2025 ASEE Northeast Section Conference, March 22, 2025, University of Bridgeport, Bridgeport, CT, USA.

Teaching Prompt Engineering Across Disciplines: Challenges, Outcomes, and Best Practices

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***Abstract*—This study investigates the outcomes and challenges of teaching prompt engineering across computational and engineering disciplines, specifically in the context of an Introduction to Databases (DB) course and an Electric Energy and Machines (EEM) course. Prompt engineering, the skill of crafting inputs to guide artificial intelligence (AI) models, is increasingly relevant across fields. However, little is known about its pedagogical challenges or impact on student learning. Using a mixed-methods approach, we collected data from 35 students (25 from DB and 10 from EEM) through pre- and post-study surveys, skills assessments, and qualitative feedback. Key findings reveal that students in both courses reported an improved understanding of AI and proficiency in prompt engineering. Students in the DB course, which has a stronger computational focus, demonstrated higher confidence in applying prompt engineering to database-related tasks, with many planning to use these skills for automating tasks, optimizing queries, and generating sample data. In contrast, EEM students, while also showing improvement, were more cautious about integrating AI into their workflows, often citing concerns about reliability and safety.**

The study identified several challenges in teaching prompt engineering, including the need for clear context and specificity in prompts, the difficulty of balancing technical depth with accessibility, and the varying levels of prior AI knowledge among students. This research highlights the importance of tailored teaching methods for prompt engineering, emphasizing the need for discipline-specific approaches. The findings suggest that prompt engineering can be integrated into both computational and engineering curricula, provided instructors address each field's unique challenges and opportunities. This study contributes to the growing body of knowledge on AI education and offers practical insights for educators aiming to enhance student learning outcomes in an AI-driven world.

Keywords*—*Prompt engineering; Critical thinking skills; Pedagogical challenges

I. Introduction

The rapid evolution of artificial intelligence (AI) has made prompt engineering—the practice of crafting inputs to optimize AI outputs—a foundational skill for interacting with generative technologies. As AI systems like large language models (LLMs) permeate professional and academic workflows, the ability to design precise, context-aware prompts is no longer confined to technical domains. Instead, it has become a cross-disciplinary competency, enabling users to automate tasks, refine problem-solving, and navigate proper considerations. Despite its growing relevance, structured education on prompt engineering remains sparse, particularly in engineering fields where AI literacy is often secondary to domain-specific training. This gap underscores the urgency of understanding how prompt engineering can be effectively taught to students with diverse academic backgrounds and career trajectories.

The significance of integrating prompt engineering into curricula spans disciplines. In computational fields, it enhances technical workflows such as code generation or database optimization, while in engineering or applied sciences, it supports data analysis, design simulations, and decision-making. Prompt engineering fosters critical engagement with AI tools even in humanities-oriented contexts, encouraging users to interrogate biases and limitations. However, teaching this skill presents challenges: students' prior AI knowledge varies widely, principled concerns complicate practical applications, and discipline-specific use cases demand tailored pedagogical approaches. Current educational frameworks often lack strategies to address these nuances, leaving educators to navigate uncharted territory when incorporating prompt engineering into their courses.

This study investigates the outcomes and challenges of teaching prompt engineering in two distinct academic contexts: an Introduction to Databases (DB) course and an Electric Energy and Machines (EEM) course. The research addresses three core objectives: (1) evaluating how prompt engineering instruction impacts students' AI proficiency and problem-solving skills, (2) identifying discipline-specific barriers to teaching the skill, and (3) proposing adaptable best practices for educators across fields. By comparing computational and engineering cohorts, the study highlights how pedagogical strategies must evolve to meet the needs of diverse learners in an AI-driven era.

The paper is structured as follows. The Introduction follows a Related Work section synthesizing existing research on prompt engineering education, including prior challenges and outcomes, and identifying gaps this study addresses. The Methodology section details the mixed-methods approach, participant demographics, and data collection via surveys, skills assessments, and qualitative feedback. Findings present quantitative and qualitative results, emphasizing contrasts between the two classes, while the Discussion interprets these outcomes, explores implications for teaching practices, and acknowledges study limitations. A dedicated Best Practices section offers actionable recommendations for educators, followed by a Conclusion summarizing key contributions and advocating for further research into the long-term impacts of prompt engineering education. Collectively, this work advances the discourse on AI pedagogy by bridging disciplinary divides and prioritizing adaptable, fittingly informed teaching frameworks.

