PEARL : Prompt Engineering Pedagogy for Teaching and Learning for Specific Technology

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***Abstract*— This study evaluates the effectiveness of prompt-based pedagogy using the PEARL framework compared to traditional classroom teaching, as applied to teaching selected topics in a machine learning course. A total of fifty undergraduate students learned two foundational topics linear regression and gradient descent through both methods: first via regular lectures and later through structured prompt-based learning activities. Their responses were collected through surveys and analyzed using statistical methods, including one-sample t-tests, chi-square tests, and a binomial test. Results showed that prompt-based learning significantly improved their knowledge about the concepts with the help of analogy based prompts .It concluded that integration of prompt based learning and traditional classroom teaching will yield better learning outcomes from a learner.**

***Keywords*: Prompt Engineering, PEARL Framework, Machine Learning, Linear Regression, Gradient Descent, AI in Education, Blended Learning, Student Engagement, Active Learning, Pedagogy.**

ICTIEE* Track*: Emerging Technologies and Future Skills
ICTIEE Sub-Track: AI, Machine Learning, and Digital Tools in Education

I. INTRODUCTION

Traditional classroom teaching usually makes students to just sit and listen without much interaction. This causes focusing on listening rather than active participation. In Prompt-based pedagogy, students interact actively using AI tools .It guides them with the help of structured prompts. The PEARL framework is a teaching model with five stages: Problem Identification, Exploration, Application, Reflection, and Learning Outcomes. In every stage, prompt engineering techniques like zero-shot, one-shot, few-shot, chain-of-thought, and critique prompts guide learners to question clearly, practice with examples and strengthen what they have learned.

In this study, the PEARL framework was applied in the context of machine learning, specifically to the topics of linear regression and gradient descent. As these topics are fundamental for understanding optimization concepts and how machine learning models are built. The Goal of PEARL is to make the learning process in step by step manner and interactive. This helps students to make them engaged by clearing out their confusion and improve understanding. This study evaluates the effectiveness of this framework compared to traditional teaching methods with comprehension, engagement, and student preference as measurements.

II. BACKGROUND AND RELATED WORKS

Adeoye (2024) showed the importance of structured design models such as ADDIE. It has a systematic process of analysis, design, development, implementation. This paper is relevant for PEARL as it also organizes learning into sequenced stages. The ADDIE model follows a sequence of stages approach. The most recent work done by Jain and Samuel (2025) has applied Bloom's framework to the generative AI-based learning. It shows that students can be guided through different levels of this framework. Mishra and Koehler (2006) proposed the TPACK framework which says the content, pedagogy and the tools must be balanced. The PEARL is an example of this framework as it uses prompt engineering together with content and learning stages. Similarly, Piaget's constructivist theory says that students learn best when they build understanding on their own rather than just taking in information. Apart from these, Chi (2009) explained active, constructive, and interactive modes of learning, which says that interaction plays major role in understanding. Our framework applies this by making students not only to answer but also revise and reuse the knowledge with the help of prompts. According to Siemens' Connectivism theory (2005) connectivism learning is about connecting to different sources of knowledge like books, people, online resources, etc. In our proposed framework AI prompts acts like these connections as they helping like bridges to learn. Zawacki-Richter et al. (2022) was a big review on how AI is being used in universities. Since PEARL also used AI to guide, check and adapt learning, it fits into present education systems. White et al. (2023) examined how prompts affect student-AI interaction. It says that if prompts are structured properly, students get better answers from AI. It is more relevant to our proposed framework as it is built on structured prompting. VanLehn (2011) compared human tutoring with AI based tutoring systems. Instead of teacher guiding every step, our framework uses AI prompts to guide student. Kojima et al. (2022) demonstrated that large language models can solve problems with zero-shot learning (without giving examples).This is important as students learn by asking questions to AI. Kasneci et al. (2023) emphasized that tools like ChatGPT are powerful, but if students use them randomly, learning may not be in effective way. So it needs a framework. PEARL framework provides that structure and it organises students to use AI so it's useful, not distracting. Luckin (2017) said AI can be used for assessment as well as for continuous feedback. In our framework, this happens in Reflection Stage.

