Received: 1 June 2023 | Accepted: 3 June 2023

DOI: 10.1002/jee.20539

GUEST EDITORIAL

JEE
Journal of Engineering Education

Envisioning the future of learning and teaching engineering in the artificial intelligence era: Opportunities and challenges

1 | INTRODUCTION

Generative artificial intelligence (AI) technologies, such as large language models (LLMs) and diffusion model image and video generators, can transform learning and teaching experiences by providing students and instructors with access to a vast amount of information and create innovative learning and teaching materials in a very efficient way (e.g., U.S. Department of Education, 2023; Kasneci et al., 2023; Mollick & Mollick, 2023; Nikolic et al., 2023). For example, Google Bard and OpenAI ChatGPT are LLMs that can generate natural language texts for various purposes, such as summaries of research papers (e.g., OpenAI, 2023). At the same time, Midjourney and DeepBrain AI are diffusion models that can create diagrams (e.g., concept maps), images, and videos from textual or visual inputs. Engineering education, in particular, can benefit from integrating and utilizing generative AI technologies to improve instructional resources, develop new technology-enhanced learning environments, reduce instructors' workloads, and provide students with opportunities to design and develop their learning experiences. These technologies can help educators to create more personalized, effective, and engaging learning experiences for engineering students.

Most engineering students struggle to acquire a deep understanding of complex engineering concepts because of the nature of the highly mathematical concepts, lack of prior knowledge, limitations of the large lectures, limited resources that prevent the use of commercially available lab equipment, and the lack of innovative teaching tools that could be utilized to enhance learning experiences (e.g., Menekse et al., 2018, 2022; Miller et al., 2011; Reeves & Crippen, 2021; Streveler & Menekse, 2017). These factors adversely affect retention and graduation rates and inhibit persistence in engineering majors (e.g., Estrada et al., 2016). Generative AI technologies and tools (e.g., CourseMIRROR) could support engineering educators to improve students' learning and engagement (e.g., Fan et al., 2015; Luo et al., 2015; Menekse, 2020).

2 | BENEFITS OF USING AI TECHNOLOGIES FOR TEACHING AND LEARNING PURPOSES

LLMs can be used to create personalized learning experiences for engineering students (e.g., Balakrishnan & Long, 2020). As an example, this can be done by providing students with different learning activities and related practice problems at different difficulty levels based on students' prior success and their misunderstanding of certain concepts. Generative AI technologies can be used to produce practice problems that can help students to prepare for exams and learn new concepts (Mollick & Mollick, 2023). They can also generate solutions and provide step-by-step explanations, similar to what human tutors do (Roscoe & Chi, 2007). When students succeed at practice problems, the benefits are amplified. However, if students become discouraged by poorly designed problems or learning activities, they often lose interest and will not receive the full benefits of the practice they have done. Adaptive practice problems at different difficulty levels generated by specific LLMs could be quite beneficial for learning purposes (Alevin et al., 2016; Walker et al., 2015).

Since new AI tools can generate text and images in response to natural language prompts, students can also create their own learning experiences based on their interests. An AI tool could be used to create a virtual learning environment where students can access a variety of engineering resources and challenges. For example, with the rapid developments in diffusion models that can create images and videos from textual inputs, it would not be surprising to have access to AI tools that could be used to generate 3D models of different bridge designs for an engineering statics course.

 |

Currently, tools such as Midjourney or DiffusionBee can successfully generate realistic images with textual input (Dawani, 2023), and anyone can create different bridge images with some textual prompts. With significant progress on these AI models, in the near future these types of AI tools would allow students to explore different bridge designs from different angles and better understand how they work and can fail under different circumstances. These AI tools can also give learners more autonomy in their decision of what to learn, when to learn, and how to learn, as well as allow them to pace and monitor their learning progress.