II. Related Work

The existing research on prompt engineering in education has recognized its transformative potential in enhancing learning experiences across various disciplines. In [1], the authors emphasize the importance of strategically designed prompts for AI tools like ChatGPT, which can foster engagement, critical thinking, and personalized instruction. The study outlines effective strategies such as assigning roles to AI, defining clear objectives, and employing iterative dialogue to refine outputs. Similarly, the authors of [2] explore integrating structured prompt engineering with generative AI tools. This demonstrates that a focused training session can significantly improve self-directed learning in programming and data analysis among novice students. These studies collectively highlight the growing consensus on the value of prompt engineering as a pedagogical tool that can bridge the gap between AI capabilities and student needs.

However, several challenges regarding teaching prompt engineering have been identified in the literature. In [3], the authors note that while structured training can enhance students' AI literacy, there are concerns about the varying levels of prior knowledge among students and the need for discipline-specific adaptations. The authors in [4] further discuss the ethical implications and potential over-reliance on AI tools, which can complicate the integration of prompt engineering into curricula.

The outcomes of prompt engineering education are promising, as evidenced by various studies. For instance, Lee and Palmer [5] found that structured frameworks for crafting AI prompts can enhance teaching and learning outcomes, preparing students for AI-augmented workplaces. Walter [6] supports this by arguing that prompt engineering fosters critical thinking and problem-solving skills essential for navigating AI-driven environments. The findings from these studies indicate that prompt engineering improves students' technical proficiency and enhances their confidence in utilizing AI tools for academic and professional tasks.

Despite the positive outcomes, this study aims to address notable gaps in the literature. Many existing studies focus narrowly on specific disciplines, limiting the understanding of how prompt engineering can be effectively taught across a broader range of fields. Additionally, there is a lack of longitudinal research examining the long-term retention of skills acquired through prompt engineering education. This study seeks to fill these gaps by investigating the outcomes and challenges of teaching prompt engineering in both computational and engineering disciplines, providing insights into best practices that can be adapted to various educational contexts. By doing so, it aims to contribute to the growing body of knowledge on AI education and offer practical recommendations for educators looking to enhance student learning outcomes in an increasingly AI-driven world.

III. Methodology

We employed a mixed-methods design to evaluate the effectiveness of a prompt engineering intervention for students enrolled in two distinct courses (DB) and (EEM). We integrated quantitative surveys, qualitative feedback, and discipline-specific skills assessments to address four research questions:

1. RQ1 How does prompt engineering training impact technical proficiency and problem-solving skills?. This question was assessed through pre/post-Likert-scale surveys (Q2, Q3) and skills assessments.
2. RQ2 What role does disciplinary context play in shaping career relevance and proper perceptions?. This was explored via Likert-scale ratings (Q5) and qualitative themes from open-ended responses.
3. RQ3 How do pre-existing attitudes influence learning outcomes? This relationship was analyzed using pre-intervention Likert data (Q1, Q4) and qualitative reflections on challenges.
4. RQ4 What pedagogical strategies are most effective in teaching prompt engineering? These were identified through qualitative critiques of teaching methods (Q6) and skills assessment performance.

We used three primary instruments:

1. Pre- and Post-Intervention Surveys: Six Likert-scale questions (1–5 scale) assessed understanding of AI (Q1), proficiency in prompt engineering (Q2), problem-solving improvement (Q3), critical thinking (Q4), career relevance (Q5), and teaching effectiveness (Q6). Surveys were administered electronically before and after an 8-week intervention. The question used are:

   Q1. How would you rate your understanding of artificial intelligence

   Q2. How would you rate your proficiency in prompt engineering

   Q3. To what extent has learning prompt engineering improved your problem-solving skills?

   Q4. How has prompt engineering affected your critical thinking abilities?

