limitations.

E. Trust

Trust in human information sources arises from perceptions of accuracy, familiarity, and the source’s expressions of confidence or uncertainty (see [12] for a review). Likewise, although the ways in which people’s trust in artificial intelligence is measured varies greatly across studies [13], perceptions of a tool or agent’s reliability have been identified as a key factor in trust in AI-based technologies such as robots and virtual agents [14].

Recent research has begun to explore students’ trust specifically in ChatGPT. One consistent finding is that although students may hold positive views of ChatGPT, they often express concerns about its accuracy and reliability [15], [16], [17], [18]. These concerns may be heightened for fields such as engineering where precision and factual correctness are essential [16]. However, students in their first year of engineering school may not yet have fully developed beliefs about ChatGPT’s reliability. Recent work suggests that students’ trust in ChatGPT diminishes as they gain more knowledge in their fields [18]. For example, American students in an introductory level computer science course showed greater trust in ChatGPT than students in a higher level computer science course at the same university [15]. Likewise, masters level students in engineering who received training in ChatGPT and were then required to use it to complete an assignment showed an increased awareness of its limitations [19].

F. Current Study

In Fall 2023, we integrated GenAI instruction in an introductory engineering course, and assessed student perceptions of GenAI that may affect their ethical decision-making. We focus in this paper on students’ perceptions of accuracy and reliability, as these are likely to be critical elements of student’s trust in the outputs provided by ChatGPT. We hypothesized that students who had more experience with ChatGPT would show less trust in it, and that, overall, students would be more skeptical of its accuracy in the post-survey than they were in the pre-survey.

III. METHODOLOGY

This study was approved by the Institutional Review Board at the University of Louisville.

A. Participants

Study participants included all students who were enrolled in the University of Louisville’s J. B. Speed School of Engineering in Fall 2023 and participated in both pre- and post-surveys ($N = 339$). Data were excluded if participants indicated that they had no experience with ChatGPT at the end of the semester despite course integrations ($N = 6$), or if participants demonstrated a lack of engagement in the survey indicated by a lack of variability in responses across questions ($N = 11$) or an unreasonable answer on a manipulation-check question ($N = 11$).

B. Materials

Survey. The survey included a prior experience question and 12 trust items. All survey questions were created by the research team for the purposes of this project. The prior experience question was worded as follows:

How much experience have you had interacting with ChatGPT?

- a. None
- b. Minimal (I’ve tried it a few times)
- c. Moderate (I’ve tried it several times with a purpose in mind)
- d. Expert level (I’ve used it regularly for specific tasks)

The trust items were framed as follows:

What is the likelihood, on a scale of 1-100 (where 1 is extremely unlikely and 100 is extremely likely), that ChatGPT will return a correct answer to the following prompt?

The listed prompts were based on the first-year engineering course integrations as well as potential applications in the engineering profession. Researchers intentionally selected tasks for which ChatGPT was unlikely to return a correct answer as well as tasks for which ChatGPT was likely to return a correct answer, based on preliminary testing. Formal testing following the study revealed that some of the questions were not specific enough to allow for “correct” answers to be possible, and ChatGPT was likely to provide relevant information but not able to answer the question exactly. These questions were categorized as Correct Response Indeterminate for this study, as follows.

Correct Response Likely:

- *Explain how to use the Unit Circle for estimating sine and cosine values.*
- *What is the formula for calculating the circumference of a circle based on the radius?*
- *Write a python program of a menu with three functions: Function 1, Function 2, and Exit. Have the menu continue to execute in a loop until user selects the Exit function.*
- *Write a program to calculate the distance between two latitude and longitude points.*
- *List some recent engineering solutions to the grand challenge of engineering “making solar energy economical.”*

Correct Response Indeterminate:

- *What was the exchange rate between the dollar and the euro in 2006?*
- *What is the friction coefficient for sandpaper?*

Correct Response Unlikely:

- *What is the distance between these two coordinates? (522222,10), (5222291, 49023)*
- *Solve this system of equations:*
 $10x + y = 26$
 $3x + 2y = 8$
- *Solve this system of equations:*
 $10x + y - 2a + b = 26$
 $3x + 2y + a + 2b = 8$
 $-x + 10y + a + 2b = 8$
 $2x - 3y - 2a + b = -4$
- *Describe the grand challenge of engineering “making solar energy economical” with references.*

Technology. ChatGPT-3.5 was used in this study, as it was the free-access version of the tool at the time.

