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Prompt Quality Analysis in AI-Assisted Learning of Database Programming: Pedagogical Insights from a University-Level Intervention

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ABSTRACT

Integration of Artificial Intelligence (AI) tools in higher education has transformed the teaching and learning strategy, especially in technical domains such as database programming. This study investigates the relationship between the quality of student-generated AI prompts and traditional database programming proficiency in higher education. Through quantitative analysis of 20 student submissions, we evaluate prompt quality across three dimensions—Specificity, Clarity, and Context—and examine their correlation with conventional assessment performance. Our findings reveal that Specificity in prompt writing shows the strongest association with traditional database skills ($r = 0.51$, $p < 0.05$), suggesting that students who craft more precise AI instructions also demonstrate stronger technical competencies. Clarity emerges as the most challenging aspect for learners ($M = 1.85/4$), highlighting gaps in technical communication. The study provides actionable insights for integrating prompt engineering into database education while maintaining focus on foundational knowledge. We discuss implications for curriculum design, including the need for explicit writing instruction and ethical considerations in AI-augmented learning. Limitations and future research directions are outlined, particularly regarding longitudinal effects of prompt-writing training and ethical dimensions of educational AI use. This work contributes to emerging scholarship on AI's role in computing education by demonstrating how prompt quality reflects and potentially enhances traditional learning outcomes.

Keywords: AI in education, prompt engineering, database programming, computing education

1. INTRODUCTION

The rapid advancement of generative Artificial Intelligence (AI) has significantly impacted higher education, particularly in technical disciplines such as Information Technology (IT) and Computer Science. For example, in a programming course, AI-powered tools, including large language models (LLMs) and code-generation platforms, offer students instant feedback, automated debugging, and even complete code solutions, which are the capabilities that were previously inaccessible without extensive human intervention [1]. While these tools present opportunities for enhancing learning efficiency, their integration into educational settings also raises critical questions about pedagogical effectiveness, cognitive engagement, and academic integrity [2].

Particularly in database programming courses, where students must develop both technical proficiency (e.g., SQL query formulation, schema design) and higher-order cognitive skills (e.g., problem decomposition, optimisation, debugging), generative AI presents a double-edged sword. On one hand, it can serve as a scaffolding tool, aiding learners in overcoming initial barriers to

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complex tasks [3, 4]. On the other hand, over-reliance on AI-generated solutions may undermine deep learning, as students might bypass essential cognitive processes such as analytical reasoning and iterative problem-solving [4].

A crucial yet underexplored factor in this dynamic is prompt quality, i.e. the instructions students provide to AI systems. Research suggests that the effectiveness of generative AI in education depends heavily on how users formulate their queries [5]. Well-structured prompts aligned with Bloom's Taxonomy (e.g., prompts that elicit analysis, evaluation, or creation) can enhance learning outcomes, whereas vague or simplistic prompts may yield superficial or incorrect outputs. However, preliminary evidence indicates that students often struggle with effective prompt engineering, limiting their ability to harness AI as a meaningful learning aid [6].

This study investigates how undergraduate students in a Malaysian public university use generative AI for database programming tasks, with a focus on assessing the quality of their prompts and the corresponding AI-generated outputs. Using a Prompt Quality Analysis (PQA) rubric, which developed in this study, we evaluate student-generated prompts based on Specificity, Clarity and Context. Additionally, we explore the ethical implications of AI reliance, including concerns about critical engagement, academic integrity, and superficial learning.

2. LITERATURE REVIEW

Scholarly discourse highlights both the pedagogical benefits and systemic challenges associated with AI adoption. On one hand, AI-powered tools (such as adaptive learning systems, automated assessment platforms, and personalised feedback mechanisms) have demonstrated measurable improvements in student engagement, knowledge retention, and individualised learning [7, 8]. These technologies align with student-centred instructional models, catering to diverse learning needs by providing real-time adjustments to content difficulty, pacing, and feedback [7].