   Q5. How relevant do you now think prompt engineering will be to your future career?

   Q6. How effective were the teaching methods used for prompt engineering?

2. Qualitative Feedback: Pre-intervention open-ended questions (Q1), anticipated challenges (Q2), and discipline-specific applications (Q3). Post-intervention questions explored future applications (Q4) and attitude changes toward AI tools (Q5). Responses were

anonymized to encourage candid reflections. The question used are:

Q1. What do you hope to learn from the prompt engineering unit in this course?

Q2. What challenges do you anticipate in learning prompt engineering?

Q3. How do you think prompt engineering might be applied in EEM/DB?

Q4. How do you plan to use prompt engineering skills in your future studies or career?

Q5. Compared to the beginning of the course, how has your attitude towards AI tools changed?

3. Skills Assessments: Discipline-specific tasks evaluated applied proficiency:

- DB Students: Designed to reflect computational workflows, the tasks included generating normalized Structured Query Language - SQL schemas (e.g., "Design a normalized database schema for an online bookstore") and optimizing slow-performing queries using rubrics that scored clarity, technical accuracy, and creativity (0–10).
- EEM Students: Focused on interdisciplinary applications, such as designing AI-driven prompts to compare digital/analog sensors in solar energy systems (e.g., "Propose a solar energy system design with voltage/current sensors"). Rubrics emphasize practical feasibility and integration of theoretical concepts.

The study involved 35 students: 25 from DB and 10 from EEM. Participants were enrolled in their respective courses at the US Coast Guard Academy, with no prior formal training in prompt engineering. The DB cohort focused on computational skills (e.g., SQL, database design, Created-Read-Update-Delete CRUD applications, etc.), while the EEM cohort emphasized applied engineering (e.g., energy systems, machinery, etc.). This disciplinary contrast allowed a comparative analysis of learning outcomes in technical versus interdisciplinary contexts.

IV. Findings

This section presents a detailed overview of the study's quantitative and qualitative results, highlighting how the intervention differentially affected technical proficiency, perceived skill development, and overall understanding of AI in the Introduction to Databases and Electric Energy and Machines courses.

A. *Technical Proficiency and Perceived Skill Development*

Quantitative data claims divergent gains in self-rated proficiency in prompt engineering (Q2). EEM students showed a marked improvement of +1.98, while DB students improved by +0.97. The Magnitude in Improvement chart (Fig 1) highlighted this disparity, with EEM's gain surpassing DB's across all competencies except problem-solving (Q3: EEM +0.10 vs. DB -0.44). Open-ended responses contextualized these trends: DB students emphasized technical automation, "Debugging code faster with AI," whereas EEM students noted challenges in domain-specific applications: "AI can't solve problems itself."