Likewise, LLMs and AI-based media generators can also produce virtual laboratories and simulations for engineering courses that may simulate physical experiments. AI-powered virtual laboratories customized for engineering courses to simulate and visualize fundamental engineering concepts could be very effective for teaching and learning purposes. For instance, in a fluid mechanics class, an AI tool could help instructors to create a simulation of a fluid flow system that can support students to experiment with different parameters and see the effects of their changes. AI-powered virtual laboratories and simulations can provide learners with a cost-effective environment to practice and apply their skills and knowledge (e.g., Koretsky et al., 2008). Previous research shows that virtual experiences complement the physical lab experience, and when virtual laboratories are coupled with traditional courses and physical laboratories, it provides meaningful and fulfilling learning experiences that are greater than the sum of their parts (e.g., Koretsky et al., 2008; Reeves & Crippen, 2021).

Another useful learning strategy that LLMs can amplify is to provide students with real-time feedback on their work. This can help students to identify areas where they need to focus on, and real-time feedback can also improve students' cognitive engagement. With rapid advances in AI technology, AI tutors or digital learning companions, for example, can become more effective in supporting students by providing personalized feedback, simplifying complex concepts, and assessing students' understanding. Students can also shape how these AI tutors behave and interact with them by prompting these AI tutors to make connections with the ideas or approaches that they find meaningful and engaging.

An alternative approach can be utilizing the "learning by teaching" method to create opportunities for learners. The learning by teaching strategy is based on the idea that students learn best when they are actively engaged in the process of teaching others (Chi et al., 2001; Duran & Topping, 2017). Similar to existing teachable agents, like "Betty's Brain" (Chase et al., 2009; Leelawong & Biswas, 2008), AI tools can be used to generate teachable agents for different goals, so students can interact with these digital agents to better understand the concepts that they are learning. When students need to explain a concept to someone else (whether a real person or a digital system), they have to think about it in a different way, identify the key points, and communicate their ideas clearly. These processes can help them to develop a deeper understanding of the material.

3 | RISKS AND CONCERNS FOR USING AI TECHNOLOGIES FOR TEACHING AND LEARNING PURPOSES

There are also some concerns associated with using LLMs in engineering education. One of the main concerns is that LLMs can sometimes generate inaccurate or misleading information. LLMs are trained on large amounts of uncontrolled data, and these types of data typically include a large number of errors. For instance, an LLM may generate a wrong formula or definition for an engineering concept, or it may generate a text that contradicts the facts. Similarly, LLMs can be biased, which can lead to discrimination against certain groups of students. An AI tool may generate a text, image, or video that stereotypes students based on their gender, race, ethnicity, or disability (e.g., Akgun & Greenhow, 2022; Sun et al., 2023). This is also because they are trained on data that is often biased. Moreover, LLMs cannot always understand the nuances of human language and culture. Similarly, it can generate an image or video that might be offensive or inappropriate for certain cultural values. Thus, engineering educators need to evaluate and curate whether the AI-generated output is suitable and valuable for teaching and learning purposes.

Privacy of student data is another concern. LLMs can collect and store students' data, which may raise privacy concerns. Likewise, LLMs can use the data they collect to create detailed student profiles. These profiles may include students' learning progress, performance, and behaviors on different digital platforms. This can be concerning for data privacy. Lastly, LLMs can be vulnerable to security breaches, which can lead to the exposure of student data. Such breaches can have severe consequences for both students and instructors. It is also important to note that the compliance of these AI systems with FERPA (The Family Educational Rights and Privacy Act) rules needs to be considered in the context of legal frameworks.

