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ORIGINAL RESEARCH

Human intelligence-based metaverse for co-learning of students and smart machines

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Abstract
This paper proposes a *Human Intelligence (HI)-based Computational Intelligence (CI) and Artificial Intelligence (AI) Fuzzy Markup Language (CI&AI-FML) Metaverse* as an educational environment for co-learning of students and machines. The *HI-based CI&AI-FML Metaverse* is based on the spirit of the *Heart Sutra* that equips the environment with teaching principles and cognitive intelligence of ancient words of wisdom. There are four stages of the Metaverse: preparation and collection of learning data, data preprocessing, data analysis, and data evaluation. During the data preparation stage, the domain experts construct a learning dictionary with fuzzy concept sets describing different terms and concepts related to the course domains. Then, the students and teachers use the developed CI&AI-FML learning tools to interact with machines and learn together. Once the teachers prepare relevant material, students provide their inputs/texts representing their levels of understanding of the learned concepts. A Natural Language Processing (NLP) tool, Chinese Knowledge Information Processing (CKIP), is used to process data/text generated by students. A focus is put on speech tagging, word sense disambiguation, and named entity recognition. Following that, the quantitative and qualitative data analysis is performed. Finally, the students' learning progress, measured using *progress metrics*, is evaluated and analyzed. The experimental results reveal that the proposed HI-based CI&AI-FML Metaverse can foster students' motivation to learn and improve their performance. It has been shown in the case of young students studying Software Engineering and learning English.

Keywords Human intelligence · CI&AI-FML Metaverse · Natural language processing · Student and machine co-learning · Learning performance

1 Introduction

Natural language processing (NLP) is a branch of AI that has been widely used to process and analyze text (Ding et al. 2022). NLP involves designing and implementing systems and algorithms enabling machines to improve their interaction with humans (Lauriol et al. 2022). Huang and You (2021) have proposed a two-phase Chinese lyrics generation system based on notes and the melody of emotions. A framework for the automatic generation of natural language descriptions of healthcare processes using quantitative and qualitative data combined with expert medical knowledge has been proposed by Fontenla-Seco et al. (2022). An ancient text of the *Heart Sutra* is the most frequently used and recited text in the Buddhist tradition (Nattier 1992) that is the pure distillation of human intelligence. It is a captivating view of the process of comprehending the world around us. It could be interpreted as "… *a brief memo for contemplating all the elements of our psychophysical existence from the point of view of what we are now, what we become as we progress on the Buddhist path, and what we attain (or do not attain) at the end of that path*" (Brunnholzl 2012). One of the possible interpretations of the *Heart Sutra* offers an interesting view of the process of education and learning. It can be perceived as a six-step approach to an interaction between teachers and students—from observations, via studies, utilization and following, to understanding and explaining.

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This paper combines the principles of the *Heart Sutra* with the core technologies of CI&AI-FML and Metaverse. As a result, the *Human Intelligence (HI)-based Computational Intelligence (CI) and Artificial Intelligence (AI) Fuzzy Markup Language (CI&AI-FML) Metaverse* for student and smart machine co-learning is developed. It integrates the elements of human intelligence taken from the *Heart Sutra* with the elements of intelligence of machine learning-based models (Lee et al. 2022). The *Heart Sutra* is the inspiration for creating a six-step learning process. It contains such steps as: observe and go, study and research (that span over 2 steps), utilize and follow, understand and know, and finally, explain and speak. The *HI-based CI&AI-FML Metaverse* classroom is fully developed around these steps. It supports teachers and educators to prepare learning materials, identify concepts required by students to learn, provide evaluation criteria, and observe students' learning progress according to their performance in auditory intelligence, verbal expression, visual intelligence, and written communication. Additionally, the *HI-based CI&AI-FML Metaverse* gives students abilities to become familiar with new concepts, provide an input representing their understanding of the concepts, gain hands-on experience, and interact with their peers—all in continuous contact with the software/hardware of the *Metaverse* which provides content that meets the student's needs and has successfully helped teachers assist students who meet real-time remedial teaching.

The learning structure of the *Metaverse* adopts Chinese Knowledge Information Processing (CKIP) Tagger (Li et al. 2020), Natural Language Toolkit (NLTK) (Steven et al. 2009), and *fastText* Deep Learning model as a text processing and analyzing mechanism. In the *Metaverse*, it is used to process the student-generated labels annotating a variety of learning textual materials. *FastText* learns representations for character n-grams and depicts words as the sum of the n-gram vectors (Bojanowski et al. 2017). It contains the pre-trained word vectors in 157 languages, trained on Common Crawl and Wikipedia using *fastText* (Grave et al. 2018). Here, it is applied to determine similarity and perform similarity-related processes on data generated by CKIP Tagger and NTLK. Based on the quantitative and qualitative data labeled by the students participating in the *HI-based CI&AI-FML Metaverse* and the knowledge experts, the students' learning performance is evaluated using *progress measures*. The experiments' results show that the *HI-based fuzzy CI&AI-FML Metaverse* for student and smart machine co-learning is a beneficial system. It has been instrumental in teaching students at different educational levels such topics as CI applications, Software Engineering, and English. For the case of learning CI applications, the proposed *Metaverse* allowed the participants, especially from the pre-university programs to (1) construct a knowledge base and a rule base of the FML-based inference system for real-world applications, (2) simulate human intelligence to control activation of the AI-FML tools, and (3) experience the Augmented Creativity of GTC Showcase App using AR (Zund et al. 2015). The participants of the taught courses consider the *Metaverse* helpful in gaining familiarity with taught topics, for example, CI, and hope to study them, for example, computer science, more in the future. The pre-university students shared a similar experience. In their own words, they "*learned a lot from the incorporation of the human and robot co-learning model, had a sense of accomplishment after the involvement in this program—learning CI&AI-FML in this way was fantastic.*"

The main contribution of the paper is the integration of the *Heart Sutra* with CI and AI technologies to design and implement a novel software/hardware environment—the *Metaverse*—for e-learning. To accomplish that a set of other contributions can be identified.

- Adaptation of the *Heart Sutra* philosophy for educational purposes and proposing a six-step e-learning human–machine co-learning process.
- Development of Heart Sutra-based ontology for e-learning purposes.
- Design and implementation of the architecture of an e-learning system that incorporates the six-steps approach in the environment spanning multiple educational sites from high schools to universities.
- Application of multiple CI and AI-based methods for executing the six-step approach with a focus on text processing and fuzzy-based evaluation/decision support mechanisms.
- Extensive case studies involving the proposed Metaverse deployed for teaching Software Engineering and English students, where a single course is composed of multiple episodes (classes).
- The developed IRT (Item Response Theory) based English speaking practice system was for high school students. This allows the student to practice public speaking using an AI-FML intelligent robot providing content that meets the student's needs.
- Using fuzzy logic and fuzzy set which are human's subjective cognition to the IRT learning system combined with the AI-FML tools to assist students who meet real-time remedial teaching.
- Success in helping teachers use the intelligent adaptive system to assist students who meet real-time remedial teaching.

In summary, we proposed *Metaverse* provides an environment for teachers, students, and machines to cooperate at different stages of learning processes. It is an example of a true co-learning paradigm where CI/AI techniques and methods are utilized to enable people—teachers and students—to interact with machines in a natural way and benefit from their—limited so far—intelligence. The remainder of this paper is structured as follows: Sect. 2 briefly introduces the related work. Section 3 describes the structure of the *Heart Sutra*-inspired fuzzy ontology for CI&AI-FML Metaverse applications. Then, in Sect. 4, we introduce the structure of the HI-based CI&AI-FML Metaverse, i.e., the intelligent knowledge concept retrieval agent and the NL-based processing agent for student and smart machine co-learning. Next, the quantitative analysis agent, qualitative analysis agent, and learning performance evaluation agent for CI&AI-FML educational applications in CI and English learning are presented in Sect. 5. Finally, experimental results are shown in Sect. 6, and the conclusions are presented in Sect. 7.

2 Related work

Between 2019 and 2022, more than 2700 participants from Taiwan, Japan, and Indonesia experienced and learned CI&AI-FML applications. The 2021 Summer School of Computational Intelligence for high school student learning promoted computational intelligence concepts and robotics knowledge for real-world applications to elementary school, high school, and university students. Lee et al. (2022) successfully inspired and encouraged senior high school students to attend these courses and workshops, and those students have successfully applied to engineering-related university programs based on their experience studying in the program. Video 1 is provided in the Appendix to get more information about the CI&AI-FML learning.

