Can't we just do that with AI? Other Misconceptions and Recommendations for Designing AI-enabled ISE Assignments

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Abstract

Artificial intelligence (AI) is an emerging pedagogical tool in engineering education that is being utilized to facilitate student understanding of core class concepts while simultaneously preparing them for AI-integrated work tasks after graduation. While AI can be a powerful resource, it can also hinder active student learning by generating answers for students instead of asking students to generate and integrate course concepts themselves. In this work-in-progress research, Bloom’s taxonomy was mapped onto a decision matrix to help professors determine how to best integrate AI into their various class activities to improve student learning without undermining foundational understanding of core concepts. Five professors from two universities created and used a decision matrix to generate multiple assignments in six different courses. Classes were all Industrial & Systems Engineering but ranged in topics and included such content as facilities design, human factors, statistics and forecasting, work design, project management, and operations research. For each assignment, a list of questions from the decision matrix were mapped onto a Bloom’s Taxonomy level and the outcomes from faculty observations were provided. Analysis of those outcomes across all the courses yielded several common themes. Recommendations include designing assignments to foster independent core knowledge, AI-dependent knowledge (e.g., how to effectively use AI), and encouraging AI-based skills in ascertaining the quality of AI-generated information.

Introduction

When ChatGPT was commercially introduced to the public for free, students began informally experimenting with AI-supported writing, explanation, ideation, and problem-solving in various educational situations. As students are informally integrating Generative Artificial Intelligence (GenAI) into their learning process, GenAI is increasingly shaping how instructors think about effective instruction and assessment when GenAI can produce work that looks correct and professional with little student input, making it harder for instructors to ascertain whether a submission reflects the student’s own understanding [1]. More deeply, however, instructors acknowledge that the 'problem’ with GenAI is not only a surface level assessment problem.

GenAI can be helpful by providing examples or explaining concepts, but it can also entirely undermine student learning by simply providing students with the answers. This can cause both deskilling (of the field’s necessary skills and of the learning process itself) and exacerbate the Dunning-Kruger Effect because students are removed from the generation process [2] and instead engaged in a recognition process. Moreover, GenAI is fallible and without critical, structured engagement, it is unclear how aware students are of its potential pitfalls. AI use is not simply “yes or no”, it is a skill that can and needs to be taught [2]. AI access isn’t the same as AI skill. In a controlled study with first-year engineering students, the AI-integrated trained group outperformed both the “AI with no training” group and the no-AI group [3].

Increasingly, employers are expecting their workforce to competently integrate GenAI into their workflow, thus necessitating the integration of GenAI into the classroom to facilitate ‘best practice' usage behavior. However, best practice usage behavior is a skill one builds once a solid conceptual foundation is in place. Thus, instructors find themselves trying to ascertain how best to integrate GenAI into their classrooms in a way that will not undermine the very learning process they are trying to facilitate.

Engineering education both demands and cultivates a broad set of skills that simultaneously demand high precision, including system modeling, mathematical reasoning, complex solution design, tradeoff analysis, effective communication, and more, all embedded in the high-accountability professions of engineering (e.g., professions in which there are many stakeholders and profound downstream consequences of the decisions made by engineers). Thus, engineering is both a sensitive and critical area of exploration for GenAI integration, and engineering simultaneously offers a rich and diverse set of technical and socio-technical competencies to investigate AI integration with.

Industrial and systems engineering (ISE) is especially well suited for this exploration. ISE students are expected not only to master core engineering skills, but to also apply them in contexts that directly involve human operators, organizations, and complex systems. This amplifies the ethical, social, and practical implications of AI assisted work.

Emerging technology integration in the classroom must be firmly grounded in educational foundations to facilitate higher efficacy [4]. Many instructors, however, have no formal pedagogical training, making this a herculean task. Domain agnostic frameworks can be an ideal starting point as they have higher scalability with other educational contexts. Bloom's Taxonomy is one such framework that classifies learning objectives into levels of demanded cognitive complexity from the learner. Thus, this work maps Bloom's Taxonomy onto a decision matrix to help guide instructors in how they can effectively integrate GenAI into existing or brand-new assignments. This framework was used by five faculty across two universities in several classrooms. Our work primarily contributes to a decision matrix mapped onto Bloom's Taxonomy that instructors can use to guide AI-integration in the classroom. We also provide some preliminary evidence via multi-course observations from the five aforementioned professors. Their feedback is used as preliminary evidence to contextualize the usage of the decision matrix.