AI tools can also lower the cognitive load to a degree that can inhibit students' transfer of learning. As the literature suggests, cognitive load indicates the amount of mental effort that is required to process information and perform a task (Sweller, 1988; Van Merrienboer & Sweller, 2005). Although AI tools can help students reduce their cognitive load by providing them with information, feedback, and support, these tools can also lower the cognitive load to a degree that can deter students' transfer of learning. One reason why AI technologies can stall learning is that they can reduce students' engagement, motivation, and self-regulation. When students rely too much on AI tools, they may lose interest and curiosity in the subject matter and may not develop a deep understanding of the concepts (Chou & Chan, 2016; Nie et al., 2023). They may also struggle to develop self-monitoring skills of their own learning process. Eventually, students may become passive learners who do not actively seek challenges and opportunities to apply their knowledge and skills (e.g., Menekse et al., 2013; Streveler & Menekse, 2017). Therefore, it is critical for educators to utilize AI tools in a balanced and proper way. The learning activities, environments, and expectations are needed to be designed in a way that requires students to use AI tools as a supplement, not a substitute, to develop their own thinking and reasoning. Engineering educators can use AI tools to challenge students to think critically and creatively about the subject matter by providing questions or scenarios that require students to evaluate or synthesize information. For instance, in an engineering statistics class, educators can use an AI tool to generate "fake" datasets for a specific scenario. Then, they can ask students to conduct certain statistical analyses with this AI-generated dataset and evaluate the results in a specific context (e.g., using the Six Sigma concepts).

Finally, engineering educators need to reconsider the assessment of learning in the age of AI technologies (Nikolic et al., 2023). Based on the Open AI GPT-4 Technical Report (OpenAI, 2023), the GPT-4 model already performs very well on standardized tests (e.g., 89th percentile on SAT Math, 99th percentile on GRE Verbal). AI tools can affect students' performance on both high-stakes examinations and low-stakes formative tasks. AI tools can change the nature and scope of student learning, and assessment of learning needs to focus on not only students' recall of factual information but their higher order thinking skills. Accordingly, AI tools pose significant challenges to how to assess student knowledge and what to assess as well (Bearman et al., 2020). Likewise, academic integrity is another major challenge that needs to be reimagined in the age of AI (e.g., Huang, 2023). AI tools can help students generate texts, images, and other types of academic outputs with minimal effort. These tools can also enable students to plagiarize their work by using an LLM to generate a report without citing the source or acknowledging the contribution of the AI tools. Therefore, it is critical to consider the ethical use of AI tools, and develop and implement relevant policies and practices that can prevent and detect academic dishonesty (Akgun & Greenhow, 2022).

4 | CONCLUSION

As AI technologies continue to evolve, we can expect to see more innovative ways to use AI tools to improve the engineering education experience. Engineering educators and policymakers need to consider how to integrate AI tools effectively and ethically into various aspects of learning and teaching experiences. Although there are significant challenges to utilize AI tools for learning and teaching purposes, it is possible to use AI to supplement and support student learning by providing opportunities for learners to refine and monitor their understanding and progress. As discussed in this guest editorial, engineering educators need to be aware of the potential risks of AI tools before integrating them into their classrooms. Additionally, they need to use AI systems in a way that supports student learning and engagement. And they also need to be transparent about how AI tools are being used, and share the potential benefits and drawbacks with their students. It is especially crucial to discuss academic integrity with students regarding what you expect and what is unacceptable usage of AI tools for your class and assignments. With strategic curating and expert oversight by instructional teams and curriculum developers, AI tools can support educators in creating engaging learning environments that make learning more meaningful and personalized. Moreover, AI tools can free up time for engineering instructors to focus on important instructional work, such as facilitating classroom discussions, mentoring students, and monitoring students' teamwork, while significantly reducing time spent on some instructional tasks by assisting with grading and generating ideas to develop different assignments.

Muhsin Menekse[1,2]

[1]*School of Engineering Education, Purdue University, West Lafayette, Indiana, USA*
[2]*Department of Curriculum and Instruction, Purdue University, West Lafayette, Indiana, USA*

Correspondence
Muhsin Menekse, School of Engineering Education, Purdue University, West Lafayette, IN, USA.
Email: menekse@purdue.edu

ORCID

Muhsin Menekse https://orcid.org/0000-0002-5547-5455

REFERENCES

Akgun, S., & Greenhow, C. (2022). Artificial intelligence in education: Addressing ethical challenges in K–12 settings. *AI Ethics*, *2*, 431–440. https://doi.org/10.1007/s43681-021-00096-7

Alevin, V., McLaughlin, E. A., Glenn, R. A., & Koedinger, K. R. (2016). Instruction based on adaptive learning technologies. In R. E. Mayer & P. A. Alexander (Eds.), *Handbook of research on learning and instruction* (pp. 522–560). Routledge. ISBN: 113883176X.