The Metaverse is a visual space that blends the physical and digital worlds (Zhao et al. 2022). A framework for visual construction and exploration of the Metaverse has been proposed. It is essential for exploring and utilizing human knowledge, especially of educators, and supporting others in accomplishing different goals (Russel and Norvig 2021). Knowledge-based agents use reasoning processes to assist decision-making processes in selecting adequate actions. One of the best examples is the AI-FML (Acampora and Loia 2005) Metaverse classroom that focuses on experiential-based learning of CI techniques developed by Lee et al. (2022). It utilizes several AI-FML-based applications like AI-FML robots, different studying-oriented tools, and MoonCars. They play the role of observers, actors, or executors. For instance, a robotic assistant agent for student-machine co-learning with AI-FML is applied to AIoT applications.

The developments in the area of NLP can be divided into three stages: the germination stage, the gradual development stage, and the rapid development stage (Ding et al. 2022). Some open-source NLP systems are widely available, such as Jieba and CKIP Tagger for the Chinese language, and NLTK, SpaCy, CoreNLP, and PanGu (Steven et al. 2009) for English. Some other mechanisms like Word2Vec, fastText, Genism, and BERT, support multi-language processing. With the recent advances in Deep Learning, NLP applications have received unprecedented performance.

CI is one of the core technologies of AI. Fuzzy logic, neural networks, as well as evolutionary computation are three fundamental pillars of CI.

Recent advances in CI-related technologies, especially the development and standardization of FML, have created opportunities to develop systems that take advantage of CI mechanisms and algorithms. One of the essential applications of CI and FML is the enhancement of e-learning systems. Most e-learning systems provide a variety of means to support students in their learning activities. It seems they focus on collecting information about students, providing appropriate learning material, and assisting teachers in the evaluation processes. However, these systems usually do not provide a whole strategy for a learning process.

CKIP Tagger is a neural CKIP-style Chinese NLP mechanism. The results of word segmentation (WS), part-of-speech tagging (POS), and named entity recognition (NER) are an input of the *Metaverse*. The NLTK is a suite of open-source Python modules supporting NLP research and development. The NLTK is mainly used to segment English words. *FastText* deep learning model is an open-source library for generating word representations and sentence classification proposed by Meta Research (Lauriol et al. 2022). The diagram of the CKIP-based NLP for HI ontology construction and understanding providing more details and some clarification on how the *Heart Sutra* is understood and applied for *CI&AI-FML Metaverse* is shown in Chinese, Fig. 1a, and English, Fig. 1b. A more thorough explanation of understanding the *Heart Sutra* for student learning is provided in Video 2 in the Appendix.

3 Heart sutra-inspired fuzzy concepts of learning domain ontology for CI&AI-FML Metaverse

This section describes the structure of the *HI-based CI&AI-FML Metaverse*. It uses fuzzy concepts of HI domain ontology representing elements of the *Heart Sutra* and includes the *Heart Sutra*-based Meta-Intelligence, computational intelligence tools and techniques to build intelligent systems, and CI learning domain ontology. The structure of the *Metaverse* is introduced in Sect. 3.1, the elements of the *Heart Sutra* used to express learning strategy are presented in Sect. 3.2, and the fuzzy terms, variables, and concepts are described in Sect. 3.3.

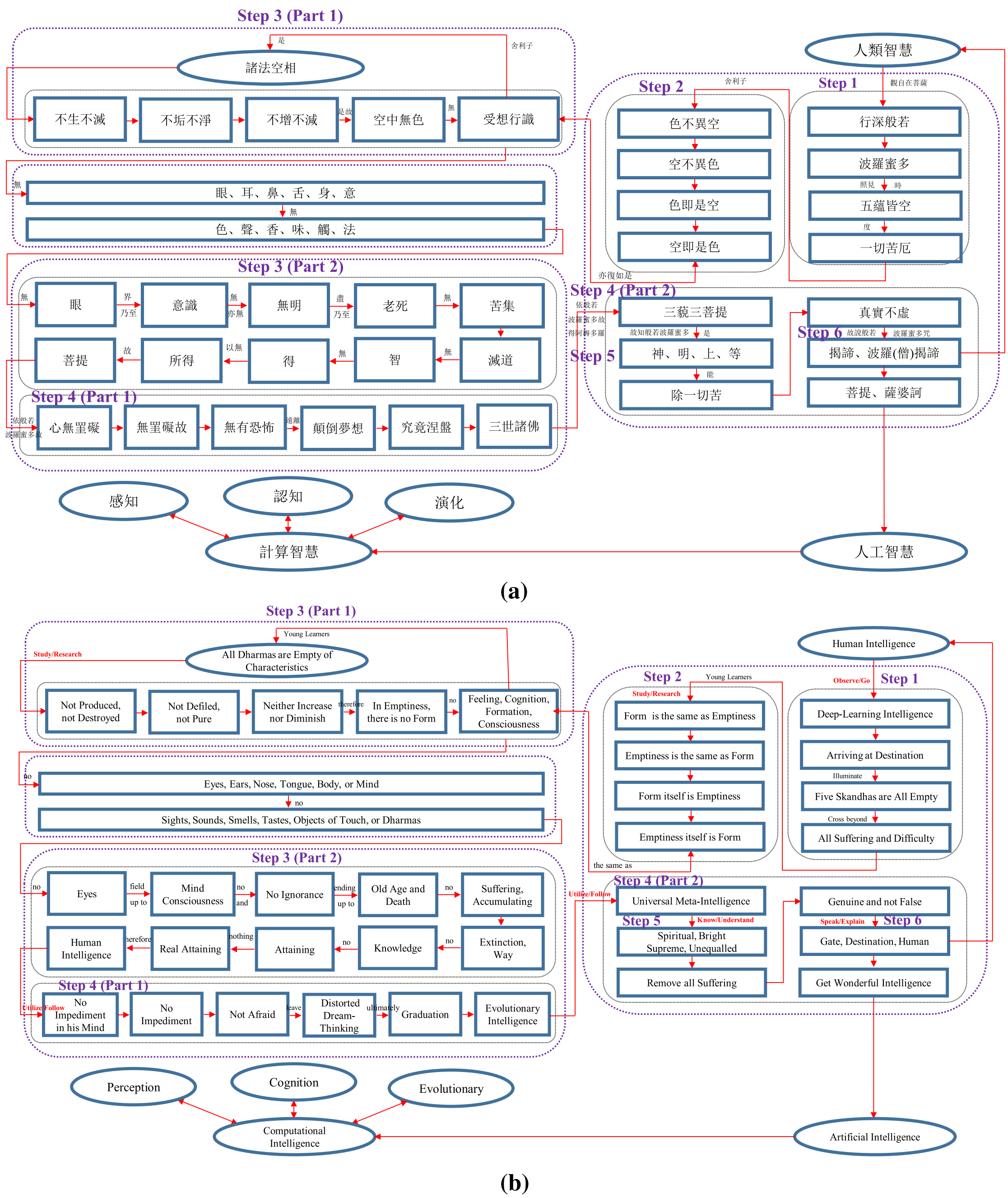


Fig. 1 Diagram of the CKIP-based NLP for HI ontology construction and understanding of *Heart Sutra* in **a** Chinese and **b** English

3.1 Heart Sutra-inspired CI&AI-FML Metaverse for student learning applications

The structure of the *HI-based CI&AI-FML Metaverse* is inspired and built around the *Heart Sutra*. Figure 2 illustrates the relationship between its components that are grouped around Eastern and Western Human Intelligence and Artificial Intelligence. The Eastern Human Intelligence is based on *Heart Sutra* Meta-Intelligence expressed with 260 Chinese words translated by Xuanzang. A Western Human Intelligence concept influenced by Aristotle's teachings—called ontology—is used to represent information/knowledge. Elements of AI are represented by agents utilizing AI-FML techniques, such as AI-FML robots, AI-FML learning tools, and AI-FML MoonCars. Their features engage computational intelligence, perceptive intelligence, and cognitive intelligence.