Finally, Holmes et al. (2022) warned that AI in classrooms must ensure fairness, trust and motivation, and this fits perfectly with our framework. The EDUCAUSE Horizon Report (2024) found that the blending of AI and human teaching gaining popularity with both teachers and students. Also it is expected to be a major trend in future. Alonso et al. (2005) study showed that rather than using only one method it is more effective to use blended learning approach. It means that prompts are helpful, but they work best when they are combined with classroom lectures. When we look across all these studies, we can conclude that there is a common agreed point that is traditional learning theories are still valuable. But when we add AI tools like prompt engineering, the way of learning becomes more easier and more engaging. Most of the earlier studies on AI in education have focused only on theory. Very few studies have actually tested a structured framework. This study tests PEARL framework in machine learning education, directly comparing it with conventional classroom methods.

III. Proposed Approach for Effective Teaching

A. Prompt Engineering

Prompt Engineering is the process of crafting well-structured instructions for large language models (LLMs) so that they produce accurate, relevant, and meaningful responses. The quality of a prompt often determines the quality of the output—whether it is a simple explanation, a worked example, or a step-by-step reasoning process. In education, prompt engineering has moved beyond being just a technical trick. It is now recognized as a teaching and learning strategy. Different techniques—such as zero-shot prompts (asking a direct question without context), one-shot prompts (guided by a previous example), few-shot prompts (using multiple examples), and chain-of-thought prompts (breaking down reasoning into steps)—make it possible for students to learn progressively, reflect deeply, and test their understanding. In this way, prompt engineering becomes a bridge between student curiosity and structured knowledge-building.

The PEARL (Prompt Engineering for Active, Reflective Learning) framework was created to organize this process into a structured cycle of learning. While it is inspired by established models such as ADDIE (Analysis, Design, Development, Implementation, Evaluation), Bloom's Taxonomy (from recall to higher-order thinking), and TPACK (integration of Technology, Pedagogy, and Content), PEARL adapts them for an AI-driven classroom. It emphasizes that students learn best not by passively consuming answers but by actively asking, refining, applying, reflecting, and assessing with the help of AI. In our study, PEARL was applied to machine learning education, focusing on linear regression and gradient descent. These concepts, which are often difficult for beginners to grasp, were taught using carefully designed prompts that guide student's step by step. The goal was not only to improve comprehension of technical material but also to help learners develop the skill of learning how to learn with AI.

B. Architecture of PEARL

The architectural design of the PEARL framework is based on a modular and layered structure that connects prompt-engineering strategies with established learning models. The aim is to make teaching both adaptive and reflective, while still systematic. The overall design is shown in Fig. 1 (PEARL UML Class Diagram), which illustrates how the five stages—Problem Identification, Exploration, Application, Reflection, and Learning Outcomes—are implemented as interconnected modules.

1) Problem Identification Hierarchy

The first stage of PEARL focuses on Problem Identification, where students begin their learning journey by framing precise and purposeful questions. AI supports this process through zero-shot prompts (asking without context) and one-shot prompts (guided by a previous example). For instance, a learner might start with "Explain gradient descent in simple words" or "Explain gradient descent the same way you explained linear regression earlier." As shown in Fig. 1, this stage acts as the foundation of the framework, ensuring that learners begin with clarity and direction before diving deeper

2) Exploration Hierarchy

Once a problem is identified, students move into Exploration, where they expand their understanding from multiple perspectives. This stage leverages chain-of-thought prompting to break reasoning into clear steps and refinement prompts to reframe explanations. For example, a learner may ask *"Explain gradient descent step by step"* and then refine it with *"Now explain it as a cooking recipe."* The decision-making process in this stage is depicted in Fig. 2 (PEARL Flowchart of Interactive Prompting), where learners move between asking, refining, and re-questioning in an active cycle. This design keeps abstract concepts relatable and prevents passive learning.

3) Application Hierarchy

The Application stage connects theory to practice. Instead of only reading and memorizing, learners will do something with knowledge like coding, problem solving etc. This can be possible through few-shot prompting (learning from examples) and error-driven prompting. For example, A learner is going through the solved regression problems for understanding concept. He wants to use that knowledge. Then he will prompt like: *"Write Python code for gradient descent using these examples.* "If the generated code has an error, he can ask: *"Fix the error and explain why it happened."* This makes the process iterative. It will improve understanding.