Literature Review

Background on AI

Most GenAI classroom tools are built on large language models (LLMs), many using transformer "attention" to focus on relevant input, and they generate text by predicting the next word (or token) from context [5]; as these models scale, they often become better at following instructions from just a few examples [6]. This helps explain why students can use tools like ChatGPT across many assignment types, with benefits such as explaining concepts, creating examples, helping with writing, and suggesting steps for solving problems. However, LLMs can also sound confident while giving wrong information that is hard to detect, especially in technical subjects [7]. Because of this, GenAI use adds a learning goal: students must learn course content and also learn responsible use, including writing good prompts, checking sources, verifying results, and making careful decisions when the AI might be uncertain. Since many students already use GenAI before entering a class, instructors need to plan for it; surveys show student use of ChatGPT for school tasks has increased over time [8]. Research on GenAI in higher education is also growing quickly, but it is still developing, with open questions about effects on learning and how schools should handle policy and assessment [9].

AI in engineering education: learning benefits and integrity risks

Across higher education, research often describes GenAI in two ways at the same time: it can help teaching and learning, but it can also create problems for assessment. Several reviews on ChatGPT in higher education point out that students are using it in many nuanced ways, and they stress that we still need clearer guidance on what works well and what the effective limits are [9] so we can effectively guide AI skill development. Other reviews focus on the main challenges of using GenAI in universities. Common concerns include ethics and the need for human oversight, data quality and privacy, fairness and bias, and the need for clear school policies and faculty training [10].

At the same time, more studies are looking at cheating and fairness. And they all point to the same thing: it's not as simple as "ban AI" or "let everyone use it." GenAI can help students work faster and understand ideas, but it can also make it easier to turn in work that isn't really theirs [11]. That's why many researchers push for teaching students how to use AI responsibly and setting clear rules about what counts as acceptable use.

More direct evidence also raises concerns about grading and detection. In one study across two universities in the UK, graders often could not reliably tell the difference between work that used GenAI and work that did not [1]. The study also suggested that simply using "real-world" or "authentic" assignments is not enough to prevent misuse, because AI can still produce convincing submissions. Instead, it recommended assessments that include more performance and interaction (for example, presentations, live problem-solving, or group discussion), rather than only take-home written work.

Other reviews agree that normal take-home work is harder to protect now. They call for better assessment plans: redesign assignments, require proof of the student's process, and make AI rules clear [12] .

Bloom's Taxonomy as a way to decide what thinking students should do

Bloom's Taxonomy is a commonly leveraged strategy to describe levels of learning. It starts with simpler skills like remembering and understanding, and moves to more radically constructivist skills like analyzing, evaluating, and creating [13]. When GenAI is involved, Bloom's can be used to decide what parts of an assignment students should do on their own and what parts should be done with AI.

Recent studies demonstrate how people are using Bloom's in AI-related course design. For example, Eideh compares lessons made by instructors to lessons made with ChatGPT and finds that the instructors tend to produce better-structured materials, and researchers can see differences in the level of thinking (Bloom's levels) included in the final lesson plans [14].

Other studies look at individual fields. In one theoretical computer science study, researchers compared ChatGPT and students on Bloom's-level tasks [15]. They argued that assignments should allow some AI help but still make students do the higher-level thinking. Similar results show up in programming and data analysis—students learn more when instructors teach them how to use GenAI well [16].

Our study differs from prior evaluations using Bloom's Taxonomy as a lens for exploring AI in the classroom by offering a decision matrix tool to help instructors integrate AI effectively into their classroom.

Why Industrial & Systems Engineering and Why use Bloom's Taxonomy

The emerging literature portrays AI in engineering education as a field in rapid transition: moving from niche intelligent tutoring and analytics systems toward pervasive, learner-controlled generative tools that blur the boundary between human and machine problem solving. Existing reviews highlight both significant potential improved performance, richer feedback, and new forms of design exploration, as well as some significant risks including equity gaps, academic integrity concerns, and the possibility that over-automation could erode foundational analytical skills. In this environment we believe that Industrial & Systems Engineering (ISE) is well poised to develop best practices for AI integration that could be generalized to other disciplines because ISE is so varied with respect to content and types of questions and methodologies. For example, a student may have a typical type of engineering calculation in operations research but may need to create a facilities design where they need to include multiple types of constraints with varying degrees of importance. Additionally, human factors design questions may explore both cognition and biomechanics, requiring students to navigate interdisciplinary lines of engineering, psychology, physiology, information processing, and business.