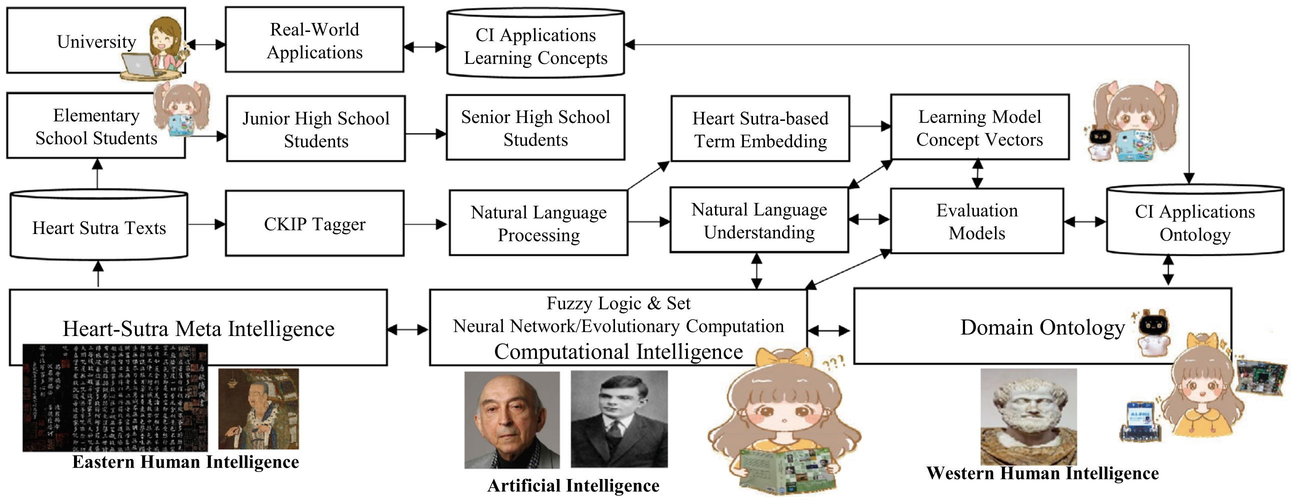


Fig. 2 Structure of *Heart Sutra*-inspired CI&AI-FML Metaverse

We incorporate the tenets of the *Heart Sutra* into the proposed teaching processes suitable for different educational levels: elementary school (ES), junior high school (JHS), senior high school (SHS), and university (U). We also build the basic concepts of CI learning domain ontology representing three pillars of CI—fuzzy logic, neural networks, and evolutionary computation for young students learning CI applications. Next, we adopt the techniques of CKIP tagger, Natural Language Processing tools, and Natural Language Understanding tools to construct a *Heart Sutra*-based term embedding and learning model. Table 1 shows the partial fuzzy neural network, fuzzy logic, and evolutionary computation concepts of basic CI learning domain ontology based on the lectures given at the 2022 IEEE CIS Summer in Taiwan. In addition, we improve the learning evaluation model by adjusting the evaluation model's parameters to optimize students' learning performance. Figure 3 shows the *CI&AI-FML Metaverse* learning cube for young students to explore and discover the proposed learning environment.

Table 1 Partial fuzzy neural network, fuzzy logic, and evolutionary computation concepts of basic CI learning domain ontology

Partial fuzzy neural network concepts		
Fuzzy set	Crisp set	Fuzzy system
Subjective	Objective	Subjective measure
Neural fuzzy system	Fuzzy rule	If–then
Approximate reasoning	Inference	Fuzzy logic
Membership function	Knowledge base	Rule base
Fuzzy inference system	Fuzzy reasoning	Machine learning
Fuzzy expert system	ANFIS	PSO
Probability	Possibility	FML
Partial fuzzy logic concepts		
Uncertainty	Decision making	Human knowledge
Fuzzy variable	Fuzzy set shape	Triangular
Trapezoidal	Gaussian	Sigmoid
Fuzzy set operation	Complement	Intersection
Union	Linguistic term	Modifier
Partial evolutionary computation concepts		
Darwin	Population	Individual
Selection	Crossover	Mutation
Parent	Children	GA
GBML	GP	IEC
Classification	Optimization	MOP

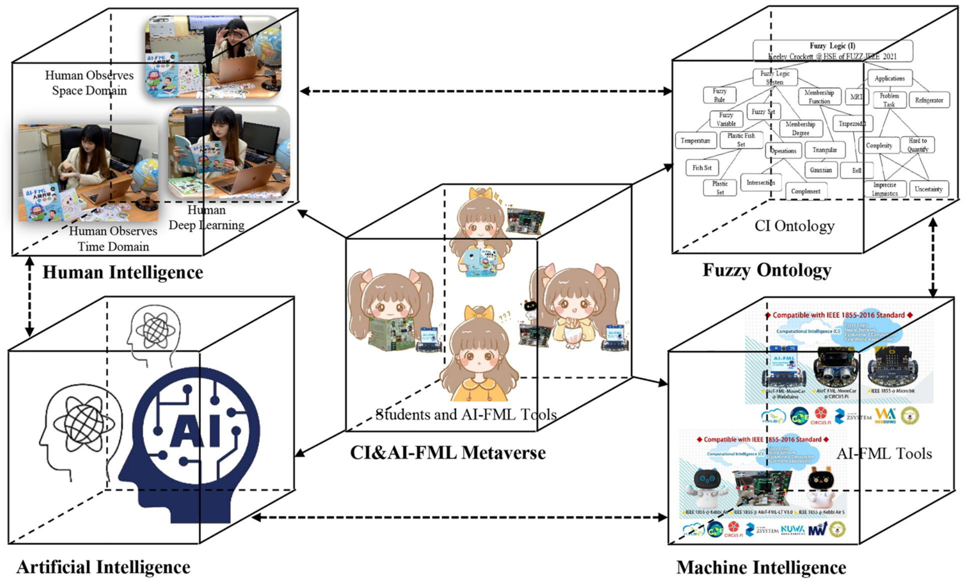


Fig. 3 Cube of the CI&AI-FML Metaverse

Let us semi-formally defined the proposed framework, as well as some of its properties.

Definition 1 (CI&AI-FML Metaverse) *The CI&AI-FML Metaverse is a space–time educational universe V(HI, FO, AI, ML, HS) inspired by Heart Sutra (HS) integrating elements of* ***human intelligence (HI), fuzzy ontology (FO), artificial intelligence (AI),*** and ***machine learning (ML) algorithms*** *for young students, including elementary school students, junior high school students, senior high school students, and university students, to learn, study, and gain experience in the basic concepts of Computational Intelligence with real-world applications.*

Definition 2 (Properties of CI&AI-FML Metaverse) *The important properties of CI&AI-FML Metaverse V(HI, FO, AI, ML, HS) enables* ***Spiritual***, *Bright*, ***Supreme***, *Unequalled, and* ***Genuine*** *attributes to be gained by young students learning and operating on various applications of Computational Intelligence using Item Response Theory, Deep Learning, and Reinforcement Learning structure.*

A schematic view of the *CI&AI-FML Metaverse V(HI, FO, AI, MI, HS)* with the learning space, time, and content for past, present, and future learning domains in various subspaces is shown in Fig. 4. These physical objects, a chunk of space–time, can be viewed as generalized events. The