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4) Reflection Hierarchy

This is the stage where don't accept the first answer they got. Instead they question it and evaluate it.Through self-consistency prompting and critique prompting AI helps learner in this stage. Self consistency prompting is asking the same question in different ways to identify if answers will match or vary. Critique prompting checks an answer for errors. For example, A student can ask AI about gradient descent in two ways like "*Explain gradient descent using real world analogy*", *"Briefly discuss about gradient descent"* and makes comparison between outputs. This process helps students to develop critical thinking skills. In Fig. 2,we can see there are feedback loops. They allow learners to go back to previous stages like Application etc. if they've not got enough understanding. It ensures deeper understanding of the concept.

5) Learning Outcomes Hierarchy

It is the final stage of the PEATL cycle. This focuses on checking what progress learner has gained and improves it further. This stage uses progressive prompting and clarification prompting. Through progressive prompting AI increases difficulty of tasks step by step. This helps learners to move from basics to advanced topics. With the help of Clarification prompting, If a learner gets stuck, the AI can re explain those concepts. The implementation can be like this: For example, A student after learning basics of gradient descent, he may ask as "*Explain how gradient descent is optimized in Adam*." If this feels too advanced, he can ask as "*Re-explain gradient descent in three simple bullets.* It ensures learners don't just stop at trying things and stay motivated This stage acts as the capstone of the framework, as shown in Fig. 3 (PEARL Layered Architecture)

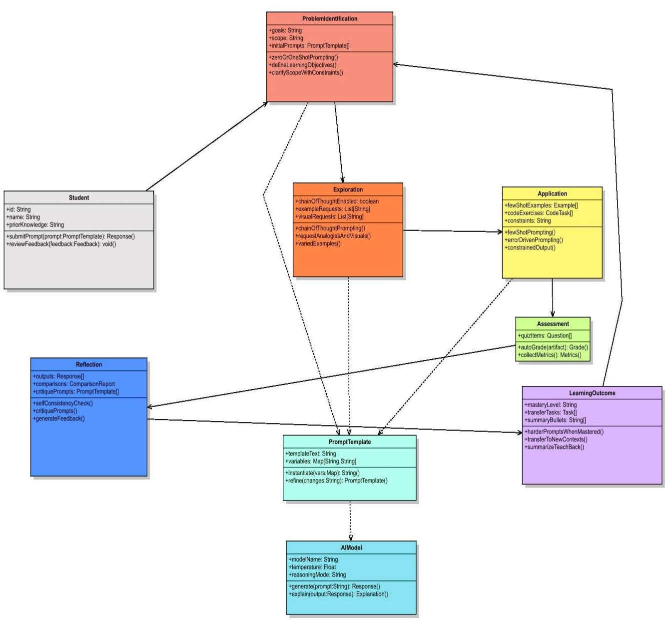

Fig. 1 PEARL UML Class Diagram

C. Illustration in Practice

The effectiveness of the PEARL framework becomes clearer when viewed in practice through its staged design. Fig. 2 (PEARL Flowchart of Interactive Prompting) illustrates how learner's cycle between stages, ensuring that the process is not linear but iterative. For instance, a student may begin in the Problem Identification stage by asking, "What is linear regression?" This establishes a clear starting point which can be seen as in Table I. As they move into Exploration, the flowchart shows how learners can branch out by reframing questions, such as "Explain gradient descent step by step," thereby unpacking the reasoning in a structured manner.

PEARL Stage	**Topic**	**Example Prompt Snippet**
Problem Identification	Linear Regression	"Explain linear regression in simple terms for first-year students."
Exploration (chain-of-thought)	Gradient Descent	"Break down gradient descent step-by-step; then re-explain as a cooking recipe."
Application (few-shot)	Linear Regression	"Given these two worked examples, solve for coefficients on this dataset."
Reflection (critique)	Gradient Descent	"Critique this explanation and correct any errors or missing steps."
Learning Outcomes (progressive)	Optimization Concepts	"Now extend basic gradient descent to Adam; list differences, equations, and when to prefer each method."

