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Integrating Generative AI into Senior Design to Cultivate Engineering Judgment and Reflective Learning

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Abstract

This paper presents a course-based research study investigating how generative artificial intelligence (AI) can be meaningfully integrated into a senior-level chemical engineering design course to foster students' engineering judgment, reflective thinking, and professional self-efficacy. The study was conducted in the capstone senior design sequence, where students worked on authentic, open-ended design problems reflective of industrial practice. Two major design challenges were incorporated: (1) optimization of utility consumption through heat integration and heat exchanger network (HEN) design, and (2) simulation and design of a vinyl chloride monomer (VCM) production process using Aspen Plus.

Each student first employed a selected AI tool—such as ChatGPT, Gemini, Claude, or Copilot—to independently generate complete solutions, including process flow diagrams, pinch analyses, distillation column parameters, and energy trade-off evaluations. Teams then collaborated to perform manual calculations, verify results, and compare AI-generated and human-generated solutions to identify conceptual and thermodynamic inaccuracies. Both individual and team reflections were collected to analyze students' reasoning processes and perceptions of AI's role in design.

This study investigates how structured AI use shapes students' engineering judgment and self-efficacy in process design. Preliminary results suggest that while AI tools improved creativity and early-stage problem framing, they frequently made unrealistic assumptions that required critical validation. The reflective analyses revealed that engaging with AI outputs deepened students' metacognitive awareness, prompting them to apply disciplinary reasoning, verify data integrity, and confront ethical considerations surrounding reliance on AI. The findings contribute to emerging frameworks for AI-augmented engineering education, emphasizing reflection, judgment, and the human-AI partnership as central to developing adaptive expertise in future engineers.

Keywords: generative AI, chemical engineering design, engineering judgment, reflective learning, process simulation, heat integration, professional identity, course-based research

1. Introduction

The rapid expansion of generative artificial intelligence (AI) tools—such as ChatGPT, Claude, Gemini, and Copilot—has begun to significantly reshape teaching and learning in higher education, including engineering programs. Global survey data indicate that more than 85% of undergraduate and graduate students now incorporate AI tools into their academic routines, with many reporting weekly or daily use [1]. Faculty adoption is also increasing, though attitudes remain mixed, reflecting ongoing concerns related to academic integrity, student overreliance, and the reliability of AI-generated technical outputs.

Within engineering education, the integration of generative AI presents discipline-specific challenges. Engineering programs are charged with preparing students not only to perform calculations or apply established methods, but also to exercise **engineering judgment**—the ability to synthesize information, reason under uncertainty, evaluate trade-offs, and make decisions that are technically defensible, safe, and professionally responsible [2,3]. Recent scholarship emphasizes that engineering judgment is closely tied to professional identity and accountability, particularly in complex, high-consequence design contexts [3]. However, traditional engineering curricula, especially in early and mid-level courses, often emphasize well-structured problems with known solution pathways, providing limited opportunities for students to critique incomplete information, interrogate assumptions, or evaluate flawed reasoning.

Senior Design I occupies a critical position in the chemical engineering curriculum, serving as a transition point between structured coursework and open-ended professional practice. In this course, students are expected to synthesize prior knowledge in thermodynamics, separations, and process analysis to develop preliminary designs that resemble real industrial workflows. These expectations make Senior Design I an especially appropriate context for examining the pedagogical role of generative AI. AI tools can rapidly generate plausible process descriptions, suggest design parameters, and propose solution pathways. Yet, such outputs may obscure unrealistic assumptions, violate thermodynamic constraints, or omit critical safety and operability considerations—limitations that are particularly consequential in process design.

At the same time, generative AI offers potential instructional benefits when used intentionally. Prior work suggests that AI can support engineering education by accelerating ideation, organizing complex information, and enabling students to explore multiple design alternatives more efficiently [4–7]. National policy guidance underscores the importance of such intentional use. President Biden's October 2023 Executive Order on Safe, Secure, and Trustworthy Artificial Intelligence identifies the responsible deployment of AI in education as a national priority, calling for the development of resources and guidance that promote safe, ethical, and accountable AI use [8]. These directives highlight the need for discipline-specific pedagogical models that clarify how AI can be integrated without undermining professional responsibility.

