Published by :
https://www.ijert.org/
An International Peer-Reviewed Journal

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 02, NCRTCS - 2026

A Study On Prompt Engineering: Techniques and Performance Enhancement In AI System

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***Abstract* - The rapid growth of Artificial Intelligence (AI) tools such as ChatGPT has significantly transformed the way users interact with intelligent systems. However, the quality of AI-generated responses depends heavily on how input instructions, known as prompts, are designed. Poorly structured prompts often result in incomplete, unclear, or inaccurate outputs. Prompt Engineering has emerged as a practical and effective approach to improving the performance of AI systems by designing precise, structured, and goal-oriented prompts.**

This study examines five prompt engineering techniques: Zero-shot, One-shot, Few-shot, Instruction-based, and Chain-of-Thought prompting. These techniques were evaluated across 20 academic tasks including conceptual questions, mathematical reasoning problems, programming exercises, and analytical writing tasks. AI-generated responses were assessed using four performance parameters: accuracy, logical reasoning, clarity, and structural organization.

The results demonstrate that structured prompting techniques significantly enhance AI output quality. Few-shot and Chain-of-Thought prompting achieved the highest performance, particularly for complex and multi-step reasoning tasks. This research highlights the importance of effective prompt design in optimizing AI systems and provides practical insights for students, researchers, and professionals using AI tools.

Keywords: Prompt Engineering, Artificial Intelligence, Few-shot Learning, Chain-of-Thought, Large Language Models

I. INTRODUCTION

Artificial Intelligence has become an integral component of modern education, industry, and research. Large Language Models (LLMs) such as ChatGPT are increasingly used for content generation, problem-solving, programming assistance, and analytical reasoning. Despite their advanced architecture, the effectiveness of these models is highly dependent on the quality of user input. AI systems operate strictly based on provided instructions. Vague or poorly designed prompts can lead to ambiguous or incorrect responses, even from highly capable models. This limitation has led to the emergence of Prompt Engineering, a discipline focused on designing structured prompts to guide AI systems toward accurate and meaningful outputs. The objective of this research is to analyze and

compare different prompt engineering techniques and evaluate their impact on AI performance across academic tasks.

II .BACKGROUND AND LITERATURE REVIEW

Large Language Models are trained on extensive datasets using deep learning techniques, enabling them to predict and generate human-like text. However, these models do not possess true understanding; instead, they rely on statistical patterns in language.

Brown et al. (2020) demonstrated that providing examples within prompts, known as Few-shot learning, significantly improves model performance. Wei et al. (2022) further introduced Chain-of-Thought prompting, which encourages models to generate intermediate reasoning steps, leading to better performance on complex reasoning tasks.

Existing literature confirms that structured prompting methods enhance contextual understanding and reasoning accuracy. This study extends prior work by experimentally comparing multiple prompting techniques using uniform evaluation criteria.

III .PROMPT ENGINEERING TECHNIQUES

FIVE PROMPT ENGINEERING TECHNIQUES WERE EVALUATED IN THIS STUDY: SAMPLE PROMPTS WERE DESIGNED CAREFULLY TO OBSERVE HOW CHANGES IN PROMPT STRUCTURE IMPACT AI-GENERATED OUTPUTS.

3.1 Zero-shot Prompting

In Zero-shot prompting, the model is given a task without any examples.

Example: "Explain Artificial Intelligence."

This approach relies entirely on the model's prior knowledge and often results in generic or shallow responses.

3.2 One-shot Prompting

In One-shot prompting, a single example is provided before the actual task.

Prompt Example:

"Example: Artificial Intelligence is the simulation of human intelligence in machines. Now explain Machine Learning."

Providing one example slightly improves context understanding and response relevance.

3.3 Few-shot Prompting

Few-shot prompting includes multiple examples to guide the model toward the desired output structure.

PromptExample:

"Example 1: Artificial Intelligence refers to machines that mimic human intelligence.

Example 2: Machine Learning is a subset of AI that learns from data. Now explain Deep Learning."

This technique significantly improves structure, consistency, and accuracy.

International Journal of Engineering Research & Technology (IJERT)
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3.4 Instruction-based Prompting

Instruction-based prompting clearly defines task requirements such as length, format, and style.

Prompt Example:

"Explain Artificial Intelligence in 150 words using simple language and one real-world example."

Explicit instructions reduce ambiguity and improve clarity and organization.

3.5 Chain-of-Thought Prompting

Chain-of-Thought prompting instructs the model to reason step-by-step before giving the final answer.

Prompt Example:

"Explain step-by-step what Artificial Intelligence is, list its components, and then provide a final definition."

This technique enhances logical reasoning and is particularly effective for complex and multi-step problems.

