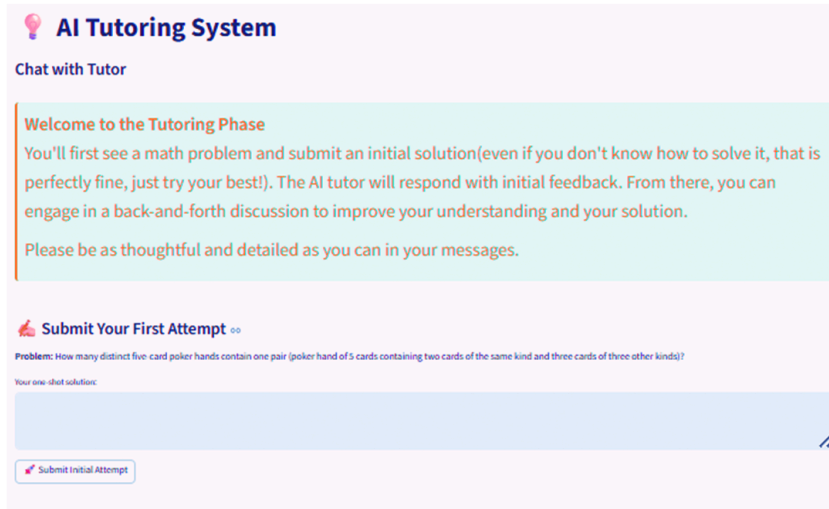


# Pedagogical ChatBot: Designing Interactive Feedback using Large Language Model(LLM)

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Learning discrete mathematics can feel like climbing a mountain without a guide. What if students had an intelligent companion that offered timely, constructive feedback at every step?



## 1. Data Preparation

From 2,534 EdForum AICCI posts(2022 - 2024), we used a hybrid filtering system to detect genuine student trial solutions.

- **Filtering** - Posts were scored with rules (keywords like "I tried to solve", "my proof", "j'ai essayé") and semantic similarity to example phrases, points added for reasoning markers ("therefore", "let ... =") and subtracted for administrative content.
- **Augmentation** - High-scoring posts augmented with their original homework statements and official solutions



## 2. Simulating interactions between Student and Tutor Agents

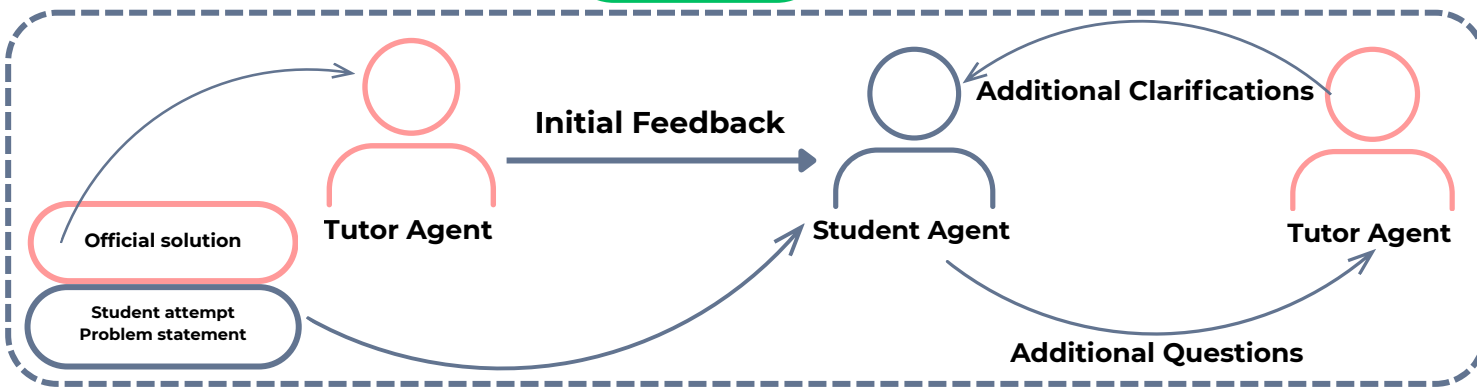
We simulated **student-tutor interactions** using GPT-4o agents to test different feedback strategies, **strengths** and **weaknesses** before running a user study.

