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Multi-Dialogue Agents for Collaborative Learning Support Through Adaptive Opinion Integration

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Abstract: This research presents a collaborative learning support system that enhances learner motivation by creating psychologically safe discussion environments using multiple LLM-powered agents. These agents are designed to validate and integrate user opinions into learning dialogues dynamically. While agent-based collaborative learning offers flexibility in time and location, achieving truly adaptive learning environments remains challenging. Our system addresses this by leveraging agents that affirm learner contributions through strategically aligned responses during discussions, fostering positive psychological effects of acceptance and belonging. Experimental evaluation with 11 participants demonstrated that 91% experienced increased learning motivation when interacting with opinion-affirming agents. This research contributes to the emerging field of LLM-based educational technology by demonstrating the effectiveness of adaptive multi-agent systems in supporting collaborative learning.

Keywords: Collaborative learning, Multi-agent systems, Dialogue-based learning, Large Language Models, Adaptive learning

1. Introduction

In recent years, collaborative learning, where learners with diverse backgrounds and perspectives work together, has emerged as a powerful educational approach that often surpasses individual study in effectiveness (Dillenbourg, 1999). This interactive methodology leverages peer interaction to deepen understanding and enhance knowledge construction. However, implementing collaborative learning faces practical challenges: it requires multiple learners studying the same content simultaneously, making it difficult for individuals to establish such environments independently.

In response to these constraints, agent-based learning has emerged as a promising alternative, offering continuous engagement without temporal or spatial limitations. Previous research demonstrates that interaction with pedagogical agents can significantly enhance learner engagement and learning behaviors (Nakata et al., 2023). Studies have shown that conversational agents can effectively support learning through scaffolding and adaptive feedback, particularly when they exhibit social presence and responsiveness (Kim & Baylor, 2016). Recent advances in Large Language Models (LLMs) have further expanded the potential for creating sophisticated conversational agents capable of natural, context-aware dialogue (Brown et al., 2020).

Research in cooperative learning has demonstrated that positive interdependence and individual accountability are crucial for effective group learning (Johnson & Johnson, 2009), yet current agent-based systems rarely implement these principles effectively.

This study addresses these gaps by proposing a multi-agent collaborative learning system that dynamically adjusts agent behaviors based on learner input. By quantifying learner opinions using language models and adjusting agent stances accordingly, our system creates a responsive learning environment that validates learner contributions while maintaining productive educational discourse.

2. Proposed System

2.1 System Outline

In this study, we propose a system to enhance learning motivation through discussions with multiple agents that consider and respond to learner opinions. The primary objective is to create a supportive learning environment where learner contributions are valued and integrated into the educational dialogue.

The system employs two distinct agents to ensure opinion diversity and encourage deeper understanding through multiple perspectives. The learner and two agents are collectively referred to as "participants" throughout the discussion. To maximize engagement and learning potential, we selected class diagram creation as the learning task—a domain that inherently lacks single correct solutions and encourages diverse approaches.

Class diagrams, a fundamental component of Unified Modeling Language (UML), visually represent system structures and relationships (Fowler, 2003). This task is particularly suitable for collaborative learning because it requires consideration of multiple design elements and trade-offs, naturally promoting discussion and knowledge exchange. The open-ended nature of design tasks aligns with Slavin's (2014) findings that collaborative learning is most effective when tasks require diverse perspectives and creative problem-solving.

The learning workflow, illustrated in Figure 1, follows a structured approach:

1. The user creates an initial draft diagram incorporating required elements
2. The user presents the draft to all participants for discussion
3. Based on discussion insights, the user refines their diagram
4. Steps 2-3 are repeated three times to allow iterative improvement
5. The process repeats for all diagram elements (classes, attributes, operations, relationships)
6. The user receives comprehensive feedback on their final diagram

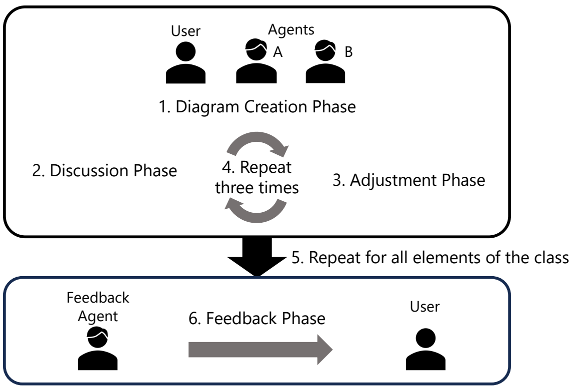

Figure 1. Learning flow of this system

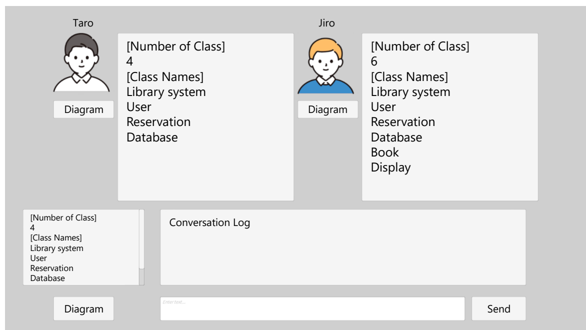

Figure 2. Multi-Agent Discussion UI

The conversation interface (Figure 2) displays all participant opinions simultaneously, enabling users to compare and contrast different perspectives. Participants take turns contributing to the discussion, with user input via keyboard and all statements logged for reference.

