Evolutionary Computation-based Assessment Model for Human-Machine Co-Learning on Taiwanese and English Language between Taiwan and Japan

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***Abstract*—This study aims to evaluate the effectiveness of a Meta AI tool using a human-machine co-learning model for practicing and learning Taiwanese and English languages between Taiwan and Japan. Teachers and students from both countries followed a six-step human-machine co-learning model that integrated both the human and machine co-learning process in the Taiwanese and English languages to conduct the study. We assessed the performance of both human intelligence and machine intelligence in Taiwanese language practice using the sentence BERT similarity approach, to measure how similar the source sentences were to the Meta AI tool-generated sentences. Human experts then extracted important features of the source sentences to construct a knowledge model, and we employed the proposed evolutionary computation-based assessment model to analyze the similarity in learning effectiveness between human and machine evaluations. Our findings indicate that the Meta AI tool has a positive impact on language practice and learning, and the human-machine co-learning model will be an effective approach for Taiwanese and English language learning between Taiwan and Japan in the future.**

Keywords*—Evolutionary Computation, Human and Machine Co-Learning Model, Taiwanese-English Language Co-Learning, Meta AI Tool, Human Intelligence, Open AI ChatGPT, Sentence BERT Agent

I. Introduction

In this study, an Evolutionary Computation (EC) model was developed to assess the effectiveness of a Meta AI tool for co-learning Taiwanese and English languages [1], and to evaluate the performance of both human intelligence (HI) and machine intelligence (MI) with computational intelligence (CI) in the learning process. A six-step process was employed during the stage of data preparation and collection to practice and study the basic concepts of CI for young students. This process integrates a human and machine co-learning model, which is depicted in Fig. 1 and described as follows:

1) **Observation and participation in CI learning activities:** The teacher observes the abilities of the learners, prepares corresponding CI teaching content, and goes to the learning site. 2) **Learning and researching CI knowledge:** In the learning field, the teacher and the learners experience CI conceptual learning together and conduct in-depth research on the corresponding CI content. 3) **Utilizing and following CI learning tools:** After CI learning, the learners can utilize and follow them for CI experiential learning. 4) **Understanding and knowing the application of CI:** After CI experiential learning, learners understand and know the principles of CI and can carry out CI practical and operational learning. 5) **Explaining and speaking CI knowledge concepts:** Learners can explain and speak the CI learning content to other learners for CI expression-based learning. 6) **Applying CI knowledge to solve real-world problems:** Learners can use the learned CI knowledge to solve practical problems and constantly improve and optimize the CI learning process [2]. Through observation, learning, experience, and application, learners can effectively express and utilize their knowledge and skills for practical problem-solving based on the studied computational intelligence knowledge.

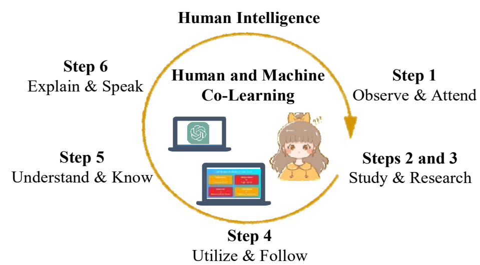

Fig. 1. Human-machine co-learning model for Taiwanese and English language practice and learning.

We extracted important features from the data collection to construct an EC-based model for assessing the performance of both HI and MI. Participant performance is evaluated by humans based on the number of key concepts translated by a CI&AI-FML human and machine co-learning agent, which is integrated with the Meta AI Speech-to-speech translation tool [1]. Meanwhile, the machine evaluates their performance based on the similarity of translated sentences to standard sentences, which is implemented by the Sentence-BERT (SBERT) agent [3]. The EC model we constructed assesses the performance of both HI and MI based on the extracted features from the collected data.

The remainder of this paper is structured as follows: Section II briefly introduces the methodology of the Taiwanese and English language co-learning with the CI&AI-FML human and machine co-learning agent and the SBERT agent. Additionally, Section II describes the EC-based assessment model. Finally, the discussion and future work are presented in Section III.

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II. METHODOLOGY

A. *Structure of Language Co-Learning with CI&AI-FML Human and Machine Co-learning Agent and SBERT Agent*

Fig. 2 describes a three-stage research design that includes the participants, procedures, and materials used in the study to understand clearly the interaction in the proposed framework. This video (https://youtu.be/dMarvERmgII) demonstrates a scene from our research project where participants read the short story in either Taiwanese or English and interact with the machine to co-learn together. The stages are as follows:

1) **Stage I: Learning data preparation**: Initially, a human designer creates a short story consisting of 5 to 10 sentences using Chinese or Taiwanese daily life vocabulary as the basis for the ground truth. The story is then translated into English using the OpenAI tool, ChatGPT, to create the English ground truth.