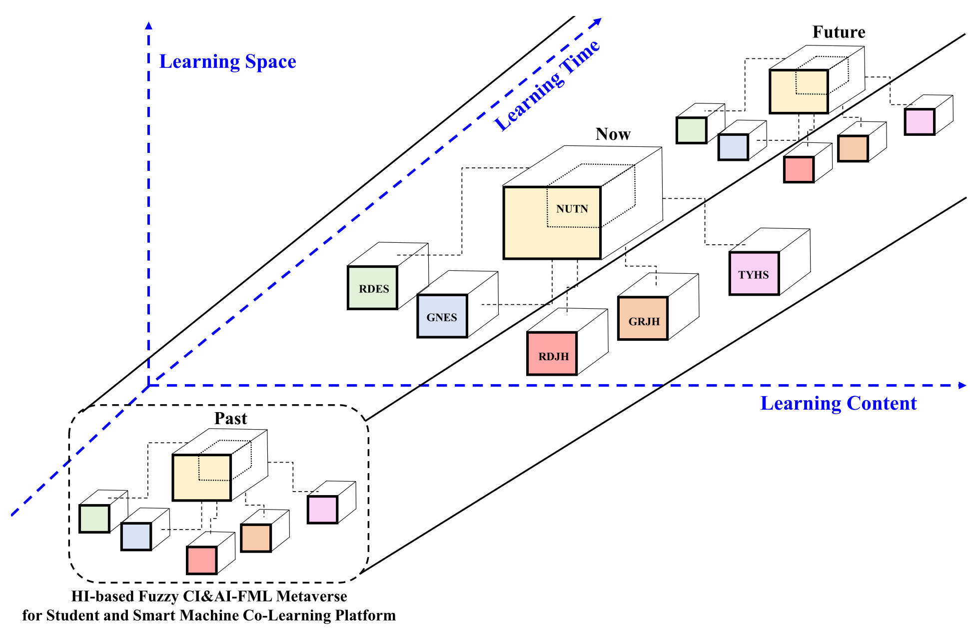


Fig. 4 CI&AI-FML Metaverse for past, present, and future learning domains

current learning space the *CI&AI-FML Metaverse* contains the following subspaces: the National University of Tainan (NUTN) subspace, Tsoying Senior High School (TYHS) subspace, Fei-Sha Junior High School (FSJH), Rende Junior High School (RDJH) subspace, Guiren Junior High School (GRJH) subspace, Rende Elementary School (RDES) subspace, and Guienan Elementary School (GNES) subspace. The students in the *Metaverse* can interact with and gain experience in the processes of designing and developing the CI&AI-FML systems for various real-life applications, and learn how to interact with the machines/robots. Finally, via interacting with the *CI&AI-FML Metaverse*, the teachers and students can gain top-level CI knowledge. It is achieved by understanding the Meta-Intelligence via the past, present, and future experiences with different subspaces.

3.2 Heart Sutra for CI&AI-FML Metaverse

A process of adapting the *Heart Sutra* to educational practices resulted in the six-step methodology. This methodology is a human understanding of the *Heart Sutra*, and its steps are shown in Fig. 5. The mapping of this six-step methodology with human understanding of the *Heart Sutra* for CI&AI-FML Metaverse with CI application is shown in Fig. 1 and the identified steps are following.

Step 1: Teachers observe the students' learning abilities, i.e., aspects of (human) intelligence, with the space–time domain in *the CI&AI-FML Metaverse*. They prepare material based on students' intellectual skills and continue to interact with them. Step 2: The teachers and students can perceive and understand the *Heart Sutra* concept of *Emptiness*, i.e., an empty space to be filled—or in other words—a need for learning and understanding, in the virtual and physical *CI&AI-FML Metaverse*. Step 3: Students use eyes (visual intelligence), ears (auditory intelligence), nose, tongue (verbal expression), body (writing intelligence), and mind to study the *CI&AI-FML* using their learning capabilities and co-learn with the machines. Step 4: Students utilize and deepen their knowledge about CI techniques and their applications. Step 5: Students comprehend and appreciate the gained knowledge in the domain. Step 6: Students can explain and talk about the CI&AI-FML applications with their peers and other teachers.

3.3 Heart Sutra-inspired CI&AI-FML Metaverse ontology model

The *CI&AI-FML Metaverse V(HI, FO, AI, MI, HS)* includes an ontology model inspired by the *Heart Sutra* that represents the students' learned concepts and the teacher's teaching concepts. The constructed ontology is composed of five layers, namely *Human Intelligence (HI)/Artificial Intelligence (AI)*, *Element*, *Vector*, *Matrix*, and *Tensor* layers.

Figure 6 shows the mapping of concepts and terms from HI (left-hand side) to AI (right-hand side) in the ontology model. Functions $f_E(\bullet)$, $f_V(\bullet)$, $f_M(\bullet)$, and $f_T(\bullet)$ denote the mappings for the elements, vectors, matrices, and tensors, respectively. The *Element* layer contains the embedded 260 Chinese words from e_1, e_2, e_3, …, to e_{260}, where E_1 = (觀, 自, 在, …, 厄) = (e_1, e_2, e_3, …, e_{25}), E_2 = (舍, 利, 子, …, 是) = (e_{26}, e_{27}, e_{28}, …, e_{52}), …, E_6 = (故, 說, 般, …, 訶) = (e_{230}, e_{231}, e_{232}, …, e_{260}).

Figure 7 includes details of HI information of E_1, E_2,.., and E_6, and $f_E(\bullet)$ denotes the mapping from the 260-word *Heart Sutra* to the E = (觀, 自, 在, …, 訶) = (e_1, e_2, e_3, …, e_{260}). The NLP analysis converts the 260-word *Heart Sutra* into 75 Chinese terms. They are a part of the *Vector* layer, where V_1 = (觀,自,在,菩,薩) = (e_1, e_2, e_3, e_4, e_5), V_2 = (行,深,般,若) = (e_6, e_7, e_8, e_9), …, and V_{75} = (薩,婆,訶) = (e_{258}, e_{259}, e_{260}). $f_V(\bullet)$ denotes the mapping from the 75 terms to the $V = [V_1, V_2, \ldots, V_{75}] = [(e_1, e_2, e_3, \mathrm{e}_4, e_5), (e_6, e_7, e_8, \mathrm{e}_9), \ldots, (e_{258}, e_{259}, e_{260})]$. Further, the 75 terms are grouped into matrixes. The matrixes are applied to evaluate the student-learned concepts using semantic similarity between them and teacher-taught concepts. The *Matrix* layer is composed of six such matrices: $M_1 = \{V_1, V_2, V_3,$

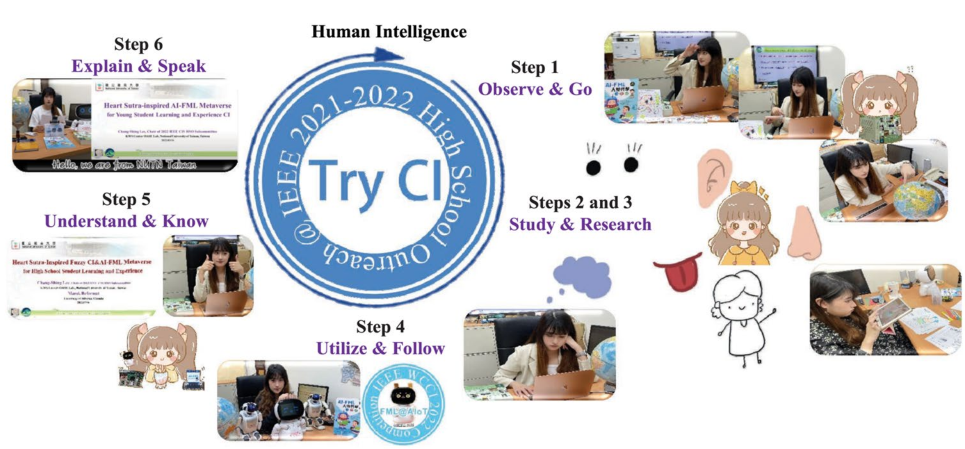


Fig. 5 HI-based human semantic understanding of Heart Sutra for CI&AI-FML Metaverse with CI application

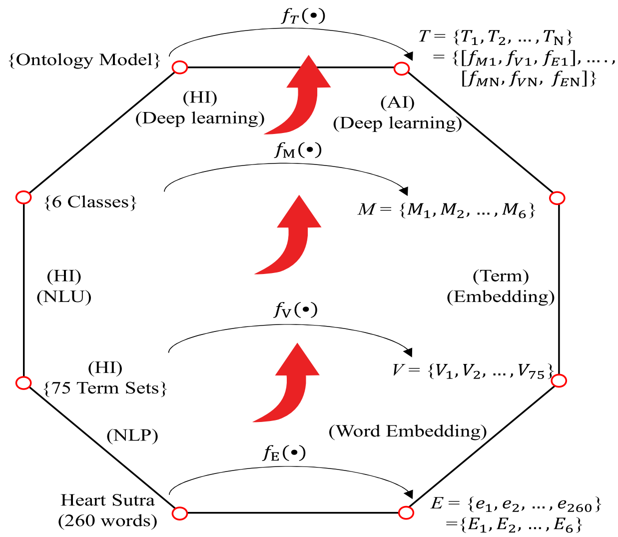


Fig. 6 Heart Sutra-based ontology model

V_4, $V_5\}$, $M_2=\{V_6, V_7, \ldots, V_{15}\}$, …, and $M_6=\{V_{67}, V_{68}, \ldots, V_{75}\}$. Figure 8a, b show the detailed HI information of $V=[V_1, V_2, \ldots, V_{75}]$ and $M=\{M_1, M_2, \ldots, M_6\}$ inspired by the *Heart Sutra* in Chinese and English, respectively. The *Tensor* layer provides the multi-episode information of student-learned concepts and teacher-teaching concepts $T=\{T_1, T_2, \ldots, T_N\}$, where T_1, T_2, …, and T_N denotes the information collected in $Episode_1$, $Episode_2$, …, and $Episode_N$, respectively.