**Tutor Agent:** "Start by assuming  $n^2$  is odd... **As  $n^2$  is a square of a number, it can also be written as  $n \times n$ .** So,  $n \times n = 2k+1$ . However, if  $n \times n$  were even ..."

✗ **Verbosity without clarity** adds little new information

✓ **Scaffolding** guides learner with focused reflective question

**Tutor Agent:** "Ask yourself: what do you assume in contraposition compared to contradiction?"



Strengths	Weaknesses
<ul style="list-style-type: none"> <li>• <b>Adaptive Explanations</b> shifted from abstract definitions to concrete examples when needed.</li> <li>• <b>Positive Reinforcement</b> highlighted what was correct before addressing mistakes.</li> <li>• <b>Scaffolding</b> asked guiding questions and broke reasoning into smaller steps.</li> </ul>	<ul style="list-style-type: none"> <li>• <b>Verbose but Shallow</b> feedback was often long without adding meaningful insight.</li> <li>• <b>Missed Misconceptions</b> sometimes failed to address the learner's actual difficulty.</li> <li>• <b>Uneven Coverage</b> explained some errors thoroughly while glossing over others.</li> </ul>

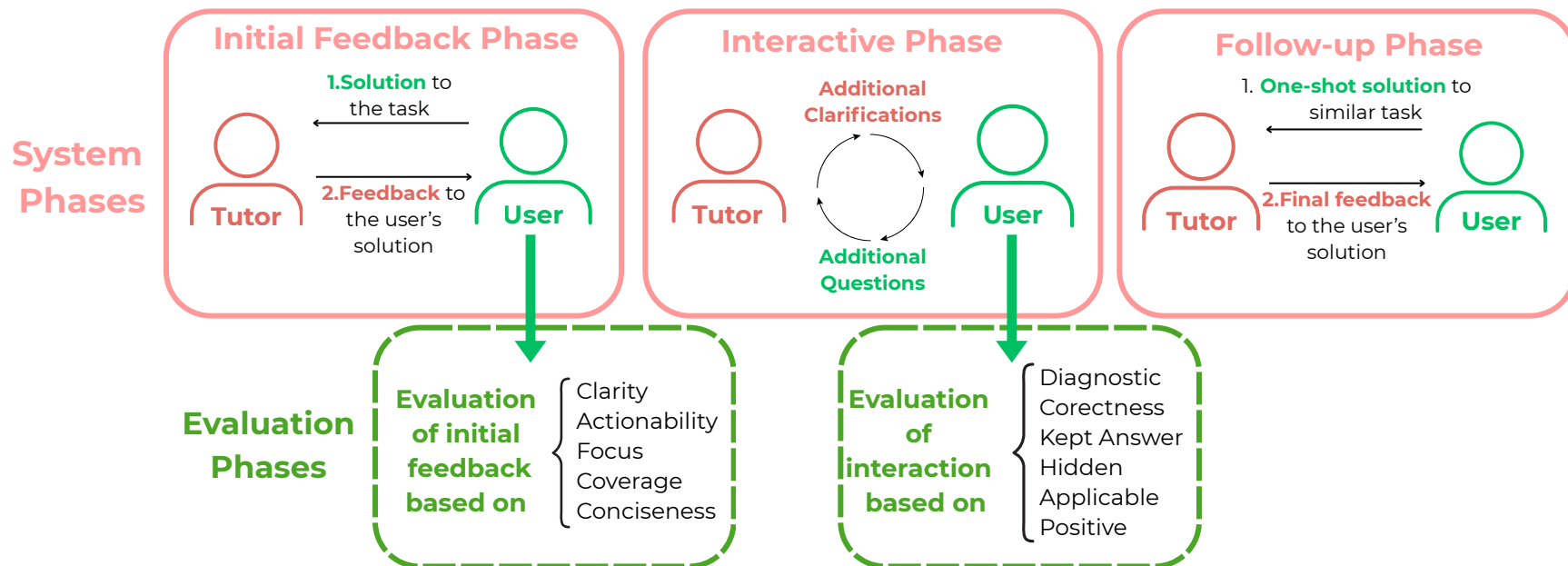
## 3. User Study Design

We built a **user-friendly web interface** powered by a **pedagogically prompted GPT-4o model** that resembled a tutoring app