In response to this need, this paper examines the structured integration of generative AI into a Senior Design I chemical engineering course through two design tasks of increasing complexity: (1) a thermodynamically constrained heat integration and heat exchanger network (HEN) design problem using pinch analysis, and (2) an open-ended preliminary process design task involving vinyl chloride monomer (VCM) production and Aspen Plus distillation simulations. In both tasks, AI was intentionally positioned as a tool for exploration and critique rather than an authoritative solver. Students were required to independently verify AI-generated outputs using first principles, simulation, and engineering reasoning.

Guided by this instructional design, the study addresses the following research questions:

> *RQ1. How do students engage with generative AI tools across thermodynamically constrained and open-ended chemical engineering design tasks in Senior Design I?*

RQ2. What limitations and failure modes arise in AI-generated solutions, and how do students apply engineering judgment to identify and correct them?

RQ3. How does structured engagement with AI influence students' perceptions of professional responsibility and ethical AI use in chemical engineering design?

By analyzing student design artifacts, simulation results, AI–manual comparison tables, and written reflections, this work contributes empirical evidence to ongoing discussions about the role of generative AI in engineering design education. Rather than positioning AI as a replacement for engineering expertise, the findings suggest that, when intentionally scaffolded, AI can serve as a catalyst for making engineering judgment, accountability, and professional reasoning more explicit and assessable in Senior Design I.

Methods

Course Context and Learning Objectives

This study was conducted in Senior Design I, a required senior-level chemical engineering course that serves as a bridge between foundational coursework and the full capstone design experience. The course emphasizes preliminary process design, process simulation, and professional engineering judgment. Students are expected to synthesize knowledge from thermodynamics, separations, heat transfer, and material balances to develop defensible engineering designs under realistic constraints.

The primary learning objectives relevant to this study include:

- Applying thermodynamic principles and separation theory to open-ended design problems
- Developing and evaluating process flow diagrams and preliminary design decisions
- Exercising engineering judgment in the presence of incomplete, ambiguous, or imperfect information
- Demonstrating professional responsibility in validating design assumptions and results

The course enrolled twenty-seven senior undergraduate chemical engineering students working in teams of four to five. Six teams participated in the study.

Intervention Design and Instructional Sequence

Generative AI was intentionally integrated into the course through a structured, scaffolded intervention designed to make engineering judgment explicit and assessable. Rather than positioning AI as a solution generator, the intervention framed AI outputs as objects of critique that required verification using engineering principles.

The intervention consisted of two major design tasks implemented sequentially:

- **Task 1:** Heat integration and heat exchanger network (HEN) design using pinch analysis

- **Task 2:** Preliminary design of a vinyl chloride monomer (VCM) production process, including distillation column simulation in Aspen Plus

The tasks were deliberately selected to progress from a thermodynamically constrained, algorithmic problem to a complex, open-ended process design problem. This sequencing allowed examination of how student engagement with AI and engineering judgment evolved as design complexity increased.

Each task followed the same three-phase instructional structure:

1. Individual AI Exploration: Students independently selected a generative AI tool and used it to attempt a complete solution. They documented all prompts and unedited AI outputs and reflected on AI strengths, limitations, and errors.
2. Team Engineering Solution (Without AI): Teams then developed a full engineering solution without relying on AI-generated results. For Task 1, this included manual pinch analysis and HEN design. For Task 2, this involved Aspen Plus simulations using both shortcut and rigorous models.
3. Comparison and Reflection: Teams compared AI-generated outputs with their validated engineering solutions and produced written reflections analyzing discrepancies, failure modes, and the role of engineering judgment.

This structure ensured that AI engagement was intentional, transparent, and critically examined, rather than passive or unregulated. A potential concern with AI-supported workflows is that students may lose the ability to initiate designs from a blank page. In this study, this risk was mitigated through a structured approach in which students engaged in parallel problem-solving pathways, developing their own solutions using first principles while also analyzing AI-generated outputs. They were required to compare, critique, and reconcile differences, ensuring that final designs were independently constructed and verified rather than AI-derived.

Role of Generative AI in the Course

Generative AI tools were permitted and encouraged during designated phases of each task, with explicit guidance on responsible use. Students were instructed that AI-generated outputs did not constitute correct solutions unless independently verified through calculations, simulation, and engineering reasoning.

