The Impact of Structured Prompt-Driven Generative AI on Learning Data Analysis in Engineering Students

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Abstract: This paper investigates the use of Generative AI chatbots, especially large language models like ChatGPT, in enhancing data analysis skills through structured prompts in an educational setting. The study addresses the challenge of deploying AI tools for learners new to programming and data analysis, focusing on the role of structured prompt engineering as a facilitator. In this study Engineering students were trained to adeptly use structured prompts in conjunction with Generative AI, to improve their data analysis skills. The t-test comparing pre-test and post-test scores on programming and data analysis shows a significant difference, indicating learning progress. Additionally, the task completion rate reveals that 45% of novice participants completed tasks using Generative AI and structured prompts. This finding highlights the transformative impact of Generative AI in education, indicating a shift in learning experiences and outcomes. The integration of structured prompts with Generative AI not only aids skill development but also marks a new direction in educational methodologies.

1 INTRODUCTION

This study highlights the significant impact of Generative AI, especially large language models like OpenAI's ChatGPT, on education. These AI systems, known for their human-like text generation, are revolutionizing education by providing interactive and tailored learning experiences (Firaina, R., & Sulisworo, D., 2023). In educational contexts, Generative AI goes beyond a simple tool, becoming key in creating dynamic learning spaces that address diverse student needs (Ruiz-Rojas, L. I., et al., 2023).

Transitioning to the specific context of programming and data analysis, the application of Generative AI assumes a critical role. These complex, data-intensive fields benefit from AI's ability to analyze intricate data and identify patterns (Dhoni, P., 2023). This transition enhances conceptual understanding, allowing learners to explore the theoretical foundations of these disciplines. Generative AI's incorporation is set to transform conventional educational models, providing a richer learning experience (Sarkar, A., 2023).

Building on this foundation, this study investigates Generative AI's role in education, especially for beginners in programming and data analysis. Previous research has focused on AI code-generators for experienced programmers, overlooking its potential for novices, particularly in introductory data analysis (Vaithilingam, P., Zhang, T., & Glassman, E. L., 2022). The research aims to fill this gap by examining how Generative AI can facilitate learning and enable independent data analysis. It is driven by a research question on Generative AI's practical use and its educational impact through structured prompt engineering.

RQ: How does structured prompt engineering with Generative AI, influence the mastery of programming and data analysis concepts among learners with no prior programming experience?

In response to the research questions, this study involved 20 participants aged 24 to 29, all beginners in text-based programming and data analysis, from various engineering fields. They participated in structured training to understand basic data analysis concepts and use Generative AI tools. During a four-hour session, they engaged in prompt engineering with Generative AI to address data analysis tasks. The study showed significant learning improvements, with a large effect size of 0.89 and a p-value < 0.05 in

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the paired sample t-test on programming knowledge and data analysis concepts. These findings suggest the benefits of incorporating Generative AI and structured prompts in education, especially in domains like programming and data analysis.

2 BACKGROUNDS AND LITERATURE REVIEW

The literature review examines the application of Generative AI in educational settings, with a focus on ChatGPT's contributions to various learning environments. This section highlights the critical role of structured prompt engineering and evaluates the limited existing studies on Generative AI's use in programming and data analysis. This section identifies areas that require further investigation to fully understand the educational benefits and opportunities of Generative AI.

2.1 Generative AI in Education

Generative AI tools, such as ChatGPT, have become popular for their capacity to generate responses and content that mimic human interaction, using advanced deep learning algorithms and vast amounts of text data (Dai, Y. et al., 2023). To explore the applications and potential advantages of these AI tools in education, a systematic literature review was conducted, The applications of Generative AI are summarized as follows

Personalized Tutoring: AI provides customized tutoring and feedback, tailoring the learning experience to each student's needs and progress (Bahrini, A. et al., 2023).

Automated Essay Grading: AI systems are trained to grade essays by identifying characteristics of effective writing and offering feedback (De Silva, D. et al., 2023).

Language Translation: AI translates educational materials into multiple languages, ensuring accurate and understandable translations (Kohnke, L., Moorhouse, B. L., & Zou, D., 2023).

Interactive Learning: AI creates dynamic learning environments with a virtual tutor that responds to student inquiries (Bahrini, A. et al., 2023).

Adaptive Learning: AI adjusts teaching strategies based on student performance, customizing the difficulty of problems and materials (Bahrini, A. et al., 2023).

Content Creation: AI generates a variety of content, including articles, stories, poems, essays, summaries, and computer code (Rajabi, P., Taghipour, P., Cukierman, D., & Doleck, T., 2023).