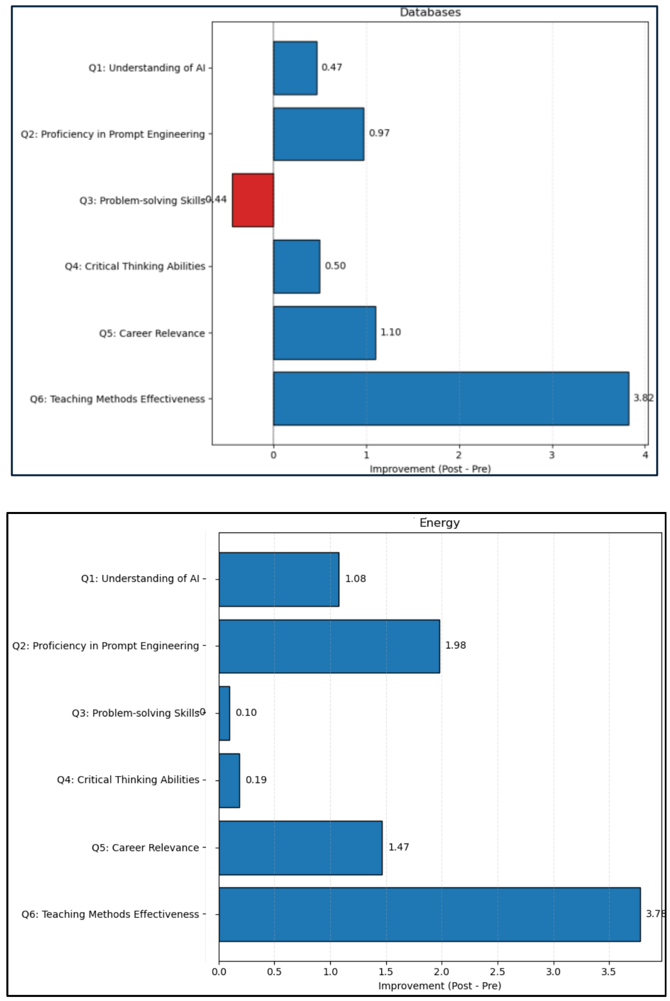

Fig 1. Magnitude in Improvement in Both Course

B. *Skills Assessments*

We used discipline-specific tasks to evaluate applied proficiency. DB students were asked to craft normalized SQL schemas (e.g., "Design a normalized database schema for an online bookstore") and optimize slow-performing queries. Rubrics scored clarity, technical accuracy, and creativity. 85% of DB students prioritized "providing clear context and specific requirements" in prompts, with common strategies including specifying data types (e.g., VARCHAR, INT) and relational constraints (e.g., foreign keys).

EEM Students' skills assessment focused on crafting AI prompts to compare digital/analog sensors in solar energy systems (e.g., "Propose a solar energy system design with voltage/current sensors"). Rubrics emphasize practical feasibility and integration of theoretical concepts. Qualitative feedback from the EEM skills assessment showed that project-specific prompts (e.g., "testing condition factors like shading in your solar panel design") yielded the most actionable AI responses, with 70% of students noting these prompts bridged theory and practice. However, some struggled with hardware implementation, as ChatGPT lacked contextual awareness of sensor placement or wiring diagrams.

C. *Career Relevance and Considerations*

Both classes rated career relevance (Q5) highly post-intervention (DB: 4.9; EEM: 4.8). Fig 1. This shows a more significant improvement for EEM students (+1.47) compared to DB students (+0.37) who were more familiar with AI use in their field. Qualitative reflections underscored discipline-specific rationales: DB students linked relevance to technical efficiency, "Handling large datasets in my capstone." In contrast, EEM students connected it to interdisciplinary innovation, such as "AI requires fact-checking" (EEM), which emerged more prominently in qualitative data from EEM students.

D. *Understanding of AI and Critical Thinking*

Post-intervention understanding of AI (Q1) improved for both groups, with EEM students demonstrating a larger gain (+1.08) than DB students (+0.47). Fig. 1 illustrates this contrast, aligning with qualitative distinctions: DB students associated understanding with technical mechanics, "I see how AI formulates responses," while EEM students emphasized pedagogical utility, "AI explains concepts simply."

E. *Teaching Methods and Baseline Knowledge*

Teaching effectiveness (Q6) showed the most significant disparity in the chart, with EEM students reporting a +3.78 improvement compared to DB's +1.08. Qualitative critiques varied: DB students cited pacing as "Too fast for beginners," while EEM students requested discipline-specific examples that "Need more lab applications." Baseline differences in AI familiarity were evident, with DB students reporting higher pre-intervention technical competency (e.g., Q1: 3.1 vs. EEM's 2.7).

F. *Cross-Class Comparisons*

Fig. 1 shows EEM's steeper improvements in proficiency (+1.98 vs. DB's +0.97). Qualitative data aligned with these trends: EEM students' lower baseline familiarity, "I didn't know how to trust AI outputs," contrasted with DB students' focus on refining existing skills, "Automating SQL queries now."

These findings illustrate the differential impact of the intervention across disciplines, with quantitative trends and qualitative narratives corroborating the diverging bar chart's depiction of more significant gains among EEM students. The results highlight the role of baseline knowledge and disciplinary context in shaping outcomes.

V. Discussion

This study examined the impact of prompt engineering instruction on students in computational DB and engineering EEM disciplines, addressing four research questions through mixed-methods analysis. Below, we interpret the findings, discuss pedagogical implications, explore discipline-specific significance, and acknowledge study limitations.