4 Structure of HI-based CI&AI-FML Metaverse

A comprehensive process leading to the complete understanding of students' learning performance has been divided into four stages of CI&AI-FML Metaverse *V(HI, FO, AI, MI, HS)*. The Metaverse also contains a structure for storing all needed learning materials and the data collected during each learning episode. First, the HI-based CI&AI-FML Metaverse structure is presented in Sect. 4.1. Then, we introduce the knowledge concept retrieval agent for students/teachers and smart machine co-learning. Finally, the NL-based preprocessing agent for humanized co-learning is presented. It analyzes text/input generated by students as labels of the learning material.

4.1 HI-based CI&AI-FML Metaverse and knowledge concept retrieval agent

The four-stage structure of the HI-based CI&AI-FML Metaverse is shown in Fig. 9. The Metaverse is composed of a number of task-oriented agents: a *knowledge concept retrieval agent*, an *NL-based preprocessing agent*, a *quantitative analysis agent*, a *qualitative analysis agent*, a *fastText model training agent*, and a *learning performance evaluation agent*.

The educational process was inspired by the *Heart Sutra* combined with NLP tools and the developed intelligent agents to communicate with the variety of AI-FML tools,

Fig. 7 Element layer of Heart Sutra-inspired ontology

E1
=[(觀,自,在,菩,薩), (行, 深, 般, 若), (波,羅,蜜,多,時), (照,見,五,蘊,皆,空), (度,一,切,苦,厄)]
=[(e1, e2, e3, e4, e5), (e6, e7, e8, e9), (e10, e11, e12, e13, e14), (e15, e16, e17, e18, e19, e20), (e21, e22, e23, e24, e25)]

E2
=[(舍,利,子), (色,不,異,空), (空,不,異,色), 色, …, 識, (亦,復,如,是)]
=[(e26, e27, e28), (e29, e30, e31, e32), (e33, e34, e35, e36), e37,…, e48, (e49, e50, e51, e52)]

E3
=[E3.1, E3.2]
E3.1
=[(舍,利,子), (是,諸,法,空,相), (不,生,不,滅), 不,… ,色, (無,受,想,行,識)]
= {(e53, e54, e55), (e56, e57, e58, e59, e60), (e61, e62, e63, e64), e65, …, e78, (e79, e80, e81, e82, e83)]
E3.2
=[(無,眼), (耳), (鼻),舌, …,故, (菩,提,薩,埵)]
=[(e84, e85), (e86), (e87), e88, …, e139, (e140, e141, e142, e143)]

E4
=[E4.1, E4.2]
E4.1
=[(依,般,若), (波,羅,蜜,多,故), (心,無,罣,礙), 無,… ,槃, (三,世,諸,佛)]
= [(e144, e145, e146), (e147, e148, e149, e150, e151), (e152, e153, e154, e155), e156, …, e173, (e174, e175, e176, e177)]
E4.2
=[(依,般,若), (波,羅,蜜,多,故), (得,阿,耨,多,羅), (三,藐,三,菩,提)]
= [(e178, e179, e180), (e181, e182, e183, e184, e185), (e186, e187, e188, e189, e190), (e191, e192, e193, e194, e195)]

E5
=[(故,知,般,若), (波,羅,蜜,多), (是,大,神,咒), 是, …,苦, (真,實,不,虛)]
= [(e196, e197, e198, e199), (e200, e201, e202, e203), (e204, e205, e206, e207), e208, …, e225, (e226, e227, e228, e229)]

E6
=[(故,說,般,若), (波,羅,蜜,多,咒), (即,說,咒,曰), 揭, …,提, (薩,婆,訶)]
= [(e230, e231, e232, e233), (e234, e235, e236, e237, e238), (e239, e240, e241, e242), e243, …, e257, (e258, e259, e260)]

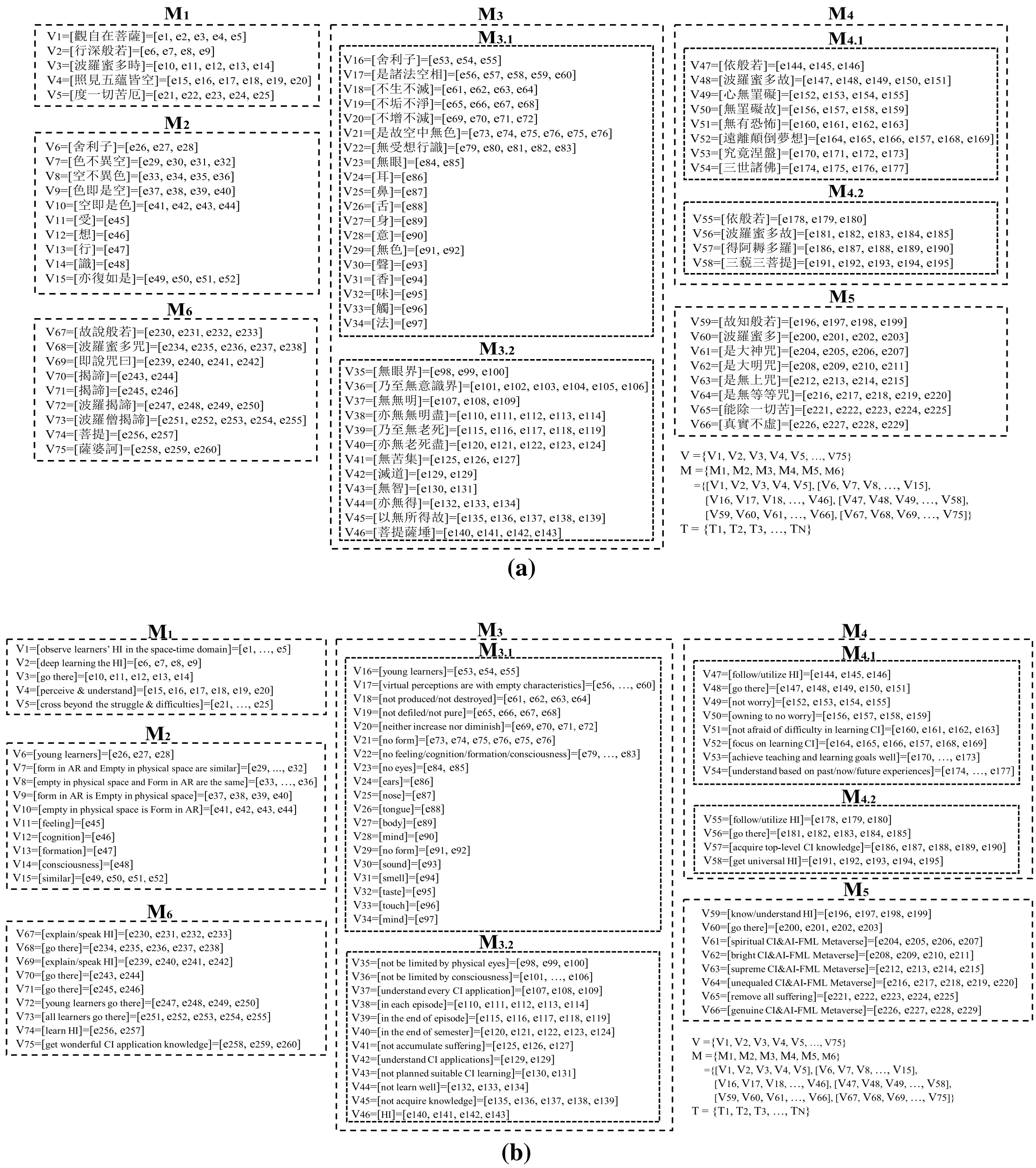


Fig. 8 HI-based *Heart Sutra* term embedding set with 75 vectors and 6 matrices in **a** Chinese and **b** English

so that young students can enjoy, play, and learn with the machines and gain knowledge of CI applications. A detailed description of the proposed structure—stages—are included in Table 2.