However, the literature also underscores critical evolving role of instructors in AI-mediated classrooms, which shifts from knowledge transmitters to facilitators of AI-augmented learning, poses institutional and pedagogical challenges [5, 9]. Compounding to these issues are gaps in digital literacy among educators and a lack of institutional infrastructure to support AI integration, which may hinder scalable adoption [9]. Within this broader context, the domain-specific implications of AI in technical disciplines course like database programming, warrant further examination.

2.1 Cognitive Load and Prompt Quality

The rise of generative AI in education has positioned prompt engineering as a critical skill for both learners and educators [10]. A "good" prompt is operationally defined as one that elicits clear, accurate, and contextually relevant responses from AI systems [5]. Frameworks for evaluating prompt quality typically emphasise three dimensions:

- Clarity – The absence of ambiguity in instructions.
- Specificity – The precision of the query or task directive.
- Context – The inclusion of relevant background or examples to guide AI output.

Emerging taxonomies further categorise prompts according to their cognitive demands, aligning with Bloom's Taxonomy to distinguish between prompts targeting lower-order (e.g., recall, comprehension) and higher-order skills (e.g., analysis, evaluation, creation) [1]. The literature underscores that well-designed prompts are pivotal for maximising AI's pedagogical value, as they directly influence the accuracy, depth, and utility of AI-generated content, as well as students' learning experiences [11].

In addition, previous research caution that over-reliance on automation risks fostering surface learning, particularly when students bypass cognitive struggle, which is a necessary component of deep learning [12]. For example, if AI routinely generates complex codes in programming without requiring students to engage in iterative problem-solving, learners may miss opportunities to develop metacognitive skills or conceptual mastery [10]. This tension highlights the need to align AI use with intended learning outcomes, ensuring tools are deployed to scaffold higher-order cognitive processes.

2.2 Ethical Considerations on AI in Education

The growing integration of AI in education has prompted significant ethical debates, particularly concerning academic integrity, pedagogical impact, and systemic biases [13]. A primary concern is academic dishonesty, as generative AI tools enable students to produce essays, code, or solutions with minimal original input, blurring the lines between legitimate assistance and plagiarism. Studies highlight cases where AI-generated content is submitted as student work, raising questions about authenticity and the erosion of critical thinking skills due to over-reliance on automated outputs [8].

The issue of authorship and intellectual property further complicates AI adoption. When AI generates content, determining ownership of the code, essays, or research has becoming contentious and challenging traditional academic norms [7]. Scholars argue that institutions must establish clear ethical frameworks to govern AI use, emphasising transparency (e.g., disclosing AI assistance), accountability (e.g., guidelines for proper attribution), and pedagogical alignment (e.g., ensuring AI tools supplement rather than replace learning processes) [14]. Beyond plagiarism, researchers warn of pedagogical risks, such as the risk of AI systems that perpetuate biases embedded in their training data, and potentially reinforcing inequities in educational outcomes. For instance, algorithmic recommendations might favour dominant cultural perspectives or exclude marginalised voices, further disadvantaging certain student groups [15].

3. METHODOLOGY

This study employs a quantitative research design to analyse the quality of prompts formulated by the students in a database programming course and their correlation with traditional assessment performance. The data collection process was designed to evaluate students' intrinsic abilities in crafting effective AI prompts for database-related tasks, as well as their traditional database programming proficiency – that is manual coding without AI assistance.

The study involved 20 participants enrolled in a database programming course. The data collection procedure consisted of two main components: (1) an AI prompt submission task and (2) a traditional database programming assessment. Students were instructed to write natural language prompts directing an AI to perform database-related tasks, such as generating SQL queries, or designing database schemas. The prompts were collected without prior exposure to evaluation criteria or examples of high-quality prompts. This blind assessment approach was implemented to minimize bias. By withholding the rubric and exemplary prompts, students' submissions reflected their natural prompt-writing abilities without external influence. It also ensures authenticity, since the lack of pre-submission coaching allowed researchers to measure students' intrinsic understanding of how to formulate effective AI instructions.