Course Integration. ChatGPT was introduced as a tool at the end of a lecture on engineering ethics and professionalism. In the lesson, students were instructed to make an account, and to validate some of ChatGPT’s responses with a Google search.

The lesson demonstrated that ChatGPT could not reliably perform computations and also could hallucinate, especially when requested to provide information sources or references.

Following this lesson, ethical and appropriate uses of ChatGPT were incorporated into two team projects. The first project was to research and report on one of the Grand Challenges for engineering in the 21st century [20] and some recent engineering solutions. Students were encouraged to use ChatGPT for ideation and identification of engineering solutions, but to verify all information provided by ChatGPT with additional sources. They were also taught how to cite ChatGPT in different contexts. In the second project, they used ChatGPT for programming, and were taught to both plan and review all generated program syntax, evaluating it with relevant test cases. Teams were required to turn in their Python programs as well as a code documentation file with details on the development and testing of the code. Further information about the course integrations is available upon request from the first author.

C. Procedures

The surveys were administered through Blackboard®, the campus-wide learning management system. The first survey was conducted at the beginning of class on the day ChatGPT was introduced in class, and the second survey was given on the last day of class.

Data was extracted, coded, and analyzed after all course grades were submitted at the end of the semester. Average trust in each category was calculated for each student. Most calculated variables had significant positive skews. Outliers for each variable, such as 0% trust in the Correct-Likely category were not removed from the study, as we were looking for changes in trust over the course of the semester for all students.

Data analysis included three mixed-factorial ANOVAs, one for each trust category, with a within-subjects factor of time (pre- or post-survey) and a between-subjects factor of prior experience (None, Minimal, Moderate, or Expert Level). Simple main effects were assessed with planned comparisons, as intended in the research design. Although normality is assumed in ANOVAs, they are relatively robust to normality violations. Future work will consider alternative analytical procedures for further data analysis.

IV. RESULTS

As reported in [21], participants’ experience with ChatGPT prior to the course integration was distributed as follows:

None, $N = 107$, 31.6%

Minimal, $N = 128$, 37.8%

Moderate, $N = 85$, 25.1%

Expert level, $N = 19$, 5.6%

For Correct Response Likely items, the mixed factorial repeated measures ANOVA revealed a significant main effect of time, $F(1, 335) = 3.93$, $p = .048$, $\eta_p^2 = .01$, with a positive change in trust from the pre-survey ($M = 78.7$, $SE = 1.2$) to the post-survey ($M = 81.2$, $SD = .96$). There was also a main effect of prior-experience, $F(3, 335) = 4.91$, $p = .002$, $\eta_p^2 = .04$. Students