4.2 NL-based preprocessing agent

This subsection introduces the *NL-based preprocessing agent*. It includes a *WS mechanism*, *POS tagging mechanism*, and *NER mechanism*. Its main task is to segment the words of students' labels according to the predefined dictionary, filter the meaningless terms such as punctuation marks or stop words to preserve the terms with a noun, a verb, or a foreign word as POS, and finally pass the results to the *Stage 3: Learning Data Analysis*. Table 3 shows the algorithm of the *NL-based preprocessing agent*. Detailed information on POS tags used by CKIP can find on the CKIP Tagger website. The open-source CKIP tagger provides 18 entity types, including PERSON (people), NORP (Nationalities or religious or political groups), DATE, TIME, PERCENT (percentage), …, and CARDINAL (Numerals that do not fall under another type). All the analysis originates in the extraction of key information from students' labels annotating the learning material during the studying process.

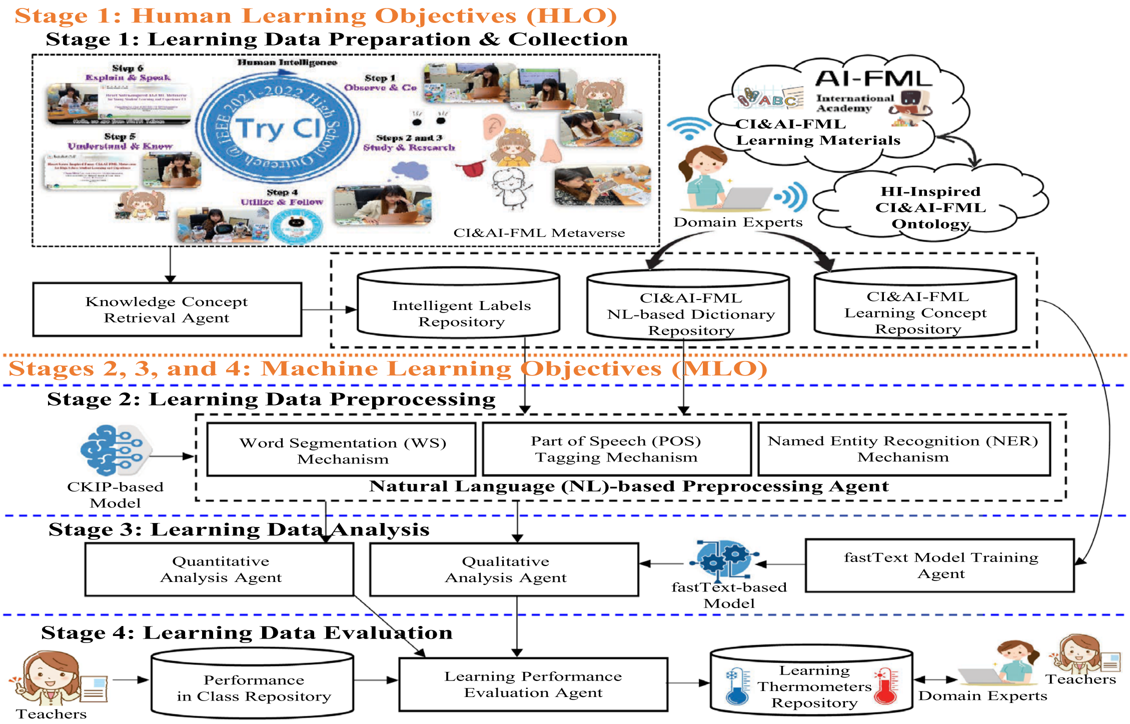


Fig. 9 Structure of HI-based CI&AI-FML Metaverse

Table 2 Operations of *HI-based CI&AI-FML Metaverse* structure

Stage 1: ***Learning data preparation & collection.*** Stage 1 involves domain experts constructing the CI&AI-FML learning concepts based on the HI-inspired CI&AI-FML ontology and storing them in the CI&AI-FML learning concept repository. In addition, the domain experts make the teaching–learning materials and publish them on the website of the AI-FML International Academy (OASE Lab. 2019). Next, the involved students log in to the Google classroom to learn and interact with the AI-FML tools to generate their intelligent labels in Google Jamboard. The *knowledge concept retrieval agent* retrieves personalized information from students' intelligent labels, categorizes them into different types of notes such as a post-it note, text box, label, or picture according to the date sheet for the CI&AI-FML course, and stores the results in the intelligent labels repository. Finally, the domain experts refer to the constructed concepts and the retrieved intelligent labels to construct the CI&AI-FML NL-based dictionary and store them in the repository
Stage 2: ***Learning data preprocessing.*** Stage 2 involves an *NL-based preprocessing agent*, including a word segmentation (*WS*) mechanism, part of speech (*POS*) tagging mechanism, and named entity recognition (*NER*) mechanism. The *WS* mechanism segments the words in the retrieved intelligent labels, the *POS* tagging mechanism tags their part of speech, and the *NER* mechanism extracts named entities from the text and annotates their types automatically, based on the deep-learning trained CKIP model
Stage 3: ***Learning data analysis.*** The *fastText model training agent* trains the fastText-based model according to the retrieved intelligent labels as well as the input NL-based dictionary and constructed concepts for qualitative analysis. At the same time, the *qualitative analysis agent* generates the analyzed qualitative results for the *learning performance evaluation agent* based on the learned fastText model and the output of the *NL-based preprocessing agent*. Moreover, the *quantitative analysis agent* quantifies how many important concepts are captured and how many words are typed in their intelligent labels by the young learners in the CI&AI-FML Metaverse
Stage 4: ***Learning data evaluation.*** The *learning performance evaluation agent* evaluates humans' learning thermometers based on the evaluated results by domain experts, the analyzed quantitative and qualitative results as well as the received young students' performance in class from their teachers. Simultaneously, the evaluated learning thermometers are validated by domain experts and their teachers

5 HI-based CI&AI-FML Metaverse for data analysis and data evaluation

The most computationally-oriented two stages of the *HI-based CI&AI-FML Metaverse* are stages 3 and 4: *Data Learning Analysis* and *Evaluation*, respectively. First, we present a *quantitative analysis agent* whose task is to quantify the performance based on the students' labels. Next, a *fastText model training agent* trains a *fastText*-based model that represents the *CI&AI-FML* important concepts as a bag of n-grams. Next, a *qualitative analysis agent* assets the quality of the students' labels via comparing them to the predefined *CI&AI-FML* concepts. Finally, a *learning performance evaluation agent* evaluates the involved students' progress in *CI&AI-FML*.

