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Education in Data Science

# Discussion of "Addressing the Challenges of AI-Generated Assignment Submissions in Education: Insights and Strategies"☆

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Wang and colleagues have done a commendable job laying out the landscape of artificial intelligence (AI) in education, specifically in the domains of data science and related fields (Wang et al., 2026). They provide numerous suggestions for assessments in a world where AI is a constant presence in the lives of our students. Many of their suggestions are commonly used in humanistic fields, but much less frequently in technical courses. While each of these suggestions has its own pros and cons, as a whole they make for a grounded approach to assessing the knowledge and skills of data science students. I find the last two, *Promoting AI Literacy and Ethical Use* and *Encouraging Human-AI Collaboration*, to be the most likely to meaningfully respond to the new era of AI in education.

When developing assessments, it is imperative to consider both the current state of AI and the learning goals of a specific program or course. Doing so may help instructors choose among the options Wang and colleagues propose as well as determine details of given assessments within these categories. The state of artificial intelligence includes both its accessibility as well as its technical "knowledge" or "ability." AI is already readily accessible for free through smartphone and computer apps and is constantly being incorporated into more tools. It is already nearly impossible to impose a meaningful AI ban on any assignment given to students to complete outside the classroom (Bertram Gallant and Rettinger, 2025). The ubiquity of AI tools means an enforceable ban on AI will only be possible when students are being assessed in real time with in-person instructor oversight, and even then enforcement may be difficult. As with accessibility, AI's technical knowledge has grown over time. The gap between questions which are clear and explicit enough that an early undergraduate student can understand but which are too complicated for AI is vanishingly small, if not already gone. With this as the current state of AI, and a general expectation that AI will continue to improve in both the short and long term, it may be time to reconsider program and course learning objectives along with assessments.

The most obvious place to address the rise of AI is in program learning outcomes, where topics like AI literacy, AI ethics, and facility with AI tools should be included in modern data science and related programs. Some of these topics may require new courses, but we can also reconsider the goals and expectations of the courses we currently teach. In introductory or service courses, we may have steered away from too much coding because the learning curve is steep (Sun et al., 2025). Do tools like GitHub Copilot lower the barrier to entry for novice students? Do they allow new students to more quickly create more attractive data visualizations or more interesting analyses? If so, maybe we should take advantage of these tools to show students the abilities that are just within their grasp. In the same way we often hold off highly mathematical

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courses for later semesters, we are reaching the point where we can now do the same with coding. An AI-forward approach in early courses could hook some students and build confidence where abstract concepts seemed too distant from their interests and too much coding created barriers.

In more advanced courses students certainly should be developing coding skills and understanding of fundamental concepts and best practices. In this setting, we need to treat AI as a new tool to help with the mundane tasks, not to replace human engagement (Mollick, 2024). This will require giving some amount of grace to students in terms of AI and academic integrity, as we are all learning these new tools and their capabilities together. We cannot boil such a sophisticated tool down to a list of dos and don'ts in a syllabus statement, nevertheless one simple enough we expect students to fully understand and remember (Bertram Gallant and Rettinger, 2025). Our expectations may even change throughout the semester. Academic integrity policies which are too rigid with regards to AI might scare students from seeking honest feedback about their workflow and stifle their long-term growth (Bertram Gallant and Rettinger, 2025). I am experimenting with the language of allowing "judicious use" of artificial intelligence in my academic integrity policies. This includes a plan to have one-on-one and small group discussions as needed to focus on why students should build their skills independent of AI while also learning the capabilities and limitations of AI as a partner or assistant. This obviously creates some grey area and students refusing to accept this guidance still need to be held to a high standard of academic integrity. However, a more collaborative approach has the potential to balance the needs to learn foundational concepts and become a modern professional (Yeager, 2024).

Laying out assessment options is a great starting point. As instructors we should also be taking the next step to reconsider what and how we teach on a more holistic level. AI has created something of a "John Henry" moment, raising the floor for what can be considered acceptable work or meaningful learning and knowledge. This is true of both student work as well as post-graduation professional expectations. It is our job as instructors and experts in our fields to make sure our students don't drown in self-doubt, existential dread, or complacency when facing this new reality. The stakes for our students' careers have been raised. Students need us to step up and help them reach these new expectations.

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