Balakrishnan, B., & Long, C. Y. (2020). An effective self-directed personalized learning environment for engineering students during the COVID-19 pandemic. *Advances in Engineering Education*, *8*(4), 1–8.

Bearman, M., Boud, D., & Ajjawi, R. (2020). New directions for assessment in a digital world. In M. Bearman, P. Dawson, R. Ajjawi, J. Tai, & D. Boud (Eds.), *Re-imagining university assessment in a digital world* (pp. 7–18). *The enabling power of assessment* (Vol. 7). Springer. https://doi.org/10.1007/978-3-030-41956-1_2

Chase, C. C., Chin, D. B., Oppezzo, M. A., & Schwartz, D. L. (2009). Teachable agents and the Protégé effect: Increasing the effort towards learning. *Journal of Science Education and Technology*, *18*(4), 334–352. https://doi.org/10.1007/s10956-009-9180-4

Chi, M. T. H., Siler, S. A., Jeong, H., Yamauchi, T., & Hausmann, T. (2001). Learning from human tutoring. *Cognitive Science*, *25*(4), 471–533. https://doi.org/10.1016/S0364-0213(01)00044-1

Chou, C. Y., & Chan, T. W. (2016). Reciprocal tutoring: Design with cognitive load sharing. *International Journal of Artificial Intelligence in Education*, *26*, 512–535.

Dawani, S. (2023). *Integrating artificial intelligence into creativity education: Developing a creative problem-solving course for higher education*. Creative Studies Graduate Student Master's Projects. https://digitalcommons.buffalostate.edu/creativeprojects/363

Duran, D., & Topping, K. J. (2017). *Learning by teaching: Evidence-based strategies to enhance learning in the classroom*. Routledge.

Estrada, M., Burnett, M., Campbell, A. G., Campbell, P. B., Denetclaw, W. F., Gutiérrez, C. G., Hurtado, S., John, G. H., Matsui, J., McGee, R., Okpodu, C. M., Robinson, T. J., Summers, M. F., Werner–Washburn, M., & Zavala, M. (2016). Improving underrepresented minority student persistence in STEM. *CBE—Life Sciences Education*, *15*(3), es5. https://doi.org/10.1187/cbe.16-01-0038

Fan, X., Luo, W., Menekse, M., Litman, D., & Wang, J. (2015). Course MIRROR: enhancing large classroom instructor-student interactions via mobile interfaces and natural language processing. *Proceedings of the 33rd Annual ACM Conference Extended Abstracts on Human Factors in Computing Systems (CHI EA '15)* (pp. 1473–1478). Association for Computing Machinery. https://doi.org/10.1145/2702613.2732853

Huang, K. (2023). *Alarmed by AI chatbots, universities start revamping how they teach*. New York Times. https://www.nytimes.com/2023/01/16/technology/chatgpt-artificial-intelligence-universities.html

Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Kasneci, E., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., … Kasneci, G. (2023). Chat GPT for good? on opportunities and challenges of large language models for education. *Learning and Individual Differences*, *103*, 102274. https://doi.org/10.1016/j.lindif.2023.102274

Koretsky, M. D., Amatore, D., Barnes, C., & Kimura, S. (2008). Enhancement of student learning in experimental design using a virtual laboratory. *IEEE Transactions on Education*, *51*(1), 76–85.

Leelawong, K., & Biswas, G. (2008). Designing learning by teaching agents: The Betty's brain system. *International Journal of Artificial Intelligence in Education*, *18*(3), 181–208.