AI tools were used by students to:

- Draft preliminary process descriptions and design narratives
- Suggest design parameters such as operating pressures, stage counts, or heat recovery targets
- Propose alternative configurations or solution pathways

However, students were explicitly assessed on their ability to:

- Identify unrealistic assumptions or violations of physical constraints

- Verify mass and energy balances
- Justify final design decisions using engineering principles

This framing aligned AI use with professional engineering practice, where external tools and heuristics must be validated before informing decisions.

Data Sources and Analysis

Data sources for this study included:

- Individual AI prompt and output logs (unedited)
- Team design reports, calculations, and Aspen simulation results
- AI–manual comparison tables
- Individual and group reflection summaries

Data were analyzed using qualitative thematic analysis to identify recurring patterns in AI use, AI failure modes, student verification strategies, and expressions of engineering judgment. Findings were synthesized across teams and across tasks to identify consistent behaviors and learning outcomes.

Results

Task 1 Results: Heat Integration and Heat Exchanger Network (HEN) Design

Task 1 provided a controlled yet rigorous context to examine how students interacted with generative AI in a thermodynamically constrained design problem. Across all six teams, students completed individual AI explorations followed by a fully manual team solution using pinch analysis. A consistent and important result emerged: AI tools were able to initiate the analysis but could not independently produce a thermodynamically feasible heat exchanger network.

Technical Convergence Through Manual Verification

After completing Phase II (manual team solution), all six teams independently converged on nearly identical design outcomes. Each team selected a minimum temperature approach of $\Delta T_{min} \approx 10$ °C and identified a pinch temperature near 155 °C, corresponding to a hot pinch temperature of approximately 160 °C and a cold pinch temperature of approximately 150 °C. These values were consistent across teams despite the use of different AI tools in Phase I.

Final designs achieved approximately 75–80% heat recovery relative to the base case, with minimum hot and cold utility demands closely aligned across teams. The resulting HENs typically required three to four process–process heat exchangers plus one heater and one cooler, and all designs satisfied classical pinch rules: no heat transfer across the pinch, no heating below the pinch, and no cooling above the pinch.

Importantly, this convergence did not occur in the AI-generated solutions. It emerged only after students reconstructed temperature-interval tables, recalculated enthalpy changes using $Q =$

$\dot{m}C_p\Delta T$, and enforced pinch constraints manually. This highlights that engineering judgment, not AI optimization, was responsible for the final correct designs.

Table 1: Summary of AI Errors and Student Detection (Task 1)

Error Type	# of AI Solutions with Error	# of Teams Identifying Error	# of Teams Correcting Error
Pinch violation	5/6	6/6	6/6
Incorrect ΔTmin application	4/6	5/6	5/6
Energy imbalance	3/6	6/6	6/6

AI Performance and Failure Modes in Task 1

AI-generated solutions varied substantially in quality. Some tools correctly identified the general pinch region and produced well-organized calculation tables. However, none of the AI tools generated a fully feasible HEN without violating at least one thermodynamic constraint.

Common failure modes observed across teams included:

- Confusion between shifted and actual temperatures, leading to incorrect pinch placement
- Heat transfer across the pinch or insufficient temperature driving forces
- Incorrect classification of hot and cold streams
- Unit inconsistencies (e.g., kW vs. MW) that inflated or deflated utility targets
- Overconfident presentation of infeasible exchanger matches

Students frequently noted that AI outputs appeared polished and authoritative, which initially obscured these errors:

"The AI solution looked very clean and professional, but once we checked the pinch rules, several of the exchanger matches were impossible."

Engineering Judgment as an Active Process

Students consistently described applying engineering judgment as an iterative validation process, rather than a single check. Teams recalculated heat duties independently, reconstructed composite curves, and rejected AI suggestions that violated ΔT_{min} or pinch rules. In many cases, AI-generated HENs were used as a reference point that students deliberately dismantled and rebuilt.

"AI gave us a fast first draft, but we had to rebuild the entire problem table ourselves to understand where it went wrong."

Students also articulated an emerging awareness of professional responsibility:

"If this were a real plant, trusting the AI result without verification could lead to unsafe equipment design."

Across Task 1, common AI errors included pinch violations, incorrect application of ΔT_{min}, and energy imbalances. Most teams successfully identified major thermodynamic inconsistencies, with all six teams detecting at least one critical error in their AI-generated solutions. However, detection was not uniform across error types; more subtle issues, such as improper exchanger sequencing, were missed by one or two teams. All teams ultimately corrected the major thermodynamic violations in their final designs.