Research gap

Our paper offers a Bloom's Taxonomy aligned decision matrix to facilitate AI-enabled assignments by considering the level of learning necessary for a given concept while balancing the demands of future careers that demand the use of AI. Our paper offers a more guided strategy to help instructors perhaps unfamiliar with Bloom's. The guided questions that were mapped to Bloom's Taxonomy provides a consistent methodology, and our observations provide an initial glimpse into what a more systematic inclusion of AI could entail. The research fills a gap for discipline-specific, instructor-integrated, empirically grounded studies that examine how engineering students use AI within concrete assignments, how this aligns with Bloom's taxonomy and course learning outcomes, and under what conditions AI supports or undermines deeper learning questions that the present study seeks to address. We are not the first to integrate Blooms Taxonomy with AI, though AI integration strategies from the perspective of educators is a comparatively understudied area [17], [18], [19].

Methodology

Bloom's taxonomy is commonly leveraged as a pedagogical strategy to determine complexity of assignments in broader curriculum design. The revised Bloom's Taxonomy has six levels:

Remember, Understand, Apply, Analyze, Evaluate, and Create (see Table 1 for definitions). Five professors from two universities created and used a decision matrix in six different courses to generate AI-enabled class activities during the Fall 2025 semester. We synthesized our reflections by comparing the detailed notes each of us recorded while using the decision matrix in our specific courses. To ensure we were analyzing the data consistently, we all answered the same 13 questions, which allowed us to identify common patterns in how students used AI across different subjects. By looking at these shared experiences together, we found recurring themes regarding when AI helped students understand difficult concepts and when it risked replacing their independent thinking. These shared findings were then organized by learning difficulty to develop the final recommendations presented in this paper.

We mapped assignments onto different Bloom's levels and considered the way using AI affected learning outcomes within our intended Bloom's levels. For example, if a given assignment asked the student to calculate the given number of machines needed to achieve a production requirement, that question would be classified as *apply* as the Bloom's level. Then, the professor would determine how they could answer the questions on the decision matrix for the given task (for this example, AI could help if used as a tutorial but would be a hindrance to learning if AI just solved the problem).

Mapping assignments onto Bloom's Levels allowed the professors to determine if certain types of AI enabled assignments yielded better or worse student learning or engagement than others. The decision matrix included a series of questions related to how student learning could have been affected using AI when completing the assignments. The assignments were then mapped on to the Bloom's Taxonomy Level for the given AI-enabled assignment (see Table 1 for Bloom's Level and the decision matrix questions are listed at the end of this paragraph). The decision matrix questions included in the study were:

- How does it help problem solving?
- How does it help to learn new information?
- How does it help the student do things better the next time they do task?
- Is this replacing student thinking?
- After using AI, can the student do the work if AI wasn't there? Will it matter in the future?
- How does the student check the work and eliminate suggestions that are hallucinations?
- What were some unanticipated results of the use of AI?
- Would you keep this AI assignment?
- How to use constraints on the AI assignment?
- Does it help the student integrate data or textual information?
- Does it improve prompt engineering?
- Does it help the student include a file and then extract, manipulate, integrate, or synthesize information?

Decision matrix questions were used as a guide to determine common observations across various assignments regarding the success of integrating AI. The data that resulted included professor reflections and evaluations for the questions in the decision matrix. Those reflections were then compared for similar concepts and are shared within the Observations section of this paper. Classes were all Industrial & Systems Engineering but ranged in topics and included such content as facilities design, human factors, statistics, work design, project management, and operations research. Not every Bloom's level is represented by every assignment. It is not always feasible to integrate all Bloom's levels into an assignment, and thus it is not the intention of the matrix to encourage that type of assignment design. Instead, the goal is to help instructors consider their core assignment goals, understand what Bloom's level those goals fit within, and then with that understanding be able to carefully integrate AI into the assignment to bolster those outcomes without undermining them. Worded differently, not all assignments were mapped onto each Bloom's level (see Table 2 for the types of assignments and onto which Bloom's levels they mapped and Table 3 for an example of how the decision matrix questions were answered for one assignment noting that 'evaluate' is not included for that example). Professor reflections and evaluations from the assignments and student learning were compiled, and observations were generated regarding best practices for AI-enabled assignments.