Table I: Example prompts Across PEARL Stages

In Application, students interact with examples more concretely, often relying on few-shot prompts to test their understanding. A practical step might be, "Write Python code for gradient descent using these examples as a guide." If errors occur, the learner loops back through the flowchart's feedback cycle to refine their prompt and seek corrections, reinforcing resilience. Reflection, which is emphasized by feedback loops in Fig. 2, is particularly important. Here, learners compare outputs by re-asking or reframing questions, such as "Summarize gradient descent in three steps" alongside "Explain gradient descent with an analogy." This builds critical evaluation skills. Finally, as shown in Figure 3 (Pearl Leard Architecture), the framework ends in the phase of the results, where the learners progress for advanced concepts such as adam. Together, these figures display how the pearl translates the principle into a practical, adaptive learning cycle.

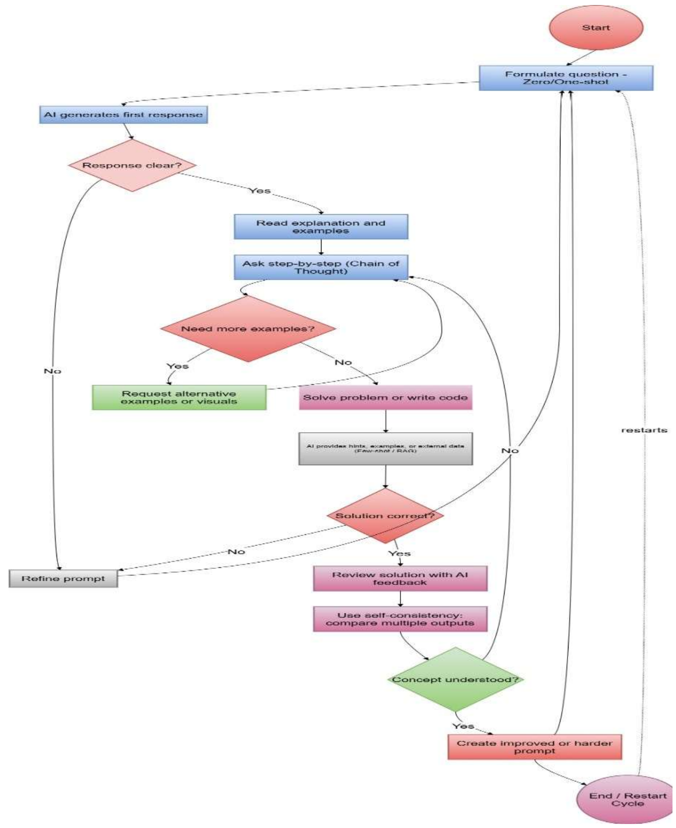

Fig. 2 PEARL Flowchart of Interactive Prompting

D. *Design Significance*

The PEARL framework is not just a collection of prompt-engineering techniques. It is a systematic framework for learning. It aims to make learning more active, reflective and adaptive. Most of the AI in education models usually stop at things like generating answers, chatbots, grading. What makes PEARL unique is it extends beyond these. Because it doesn't use only AI, it integrates AI into proven theories like Bloom's Taxonomy TPACK. This means that AI is not used to replace the teacher but works with the teacher as a partner. PEARL can be applied to any subject area, not only for machine learning. The only thing is the one who uses must change the type of prompts. This tells us about flexibility of our framework. This framework uses step by step progression. Students gradually move from easy recall to complex reasoning and problem solving. This is similar to how humans naturally learn. The flow will be as follows: Zero-shot → One-shot → Few-shot → Chain-of-thought → Critique. Most AI tools stop at just giving answers. This framework forces learners to stop, question and make comparison of AI's output. This helps students to identify missing points, compare different answers and create complex thinking. This is necessary these days because students should learn not only to use AI, but also to judge their credibility.

Pearl directly addresses this difference by embedding the reflection as a main phase. As prompt engineering develops, new strategies such as multimodal pro*mpts* (with images, audio, or code) can be integrated easily. This ensures that the framework is not only effective today but is also capable of growing with advances in AI. Finally, PEARL has been designed with future extensibility in mind. In short , PEARL is both unique and necessary because it combines the strength of traditional teaching methods with the flexibility of AI. As shown in Fig. 1–3, the framework provides a blueprint for AI-assisted pedagogy and helps the classrooms to learn actively from passive teaching and strong in important thinking.