3.1 Prompt Quality Analysis Rubric Development

To ensure a robust and objective measure of prompt quality, a comprehensive Prompt Quality Analysis (PQA) rubric was developed in this study. This rubric was based on a thorough review of existing literature on effective AI prompting and common challenges students face when interacting with AI tools in educational contexts [1, 5, 10] .

Table 1 Rubric for Prompt Quality Analysis

Dimension	Score	Description	Sample Prompt
Specificity	1	The prompt is vague and provides no guidance on the desired format, structure, or content of the output.	"*Write a query to find some books*" (what books? what criteria?)
	2	The prompt provides some details but is missing key information, which may lead to a generic or incomplete AI response.	"*Write a SQL query to get books published after 2000*" (what table? what columns?)
	3	The prompt includes most of the necessary details and constraints. It specifies the table name, relevant columns, and the desired output format, allowing the AI to generate a mostly accurate and useful response.	"*Write a SQL query for the 'Books' table to select all books published after the year 2000. Include the book title and author in the results*."
	4	The prompt is highly detailed and comprehensive. It includes all necessary parameters, explicit constraints, and formatting requirements.	"*Using the Books table with columns book_id, title, author, and publication_year, write a single SQL query that finds the top 5 most recently published books by author 'J. Creswell'. The output should be a set of single result with columns for title and publication_year*."
Clarity	1	The prompt is ambiguous, grammatically incorrect, or poorly structured.	"*Make a table for this assignment*" (unclear which assignment)
	2	The prompt contains some grammatical errors or is slightly ambiguous, but the student's general intent can be inferred.	"*Create a data base for a library with books and authors*" (ambiguous; what specific fields or relationships?)
	3	The prompt is clear, grammatically correct, and straightforward. The user's request is easily understood by the AI, and the prompt is well-organized.	"*Create a SQL table named 'Books' with columns for BookID (integer, primary key), Title (varchar), Author (varchar), and PublicationYear (integer)*."
	4	The prompt is very clear, concise, and well-structured. There is no ambiguity, and it uses appropriate terminology that directly guides the AI to the desired output.	"*Write an SQL script for a PostgreSQL database named 'library', and creates a table called 'Books' with the following columns: book_id (PRIMARY KEY), title, author, year_published*."
Context	1	The prompt provides no context, which leads to a high probability of a generic, irrelevant, or incorrect response.	"*Create a database*" (No mention of the database's purpose, tables, or fields.)
	2	The prompt provides minimal or vague context, and lacks the detail needed for specific and useful output.	"*Create a database for an online store*" (Fails to specify necessary entities.)

	3	The prompt includes adequate context. It defines the basic scope of the problem, mentions key entities, and provides some constraints.	"*Create an SQL schema for a bookstore database with tables for 'books', 'authors', and 'publishers'. The 'books' table should link to the other two.*"
	4	The prompt provides rich and comprehensive context. It includes a detailed problem description, specifies all relevant entities and attributes, defines relationships, and may even offer constraints, examples, or the desired output format.	"*You are an expert database designer for a university. Create a set of SQL CREATE TABLE statements for a library management system. The system needs to track students, books, and borrowing records. The students table should have a student_id (PK), first_name, and last_name. The books table needs a book_id (PK), title, and author_id. The borrowing_records table should link a student_id to a book_id with a borrow_date and return_date.*"

Specifically, as previously highlighted in the literature review section, this study identified three critical areas of concern in the literature: the lack of sufficient detail in prompts (Specificity), the use of ambiguous or vague language (Clarity), and the omission of necessary background information or constraints (Context). Based on these concerns, a detailed rubric with specific criteria for each dimension was formulated, aligning our analytical framework with established best practices in prompt engineering. The design of this rubric ensures our assessment is grounded in the key principles of effective AI use in teaching and learning. The details of the rubric used in this study is shown in Table 1.