2.2 Class Diagram Elements

The system focuses on four essential class diagram components:

- **Class Names**: Identification and naming of required classes
- **Operations**: Methods and behaviors associated with each class
- **Attributes**: Data properties and fields within classes
- **Relationships**: Connections and associations between classes

This structured approach enables systematic exploration of each diagram component while maintaining focus on specific design decisions.

2.3 Adaptive Agent Opinion Adjustment

The core innovation of our system lies in its adaptive adjustment mechanism, illustrated in Figure 3. The process employs vector-based semantic analysis to align agent opinions with user perspectives while maintaining educational value.

First, both agent and user drafts are converted to 768-dimensional vector representations using Sentence-LUKE, a state-of-the-art Japanese language model specifically trained for semantic similarity tasks. The system then calculates the semantic midpoint between agent and user positions in this high-dimensional space.

Next, the system searches a curated database of candidate diagrams to find the entry with minimum Euclidean distance to this midpoint. This selected candidate becomes the agent's updated draft, effectively moving the agent's position closer to the user's perspective while maintaining pedagogical validity.

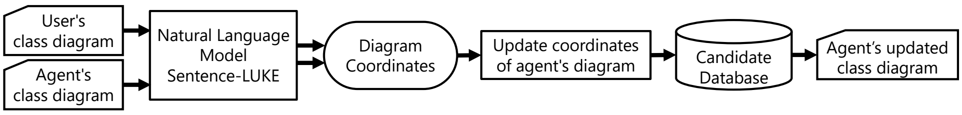

Figure 3. Adaptive Agent Opinion Adjustment Process.

3. Experimental Evaluation

This experiment was approved by the Research Ethics Review Committee of Organization for Research and Development of Innovative Science and Technology (ORDIST) in Kansai University, Japan.

3.1 Outlines

We conducted an evaluation study with 11 university students (mixed gender) to assess the system's effectiveness in enhancing learning motivation. Participants had no prior knowledge of object-oriented design or UML.

The experimental procedure consisted of:

1. Preliminary instruction on object-orientation and class diagram fundamentals
2. Collaborative diagram creation for a library book search system use case
3. Iterative refinement through multi-agent discussion following the system workflow
4. Post-experiment questionnaire and open-ended feedback collection

Table 1 presents the questionnaire items used for system evaluation.

Table 1. *System Evaluation Questionnaire.*

Q1	Was the experimental task difficult?
Q2	Did using the system increase your motivation to learn?
Q3	Did you enjoy using the system?
Q4	Would you like to use the system again?

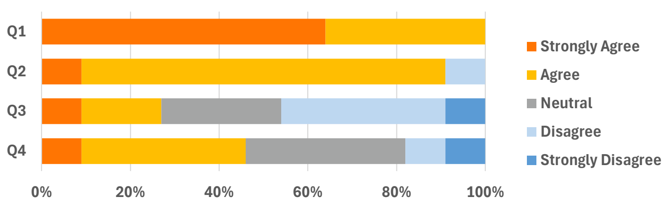

Figure 4. Post-Experiment Questionnaire Results.

3.2 Results and Discussion

All participants (100%) found the experimental task challenging (Q1), confirming the appropriateness of class diagram design as a learning domain requiring support. Significantly, 91% of participants reported increased learning motivation (Q2), strongly supporting our hypothesis that opinion-validating agents enhance engagement even with difficult content. This finding aligns with Dillenbourg's (1999) framework of collaborative learning, which emphasizes the importance of mutual engagement and shared understanding in learning interactions.

However, results for enjoyment (Q3) and reuse intention (Q4) were mixed. Only 27% found the system enjoyable, while 46% did not, suggesting that increased motivation does not necessarily translate to enjoyment. Similarly, reuse intention showed 46% positive and 18% negative responses, with many participants remaining neutral.

Free-form feedback identified several issues requiring attention:

- Extended experiment duration (approximately 1.5 hours) caused fatigue
- User interface complexity hindered smooth interaction
- Some agent discussions lacked sufficient depth or relevance
- The system occasionally generated repetitive or superficial responses

These findings suggest that while the core concept of adaptive multi-agent support is effective for motivation, implementation improvements are needed to enhance overall user experience.

4. Conclusion

This study proposed and evaluated a multi-agent collaborative learning system that adapts to learner opinions through dynamic stance adjustment. Our experimental results demonstrate the system's effectiveness in enhancing learning motivation, with 91% of participants reporting increased engagement despite challenging content.

However, significant challenges remain. The cognitive load imposed by extended interaction sessions proved excessive for many participants, and the system sometimes struggled to generate sufficiently substantive discussions. Practical discussions require deeper understanding of diverse perspectives, which our current implementation does not fully achieve.

Future work will focus on redesigning tasks to reduce cognitive burden while incorporating ideation support mechanisms to encourage more meaningful collaborative exchanges. Through these improvements, we aim to develop a system that not only motivates learners but also facilitates deeper understanding through genuine collaborative knowledge construction.

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