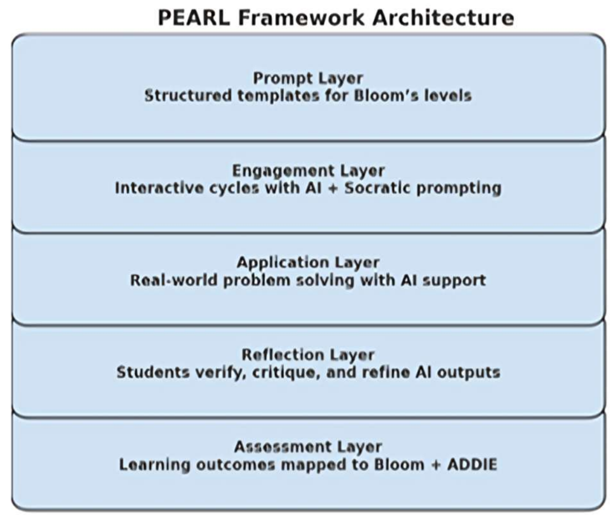

Fig. 3 PEARL Layered Architecture

IV. Survey Design and Evaluation

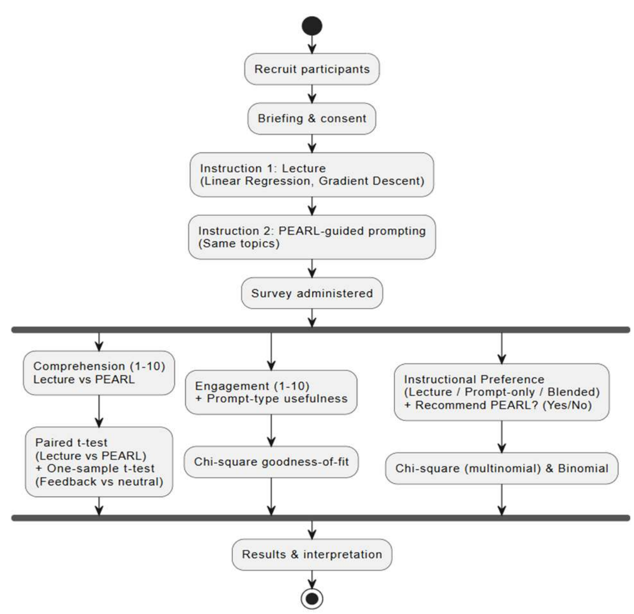

Fig.4 Survey Questions Structure

To evaluate effectiveness of the PEARL framework we have created a structured survey. It examined three main areas such as comprehension, which measured how well students understood the concept ; engagement, which assessed their active participation; and learning preference, which analyzed whether students favored PEARL or traditional lectures. The survey was distributed to participants after they experienced both instructional methods—first through a regular lecture on linear regression and gradient descent, and then through a PEARL-guided prompt-based learning session on the same topics.

A. Survey Design

The survey was designed to compare the effectiveness of the PEARL framework with traditional lecture-based instruction. Participants first attended a lecture session covering linear regression and gradient descent, delivered in the conventional classroom style. Following this, they engaged in a PEARL-guided session on the same topics, where learning was scaffolded through staged prompts corresponding to problem identification, exploration, application, reflection, and learning outcomes. After completing both instructional methods, students completed a structured survey measuring comprehension, engagement, and instructional preference.

B. Experimental Setup

The study involved 50 participants (undergraduate computer science students).The lecture introduced the theoretical background and derivations of linear regression and gradient descent. The PEARL-guided session then used prompt-based scaffolding, including zero-shot, one-shot, chain-of-thought, and critique prompts, to encourage active learning and better reflection. This design allowed for direct within-subject comparison of traditional and PEARL-based teaching approaches.

C. Evaluation Dimensions

To evaluate the effectiveness of the PEARL framework for prompt engineering pedagogy compared to traditional lecture-based instruction, we designed a structured survey focusing on three key dimensions: comprehension, engagement, and learning preference.