Transitioning from the applications of generative AI to its specific role in programming, recent studies have explored the impactful role of generative AI. An experimental study showcased how the programming tool Codex, powered by generative AI, outperformed learners in a CS1 class on a rainfall problem, ranking in the top quartile (Denny, P. et al., 2023). Another investigation used the flake8 tool to assess code generated by AI against the PEP8 coding style, revealing a minimal syntax error rate of 2.88% (Feng, Y. et al., 2023). A notable study involved Github's generative AI platform, which initially failed to solve 87 Python problems; however, applying prompt engineering techniques enabled it to resolve approximately 60.9% of them successfully (Finnie-Ansley, J. et al., 2022).

The Above findings collectively highlight the efficacy of generative AI in code generation. This transition into the realm of prompt engineering, a critical aspect of maximizing the potential of generative AI in educational contexts, leads us to the next section of the literature review, focusing on the nuances of prompt engineering.

2.2 Prompt Engineering

Maximizing Generative AI's benefits in education relies on the proficient use of prompt engineering, a key skill that significantly affects AI model interactions (Kohnke, L., Moorhouse, B. L., & Zou, D., 2023). Effective prompt engineering requires understanding AI's operational principles, and ensuring prompts are clear and precise to improve tokenization and response accuracy. Including detailed context in prompts also enhances the AI's ability to form relevant connections, boosting response quality.

The art of prompt engineering also involves specifying the desired format of the AI's responses, ensuring they align with user expectations in terms of structure and style. Controlling verbosity within prompts is another key aspect, allowing users to manage the level of detail in the AI's responses, thus tailoring the information density to suit specific needs.

However, understanding these principles is just the beginning. Practical application demands a structured approach, embodied in the CLEAR framework. This framework provides a systematic strategy for crafting prompts that effectively harness the capabilities of AI language models. It's a synthesis of clarity, context, formatting, and verbosity control, all working in concert to elevate the communication process with AI, making it efficient and impactful in educational settings (Lo, L. S., 2023). The framework elements are presented below as

Concise: Prompts should be succinct, clear, and focused on the task's core elements to guide AI towards relevant and precise responses.

Logical: Prompts need a logical flow of ideas, helping AI understand context and relationships between concepts, resulting in coherent outputs.

Explicit: Prompts must specify the expected output format, content, or scope to avoid irrelevant responses.

Adaptive: Prompts should be flexible, allowing experimentation with different structures and settings to balance creativity and specificity.

Reflective: Continuous evaluation and refinement of prompts are crucial, using insights from previous responses to improve future interactions (Lo, L. S., 2023).

Additionally, some strategies mentioned in open AI documentation for writing prompts are presented below

Strategy: Write Clear Instructions

I. Include details in your query to get relevant answers.
II. Ask the model to adopt a persona using the system message.
III. Use delimiters to indicate distinct parts of the input.

Strategy: Provide Reference Text

I. Instruct the model to answer using a reference text.
II. Instruct the model to answer with citations from a reference text.

Strategy: Split Complex Tasks into Simpler Subtasks

I. Use intent classification to identify the most relevant instructions.
II. Summarize long documents piecewise and construct a full summary recursively (OpenAI, 2023).

The strategic application of prompt engineering tactics significantly refines AI interactions, ensuring responses are both precise and contextually relevant.

2.3 Gaps in Existing Literature

The existing research focuses on generative AI's ability in code generation and problem-solving but often misses its wider educational effects and interactions with learners. Key areas needing further exploration include:

Educational Impact in Data Analysis: The educational benefits of using tools like ChatGPT in teaching data analysis are unclear. Their influence on student motivation, comprehension of data analysis principles, and lasting skill acquisition needs examination, especially for newcomers to data analysis.

Prompt Engineering in Education: The role of prompt engineering in educational settings is largely unexplored. Recognized for enhancing AI performance, it has the potential to help learners articulate data analysis problems, think critically, and engage creatively with tasks that need exploration.

The literature review highlights the need for this study, focusing on prompt engineering's unexplored potential in education, especially in data analysis. It identifies a gap in understanding how Generative AI, with structured prompts, affects analytical skills and self-directed learning. This research aims to bridge this gap, providing insights into integrating Generative AI effectively in education and advancing data analysis practices.

3 STUDY DESIGN

In this part, the research method is explained, including the tasks created, the data used for these tasks, and the tests conducted before and after to assess the results. The discussion also covers the SUS survey used to evaluate user satisfaction and the training provided for effective prompt crafting.