Table 1. Revised Bloom's Taxonomy Levels

Revised Bloom's	**Description**
Create	Produce a new work (e.g., design a new workstation given a list of criteria)
Evaluate	Justify a decision (e.g., given your calculated result, justify the decision to implement a new lifting device)
Analyze	Draw connections (e.g., compare and contrast two different approaches to optimization)
Apply	Use Information in a new situation (e.g., given these factors calculate a confidence interval for…)
Understand	Explain ideas (e.g., describe some reasons why financial reasons alone would not justify a location for the new location of a facility)
Remember	Recall facts and basic concepts (e.g., provide a list of risk factors for repetitive stress injuries)

Table 2. Type of AI-Enabled Assignment and the Bloom Level onto which Components of it Mapped

Type of Assignment	R	U	AP	AN	E	C
This Facilities Design Project included a design for a Center for Entrepreneurship (multiple assignments resulted from it and it included initial design as well as calculation for makerspaces that included equipment and production needs).	✓	✓	✓		✓	✓
This homework-based individual assignment requires students to forecast product demand using AI/ML techniques such as Random Forest and Linear Regression with validation, compare these results to traditional Excel forecasting methods, evaluate model accuracy using R^2, MSE, and MAE, and apply the forecasts to calculate EOQ and ROP for inventory control decisions.	✓	✓	✓	✓	✓	✓
(Human Factors) Students were asked to find a poorly designed interface, tool, device, etc. And to propose a redesign justified with class concepts. After their presentation, students are asked to use three separate GenAI's to 1) do the design on its own from scratch just based on their prompting, 2) upload their design and ask for critiques, and 3) ask a third AI to pick the 'best' redesign (the AI generated one or theirs) and then combine the two designs to generate a third design. Students were then asked to evaluate the efficacy of the AI compared to their own version.		✓	✓		✓	✓
This lab assignment had students compare traditional results (Largest Candidate Rule and Ranked Positional Weight) along with stochastic Monte-Carlo modeling of line balancing to AI results.	✓	✓	✓	✓	✓	✓
Students built a complete Auto Regressive workflow (simulate - forecast - interpret) and wrote a short explanation/report, with optional AI support.		✓	✓	✓	✓	✓
This assignment had students use AI to research a problem of their choice in a project management course. The topics ranged from work breakdown structure to risk analysis.		✓	✓	✓		

*R = Remember, U = Understand, AP = Apply, AN = Analyze, E = Evaluate, and C = Create

Table 3. An Example of How the Decision Matrix was used for a Specific Assignment

Assignment:	Center for Entrepreneurship (Note: Analyze was not used)				
Bloom's Taxonomy	**Remember**	**Understand**	**Apply**	**Evaluate**	**Create**
Assignments that were used	What rooms go into the building? (list) What criteria are you going to use to evaluate the success of the building?	Develop a narrative for the building	Construct a relationship chart for the building. Solve for how many machines go in the makerspaces.	Create several options and compare. You should list the parameters on your own for the selection criteria	Create final proposed design
Describe how AI was used	Students had to list the elements on their own and then they checked it with AI.	Students developed a narrative for the building; they used AI to understand how such centers could function.	Students calculated number of machines then checked with AI	Students had to create designs and list parameters. They asked AI to create a design and then they compared them	Students had to create the final design
How does it help problem solving?	N/A	N/A	Helped with determining relationships	It brought some things to their attention	The final design was the result of the comparison
How does it help to learn new information?	It made evident ideas or concepts not known to the student	It made evident ideas or concepts not known to the student	It made evident ideas or concepts not known to the student	It made evident ideas or concepts not known to the student	It made evident ideas or concepts not known to the student
How does it help the student do things better the next time he/she does task?	N/A	Might be translated to another assignment	Might be translated to another assignment	Students learned how to create better prompts	Students learned how to create better prompts
Is this replacing student thinking?	No because students always started with some concept	No because students always started with some concept	No because students always started with some concept	No because students always started with some concept	No because students always started with some concept