2) **Stage II: Learning data collection:** The Meta AI tool is integrated into the developed *CI&AI-FML* (Artificial Intelligence-Fuzzy Markup Language) *human and machine co-learning agent* to provide speech-to-speech translation between Taiwanese and English. Participants read the short story in either Taiwanese or English, and Meta AI Tool translates it into speeches in English and Taiwanese, as well as texts in English and Chinese. The source of the speeches and the output of speeches and texts are all stored.

3) **Stage III: Learning data analysis**: The evaluation of participant performance by humans is based on the number of key concepts translated by Meta AI tools compared to the ground truth. Meanwhile, the machine analyzes the similarity between the translated texts and the ground truth using the Sentence-BERT (SBERT) agent. The results evaluated by humans are stored in the HI repository, while those evaluated by machines are stored in the MI repository.

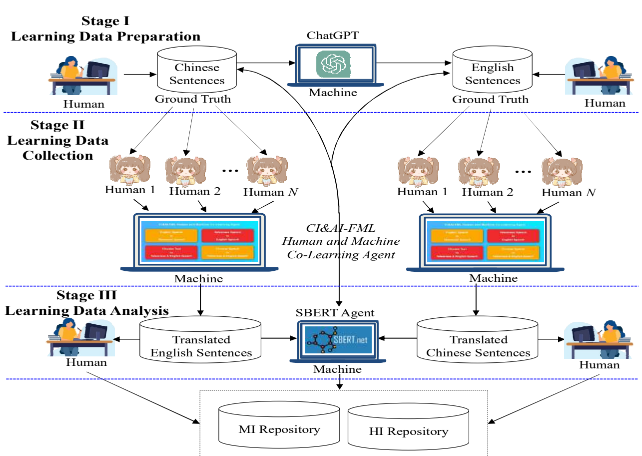

Fig. 2. Structure of Taiwanese and English language co-learning with CI&AI-FML human and machine co-learning agent and SBERT agent.

B. *Evolutionary Computation-based Assessment Model*

In this section, the construction of an EC-based assessment model and its connection to a six-step human and machine co-learning model are described. Fig. 3 illustrates the EC-based assessment model construction and its link to the six-step human and machine co-learning model. The model's performance is assessed using three input features, namely *the level of learner participation*, *the level of learner tool utilization*, and *the extent to which the learner follows the learned knowledge*, which is extracted from Steps 1, 4, and 5, respectively. The objective is to predict the effectiveness of the learner's speaking proficiency extracted from Step 6. The target data may include results evaluated by both humans and machines, which can be used to validate the performance of both. Using the collected data, we construct the knowledge base (KB) and rule base (RB) of the model. We then optimize its parameters using EC-based methods, such as GA-based fuzzy markup language (GFML), PSO-based fuzzy markup language (PFML), and Genetic Algorithm Neural Network (GANN) methods.

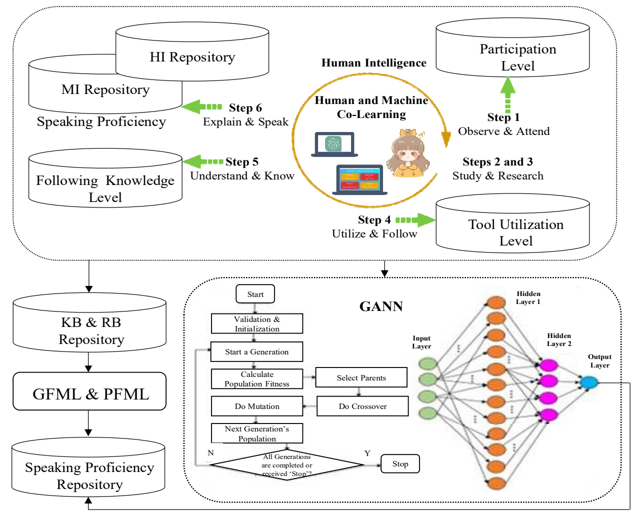

Fig. 3. EC-based assessment model construction linking the six-step human and machine co-learning.