3.1 Selection of Concept of Data Analysis for the Task

The study focuses on two essential data analysis skills: data aggregation and merging. Aggregation simplifies data, revealing trends and easing novices into complex tasks, much like learning the alphabet before forming sentences (McKinney, W., 2022). Merging integrates diverse datasets, essential in the data landscape, offering a unified view (McKinney, W., 2022).

3.2 Dataset for the Task and Problem Statement for the Task

3.2.1 Dataset

The dataset includes data from September to January, capturing attributes such as student video usage, student ID, school ID, view count, and last access date and time. Each month's dataset contains over 10,000 observations, providing a comprehensive view of student engagement with video content. This dataset is created for the task and the discussed concept of data analysis. However, this dataset draws inspiration from the school education program where students are provided tablets to enhance learning.

3.2.2 Task

Based on the given dataset, the task is designed that way so that it cannot be completed with no programming software like Excel and Tableau, etc., The following are the problem statements of the task
T1: Calculate the total daily video usage for each student across all months.
T2: Given the unique data capture cycle of student video usage (the 26th of one month to the 25th of the next), compute the monthly total video usage for each student, for example, compute the student total video usage for October (1st October to 31st October).
T3: Calculate the monthly video usage for each school over all the months.

For the completion of the tasks, Python programming is selected because it is preferred in data analytics due to its simplicity, extensive libraries like pandas and NumPy, and compatibility with big data and machine learning. Its strong community and relevance in real-world applications, along with market demand as highlighted by Zheng, Y. (2019), make it superior to alternatives like R and Weka, justifying its choice for this study.

3.3 Instrument Designed

The study selects specific tools to ensure the findings are valid and reliable. It aims to closely examine the experiences, needs, and performance of participants to fully understand the research goals.

3.3.1 Pre and Post-Test

A set of 15 MCQs was designed, focusing predominantly on the concepts of aggregation and merging. These questions aimed to assess the participants' comprehensive understanding of the concepts through Python programming. These Questions are designed across three levels of Bloom's taxonomy, the test comprises five questions each

- Understanding (L1)
- Applying (L2)
- Analyzing (L3)

These questions emphasized practical application also over mere rote learning and ensured relevance to the task at hand. These questions originated from the official panda's documentation and underwent multiple validations by industry experts, ensuring their efficacy in gauging participant performance.

3.3.2 SUS Survey

The System Usability Scale (SUS) was adapted to gather feedback on the Generative AI tool in data analysis, providing a reliable evaluation of its effectiveness and user experience (Brooke, J., 1995). Combining SUS scores with task performance and learning metrics allows for a detailed assessment of the tool's impact on user proficiency.

3.4 Design of Structured Prompt Training

A one-hour training session has been designed to introduce participants to prompt engineering, employing an example-based approach. Initially, the CLEAR framework and strategies from OpenAI's documentation are explained to lay the foundation. Subsequently, two examples of structured prompts are presented to illustrate the concepts in practice. The first example is non-contextual, featuring a question from the Union Public Service Commission ethics exam, a well-known civil service recruitment examination in India as shown in Figure 1. This example is chosen for its general nature, ensuring that even students with limited programming or data analysis experience can grasp the concept of structured prompts. The structured prompt for this question is crafted to build trust and provide an easy introduction to the topic. However, the prompt for this case is written this way "At the beginning of the prompt, the full question is clearly stated, followed by a detailed context explaining that this is a UPSC exam question, the nature of the exam, the selection process, and the roles of those selected. The requirement to limit the response to 250 words is specifically highlighted. The prompt then instructs to adopt the persona of an evaluator, whose profile is clearly outlined, to ensure the response meets the evaluator's expectations. Additionally, a strategy is provided to organize the answer logically, enhancing the overall response utilizing concepts from the CLEAR framework and Open AI strategies.

Question asked in the examination : 'Attitude is an important component that goes as input in the development of human being. How to build a suitable attitude needed for a public servant?'

Prompt for answer : This question is UPSC exam question of ethics mains paper, this exam is conducted to select the civil servant for Government of India who plays important roles in policy formation to ground level implementation of these policy and administrative work, write this question answer in 250 words, while writing this question adopt a persona that you are Examiner of this exam and having a 30 years of experience in academic and public life as administrator also, this question answer will required holistic thinking, so decompose first the question in smaller set to think holistically and then provide answer in the above mentioned format, it is important, take time to think"

Figure 1: Example 1- Structured prompt for answering UPSC exam question.