Through Task 1, students reframed AI from a solution authority to a hypothesis generator whose outputs required disciplined scrutiny. This reframing was consistent across all six teams and represents a key learning outcome of the assignment.

Task 2 Results: VCM Process Design and Distillation Simulation

Task 2 extended AI integration into a significantly more complex and realistic design context involving process synthesis, Aspen Plus simulation, recycle management, and safety-critical decisions. Compared to Task 1, AI limitations became more consequential, less immediately visible, and more tightly coupled to professional accountability.

AI Contributions to Process Scoping and Organization

Across all teams, AI tools successfully identified the standard industrial route for vinyl chloride monomer (VCM) production via ethylene dichloride (EDC) cracking. AI-generated outputs correctly outlined major unit operations, including direct chlorination, oxychlorination, EDC purification, thermal cracking, quenching, hydrogen chloride (HCl) recovery, and VCM/EDC separation with recycle.

Students consistently reported that AI was especially valuable during the blank-page stage of the project: *"Within minutes, the AI produced a professional-looking process description and report structure that helped us get started."*

AI tools also highlighted relevant design considerations such as energy integration opportunities, pressure effects on separation, and safety concerns associated with chlorine and VCM handling. In this role, AI functioned as a junior consultant, accelerating early-stage thinking and communication.

Breakdown of AI Suggestions During Simulation

When teams attempted to translate AI-generated design parameters into Aspen Plus simulations, substantial deficiencies emerged. AI-recommended operating pressures, reflux ratios, and stage counts were frequently inconsistent with vapor–liquid equilibrium behavior or condensation feasibility.

For example, several AI tools suggested near-atmospheric operation for the HCl removal column, which students identified as infeasible because HCl cannot be condensed at such conditions without extreme refrigeration: *"The AI suggested operating the HCl column near 1 bar, but Aspen showed that condensation was impossible at those conditions."*

Similarly, AI-recommended stage counts were often excessively high. Claude and Gemini suggested columns with 50–120 theoretical stages, while Aspen RadFrac simulations converged at far lower values for comparable purities. These inflated stage counts led to unrealistic column heights and exaggerated energy duties.

Students also observed that AI frequently proposed reflux ratios based on generic heuristics rather than Underwood–Gilliland relationships or simulation results: *"AI gave reflux ratios that sounded reasonable, but Aspen showed stable operation at much lower values."*

Energy Duties, Mass Balance Closure, and Traceability

One of the most significant findings in Task 2 was AI's inability to maintain traceability between mass balances, energy duties, and design decisions. Several AI tools reported condenser and reboiler duties in the tens of megawatts without reconciling these values to the stated plant capacity or recycle flows. *"The energy numbers looked precise, but once we closed the mass balance, they didn't make sense."*

By contrast, teams that relied on Aspen Plus outputs and first-principles checks produced internally consistent designs with defensible energy consumption. Students repeatedly emphasized that numbers without traceability were more dangerous than obvious errors, because they appeared credible while being fundamentally flawed.

Safety, Materials, and Operability Gaps

Across all six teams, students identified systematic omissions in AI-generated designs related to safety and materials of construction. AI tools rarely addressed polymerization inhibition, corrosion from wet HCl, metallurgy selection, or relief system integration—issues that are central to real VCM facilities. *"None of the AI models addressed polymerization risk or corrosion control, which are critical in VCM service."*

These gaps required students to apply knowledge beyond thermodynamics and simulation, reinforcing that process design is inseparable from safety and operability considerations.

Engineering Judgment in Task 2

Students consistently described engineering judgment as essential in selecting defensible operating pressures, choosing appropriate thermodynamic models, reconciling recycle loops, and interpreting Aspen convergence behavior. Unlike Task 1, where errors were algorithmic and quickly detectable, Task 2 errors were embedded in plausible narratives and incomplete assumptions, making them more difficult to identify. *"The AI sounded convincing, but once we tried to build the flowsheet and run Aspen, the design fell apart."*

Students concluded that AI was best suited for scoping, documentation, and idea generation, while final design decisions required human accountability.

Synthesis of Results Across Tasks

Taken together, Tasks 1 and 2 reveal a consistent pattern: as problem complexity, interdependence, and safety consequences increase, the limitations of AI become more pronounced and the importance of engineering judgment increases.