4. RESULTS AND DISCUSSION

The analysis of student prompt quality across three key dimensions (i.e. Specificity, Clarity, and Context) revealed distinct patterns in students' ability to formulate effective AI instructions. As shown in Figure 1, Specificity emerged as the highest-scoring dimension (M = 2.70, SD = 0.92), with scores ranging from 1 to 4. The distribution was slightly right skewed, indicating that while some students demonstrated excellent specificity in their prompts, a significant portion (35%) scored at the lower end (scores of 1-2). Clarity proved to be the most challenging aspect for students (M = 1.85, SD = 0.67), with 60% of prompts receiving scores of 1 or 2, suggesting widespread difficulties with grammatical precision and structural organisation. Context scores showed moderate performance (M = 2.30, SD = 0.66), with most students (65%) scoring 2 or 3, demonstrating basic but inconsistent ability to provide adequate background information.

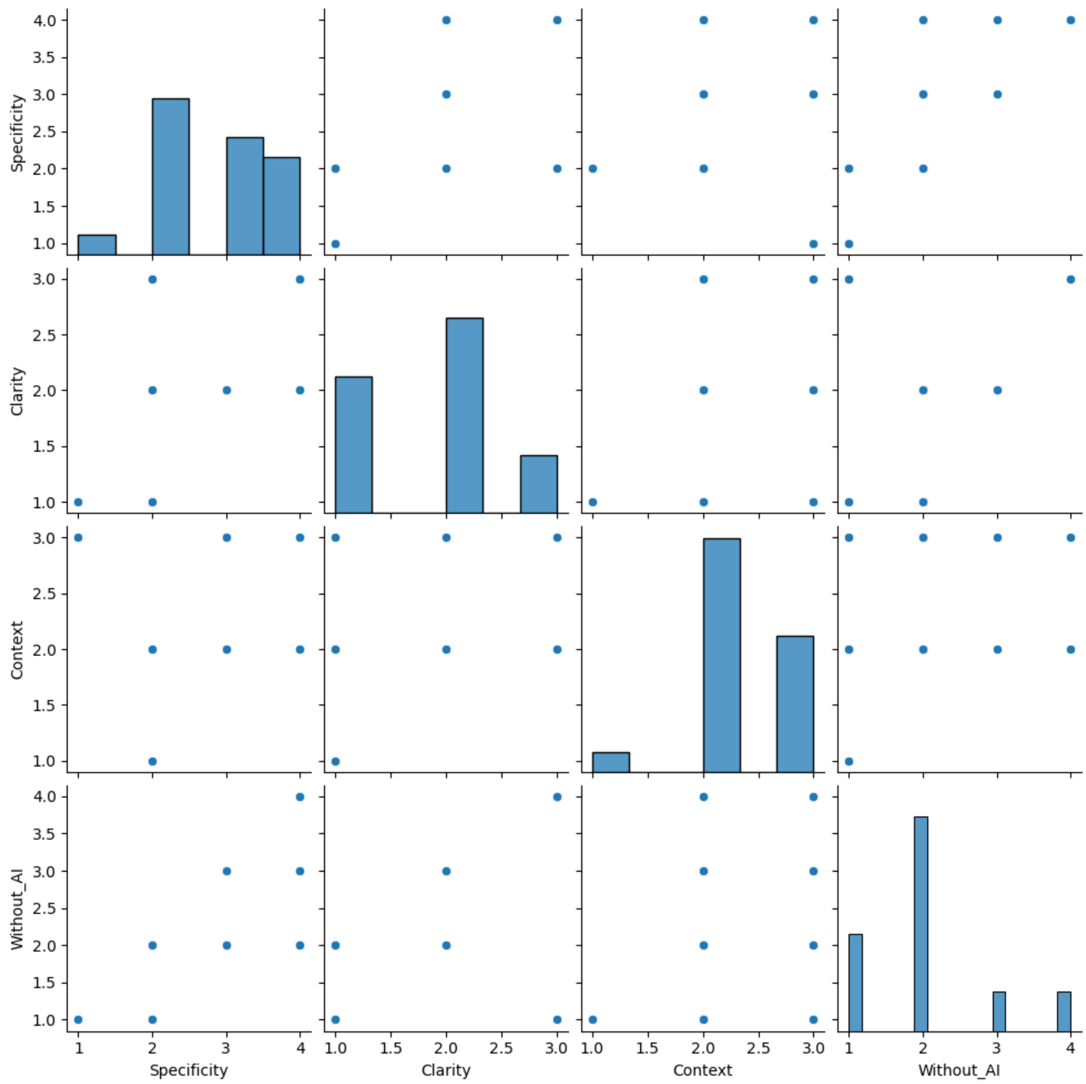

Figure 1. Pairwise Relationships between Dimensions.

Furthermore, as shown in Figure 1, traditional assessment scores without AI assistance (M = 2.05, SD = 0.89) displayed a bimodal distribution, with clusters around scores of 2 (45% of students) and 4 (20% of students). This pattern suggests a polarisation in fundamental database skills among the cohort. The standard deviations for all dimensions (ranging from 0.66 to 0.92) indicate moderate variability in student performance, with no ceiling effects observed in any of the measures.

Table 2 Pearson Correlation Coefficients Between Prompt Quality Dimensions and Traditional Assessment Scores

Variable	1	2	3	4
1. Specificity	1.00			
2. Clarity	0.45*	1.00		
3. Context	0.32*	0.28	1.00	
4. Without AI	0.51**	0.42*	0.35*	1.00

Notes:

- *p < 0.05, **p < 0.01 (two-tailed).
- N = 20 for all correlations.

