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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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1 Beyond Policing AI: What Are We Really Trying to Teach?

Our position is simple and direct: Protecting academic integrity in the age of generative AI is essential, but if that is where the conversation ends, we will graduate students who can pass our courses yet are poorly prepared for an AI saturated world. The goal cannot only be to keep AI out of assignments. It must be to help students learn how to think, decide, and act well with powerful AI at their fingertips.

Wang et al. (2025)'s article is an important contribution to the integrity side of this story. They show that AI detectors are unreliable and often biased, and propose practical strategies such as oral assessments, process documentation, and AI aware task design to better align assessment with current realities. (Bittle and El-Gayar, 2025) We agree that these are necessary steps. Our argument is that they are not sufficient.

Across recent systematic reviews and policy reports, a pattern is clear. Generative AI is rapidly becoming embedded in everyday academic tools and professional workflows (Jin et al., 2025). Students use it routinely to brainstorm, explain concepts, summarize readings, and draft text (Adams, 2025). Employers, meanwhile, expect graduates who can work fluently with AI, not pretend it does not exist Galeano et al. (2025). If our primary institutional response is to harden proctoring and refine the detection, we are aiming at the wrong target.

2 Shift from "Did AI Write This?" to "What Did the Student do?"

Much current practice treats AI mainly as a threat to be controlled. Institutions must certify that grades represent meaningful individual achievement, and there is ample evidence that detecting AI generated text is difficult and error prone (Bittle and El-Gayar, 2025). But if we design everything around the question "Did AI write this?" we overlook a more educationally valuable question: How did the student use AI, data, and domain knowledge together to produce and justify this work?

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In real workplaces, people will not be rewarded for avoiding AI. They will be rewarded for using it responsibly and effectively. That involves decisions about when to use it, how to check it, when to override it, and how to explain that process to others. Studies are already finding that when use is guided and transparent, tools can support understanding and productivity, while unguided use risks shallow learning and over-reliance (Bittle and El-Gayar, 2025). Assessment can either hide or reveal these skills. A "no AI allowed" assignment hides them by definition. An assessment that assumes AI will be used, and then asks students to document, critique, and improve upon what the model produces, brings these skills into the open and makes them teachable.

3 A Data Science View: GenAI as One More Model

From a data science perspective, generative AI is not magic. It is another kind of model, trained on large datasets, with a particular error profile. Therefore, it belongs in the same mental category as other predictive or simulation models that students already learn to use and evaluate. The questions we routinely ask about models apply directly here: what data and tasks was this model implicitly trained for? under what shifts in context or distribution is it likely to fail? and how should its outputs be validated, given that we cannot fully inspect its internals?

Recent work on assessment and GenAI argues that the real opportunity is to help students become supervisors and interpreters of such models, not just end users (Williams, 2025). This means treating AI use itself as an object of learning. Students should practice:

- Designing simple stress tests for AI by asking for alternative approaches, probing edge cases, and comparing results with other models or sources.
- Identifying when the model extrapolates beyond its training data or silently imposes assumptions that do not fit the situation.
- Explaining, in plain language, how they combined AI outputs with data, theory, and local knowledge to reach a conclusion.

These are core data science skills and are transferable across disciplines.

4 Rethinking "Fundamentals"

We often insist that "fundamentals" must not be sacrificed. We agree, but we want to be precise about what counts as fundamental. In many technical courses, what we grade as "fundamentals" are manual procedures that once were the only way to demonstrate understanding: algebraic manipulations, hand-computed solutions, rigid step-by-step methods. Generative AI already reproduces these procedures well, and it will only get better.

The deeper fundamentals look different. They include: 1) Core concepts and invariants that any acceptable solution must satisfy. 2) A sense for scales, orders of magnitude, and plausible ranges. 3) The ability to see which assumptions matter, and where they are likely to break. 4) Judgment about which tools and models are appropriate for which kinds of problems. If we redesign learning and assessment so that students use AI where it is strong, and use these fundamentals to interrogate and refine what the model produces, we are not lowering the bar. We are moving it to where human expertise will actually be needed.

5 A New Cluster of Skills We Must Name and Teach

When we look across recent analyses of AI in higher education and the future of work, a common message emerges. The skills that become more important, not less, in an AI rich world include: problem framing, collaboration, critical thinking, communication, and ethical responsibility (Jin et al., 2025). For data oriented disciplines in particular, we would highlight four clusters:

1. Framing problems in the presence of powerful tools, rather than starting from the tools themselves.
2. Collaborating with AI as a model to be tested, not as an authority to be obeyed or a toy to be "tricked."
3. Reasoning across multiple models and sources, including statistical, mechanistic, and generative systems, and explaining disagreements among them.
4. Communicating uncertainty and residual risk to non experts while remaining accountable for the judgment, not hiding behind "the AI said so."

These capacities do not show up clearly in a traditional closed book exam designed before generative AI. They show up when we require students to reveal and justify how they are working with AI.

6 Integrity as a Starting Point, Not the Finish Line

In short, we read Wang et al. (2025) as a crucial starting point. Institutions must update policies, redesign vulnerable assessments, and abandon naive faith in AI detectors (Bittle and El-Gayar, 2025). Our contribution is to argue that this should not be framed as a defensive exercise but as the first step in a broader realignment of educational goals.

If we cling to longstanding assessment traditions, we may protect grades but fail to prepare students for the realities of their future work. The more GenAI improves, the more important it becomes to ask what distinctly human forms of expertise we are trying to cultivate and to let that answer reshape our teaching and assessment.

Academic integrity is non negotiable. It is also not the whole story. The deeper task is to ensure that when our students graduate into a world full of capable models, they are ready to do the kind of thinking those models cannot do for them.

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