In Task 1, AI errors were primarily thermodynamic and detectable through rule-based checks. In Task 2, AI errors affected mass balance closure, energy consumption, and safety considerations, requiring deeper expertise and simulation-based validation. Across both tasks, students did not disengage from learning; instead, structured AI integration prompted increased skepticism, verification, and reflection. Table 2 below summarizes both Task 1 and 2 comparisons. Students ultimately articulated a shared conclusion: *"AI can help us move faster, but engineers are still responsible for making sure the design is correct and safe."*

Table 2: Comparison of AI Performance and Engineering Judgment in Task 1 and Task 2

Dimension	Task 1: Heat Integration & HEN Design	Task 2: VCM Process & Distillation Design
Problem structure	Well-defined, algorithmic, bounded	Open-ended, multi-unit, safety- and simulation-driven
Primary tools	Pinch analysis, composite curves, hand calculations	Aspen Plus (DSTWU, RadFrac), process synthesis
Role of AI	Rapid hypothesis generator for pinch and HEN layouts	Front-end scoping, report structuring, option enumeration
Accuracy of AI outputs	Moderate for pinch identification; poor for HEN feasibility	Low for mass balance closure, energy duties, and column design
Typical AI failure modes	Misuse of shifted temperatures; pinch rule violations; unit errors	Unrealistic pressures, reflux ratios, stage counts; missing recycles; unsafe assumptions
Visibility of AI errors	Errors detectable through hand calculations	Errors often hidden until simulation convergence or safety review
Engineering judgment required	Verification of pinch rules and exchanger feasibility	Pressure selection, thermodynamics, recycle logic, safety, operability
Student learning emphasis	Thermodynamic rigor and constraint enforcement	Professional responsibility, traceability, and design accountability
Educational value of AI	Makes judgment visible by being wrong in constrained ways	Reveals limits of AI in high-consequence, real-world systems

Discussion

AI as a Cognitive Partner, Not a Design Authority

Taken together, the findings from Tasks 1 and 2 demonstrate that generative AI is most effective in chemical engineering design education when positioned as a cognitive partner that accelerates exploration, rather than as a solver that replaces engineering judgment. In the thermodynamically constrained context of Task 1, AI errors were largely algorithmic in nature and could be detected through systematic application of first-principles checks, such as enforcing pinch rules and verifying heat duties. In contrast, Task 2 revealed a more subtle and potentially dangerous pattern: AI-generated errors were embedded within polished narratives, incomplete mass balances, and unjustified assumptions about operating conditions. These issues were not immediately apparent and required deeper professional expertise, simulation-based validation, and engineering intuition to uncover.

Students explicitly articulated this distinction in their reflections, recognizing that while AI could generate answers faster than humans, it could not assume responsibility for design decisions. This shift in perception—from AI as an answer source to AI as a tool requiring oversight—represents a critical outcome of the instructional design and aligns closely with professional engineering expectations.

Escalating Risk with Increasing Design Complexity

A central finding of this study is that the risks associated with AI use increase as design problems become more realistic and open-ended. In Task 1, AI errors primarily affected energy targets, exchanger matches, and feasibility of heat recovery. While these errors were significant, they largely remained within the scope of a classroom grading context. In Task 2, however, AI-generated inaccuracies had far more consequential implications, including unrealistic equipment sizing and capital cost estimates, infeasible refrigeration requirements, overlooked polymerization and corrosion risks, and incomplete consideration of environmental and safety compliance.

This escalation fundamentally transformed AI misuse from an academic issue into a professional liability concern, a distinction that students themselves recognized. Reflections indicated growing awareness that accepting AI-generated results without verification in an industrial setting could lead to unsafe designs or costly failures. This recognition underscores the importance of exposing students to AI limitations in contexts that resemble real engineering practice, where consequences extend beyond numerical correctness.

Engineering Judgment as a Learnable and Observable Outcome

Rather than treating engineering judgment as an abstract or implicit professional trait, the course design made judgment visible, learnable, and assessable. Across both tasks, students demonstrated judgment through concrete actions: rejecting AI outputs that violated physical constraints, explicitly verifying mass and energy balances, selecting defensible operating pressures and thermodynamic models, and prioritizing safety and operability over apparent numerical optimization.