The second example is contextual and directly related to the field of study. It involves showing students an Excel file with a dataset different from the one used in the tasks. For this dataset, a structured prompt is written based on a specific problem statement as shown in Figure 2,

Problem: Compare the pre test perofrmance with post test performance for subject math of class 10th studnets for given dataset

Prompt for pyhton code: this is the path file of dataset ""E:\kef raw dataset\DATA-20230528T044334Z-001\DATA\Students\Usage-KEF App\m-anova\10th student performance.xlsx" this file has column name Student ID, Science-Pre, Science-Post, Math-Pre, Math-Post, English-Pre, English-Post, these column have score of the students, so consider only math subject score for comparison, and first calculate descriptive stats (mean, median, mode, standard devaition) and then do significant analysis, conduct t-test but before doing t-test check the normality assumption , if it fails do non parametric test, write the python code for this (inlcude all necesaary libararies), think in step and take time, and in the end explain the code syntax step by step

Figure 2: Example 2-Structured Prompt for writing Python code for the comparison of scores for the given training dataset.

In this case, the prompt is structured using the CLEAR framework and Open AI strategies. It starts by clearly defining the problem statement. Next, it specifies the requirement for a Python code, it begins by stating the file path of the dataset, followed by explicitly naming the columns in this dataset. It then instructs to focus only on the columns relevant to the problem. Based on the problem statement, it first outlines the comparison metrics and then provides instructions for advanced analysis, including checking assumptions. It also clearly states what actions to take if the assumptions are not met. This is all organized in a logical sequence. At the end of the prompt, there's a request to provide the code and explain each part of the syntax step by step. This helps the user understand the process and learn in segments. This approach not only demonstrates the application of structured prompts in a relevant context but also prepares students for the types of tasks they will encounter. This careful, step-by-step approach ensures that all participants, regardless of their background, can effectively engage with and understand the principles of prompt engineering, setting a solid foundation for their subsequent tasks in data analysis

4 USER STUDY

This study examined the impact of Generative AI and structured prompt engineering on novices learning data analysis, using a four-hour session with Python and AI tools. Participants independently completed tasks, with researcher guidance and continuous AI access, to assess how structured prompts affect learning in a condensed time frame.

4.1 Participants

This study involved 20 graduate-level participants, all familiar with ChatGPT or similar AI tools but without formal training in programming or data analytics. This selection ensured a uniform baseline of understanding across the 12 male and 8 female participants, aged 24 to 29. Each participant had access to ChatGPT 3.5 and shared English as their formal education language, minimizing language barriers. Their lack of prior prompt engineering experience set a consistent starting point for all, crucial for examining the impact of structured prompt training on their data analysis skills using Generative AI. This Purposive sampling was important for maintaining a controlled study environment and focusing on the specific research objectives.

4.2 Study Procedure

In this study, as shown in Figure 3 participants were initially briefed on the impact of Generative AI in data analysis and consented to ethical data collection and privacy practices. A pre-test then assessed their existing knowledge, establishing a baseline for subsequent phases. During the training phase, they engaged in a one-hour session on structured prompt writing, essential for effective interaction with Generative AI tools like OpenAI's ChatGPT, and practiced crafting prompts through contextual and non-contextual examples. In the task phase, they applied prompting skills over three hours, tackling various data analysis tasks and refining their proficiency. Post-intervention, their skills were reassessed to quantify the training's effectiveness.

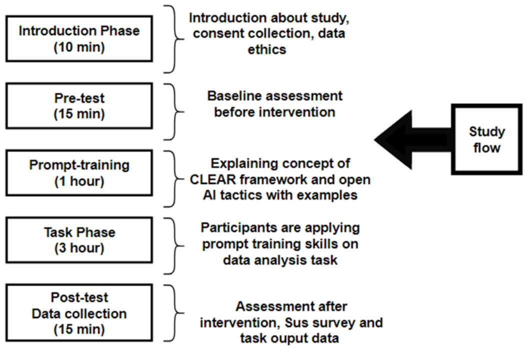

Figure 3: Flow chart of conducted study.

Comprehensive data collection included a consent form, pre and post-tests, output file task-wise, and a System Usability Scale survey, providing a multidimensional understanding of the participants' learning journeys and the influence of Generative AI tools on enhancing data analysis learning.

5 RESULT

In this part, we look at the data gathered to understand how structured prompt engineering and Generative AI affect learning results.

Following the initial overview, the analysis began with the Levene Test on pre-test scores for Bloom's taxonomy levels: understanding (L1), applying (L2), and analyzing (L3), to check variance homogeneity among participants, it is essential for valid statistical analysis. The Levene test's null hypothesis assumed no difference in the variance of scores across all three levels. Detailed test results are presented in Table 1, laying the groundwork for further analysis.