IV. METHODOLOGY

A dataset of 20 academic tasks was designed for evaluation:

- 5 conceptual theory questions
- 5 mathematical reasoning problems
- 5 programming-related tasks
- 5 analytical writing tasks

Each task was executed using all five prompting techniques, resulting in 100 AI-generated responses.

4.1 Evaluation Criteria

Responses were evaluated based on four parameters:

- Accuracy
- Logical Reasoning
- Clarity
- Structural Organization

Each parameter was scored on a scale of 0 to 10.

Final Score Formula:

Final Score = (Accuracy + Reasoning + Clarity + Structure) / 4

Uniform evaluation standards were applied to ensure fairness and consistency.

V . EXPERIMENTAL RESULTS

5.1 Performance Scores

Prompting Technique	**Final Score (Out of 10)**
Zero-shot	5.5
One-shot	6.5
Few-shot	8.1
Instruction-based	7.7
Chain-of-Thought	8.8

5.2 Graphical Representation

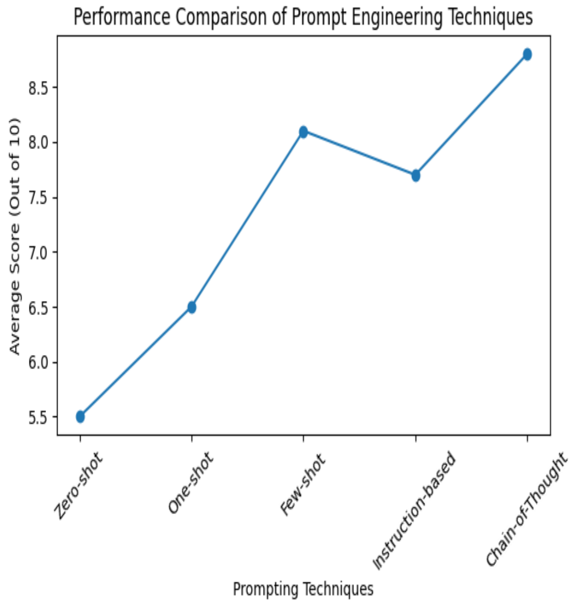

Fig. Performance comparison of prompt engineering techniques

Fig. 1 shows a simple bar chart representing the average final scores obtained by different prompt engineering techniques. The X-axis represents the prompting techniques, while the Y-axis represents the final performance score (out of 10). Each bar corresponds to the average score achieved across all academic tasks.

The graph clearly indicates that Zero-shot prompting produces the lowest performance due to the absence of guidance. One-shot prompting shows a moderate improvement by providing a single example. Few-shot prompting achieves higher performance as multiple examples help the model understand patterns and expectations. Instruction-based prompting further improves clarity by explicitly defining constraints. Chain-of-Thought prompting achieves the highest score, as it encourages step-by-step reasoning, resulting in more accurate and logically structured responses.

The simple graphical representation makes it evident that increased prompt structure leads to improved AI performance, validating the core objective of this research.

5.3 Statistical Analysis

- Mean Score = 7.32
- Standard Deviation ≈ 1.25

VI. DISCUSSION

The experimental results clearly indicate that structured prompt engineering techniques significantly enhance AI performance. Zero-shot prompting produced basic responses with limited depth. One-shot prompting offered moderate improvements by providing minimal guidance.

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Few-shot prompting improved consistency and structural organization by demonstrating expected output patterns Instruction-based prompting enhanced clarity and formatting. Chain-of-Thought prompting achieved the highest scores by improving reasoning transparency and logical flow

The study observed approximately a 60% improvement in performance from Zero-shot to Chain-of-Thought prompting, emphasizing the critical role of prompt design.

VII. APPLICATIONS

Prompt engineering techniques can be effectively applied in:

- Education (concept explanation, assignment assistance)
- Software development (code generation and debugging)
- Research and academic writing
- Data analysis and reporting
- Business communication

Effective prompting improves precision, reduces ambiguity, and enhances productivity.

VIII . LIMITATIONS

This study was conducted using a limited dataset of 20 tasks. Larger datasets and automated evaluation metrics could provide stronger statistical validation. Additionally, AI performance may vary across different models and system versions.

IX. CONCLUSION

This research demonstrates that prompt engineering is a critical factor in optimizing AI system performance. Structured prompting techniques, particularly Few-shot and Chain-of-Thought prompting, significantly improve accuracy, reasoning depth, clarity, and consistency.

The findings confirm that AI effectiveness depends not only on model sophistication but also on the clarity and structure of human instructions. As AI adoption continues to grow, prompt engineering will become an essential skill for effective human–AI interaction.

Future research may explore adaptive prompting systems and automated prompt optimization techniques.

.X. REFERENCES

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