Importantly, these behaviors were not diminished by AI use; they were activated by it. The presence of AI-generated but imperfect solutions prompted students to become more vigilant, skeptical, and reflective. Instead of disengaging from learning, students engaged more deeply with core principles, repeatedly cross-checking AI outputs against simulations and engineering reasoning. This finding challenges common fears that AI inherently undermines learning and instead suggests that, when properly scaffolded, AI can surface the very judgment skills that engineering education seeks to cultivate.

Pedagogical Implications for Chemical Engineering Education

The findings of this study suggest several implications for chemical engineering educators navigating the integration of generative AI. First, AI should be intentionally embedded rather than prohibited. When AI use is structured and transparent, it exposes misconceptions and accelerates learning rather than providing shortcuts. Second, verification must be treated as an explicit learning objective. Assignments should require students to validate, critique, and, when necessary, disprove AI-generated outputs using engineering fundamentals. Third, simulation-based and open-ended design tasks are essential. Compared to closed-form problems, Aspen-driven design exercises more effectively reveal AI's limitations and highlight the necessity of professional judgment. Finally, structured engagement with AI can support professional identity formation, as confronting AI failure in safety- and decision-critical contexts helps students internalize responsibility alongside technical competence.

Implications for AI Use in Professional Practice

The combined results of Tasks 1 and 2 closely mirror real industrial workflows. AI excels at drafting early design narratives, enumerating possible options, identifying trade-offs, and accelerating documentation and communication. However, the findings reinforce that design ownership must remain human. Students consistently concluded that only results that are traceable to stream tables, simulation inputs, and verified assumptions should advance through decision gates. This principle aligns directly with professional engineering standards and highlights the role of AI as an augmentative, not authoritative, component of engineering practice.

This study contributes to engineering education research by demonstrating how generative AI can strengthen engineering judgment when used intentionally and critically, rather than undermining it. The two-task instructional framework provides a scalable model that spans algorithmic and open-ended design contexts, offering a practical approach for integrating AI into core chemical engineering courses. By grounding the analysis in authentic student artifacts and reflections, this work reframes AI not as a threat to learning, but as a catalyst for professional formation, making judgment, accountability, and responsible decision-making more explicit and teachable in Senior Design I.

Limitations & Future Work

This study has several limitations that should be acknowledged. First, the findings are based on a single implementation within one Senior Design I chemical engineering course at a single institution, which limits statistical generalizability. While the use of multiple teams and rich design artifacts supports analytical generalization, future studies across different institutions, course structures, and student populations are needed to examine the robustness of these findings. Second, students self-selected their AI tools during individual exploration, resulting in variation across AI platforms and versions. Although this reflects authentic student practice, it complicates direct comparison of specific tools and models.

Additionally, this study relied primarily on qualitative analysis of student artifacts and reflections. While this approach was appropriate for examining engineering judgment and professional reasoning, future work could incorporate quantitative measures—such as pre/post assessments of judgment, verification behavior, or simulation accuracy—to triangulate findings. Longitudinal studies following students into Senior Design II or early professional practice could also provide insight into whether AI-supported judgment skills persist beyond a single course.

Future work will focus on refining the instructional scaffolding around AI use, including the development of structured verification checklists and prompts that explicitly guide students in auditing AI-generated outputs. Further research could also explore how similar AI-integrated design frameworks perform in other core chemical engineering courses, such as separations or process control, and how industry practitioners perceive the alignment between these pedagogical approaches and professional engineering workflows.

Conclusions

This study examined the structured integration of generative AI into a Senior Design I chemical engineering course through two design tasks of increasing complexity: a thermodynamically constrained heat integration problem and an open-ended process design and simulation task. Across both tasks, results show that generative AI can effectively support early-stage exploration and organization, but cannot replace engineering judgment. As design complexity increased, AI-generated errors became less transparent and more consequential, underscoring the need for rigorous verification, simulation-based validation, and professional oversight.

Importantly, the findings demonstrate that engineering judgment is not diminished by AI use when appropriately scaffolded. Instead, AI interaction prompted students to engage more deeply with first principles, mass and energy balance closure, and safety- and operability-focused decision-making. By positioning AI outputs as objects of critique rather than authoritative solutions, the course design made engineering judgment visible, learnable, and assessable.

Overall, this work contributes a practical instructional framework for responsible AI integration in chemical engineering design education. The results suggest that generative AI, when intentionally embedded, can serve as a catalyst for professional formation—strengthening students' capacity for critical evaluation, accountability, and human-centered decision-making in engineering practice.

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