- three discrete mathematics tasks(Easy, Medium, Hard)
- 25 participants

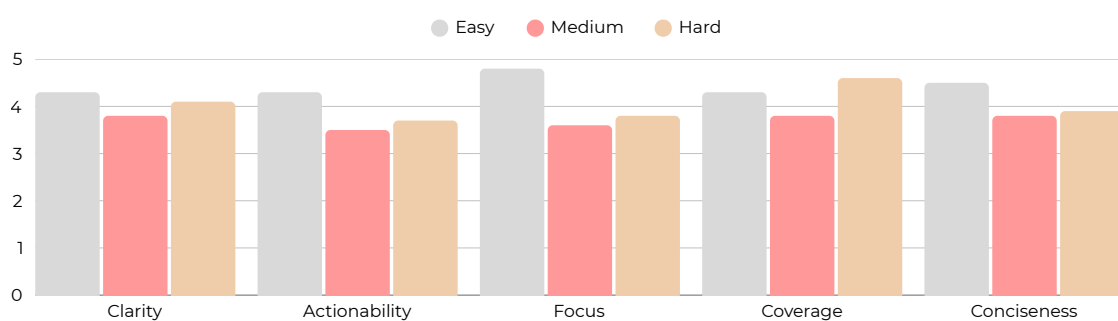
To address weaknesses identified in the simulations, we refined the tutor prompts:

- **Conciseness enforced** - initial feedback capped at ~120 words.
- **No spoilers** - hints and analogies only, never direct formulas.
- **Progressive scaffolding** - solution revealed gradually

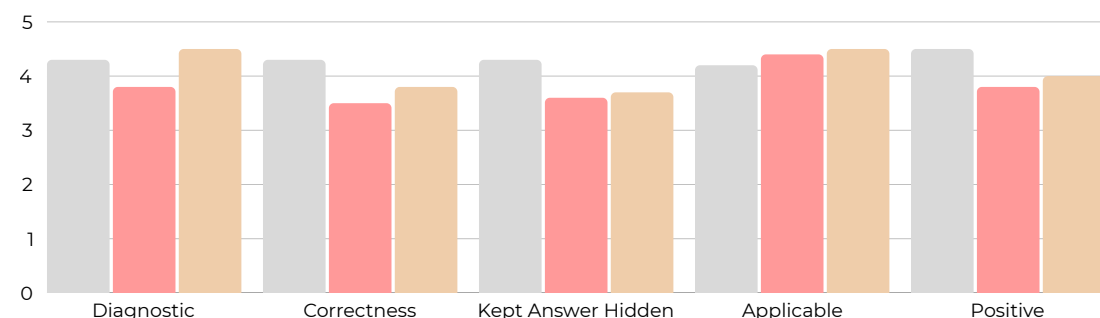


## 4. User Study Rubrics Ratings

Mean Ratings after Initial Feedback



Mean Ratings after Interactive Phase



## 5. Future Work

- **Reduce Verbosity, Increase Precision**  
Explore techniques (e.g., reinforcement learning with human feedback) to make feedback more concise, preserving clarity
- **Improve Misconception Diagnosis**  
Train or fine-tune models on annotated student data to better identify where reasoning goes wrong
- **Tone Calibration**  
Adjust prompts or fine-tune to prevent feedback from sounding harsh, especially on follow-up attempts.

## 6. Acknowledgements

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