Table 3 *NL-based preprocessing agent* algorithm

Input:
1. NL-based stop words set *SWset*
$SWset = [sword_1, \ldots, sword_M\}$
2. NL-based dictionary set *Dset* that is for *WS* mechanism special consideration
$Dset = \{[dword_1, weight_1], \ldots, [dword_N, weight_N]\}$, where the value of the weight equals the length of the word
3. Pre-trained CKIPTagger-based model ($Model_{CKIP}$)
4. Retrieved *S* students' intelligent labels set of an episode, where
$S_1 = \{[PIN_{1.1}, \ldots, PIN_{1.O1}], [TN_{1.1}, \ldots, TN_{1.P1}], [PIC_{1.1}, \ldots, PIC_{1.Q1}]\}, \ldots$, and $S_S = \{[PIN_{S.1}, \ldots, PIN_{S.OS}], [TN_{S.1}, \ldots, TN_{S.PS}], [PIC_{S.1}, \ldots, PIC_{S.QS}]\}$
/*where
1) *PIN*, *TN*, and *PIC* denote the message of the post-it note, text, and picture,
2) O_1, P_1, and Q_1 denote the number of post-it notes, text notes, and pictures that the first student S_1 chooses from to type his notes or upload related pictures in the Jamboard, respectively, and
3) O_S, P_S, and Q_S denote the number of post-it notes, text notes, and pictures that the S^{th} student S_S chooses from to type his notes or upload related pictures in the Jamboard, respectively.*/
Output:
1. $FWSset = \{[ws_{1.1}, \ldots, ws_{1.T1}], \ldots, [ws_{S.1}, \ldots, ws_{S.TS}]\}$: Filtered word segmentation set
2. $NERset = \{[ner_{1.1}, \ldots, ner_{1.R1}], \ldots, [ner_{S.1}, \ldots, ner_{S.RS}]\}$: Named entity recognition set
3. $EPINCountset = \{EPINCount_1, \ldots, EPINCount_S\}$: Effective number of post-it notes
4. $ETNCountset = \{ETNCount_1, \ldots, ETNCount_S\}$: Effective number of text boxes or labels
5. $EPICCountset = \{EPICCount_1, \ldots, EPICCount_S\}$:: Effective number of pictures
6. *EStudentDataset*: Effective texts of *S* student's intelligent labels
Method:
Step 1: Initialize
Step 1.1: $FSWset \leftarrow \varnothing$, $NERset \leftarrow \varnothing$, and $EPINCountSet \leftarrow \varnothing$
Step 1.2: $ETNCountset \leftarrow \varnothing$, $EPICCountSet \leftarrow \varnothing$, and $EStudentDataset \leftarrow \varnothing$
Step 2: For $i \leftarrow 1$ to S
Step 2.1: Read post-it notes $PIN_{i.1}$, $PIN_{i.2}$, …, and $PIN_{i.Oi}$ of the *i*th student, add them to *EPINCountset*, and remove the duplicate from the *EPINCountset*
Step 2.2: Read text notes $TN_{i.1}$, $TN_{i.2}$, …, and $TN_{i.Pi}$ of the *i*th student, add them to *ETNCountset*, and remove the duplicate from the *ETNCountset*
Step 2.3: Read pictures $PIC_{i.1}$, $PIC_{i.2}$, …, and $PIC_{i.Qi}$ of the *i*th student, add them to *EPICCountset*, and remove the duplicate from the *EPICCountset*
Step 2.4 Combine *EPINCountset* with *ETNCountset* to be *EStudentDataset*
Step 3: For $i \leftarrow 1$ to S
Step 3.1: For $j \leftarrow 1$ to $LENS_i$ /*where $LENS_i$ denotes the number of the effective data labeled by the *i*th student*/
Step 3.1.1: $data_{ij} \leftarrow$ Read the *j*th data of the *i*th student's data from *EStudentDataset*
Step 3.1.2: Filter out non-Chinese, non-English, non-numbers, and non-punctuation marks from $data_{ij}$ and assign the results to $filterdata_{ij}$
Step 3.1.3: Update *EStudentDataset* based on $filterdata_{ij}$
Step 4: Start NLP for the *EStudentDataset*
Step 4.1: Read NL-based stop words from *SWset*
Step 4.2: Read the NL-based dictionary from *Dset* to further ensure the performance of word segmentation
Step 4.3: Load the pre-trained CKIP-based model ($Model_{CKIP}$) to get *ckipWS*, *ckipPOS*, and *ckipNER* models
Step 4.4: For $i \leftarrow 1$ to S
Step 4.4.1: $sentenceList \leftarrow EStudentDataset$ of the *i*th student
Step 4.4.2: Execute the *WS mechanism* based on *ckipWS* and predefined dictionary *Dset* to get *wsList* by
$wsList \leftarrow ckipWS\ (sentenceList, Dset)$
Step 4.4.3: Execute the *POS tagging mechanism* based on *ckipPOS* to get *posList* by
$posList \leftarrow ckipPOS\ (wsList)$
Step 4.4.4: Execute the *NER mechanism* based on the *ckipNER* to get *nerList* by
$nerList \leftarrow ckipNER\ (wsList, posList)$
Step 4.4.5: For $j \leftarrow LEN$ /*where *LEN* denotes the data length of the *posList**/
Step 4.4.5.1: $ws \leftarrow wsList_j$
Step 4.4.5.2: $pos \leftarrow posList_j$
Step 4.4.5.3: if (*pos* is not a POS tag of a punctuation mark but a foreign word or a noun or a verb) and (*ws* is not an element in *SWset*)
Step 4.4.5.3.1: Add *ws* to $FWSset_i$
Step 5: End

5.1 Quantitative analysis agent for data evaluation

The process of evaluating students' performance is completed over learning episodes. Let us assume there is a quantitative analysis matrix $QuanR(S, E)$ for S students and E episodes, and its size is $|S| \times |E|$, where rows represent students and columns represent episodes. The cells' contents are the students' quantitative ranking performance for the learning materials in each episode. The proposed *quantitative analysis agent* uses a fuzzy-based procedure of transforming a numerical ranking into linguistic terms. It is performed as follows. The membership functions for *fuzzy linguistic terms* Q_1 *to* Q_8 versus *Ranking* are depicted in Fig. 10. The *quantitative analysis agent* flowchart is depicted in Fig. 11 and described as follows.

- **Input**: the results of the *NL-based preprocessing agent*; and default values for weight parameters, including sets of w_{postit}, $w_{textnote}$, $w_{picture}$, $w_{datalength}$, w_{ckipws}, and $w_{ckipner}$, where each set is linked to a different age group of students.
- **Phase 1**: Quantify the following measures: (1) a number of post-it notes, text notes, and pictures (*postitNo*, *textnoteNo*, and *pictureNo*); (2) the effective length of data in the post-it and text notes (*dataLength*); and (3) a number of the filtered *WS* and *NER* after CKIP-based NLP (*wsNo* and *nerNo*). Calculate a quantitative metric *QuanScore* as a weighted sum of the measures using the default parameters of weights. Find the best suitable weights for different age groups of students by a process of trial and error.
- **Phase 2**: Standardize the quantitative metric (*QuanScore*) using the ranking of all *S* students in episode e_i. Let FN_1, FN_2, …, and FN_7 in Fig. 11 denote fuzzy numbers 0.05, 0.35, 0.55, 0.65, 0.75, 0.85, and 0.95, respectively. Figure 10 shows that there are eight *fuzzy linguistic terms* Q_1 *to* Q_8 for standardizing the quantitative analysis. The term 'Q_{index}' refers to the ranking of a student's quantitative learning performance within a given episode. Each student's quantitative performance is classified into one of eight fuzzy terms: Q_1 covers the bottom 5% of all involved students, Q_2 is assigned to students with a performance from 5 to 35%, …, and Q_8 is populated by students in the range from 95 to 100%. The 8-quantile results of each involved student in a single episode, $QuanQ_i$, are stored in the *Quanset*. Finally, the agent calculates the final quantitative results $QuanS_i$ by Eq. (1).