After using AI, can the student do the work if AI wasn't there? Will it matter in the future?	Not sure	It helps as long as student has some fundamental knowledge	It helps as long as student has some fundamental knowledge	Yes, I think by the end the students had learned a lot that they could use in the future	Yes, I think by the end the students had learned a lot that they could use in the future
How does the student check the work and eliminate suggestions that are hallucinations?	Not sure	Hallucinations could be determined if AI suggestions did not make sense to the original concept	Would have to compare with a key	Evaluation and comparisons have to be consistent with student model	Evaluation and comparisons have to be consistent with student model
What were some unanticipated results of the use of AI?	No	AI narrative didn't always make sense	AI could be wrong if incorrect information was put in the prompt	AI could be wrong if incorrect information was put in the prompt	AI could be wrong if incorrect information was put in the prompt
Would you keep this AI assignment?	Yes	Yes	Yes	Yes	Yes
How to use constraints on the AI assignment?	I would require more student information first before AI was used	I would require more student information first before AI was used	I would require more student information first before AI was used	I would require more student information first before AI was used	I would require more student information first before AI was used
Does it help the student integrate data or textual information?	N/A	N/A	Not really	Yes, in the comparisons and the evaluations	Yes, in the comparisons and the evaluations
Does it improve prompt engineering?	Yes	Yes	Yes	Yes	Yes
Does it help the student include a file and then extract, manipulate, integrate, or synthesize information?	Yes	Yes	Yes	Yes	Yes

Observations

Professors used the aforementioned decision matrix questions for each assignment a professor intended to integrate AI into. The topics ranged from using a machine learning tool (e.g., Orange) to aid in producing predictive analyses to using AI to confirm answers, supplement answers, or provide data-supported evaluations and comparisons for facilities design, human factors, project management and operations research. The main types of assignments that included use of AI included: determining if a GenAI-generated answer matched the student-generated answer for a given problem, evaluating whether the AI's answer was sufficient, or using AI to provide a list of concepts, expand on a given list of items (e.g., rooms in a facility), answer a problem, provide a predictive analysis, compare results, or create an explanation or discussion relating to a problem.

Although this research is a work-in-progress effort, analysis of the decision matrix for each of the professor's assignments yielded observations related to the use of AI, design of AI-enabled assignments, and student learning and subsequent evaluation.

First, lower-level Bloom's levels are fundamental to upper-level learning, so AI generated results that replace the student learning do not seem to be beneficial. Students need to remember and understand the fundamental concepts so that they can develop an adequate prompt and critically evaluate the output from AI (e.g., is it reasonable or not? What elements have not been included?). Students also need to understand constraints and assumptions to be sure that an AI result could be accurate. This was true for the operations research, predictive analyses, and facilities design questions. One professor noted it is very important that the fundamental kernels of the algorithm/application be fundamentally presented. He believed it would be foolhardy to expect that the student could extrapolate or to integrate other techniques without these kernels, regardless of AI/ML and did not believe that AI/ML would be successful (at least not yet) at the level of extrapolation expected of a competent engineer.

Second, the use of AI to check student-generated answers seemed to be very beneficial. AI could be used as an intelligent tutor after the fact or be asked to produce the results step-by-step in the learning stage. So, a student could use AI to understand how to solve a problem, then solve a different problem and use AI to check the given answer. These skills could be mapped to the understand and apply levels. The caveat to be wary of here is that if an AI teaches a student incorrectly, it would mean a student may spend time applying an incorrect strategy and thus cementing in an incorrect way of completing an analysis. This would require re-learning, which can be more difficult than learning from scratch. One professor had an assignment on using AI to brainstorm techniques in a project management course. The professor believed that it was too vague to promote learning. Rather, the professor stated that in the future he would assign more specific and directed homework (e.g., given a certain weekly project update, have the student create a trend analysis using AI).