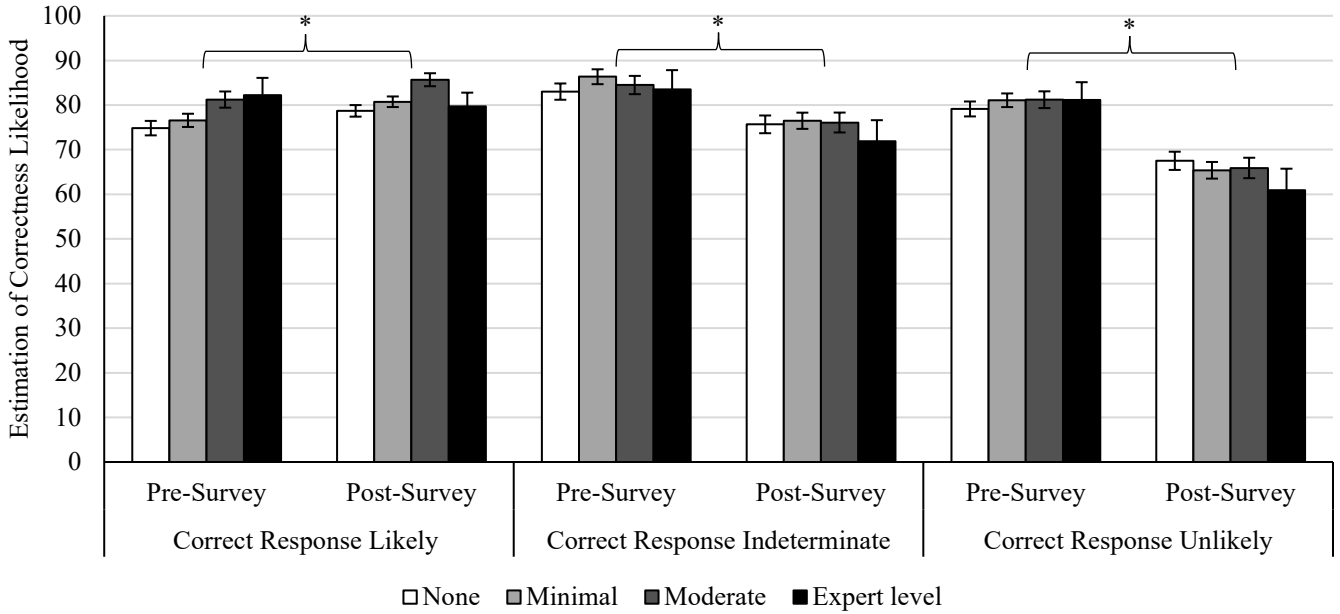


Figure 2: Student responses to trust questions in the pre- and post-survey, averaged across questions for which correct responses were Likely, Indeterminate, and Unlikely, and separated by experience level at the beginning of the semester. Mean responses shown with error bars representing ± 1 standard error. * indicates statistically significant change from pre-survey to post-survey for all students.

who had Moderate experience levels had significantly higher trust ($M = 83.5$, $SE = 1.3$) than students with no ($M = 76.8$, $SE = 1.2$) or minimal ($M = 78.7$, $SE = 1.1$) experience, with no other significant differences. The interaction between prior experience and time was not significant, $F < 1$. Mean student responses for all categories are shown in Figure 2.

For Correct Response Indeterminate items, there was again a significant main effect of time, $F(1, 335) = 33.74$, $p < .001$, $\eta_p^2 = .09$, with a negative change in trust from the pre-survey ($M = 84.3$, $SE = 1.3$) to the post-survey ($M = 75.0$, $SD = 1.5$). The effect of prior experience was not significant, $F < 1$, and the interaction between prior experience and time was not significant, $F < 1$.

For Correct Response Unlikely items, there was also a significant main effect of time, $F(1, 335) = 87.15$, $p < .001$, $\eta_p^2 = .21$, with a negative change in trust from the pre-survey ($M = 80.64$, $SE = 1.2$) to the post-survey ($M = 64.9$, $SD = 1.5$). There was not a significant effect of prior experience, $F < 1$, and the interaction between prior experience and time was not significant, $F = 1.05$, $p = .371$.

V. DISCUSSION

In summary, there was a significant increase in trust over time for items where correct responses were likely to occur, while there was a significant reduction in trust over time for items that were indeterminate or where correct responses were unlikely. These results indicate that students improved in the identification and differentiation across tasks, which was a key learning outcome of the GenAI course interventions. The means indicate that at the beginning of the semester, students were unable to differentiate correctly between capabilities and

limitations of ChatGPT. However, at the end of the semester, students' were able to recognize what types of questions ChatGPT answers reliably or unreliably. This is important, because students' abilities to recognize capabilities and limitations of GenAI can help them use it more appropriately. Increased exposure and experience with ChatGPT enabled the users to become familiar with the program's abilities, enhancing digital literacy.