1. Comprehension

Students rated their understanding of linear regression and gradient descent on a 1–10 Likert scale after both instructional methods. A paired t-test was used to compare lecture-based ratings with PEARL-based ratings. In addition, a one-sample t-test evaluated whether prompt feedback effectiveness was rated significantly higher than a neutral baseline value of 3.

2.Engagement

Engagement was assessed using a combination of scaled and categorical questions. First, students rated how engaging they found each instructional method on a 1–10 scale. Additional items asked whether specific PEARL strategies (e.g., zero-shot prompts, step-by-step chain-of-thought, critique prompts) enhanced their motivation to explore the material.

Test Type	**Null Hypothesis**	**p-value**	**Conclusion**
One-sample t-test	Prompt helpfulness = 3 (neutral)	0.000	Reject H_0 → Prompts were rated significantly more helpful than neutral
Chi-square goodness-of-fit	All steps in the prompt-based learning cycle are equally useful	0.002	Reject H_0 → Reflection (35%) and Exploration (30%) were chosen more often than other steps
Binomial test	Students equally likely to prefer prompt-based learning or not	0.010	Reject H_0 → 72% preferred combining prompts with regular classes vs 28% who did not
One-sample t-test	Prompt feedback effectiveness = 3 (neutral)	0.000	Reject H_0 → Feedback from prompts significantly improved student learning outcomes
Chi-square goodness-of-fit	All study methods equally engaging	0.015	Reject H_0 → Prompt-based learning was rated as more engaging compared to usual study habits

Table II: Hypothesis Testing on Prompt-Based Learning Survey

Responses to scaled engagement questions were analyzed using a chi-square goodness-of-fit test, while categorical responses were summarized to identify preferred prompt types.

3. Instructional Preference (Blended Learning Preference)

Students were asked to indicate their preferred method for future learning: lecture, prompt-only, or a blended model.

They also responded to binary questions on whether they would recommend prompt-based strategies for teaching abstract or technically challenging topics. A chi-square test analyzed categorical distributions, while a binomial test assessed the binary preference outcomes.

D. Statistical Analysis

The statistical methods employed in the study are summarized in **Table II**. The table lists each hypothesis test, the corresponding null hypothesis, the observed p-value, and the conclusion regarding the acceptance or rejection of the null. This provides a clear overview of how survey responses were analyzed and ensures consistency with the evaluation framework illustrated in Fig.4

V. RESULTS AND FINDINGS

The results from the survey highlight clear differences between traditional lecture-based instruction and PEARL-guided prompt-based learning. Analysis focused on four key dimensions—comprehension, reflection, engagement, and instructional preference—corresponding to the framework's evaluation model. The statistical outcomes are summarized in Table II, while detailed distributions of student responses are presented in Fig. 5(a–h).

A. Comprehension & Reflection Results

Students reported noticeably higher comprehension when learning through PEARL. As illustrated in Fig. 5(a–c), 75% of participants rated prompt helpfulness at 8 or above, with none rating below 4. Practice-oriented prompts and error-correction guidance were also rated highly, confirming that scaffolded prompting simplified abstract concepts such as gradient updates and regression coefficients. A one-sample t-test validated that comprehension scores were significantly above neutral ($p < 0.05$).Reflection was another strong outcome of PEARL. Summarization and critique prompts (Fig. 5d) were particularly valued, with over one-third of students rating them as "excellent." Feedback cycles, where learners refined answers and debugged codes through AI support, also showed significant gains in confidence, supported by the statistical analysis in Table II.

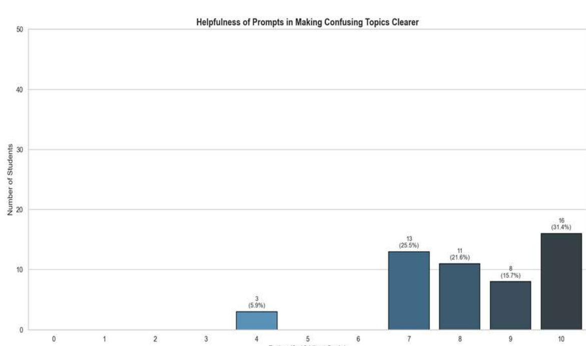

Fig 5(a): Helpfulness of prompts in clarifying confusing topics.