The correlation matrix shown in Table 2 revealed significant positive relationships between all prompt quality dimensions and traditional assessment performance. Specificity showed the strongest association with traditional scores ($r = 0.51$, $p < 0.05$), indicating that students who provided more detailed, precise prompts also tended to perform better in conventional database tasks. This relationship was visually confirmed in the scatterplot (Figure 2), which showed a clear upward trend with relatively tight clustering of data points around the regression line.

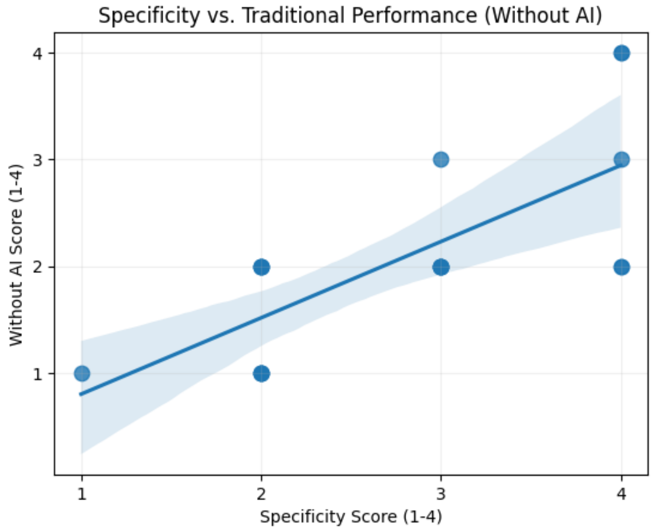

Figure 2. Specificity vs. Traditional Performance (Without AI).

Clarity demonstrated a moderate correlation with traditional performance ($r = 0.42$, $p < 0.05$), while Context showed the weakest but still significant relationship ($r = 0.35$, $p < 0.05$). The intercorrelations among prompt quality dimensions were all positive, with Specificity-Clarity ($r = 0.45$) and Specificity-Context ($r = 0.32$) showing the strongest connections. These patterns suggest that prompt writing competence represents a somewhat unified skill set, but with distinct dimensions that relate differently to traditional database proficiency.

Finally, a post hoc analysis of performance quartiles revealed striking differences between top-performing students (scoring 3-4 on traditional assessment) and their lower-performing peers (scoring 1-2). High performers consistently excelled in Specificity ($M = 3.25$ vs. 2.15 for low performers, $p < 0.01$) and Clarity ($M = 2.50$ vs. 1.45, $p < 0.05$), while Context showed a smaller but still significant difference ($M = 2.75$ vs. 2.05, $p < 0.05$). The boxplot comparison (Figure 3) illustrated these disparities, with high performers showing substantially less variability in their prompt quality scores.