Luo, W., Fan, X., Menekse, M., Wang, J., & Litman, D. (2015). Enhancing instructor-student and student-student interactions with mobile interfaces and summarization. *Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Demonstrations* (pp. 16–20, May 31 – June 5, 2015). https://doi.org/10.3115/v1/N15-3004

Menekse, M. (2020). The reflection-informed learning and instruction to improve students' academic success in undergraduate classrooms. *The Journal of Experimental Education*, *88*(2), 183–199. https://doi.org/10.1080/00220973.2019.1620159

Menekse, M., Anwar, S., & Akdemir, Z. G. (2022). How do different reflection prompts affect engineering students' academic performance and engagement? *The Journal of Experimental Education*, *90*(2), 261–279.

Menekse, M., Anwar, S., & Purzer, S. (2018). Self-Efficacy and mobile learning technologies: A case study of course MIRROR. In C. Hodges (Ed.), *Self-efficacy in instructional technology contexts*. Springer. https://doi.org/10.1007/978-3-319-99858-9_4

Menekse, M., Stump, G., Krause, S., & Chi, M. T. H. (2013). Differentiated overt learning activities for effective instruction in engineering classrooms. *Journal of Engineering Education*, *102*(3), 346–374. https://doi.org/10.1002/jee.20021

Miller, R. L., Streveler, R. A., Yang, D., & Santiago Román, A. I. (2011). Identifying and repairing student misconceptions in thermal and transport science: Concept inventories and schema training studies. *Chemical Engineering Education*, *45*(3), 203–210.

Mollick, E. R., & Mollick, L. (2023). *Using AI to implement effective teaching strategies in classrooms: five strategies, including prompts* (March 17, 2023). Available at SSRN: https://ssrn.com/abstract=4391243 or https://doi.org/10.2139/ssrn.4391243

Nie, J., Yuan, Y., Chao, X., Li, Y., & Lv, L. (2023). In smart classroom: Investigating the relationship between human–computer interaction, cognitive load and academic emotion. *International Journal of Human–Computer Interaction*. https://doi.org/10.1080/10447318.2023.2190257

Nikolic, S., Daniel, S., Haque, R., Belkina, M., Hassan, G. M., Grundy, S., Lyden, S., Neal, P., & Sandison, C. (2023). ChatGPT versus engineering education assessment: A multidisciplinary and multi-institutional benchmarking and analysis of this generative artificial intelligence tool to investigate assessment integrity. *European Journal of Engineering Education*. https://doi.org/10.1080/03043797.2023.2213169

OpenAI. (2023). *GPT-4 technical report*. https://arxiv.org/pdf/2303.08774.pdf

Reeves, S. M., & Crippen, K. J. (2021). Virtual laboratories in undergraduate science and engineering courses: A systematic review, 2009–2019. *Journal of Science Education and Technology*, *30*, 16–30.

Roscoe, R. D., & Chi, M. T. (2007). Understanding tutor learning: Knowledge-building and knowledge-telling in peer tutors' explanations and questions. *Review of Educational Research*, *77*(4), 534–574.

Streveler, R., & Menekse, M. (2017). Taking a closer look at active learning. *Journal of Engineering Education*, *106*(2), 186–190. https://doi.org/10.1002/jee.20160

Sun, L., Wei, M., Sun, Y., Suh, Y. J., Shen, L., & Yang, S. (2023). *Smiling women pitching down: Auditing representational and presentational gender biases in image generative AI*. arXiv preprint arXiv:2305.10566.

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science*, *12*(2), 257–285.

U.S. Department of Education. (2023). *Artificial intelligence and future of teaching and learning: Insights and recommendations*. Office of Educational Technology. https://tech.ed.gov/ai-future-of-teaching-and-learning/

Van Merrienboer, J. J., & Sweller, J. (2005). Cognitive load theory and complex learning: Recent developments and future directions. *Educational Psychology Review*, *17*, 147–177.

Walker, E., Rummel, N., & Koedinger, K. R. (2015). Adaptive intelligent support to improve peer tutoring in algebra. *International Journal of Artificial Intelligence in Education*, *24*, 33–61. https://doi.org/10.1007/s40593-013-0001-9