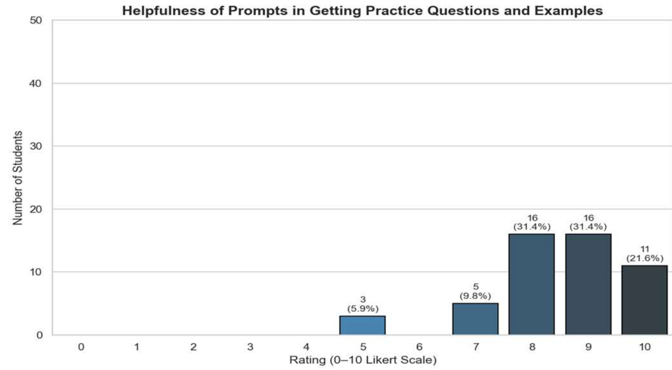

Fig.5(b): Helpfulness of prompts in providing practice questions and examples.

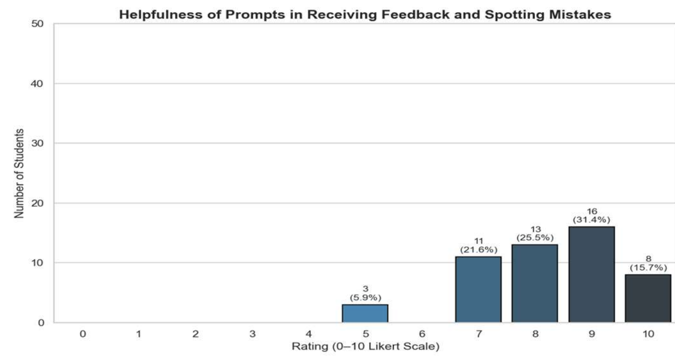

Fig.5(c): Helpfulness of prompts in receiving feedback and spotting mistakes

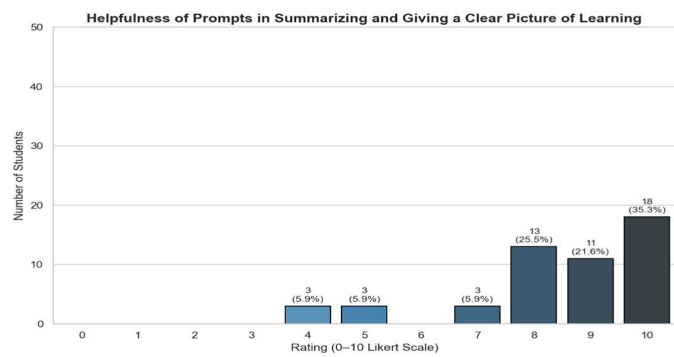

Fig.5(d): Helpfulness of prompts in summarizing and giving a clear picture of learning.

B. Engagement Results

Engagement ratings further favored PEARL, with more than 75% of responses scoring engagement levels above 8 (Fig. 3e). The chi-square test confirmed that the difference was statistically significant, with exploration and reflection prompts emerging as the most motivating activities. Students consistently reported that step-by-step reasoning and analogy-based explanations helped sustain attention and interest compared to conventional lectures.

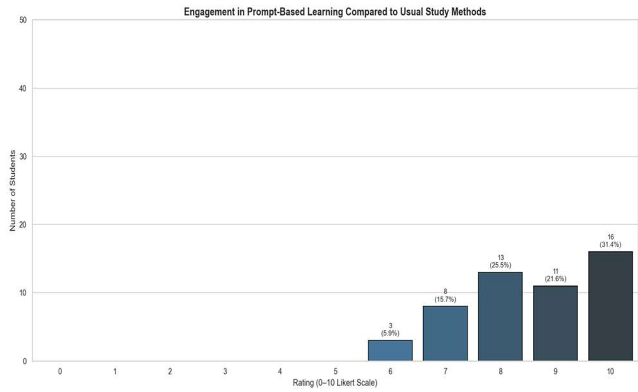

Fig.5(e): Engagement in prompt-based learning compared to usual study methods.