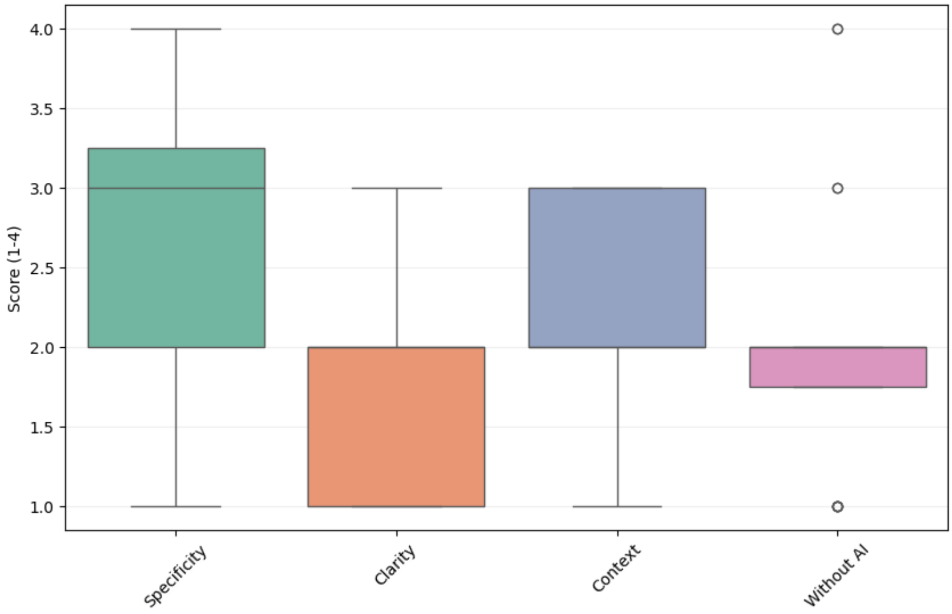

Figure 3. Distribution of Scores Across Dimensions.

As can be seen in Figure 3, all students who achieved the maximum score (4) on the traditional assessment also scored ≥3 on all prompt quality dimensions, suggesting a threshold effect where comprehensive database knowledge may enable superior prompt construction. On the contrary, the lowest traditional performers (score = 1) uniformly struggled with Clarity (all scoring 1) and showed minimal Specificity (M = 1.33), indicating that deficiencies in fundamental database understanding may manifest particularly in unclear prompt formulation.

5. CONCLUSION

This study demonstrates a significant relationship between students' prompt-writing quality and their traditional database programming skills, with specificity emerging as the strongest predictor of performance. The findings suggest that the ability to craft clear, detailed AI prompts reflects deeper technical understanding, positioning prompt engineering as both a valuable skill and potential diagnostic tool for database proficiency. For educators, these results highlight the importance of integrating communication training with technical instruction, particularly in developing students' capacity to articulate precise requirements—a skill essential for both AI interaction and professional practice.

The pedagogical implications call for a balanced approach to AI integration in computing education. While leveraging AI tools can enhance learning, the persistent challenges with clarity and context in student prompts reveal gaps in technical communication that require targeted instruction. Future research should explore ethical dimensions of AI use in education, including how prompt-writing practices affect academic integrity, skill development, and equity in learning outcomes. Such investigations could inform guidelines for responsible AI adoption in higher education settings.

Although limited by sample size, this study establishes a foundation for understanding how AI literacy intersects with traditional computing competencies. Further research should expand to diverse institutional contexts and examine longitudinal effects of prompt-writing instruction on skill retention. As AI becomes ubiquitous in education and the workplace, developing evidence-based strategies for teaching effective, ethical AI use will be crucial for preparing students to navigate an increasingly AI-augmented professional landscape.

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