III. DISCUSSION AND FUTURE WORK

The objective of this study was to evaluate the effectiveness of learning Taiwanese and English languages using a human-machine co-learning approach. The initial experiment was conducted in Taiwan and Japan from Dec. 2022 to Feb. 2023, with a total of 117 participants, including 43 involved in Taiwanese language practice and learning, and 74 involved in English practice and learning. The participants in this experiment were from Taiwan, Japan, China, and Malaysia. Fig. 4 shows their language level in Taiwanese and English, including *below-basic*, *basic*, *proficient*, and *advanced*. Additionally, we designed seven short stories in Taiwanese and English languages for the participants to read, consisting of 534 and 739 sentences, respectively.

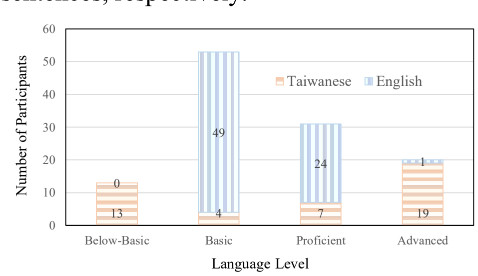

Fig. 4. Participants' language level of Taiwanese and English.

Fig. 5 compares the results of the average sentence similarity, evaluated by humans and machines, as well as the accuracy of the machine. In this experiment, four speakers from Taiwan (TW 1 to TW 4), three speakers from Japan (JP 1 to JP 3), and two speakers from China (CN 1 and CN 2) spoke short and simple Taiwanese daily life vocabulary. The results indicate that: 1) The machine's accuracy can reach 0.6, except for JP 2. 2) There is a large difference between the averages evaluated by humans and machines for JP 2 and JP 3. 3) People with a below-basic level of Taiwanese can achieve good performance after co-learning with the machine, as seen in TW 4, JP 1, CN 1, CN 2, and JP 3. 4) The accuracy of JP 3 reaches 1.

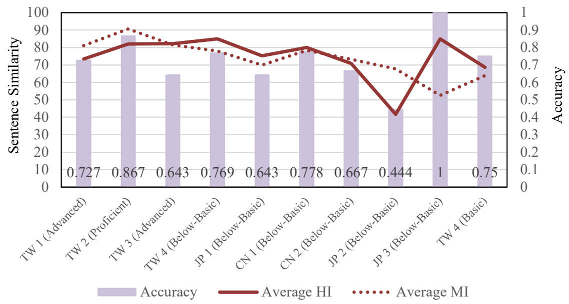

Fig. 5. Average sentence similarity evaluated by humans and machines and the accuracy of the machine.

Moreover, we found that JP 1, a junior high school student, was able to speak certain specific Taiwanese daily life vocabulary, such as 洗衣褲 (laundry pants), 腳踏車 (bicycle), 讀書 (study), 真有趣 (really interesting), and 可愛 (cute), well enough for the machine to understand after trying about three times with the necessary guidance from CN 1, who is proficient in Japanese and advanced in Chinese. This guidance includes providing the Romanization of Taiwanese. JP 1 was very happy and gave applause when the machine translated her Taiwanese into English and spoke translated English correctly, indicating her good performance. However, we found this sentence 老師和機器人讀書 (The teacher and the robot are studying) is still difficult for her to read, especially the Taiwanese pronunciation of 機器人 (robot).

The experimental results indicate that the human and machine co-learning model has a positive impact on language learning. In the future, we plan to implement this approach using EC-based methods and quantum fuzzy inference engines to validate the performance of humans and machines. By doing so, we will gain a deeper understanding of the potential of combining our developed systems with AI tools such as Meta AI S2ST, OpenAI ChatGPT, and machine translators in human-machine co-learning for language learning.

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References

[1] P. J. Chen, K. Tran, Y. Yang, J. Du, J. Kao, Y. A. Chung, P. Tomasello, P. A. Duquenne, H. Schwenk, H. Gong, H. Inaguma, S. Popuri, C. Wang, J. Pino, W. N. Hsu, and A. Lee, "Speech-to-speech translation for a real-world unwritten language," 2022 [Online] Available: https://arxiv.org/abs/2211.06474.

[2] C. S. Lee, M. H. Wang, M. Reformat, S. H. Huang, "Human intelligence-based Metaverse for co-learning of students and smart machines," *Journal of Ambient Intelligence and Humanized Computing*, 2023. (DOI: 10.1007/s12652-023-04580-2).

[3] N. Reimers and I. Gurevych, "Sentence-BERT: sentence embeddings using siamese BERT-networks," 2022 [Online] Available: https://arxiv.org/abs/1908.10084.