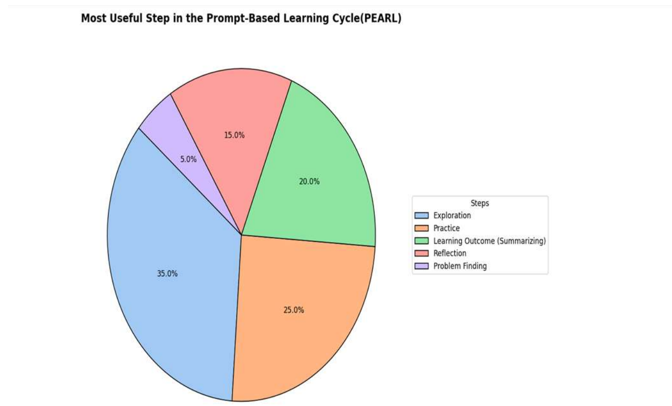

Fig.5(h):Most Useful step in PEARL Cycle

Fig. 5: Survey results

When asked about future learning preferences (Fig. 3f–h), a majority of 68% favoured a blended model that combines lectures with PEARL-guided prompting. Very few supported prompt-only sessions, and none preferred lectures as the sole method. A binomial test validated the preference for blended instruction ($p < 0.05$). When ranking the most useful PEARL stages, exploration (35%) and reflection (30%) were chosen more frequently than application or summarization, as confirmed by a chi-square test ($p = 0.002$).

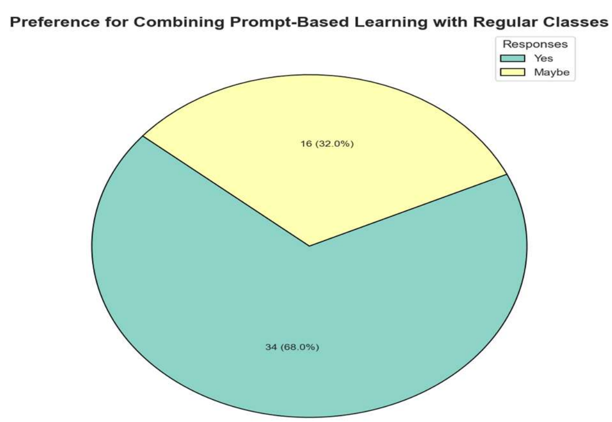

Fig.5(f): Preference for combining prompt-based learning with regular classes.

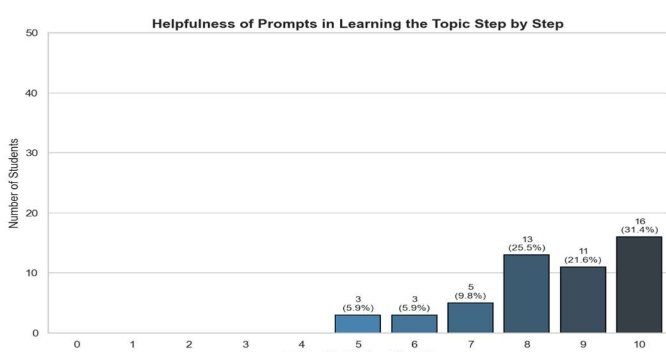

Fig.5(g): Helpfulness of Prompts in Learning the Topic Step by Step

Taken together, these findings show that PEARL enhances comprehension, sustains engagement, and promotes reflective learning more effectively than lectures alone. Students appreciated the structured use of prompts but expressed a preference for combining them with lectures, reinforcing the value of PEARL as a complementary, rather than replacement, pedagogical model

VI. Conclusion

This study shows clear evidence that prompt-based learning can be a powerful way to teach machine learning topics like linear regression and gradient descent. Compared to traditional lectures, the use of prompts through the PEARL framework helped students understand better, stay engaged, and reflect more deeply on what they learned. At the same time, the results make it clear that prompts work best when used alongside regular teaching. Most students preferred a blended model that combines prompt-based activities with classroom lectures and discussions, rather than using prompts alone. This means that while prompts add strong support for learning, traditional methods such as direct explanation and teacher interaction are still very important especially for mastering complex ideas. In the end, the real strength of prompt-based pedagogy is in integration. When combined with regular teaching, it can make learning machine learning concepts more effective, engaging, and complete. This also shows that prompt engineering can be used as a practical teaching tool for specific technologies in higher education, making lessons both modern and student friendly.

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