Table 1: Levene’s test on pre-test score of participant.

Sr. No	Level	Levene’s Test value	P value
1	L1_Pre_Test	0.13	0.72
2	L2_Pre_Test	2.66	0.12
3	L3_Pre_Test	0.13	0.72
4	Total_score_Pre_Test	0.15	0.70

P value >0.05 from Table 1, suggests that the null hypothesis is accepted and it confirms homogeneity among participants, the analysis advanced to compare pre and post-intervention test performances across Bloom's taxonomy levels: understanding, applying, and analyzing and overall scores, for the comparison paired sample t-test is used with the null hypothesis that there is no significant difference between test score before and after the intervention.

From Table 2, for all three levels of Bloom's taxonomy and the total score, the null hypothesis for the t-test was rejected, indicating a statistically significant difference in scores post-intervention test.

Table 2: Paired sample t-test statistics for pre-test and post-test scores of the participants.

Sr. No	Level	Test Statistic t (1,19)	P value	Effect Size
1	L1	6.77	9.04E-07	0.84
2	L2	6.097	3.66 E-06	0.81
3	L3	4.29	1.97 E-04	0.70
4	Total score	8.66	2.51 E-08	0.89

From the assessment of task output files, the task completion data reveals a clear trend in students' performance, with a higher success rate observed in the initial task (T1) compared to the complex subsequent task (T2, T3). Specifically, 70% of students completed T1 successfully, while only 55% and 45% of students were able to complete tasks T2 and T3 respectively. This trend shows that while students could manage simple data analysis tasks, they found it difficult when the tasks needed more advanced skills, especially in merging data.

The System Usability Scale (SUS) survey yielded a mean score of 72.38 and a standard deviation of 8.45, indicating a generally positive reception of the Generative AI tool's usability in data analysis learning. Participants perceived the tool as user-friendly and effective, reflecting a satisfactory user experience overall.

Concluding the data analysis, we observed significant advancements in learning outcomes through structured prompt engineering and Generative AI. Moving into the discussion section, we explored the deeper implications of these findings.

6 DISCUSSION AND CONCLUSION

In addressing RQ, the study's focus was to understand the influence of structured prompt engineering with Generative AI on the mastery of programming and data analysis concepts among learners with no prior experience. The quantitative analysis, initiated with the Levene Test, established a uniform baseline across participants, ensuring the validity of subsequent comparisons. The paired sample t-tests revealed a statistically significant improvement in participants' performance across all levels of Bloom's taxonomy post-intervention, indicating an improved understanding and application of programming concepts crucial for data analysis.

The substantial effect sizes reported in the t-test results underscore the profound impact of the intervention on learners' ability to grasp and apply programming principles within the context of data analysis. Additionally, task completion rates after structured prompt training with Generative AI suggest the significant influence of the intervention on participants' ability to understand and execute data analysis tasks. This progress goes beyond mere memorization, indicating a shift towards the comprehension of the underlying principles.

Furthermore, the System Usability Scale (SUS) survey results, indicating a positive reception of the Generative AI tool's usability, complement the study's findings. A user-friendly and effective tool is crucial in an educational setting, as it can significantly reduce the cognitive load on learners, allowing them to concentrate on understanding and applying the concepts rather than navigating the tool itself.

This study sheds light on the potential of Generative AI and structured prompt engineering to transform educational methods. The results of this research suggest that Generative AI can play a crucial role in helping learners understand complex subjects like programming and data analysis. Moreover, the usability of structured prompts has been instrumental in providing students with clear, actionable guidance through intricate learning tasks, enhancing their engagement and help them to master skills.

However, the study acknowledges its limitations, including the absence of log data analysis and qualitative data like interviews which could provide deeper insights into the behavioral patterns of high and low performers. The relatively small sample size also restricts the generalizability of the findings.

7 FUTURE WORK

Future research on integrating Generative AI and structured prompt engineering in education, especially in programming and data analysis, is set to deepen our understanding of its effects on learning. Planned comparative studies can examine the learning outcomes of groups with varying levels of access to ChatGPT and prompt training, aiming to understand the role of Generative AI in learner engagement and educational processes. These studies can expand participant diversity and employ methods like structured interviews and task analysis to capture detailed learner interactions and perceptions. A key focus will be evaluating the quality of participants' prompts to enhance critical thinking and refine training methods. Expected to enrich learning theories and Human-Computer Interaction frameworks, this research will help explore how Generative AI can innovate pedagogy and create personalized, accessible educational experiences worldwide.

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