A. *Interpretation of Findings*

The intervention led to significant improvements in both cohorts, but the magnitude of gains differed. EEM students who began with lower baseline AI understanding (pre-intervention Q1: 2.7 vs. DB's 3.1) demonstrated steeper improvements in proficiency (+1.98 vs. DB's +0.97). This aligns with RQ1 (technical proficiency and problem-solving), suggesting that students with limited prior AI exposure experience accelerated skill acquisition when provided with structured training.

Contrasting career relevance rationales address RQ2 (disciplinary context): DB students emphasized technical efficiency (e.g., "handling large datasets"), while EEM students linked relevance to interdisciplinary innovation (e.g., "optimizing energy forecasts"). Proper concerns also diverged, with EEM students prioritizing academic integrity ("using AI within policy") and DB students focusing on systemic risks like data privacy.

Pre-existing attitudes (RQ3) mediated outcomes, as DB's prior AI exposure likely tempered their perceived gains. For instance, their moderate improvement in understanding AI (+0.47) contrasted with EEM's sharper rise (+1.98), which students attributed to AI's role in clarifying abstract concepts.

B. *Implications for Teaching Practices*

The results underscore the need for tailored pedagogical strategies (RQ4). EEM students' requests for discipline-specific examples (e.g., lab applications) and DB students' critiques of pacing ("too fast for beginners") highlight the importance of adapting content delivery to disciplinary needs. Instructors in technical fields might prioritize hands-on coding tasks, while engineering courses could integrate AI into problem-solving frameworks (e.g., simulating energy systems). Addressing decent concerns explicitly in engineering contexts may mitigate skepticism about AI reliability.

C. *Discipline-Specific Approaches*

The study underscores the value of aligning prompt engineering education with disciplinary goals. DB students leveraged AI for technical automation (e.g., "debugging code faster"), whereas EEM students applied it to interdisciplinary tasks (e.g., "generating equations for experiments"). This divergence suggests curricula should balance universal competencies (e.g., prompt structuring) with domain-specific applications. For example, DB courses might emphasize syntax-driven tasks, while EEM courses could focus on translating domain knowledge into effective prompts.

D. *Limitations and Biases*

Several limitations warrant consideration. First, the small sample size (especially in the EEM cohort) limits generalizability. Second, self-reporting biases may inflate proficiency ratings, particularly in technical cohorts where AI familiarity is valorized. Third, the homogeneity of participants (cadets from a single technical institution) may skew outcomes, as prior exposure to computational concepts varies widely in broader populations. Finally, pre-existing attitudes in DB (e.g., higher baseline technical confidence) may have influenced their moderated gains, suggesting that future studies should control for prior knowledge.

VI. Best Practices for Teaching Prompt Engineering

Practical instruction in prompt engineering requires strategies that balance universal principles with discipline-specific adaptations. Educators should prioritize teaching iterative prompt refinement, emphasizing the importance of clarity, context, and specificity. For instance, students benefit from structured frameworks that guide them in breaking down complex queries into stepwise instructions (e.g., "Specify the task, define constraints, and request examples"). To address inaccurate AI outputs, instructors can integrate exercises that teach students to identify and correct errors, such as analyzing mismatches between prompts and generated responses. Emphasizing the role of follow-up prompts to refine outputs (e.g., "Revise your query to narrow the scope") helps students navigate AI limitations while fostering critical evaluation skills. Additionally, discussing proper considerations—such as data privacy in database contexts or academic integrity in engineering projects—equips students to use AI tools responsibly.

Tailoring instruction to disciplinary needs is critical. In computational courses like Introduction to Databases (DB), where students often have higher baseline AI familiarity, educators can accelerate pacing and focus on advanced applications, such as automating SQL queries or generating synthetic data. Technical examples (e.g., "Use prompts to debug Python code") resonate with these learners, aligning with their career-driven goals. In contrast, engineering disciplines like Electric Energy and Machines (EEM) require foundational scaffolding. Instructors should begin with relatable, domain-specific scenarios (e.g., "Design prompts to simulate power grid failures") and explicitly address skepticism about AI's reliability. For EEM students, integrating prompts into lab workflows (e.g., optimizing experiment parameters) bridges theoretical and practical learning, while slower pacing accommodates varied technical exposure.