Although results demonstrated an increase in student recognition of ChatGPT's capabilities (and limitations), student trust in GenAI was still relatively high on the scale for correct-response-unlikely items at end of semester (over 60% on average). This could be because the lesson that explained GenAI limitations was short. That said, the effect size of the change over the semester ($\eta_p^2 = .21$) indicated that even this single lesson decreased trust in a meaningful way, and more time or experience may result in better student understanding of the limitations of GenAI tools. Moreover, prior experience with ChatGPT was related to students' recognition of its strengths, but was not related to their trust in information that ChatGPT cannot reliably provide. This indicates that the experience obtained in class similarly gave students similar contexts for limitations, which can be improved in future integrations.

More work is needed to fully de-mythicize GenAI. One powerful way to help students understand the capabilities and limitations of GenAI is to integrate GenAI-literacy as official course outcomes, with time in class, activities, and evaluated assignments. Additional work is needed to understand and improve students' ethical understanding and use of GenAI tools in education.

A. Limitations

This study was conducted with one cohort at one university at a single point in time. The generalizability of the results is therefore untested. In addition, the survey items had not been validated or analyzed outside of the present work. However, the framing of the trust questions as objective evaluations of likelihood was based on established practices in experimental psychology. The novelty of GenAI is such that validated survey scales are still being established, and these survey items were a good starting point.

The quantitative pre-post survey design is also limited in that it only tests mean scores across the class. Little is known about individual students' experiences interacting with GenAI, engagement with the assignments, and how and when trust values changed. This information would help to further develop course integrations.

VI. CONCLUSION

In this paper, we examined student trust in GenAI to give accurate and reliable outputs, and whether students' experience influences their trust in GenAI. This study revealed that an in-course lesson about GenAI and two assignments that integrated uses of GenAI changed students' trust in GenAI outputs. Students' trust significantly increased for items that are likely to produce correct responses, and significantly decreased for items that were indeterminate, or likely to produce incorrect responses. These results indicate that course integrations successfully improved students' understand of the capabilities and limitations of GenAI. More work like this is needed to support our current engineering students as well as understand what needs to change within engineering education due to the existence of modern GenAI tools.