Third, the use of AI to supplement answers (e.g., provide all the ergonomics risk factors) or to provide comparisons between different models can be very useful. Comparisons, however, should be used in the learning phase as students should be able to evaluate two or more given alternatives or results without the use of AI. Moreover, some foundational AI literacy is needed by this phase so that students can meaningfully evaluate the limitations of AI answers. These skills are mapped onto understand, apply, and analyze and could aid in promoting student critical thinking as the AI provided additional results that could promote more discussion and thought. Using AI to perform faster iterative solutions could also improve student engagement in that their comparisons could be made at a faster pace.

Using AI to complete an entire question or design problem comes down to the prompt, deep understanding of foundational class concepts, and AI literacy. So, students need to have adequate foundational knowledge to provide the prompt that will allow for complete and accurate answers given a set of parameters that consider the limitations of the AI. Such use could be limiting if students' learning of fundamentals and theories are omitted from their training. Additionally, taking the student completely out of the loop from answering the question is not recommended as holistic design is its own skill demanding integration of several pre-learned skills The professor facilitating the human factors design assignment (Table 2, row 3) noted that GenAI will pull concepts that are not explicitly asked for in a prompt. This results in concepts being pulled in that were not taught in class, meaning students did not have the knowledge base to parse whether these were hallucinations. Moreover, even if they were not hallucinations, students did not know enough to meaningfully integrate unprompted content ideas. Thus, students spent quite a bit of time doing their own research (not facilitated by AI) to make sense of these interruptive concepts. While this could be helpful to expand a student's knowledge base, it is unclear how often students will actually spend the time to parse these interruptions instead of just accepting them as fact.

While AI seemed to augment learning across all Bloom's levels, failure modes and misconceptions could exist. For example, in the Center for Entrepreneurship example, sometimes AI came up with drawings that were inadequate (e.g., rooms with no doors or connecting hallways). If students didn't start with base information, then the AI could serve to replace rather than to augment student learning, while iterations with AI prove helpful, students often didn't know when to stop them.

Discussion and Conclusions

Our observations from this work yielded common recommendations including designing assignments by considering the Bloom's Level to foster independent core knowledge, AI-dependent knowledge (e.g., how to effectively use AI), and encouraging AI-based skills in ascertaining the quality of AI-generated information. As a work-in-progress, the research is limited by its small sample size and the limited qualitative analysis. Additionally, the decision matrix has not been validated but rather was a grouping of questions based on the expertise of the professors involved in this work.

Other professors may benefit from this work by analyzing the complexity of their assignments and when and how they allow students to use generative AI. As a start, professors could utilize the questions in the decision matrix and determine which types of assignments to allow AI and how AI could improve the assignments by perhaps including a broader perspective or a sensitivity analysis.

As with other technologies, AI is here to stay, but its use will determine the ultimate set of engineering skills with which students graduate. It is likely that if students are not taught the theories, constraints, and assumptions for a given topic, they will never learn those, and their future work may be insufficient. As educators, we must guard against the expediency of simply "plugging" it into an AI/ML engine without the understanding of the theory behind the techniques.

Just as the use of software systems allows us to do faster and more complex analyses, we must be aware of the level of complexity of our assignments. Instead of asking whether to utilize AI, we may be trying to determine whether using AI indicates that we need to raise the level of the complexity of the questions and assessments in class. How would learning expectations be altered from our current expectations regarding student outcomes? Only continued exploration of this topic along with careful study of how our undergraduate students are prepared for industry and graduate school will provide possible future answers.

Future Work and Recommendations

The main contribution of his work-in-progress scholarship was the creation of a Bloom's Taxonomy aligned decision matrix that could be used to determine how to prioritize the use of AI enabled assignments in Industrial & Systems Engineering courses. Multi-course observations from five professors served to refine and contextualize its use. The work focused on professors' evaluations and reflections on the success of the use of AI for a given assignment of a certain level of complexity. The work was successful in that it demonstrated that that the use of AI should be a function of the goals of the professor, the role of AI in augmenting learning rather than replacing it, and how it improved the systematic building of more difficult concepts within a course.

Future work includes validating the prompting matrix questions within a larger and more systematic study in which student outcomes, student reflections, and realized student learning across a grouping of assignments completed with and without the use of AI. Such an approach could help to answer whether using the proposed decision matrix is effective in helping AI-integration that augments and accelerates learning instead of hindering it. Additionally, assignments could be grouped by learning domain and the influence of prompt design on AI outcome, number of AI iterations, and a student's ability to apply the information could be evaluated.

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