Integrating prompt engineering into existing curricula need not require structural overhauls. Educators can embed prompt design into coding assignments in computational courses, such as tasking students using AI to troubleshoot database errors or generate CRUD application templates. Prompt engineering can enhance project-based learning for engineering fields: EEM students might employ AI to analyze energy consumption patterns or draft equipment maintenance protocols. Modular workshops on prompt crafting, offered early in the term, provide a low-barrier entry point across disciplines. Collaborative activities, such as peer reviews of prompts, further reinforce learning. Educators can cultivate AI literacy by aligning prompt engineering with existing learning objectives—whether automating technical tasks or solving applied problems—without displacing core content. These approaches, informed by the study's findings, ensure that prompt engineering enhances, rather than disrupts, disciplinary education.

VII. Conclusion

This study demonstrates the transformative potential of prompt engineering education in enhancing technical proficiency across computational and engineering disciplines. Students in the Introduction to Databases (DB) and Electric Energy and Machines (EEM) courses exhibited significant improvements in self-reported AI understanding, prompt engineering skills, and problem-solving abilities following the intervention. Notably, EEM students who began with lower baseline AI familiarity achieved steeper gains in proficiency (+1.97), underscoring the value of targeted instruction for learners with limited prior exposure. In contrast, DB students leveraged their computational backgrounds to apply prompt engineering to advanced tasks, such as SQL automation and data generation, albeit with more moderate gains. These findings highlight the role of disciplinary context in shaping learning trajectories and affirm that engineering education adapts to diverse knowledge foundations.

The skills assessments further reinforced this disciplinary alignment: DB students excelled in technical automation (e.g., optimizing queries), while EEM students refined project-specific prompts (e.g., exploring solar panels voltage and current analysis and design), illustrating how AI literacy aligns with distinct pedagogical goals. Future research should explore longitudinal retention of these skills, particularly in hardware-centric fields like EEM, where AI's limitations in practical implementation (e.g., sensor calibration) necessitate complementary human expertise. Collectively, the results emphasize that effective, prompt engineering instruction must balance universal principles with discipline-specific applications to maximize its transformative impact.

The results contribute to the broader discourse on AI education by illustrating how structured, prompt engineering training fosters technical and analytical competencies. Students iteratively refined prompts, evaluated outputs, and troubleshoot errors. The intervention cultivated critical skills essential for navigating AI's limitations and biases. This dual focus on technical mastery and engagement positions prompt engineering as a pedagogical tool that transcends mere tool proficiency, encouraging students to approach AI as critical collaborators rather than passive users.

The growing ubiquity of AI tools across industries underscores why prompt engineering is becoming an indispensable career skill. For computational fields like DB, it streamlines workflows, enhances efficiency, and prepares students for roles in data management and software development. Engineering domains like EEM empower learners to tackle interdisciplinary challenges, from optimizing energy systems to simulating engineering scenarios. The universal relevance of prompt engineering and its adaptability to discipline-specific needs suggests it will play a pivotal role in bridging the gap between human expertise and machine capabilities in the workforce.

However, further research is needed to realize its educational potential fully. Longitudinal studies could assess the retention of prompt engineering skills and their transferability to real-world contexts. Comparative analyses of pedagogical strategies—such as project-based learning versus modular workshops—may identify best practices for diverse student populations. Additionally, exploring how prompt engineering intersects with emerging AI technologies, such as multimodal models or domain-specific LLMs, could refine its application in specialized fields. By addressing these gaps, educators and policymakers can ensure that prompt engineering instruction evolves to meet the demands of an AI-driven future, equipping learners across disciplines with the skills to innovate properly and effectively.

In conclusion, this study affirms that prompt engineering is not merely a technical skill but a critical component of modern education, fostering adaptability and analytical rigor. Its integration into curricula represents a proactive step toward preparing students for careers where human-AI collaboration is inevitable, ensuring they can harness AI's potential while navigating its complexities.

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