VII. REFERENCES

- [1] OpenAI, "Introducing ChatGPT." Accessed: Dec. 01, 2023. [Online]. Available: <https://openai.com/blog/chatgpt>
- [2] J. Qadir, "Engineering Education in the Era of ChatGPT: Promise and Pitfalls of Generative AI for Education," in *2023 IEEE Global Engineering Education Conference (EDUCON)*, May 2023, pp. 1–9. doi: 10.1109/EDUCON54358.2023.10125121.
- [3] E. Mollick, *Co-Intelligence: Living and Working with AI*. New York: Portfolio, 2024.
- [4] S. Feuerriegel, J. Hartmann, C. Janiesch, and P. Zschech, "Generative AI," *Bus. Inf. Syst. Eng.*, vol. 66, no. 1, pp. 111–126, Feb. 2024, doi: 10.1007/s12599-023-00834-7.
- [5] Y. Chen, S. Jensen, L. J. Albert, S. Gupta, and T. Lee, "Artificial Intelligence (AI) Student Assistants in the Classroom: Designing Chatbots to Support Student Success," *Inf. Syst. Front.*, vol. 25, no. 1, pp. 161–182, Feb. 2023, doi: 10.1007/s10796-022-10291-4.
- [6] R. Kaplan-Rakowski, K. Grotewold, P. Hartwick, and K. Papin, "Generative AI and Teachers' Perspectives on Its Implementation in Education," *J. Interact. Learn. Res.*, vol. 34, no. 2, pp. 313–338, 2023.
- [7] B. A. Anders, "Why ChatGPT is such a big deal for education," C2C Digital Magazine (Fall 2022 - Winter 2023). Accessed: Apr. 24, 2024. [Online]. Available: <https://scalar.usc.edu/works/c2c-digital-magazine-fall-2022---winter-2023/why-chatgpt-is-bigdeal-education>
- [8] D. Baidoo-Anu and L. Owusu Ansah, "Education in the Era of Generative Artificial Intelligence (AI): Understanding the Potential Benefits of ChatGPT in Promoting Teaching and Learning," Jan. 25, 2023, *Rochester, NY*: 4337484. doi: 10.2139/ssrn.4337484.
- [9] OpenAI *et al.*, "GPT-4 Technical Report," Mar. 04, 2024, *arXiv*: arXiv:2303.08774. doi: 10.48550/arXiv.2303.08774.
- [10] M. S. Schwartz, "Ethical Decision-Making Theory: An Integrated Approach," *J. Bus. Ethics*, vol. 139, no. 4, pp. 755–776, Dec. 2016, doi: 10.1007/s10551-015-2886-8.
- [11] I. Bhatt and A. MacKenzie, "Just Google It! Digital Literacy and the Epistemology of Ignorance," *Teach. High. Educ.*, vol. 24, no. 3, pp. 302–317, 2019, doi: 10.1080/13562517.2018.1547276.
- [12] P. L. Harris, M. A. Koenig, K. H. Corriveau, and V. K. Jaswal, "Cognitive Foundations of Learning from Testimony," *Annu. Rev. Psychol.*, vol. 69, no. Volume 69, 2018, pp. 251–273, Jan. 2018, doi: 10.1146/annurev-psych-122216-011710.
- [13] O. Vereschak, G. Bailly, and B. Caramiaux, "How to Evaluate Trust in AI-Assisted Decision Making? A Survey of Empirical Methodologies," *Proc. ACM Hum.-Comput. Interact.*, vol. 5, no. CSCW2, p. 327:1-327:39, Oct. 2021, doi: 10.1145/3476068.
- [14] E. Glikson and A. W. Woolley, "Human Trust in Artificial Intelligence: Review of Empirical Research," *Acad. Manag. Ann.*, vol. 14, no. 2, pp. 627–660, Jul. 2020, doi: 10.5465/annals.2018.0057.
- [15] M. Amoozadeh *et al.*, "Trust in Generative AI among students: An Exploratory Study," Oct. 06, 2023, *arXiv*: arXiv:2310.04631. doi: 10.48550/arXiv.2310.04631.
- [16] C. Baek, T. Tate, and M. W. Uci, "'ChatGPT Seems Too Good to be True': College Students' Use and Perceptions of Generative AI," Dec. 12, 2023, *OSF*. doi: 10.31219/osf.io/6tjpk.
- [17] A. Shoufan, "Exploring Students' Perceptions of ChatGPT: Thematic Analysis and Follow-Up Survey," *IEEE Access*, vol. 11, pp. 38805–38818, 2023, doi: 10.1109/ACCESS.2023.3268224.
- [18] X. Xu, Y. Su, Y. Zhang, Y. Wu, and X. Xu, "Understanding learners' perceptions of ChatGPT: A thematic analysis of peer interviews among undergraduates and postgraduates in China," *Heliyon*, vol. 10, no. 4, p. e26239, Feb. 2024, doi: 10.1016/j.heliyon.2024.e26239.
- [19] M. Bernabei, S. Colabianchi, A. Falegnami, and F. Costantino, "Students' use of large language models in engineering education: A case study on technology acceptance, perceptions, efficacy, and detection chances," *Comput. Educ. Artif. Intell.*, vol. 5, p. 100172, Jan. 2023, doi: 10.1016/j.cacai.2023.100172.
- [20] National Academy of Engineering "Grand Challenges for Engineering." Accessed: Apr. 24, 2024. [Online]. Available: <https://www.engineeringchallenges.org/>
- [21] C. R. Bego *et al.*, "Working Towards GenAI Literacy: Assessing First-Year Engineering Students' Attitudes towards, Trust in, and Ethical Opinions of ChatGPT," presented at the American Society for Engineering Education Annual Conference, 2024.