Integrating Quantum CI and Generative AI for Taiwanese/English Co-Learning

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***Abstract*—This study investigates the integration of Quantum Computational Intelligence (QCI) and Generative AI (GAI) within a co-learning framework, targeting Taiwanese-English language education. Key methodologies include the Content Attention Ontology (CAO) and advanced AI models like SBERT and Meta AI UST agents. Experimental results highlight enhanced co-learning efficiency through human-machine interaction, speech-to-speech translation, and semantic analysis. Future work aims to refine QCI and expand the system for broader multilingual applications.**

***Index Terms*—Human-Machine Co-Learning, Quantum Computational Intelligence, Generative AI, Taiwanese-English Language Learning**

I. Introduction

Computational Intelligence (CI), incorporating principles like Fuzzy Markup Language (FML), has been widely recognized for enhancing educational frameworks. This study builds upon CI by integrating Quantum Computational Intelligence (QCI) and Generative AI (GAI) to address challenges in bilingual co-learning. The Content Attention Ontology (CAO) framework underpins the system, enabling semantic analysis and adaptive learning, while tools like BERT, SBERT, and FAIRSEQ speech-to-speech translation facilitate deeper interaction between human and machine intelligence. This research demonstrates the applicability of these technologies in Taiwanese-English language education, showcasing improved semantic understanding and interactive learning environments.

II. Methodology

The proposed methodology is grounded in the Content Attention Ontology (CAO) framework, integrating Quantum Computational Intelligence (QCI) and Generative AI (GAI) to facilitate co-learning between human students and robotic agents. This section provides a detailed explanation of the system architecture, components, and their interactions.

A. The Content Attention Ontology Framework

The CAO framework forms the backbone of this study, designed to optimize the interaction between human and machine learning processes. At its core, CAO emphasizes the hierarchical organization of learning content and the application of semantic embedding for enhanced understanding.

To achieve this, SBERT (Sentence-BERT) is employed as a primary tool for semantic representation. By generating sentence embeddings that capture contextual meanings, SBERT facilitates precise evaluations of student responses and robotic interactions. For instance, during language co-learning, Taiwanese and English phrases are encoded into vector representations, enabling semantic similarity comparisons with predefined gold standards.

The CAO framework further incorporates FAIRSEQ-based Speech-to-Speech Translation (S2ST) for bilingual auditory interactions. This tool processes spoken inputs, translates them into the target language, and generates audio outputs, enabling seamless communication between students and robots. The integration of S2ST ensures that both linguistic and auditory nuances are preserved, critical for the bilingual learning environment.

Lastly, Generative AI (GAI) enhances multimodal learning by creating visual content based on textual or auditory inputs. For example, when a student describes a scenario in Taiwanese, the system can generate corresponding images, providing a tangible representation of abstract ideas. This feature not only reinforces language comprehension but also engages students in interactive, visually enriched learning experiences.

B. Design of the Learning Model

The learning model is structured around three interconnected components:

1) **Human-Machine Interaction:** The interaction design ensures active engagement between students and robots. Robots are equipped with CAO-aligned content, allowing them to adapt their responses based on student proficiency levels. This adaptability is particularly evident in language tasks, where sentence complexity is dynamically adjusted to match the learner's abilities.
2) **Knowledge Representation:** The system leverages QCI to refine semantic understanding, addressing the subtleties of language translation and sentence structure. By utilizing quantum-inspired optimization techniques, the model achieves a balance between linguistic precision and computational efficiency.
3) **Evaluation Metrics:** A fuzzy logic-based approach evaluates learning outcomes. Metrics include semantic

similarity scores, pronunciation accuracy, and task completion rates. These quantitative measures are complemented by qualitative observations, providing a holistic assessment of the co-learning process.

C. Operational Workflow

The system operates in three phases to maximize learning outcomes:

- **Phase 1:** Data Collection. Students interact with the platform by uploading assignments or participating in speech tasks. Robotic agents process these inputs, applying semantic embedding and speech recognition tools to extract meaningful data.
- **Phase 2:** Co-Learning Execution. Robots engage students in tasks such as translating sentences, practicing pronunciation, or generating context-specific images. The bilingual framework ensures that tasks align with educational objectives, while the S2ST and GAI components enhance accessibility and engagement.
- **Phase 3:** Performance Evaluation. Using fuzzy logic, the system analyzes semantic similarity scores and other metrics to provide feedback. For instance, if a student struggles with a particular sentence structure, the robot adjusts future tasks to target this weakness, fostering a personalized learning trajectory.

This methodology ensures that human and machine intelligence work in tandem, creating a dynamic and adaptive educational ecosystem. Each component is meticulously designed to address the complexities of bilingual learning, ensuring that both linguistic and cognitive development are achieved.

III. Experiments and Results

To evaluate the effectiveness of the proposed framework, we conducted a series of experiments focusing on Speaking Performance Evaluation and Writing Performance Evaluation within a bilingual co-learning environment. The experiments involved university students engaging with Content Attention Ontology (CAO) robots, using tools like SBERT, FAIRSEQ, and Meta AI UST agents.

A. Speaking Performance Evaluation

1) Experimental Design: Participants were divided into three proficiency levels in Taiwanese: Proficient (A), Basic (B), and Below Basic (C). Each participant practiced speaking 124 Taiwanese sentences. The Meta AI UST agent transcribed the spoken content into English text, which was then compared against a gold standard using semantic similarity scores generated by SBERT.

2) Results Analysis: The semantic similarity scores revealed clear trends:

- Proficient speakers achieved an average similarity score of 0.82, indicating strong alignment with the gold standard.
- Basic speakers scored 0.72 on average, reflecting moderate fluency but occasional errors in pronunciation.
- Below Basic speakers achieved 0.65, highlighting significant challenges in sentence structure and pronunciation accuracy.

3) Significance of Results: These findings underscore the effectiveness of the CAO robot in identifying and addressing specific learning gaps. The integration of SBERT allowed for nuanced evaluation of pronunciation and semantic understanding. However, the results also indicate that the robot's recognition system struggles with certain accents and complex sentence constructions, pointing to areas for improvement in future iterations.

B. Writing Performance Evaluation

1) Experimental Design: Participants were tasked with writing assignments in both Taiwanese and English, focusing on specific themes provided by the CAO framework. The submissions were evaluated based on semantic content, coherence, and adherence to grammatical rules using SBERT similarity scores and a fuzzy logic-based grading system.

2) Results Analysis: We analyze the semantic similarity of SBERT by varying the chunk size, with the goal of determining the optimal chunk size for this analysis. The Assignment Transformer, a component selected from the Computer Science (CS), Artificial Intelligence (AI), and Machine Learning (ML) courses, was utilized for this purpose. As shown in Figure 1, it can be observed that as the chunk size decreases, the similarity score increases.

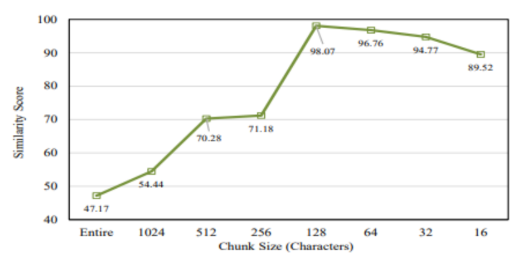

Fig. 1. Relationship between chunk size and similarity score

IV. Conclusion

The proposed CAO-based framework effectively combines QCI and GAI to enhance Taiwanese-English co-learning. Semantic tools and generative technologies create an adaptive and engaging learning environment. Future work will focus on refining the system for multilingual applications and extending its use in metaverse-based educational models.

References

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