$$QuanS_i = QuanQi \times 100 \quad \text{where} 1 \le i \le |S| \tag{1}$$

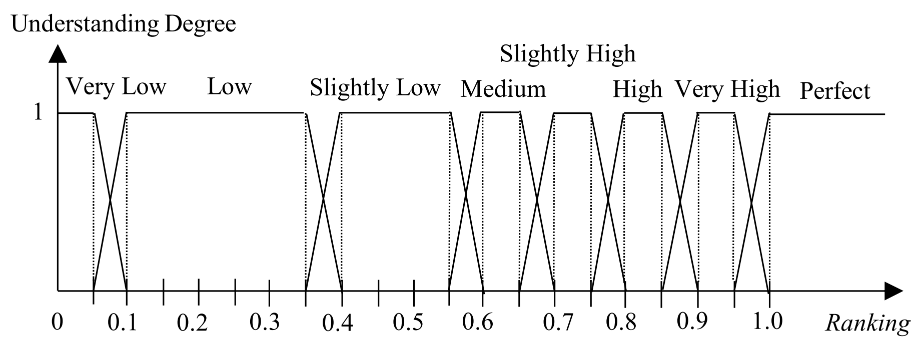


Fig. 10 Membership functions of the *Ranking* with eight fuzzy sets Q_1 *to* Q_8

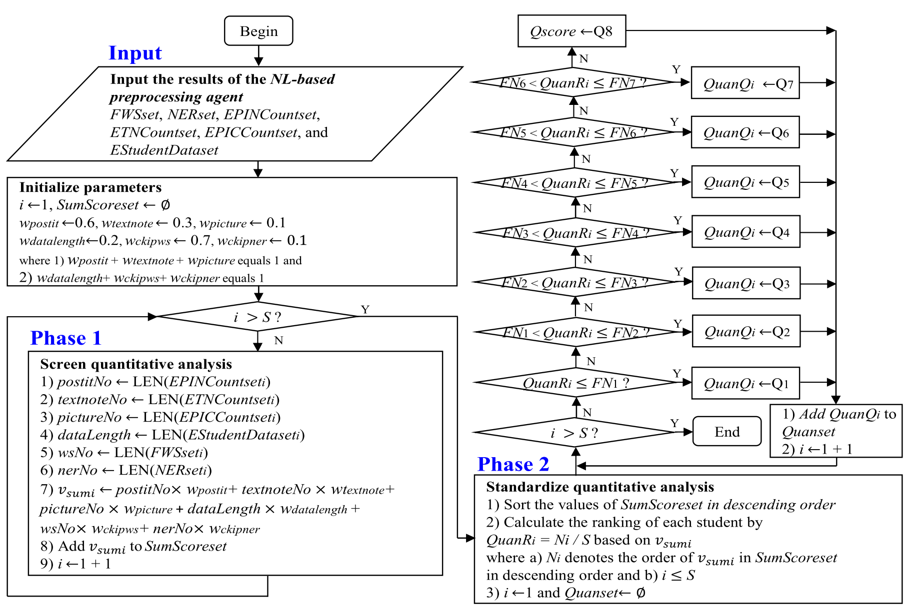


Fig. 11 Quantitative analysis agent flowchart

5.2 Qualitative analysis agent and learning performance evaluation agent

The *Metaverse* adopts the *fastText* library to pre-train the word vectors on Chinese Wikipedia and important learning concepts of the *CI&AI-FML*. The *fastText model training agent* trains the word embedding on (1) the latest Chinese Wikipedia corpus downloaded from the Internet; (2) the partially constructed *CI&AI-FML* concepts & NL-based dictionary constructed by domain experts; and (3) the collected data from parts of the students' labels using the *fastText* model. The word embedding vectors of the *fastText*-based model are obtained using the skip-gram model with default parameters except for learning rate = 0.025 and the minimal number of word occurrences = 1 (Bojanowski et al. 2017).

The details of the *qualitative analysis agent* are presented in Fig. 12. It estimates the quality of the students' learning by computing the cosine similarity (*sim*) between word-embedding vectors of the constructed *CI&AI-FML* concepts and filtered word segmentation results based on the pre-trained *fastText*-based model ($\mathrm{Model}_{\mathrm{fastText}}$). The cosine similarity between two vectors is calculated by Eq. (2).

$$sim(x, y) = \frac{x.y}{|x|\,|y|} \tag{2}$$

where x and y denote the constructed *CI&AI-FML* concepts $[c_1, c_2,.., c_N]$ and the filtered word segmentation results $\{[ws_{1.1}, \ldots, ws_{1.T_1}], \ldots, [ws_{S.1}, \ldots, ws_{S.T_S}]\}$, respectively.

We use a *sim* value to qualify the similarity between the pre-constructed concepts and student-labeled data. A *sim* value of 0 means that the two vectors are at 90° to each other and have no match. As the *sim* value gets closer to 1, the smaller the angle and the greater the match between vectors. That is, the semantic similarity between student-labeled data and the pre-constructed concepts is high. After that, we follow three stages to obtain the qualitative analysis results: let us take the first student s_1 as an example.

- **Stage 1**: We calculate the sum of similarities of a given concept c_i $(1 \le i \le N)$ to all concepts from T_1 filtered *WS* words of student s_1 and average them. On the contrary, the sum of similarities of a given filtered *WS* word $ws_{1.k}$ $(1 \le k \le \mathrm{T}_1)$ of student s_1 with all N concepts is summed and averaged. Next, the values of sum and average are computed by the same procedure as student s_1 for the remaining students.
- **Stage 2**: We sum the average of each student (v_{avgsum_j}, $1 \le j \le S$) and rank S averages of all S students in episode E using the same approach as the *quantitative analysis agent* and each student has a ranking value ($QualScore_j$).
- **Stage 3**: We consider the ranking value ($QualScore_j$, $1 \le j \le S$) and the average of all the average values (v_{avgavg_j}) by assigning suitable weights for the different age groups of students to get the final qualitative result of each student ($QualR_j$) and store each of them into *QualRset*.

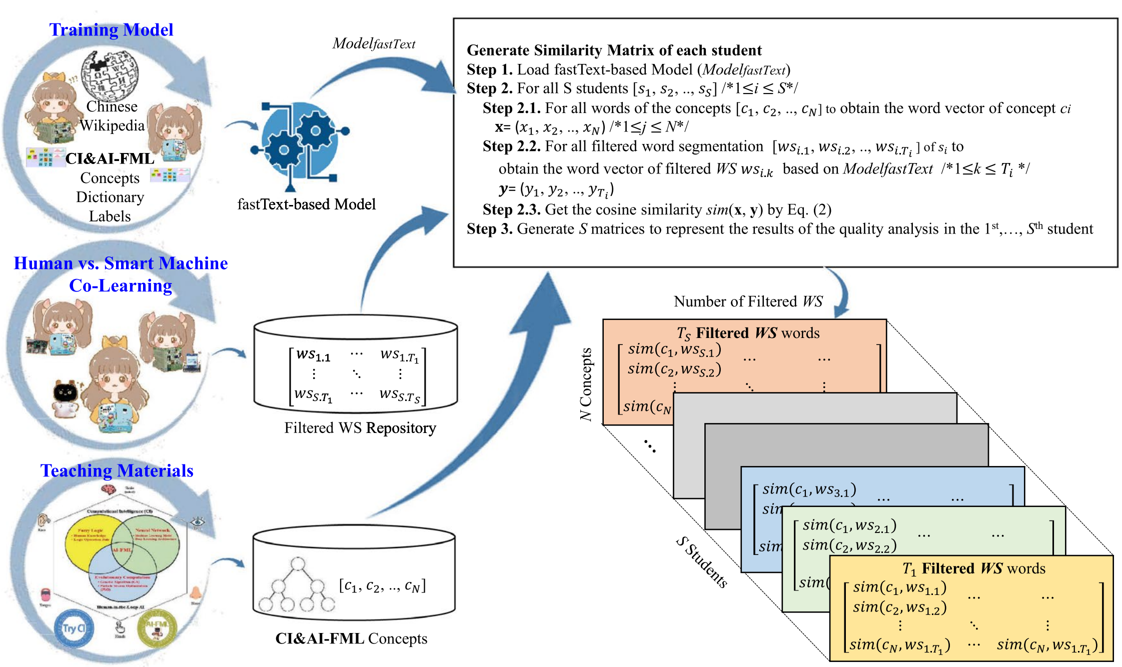


Fig. 12 Qualitative analysis agent diagram

With the analyzed quantitative and qualitative results, the *learning performance evaluation agent* estimates the involved students' learning progress.

The weights given for quantitative and qualitative results vary with different age groups of students in the CI&AI-FML learning fields. For example, the weights of the quantitative results are likely higher than that of the ones for elementary-school students. However, the weights of the qualitative results are possibly higher for university students. Meanwhile, their overall performance in class scored by their teachers is also considered by the agent. Finally, the evaluated progress measures are given to domain experts and teachers to confirm if the students meet the required performance levels and if the CI&AI-FML teaching model needs to be adjusted next episode.

6 Experimental results

This section introduces the HI-based *CI&AI-FML* Metaverse *V(HI, FO, AI, MI, HS)* for student and smart machine co-learning performance in the spring semester of 2022. The following subsections show the experimental results for *CI&AI-FML* Metaverse applications to the *Software Engineering* course at NUTN, the *English* course at Feisha Junior High School (FJHS), and the *AI* course at RDES in Taiwan to measure the system's performance.

6.1 Quantitative evaluation for CI&AI-FML Metaverse on software engineering applications

To measure the system's performance on the quantitative evaluation, this section presents the learning data evaluation on the software engineering course offered for third-year students at NUTN in the spring semester of 2022. Thirty-five students take this course, the total number of episodes is sixteen from Feb. 25 to Jun. 15, 2022, and each week is three continuous hours. These students have been categorized into 11 groups. Figure 13 shows an example of a student's (first student of Group 9, No. G9.1) intelligent labels in the third episode (episode 3) of Software Engineering on Mar. 11, 2022.

The teaching topic on that day is requirements engineering and object-oriented software development. The *knowledge concept retrieval agent* first parses HTML elements from the webpage stored in the Google Jamboard and stores the retrieved data in the *Intelligent Label Repository*. In Fig. 13, this student labeled the learned concepts using four post-it notes (orange frames), four text notes (blue frames), and two pictures (green frames). The total length of the notes is 241. The post-it notes include需求種類(Requirement Category), 軟體品質(Software Quality), 需求工程(Requirement Engineering), and雛型法(Prototyping). The *NL-based processing agent* outputs 70 filtered words segmented into POS ($wsNo = 70$) but no extracted entities ($nerNo = 0$). In addition, the *quantitative analysis agent*

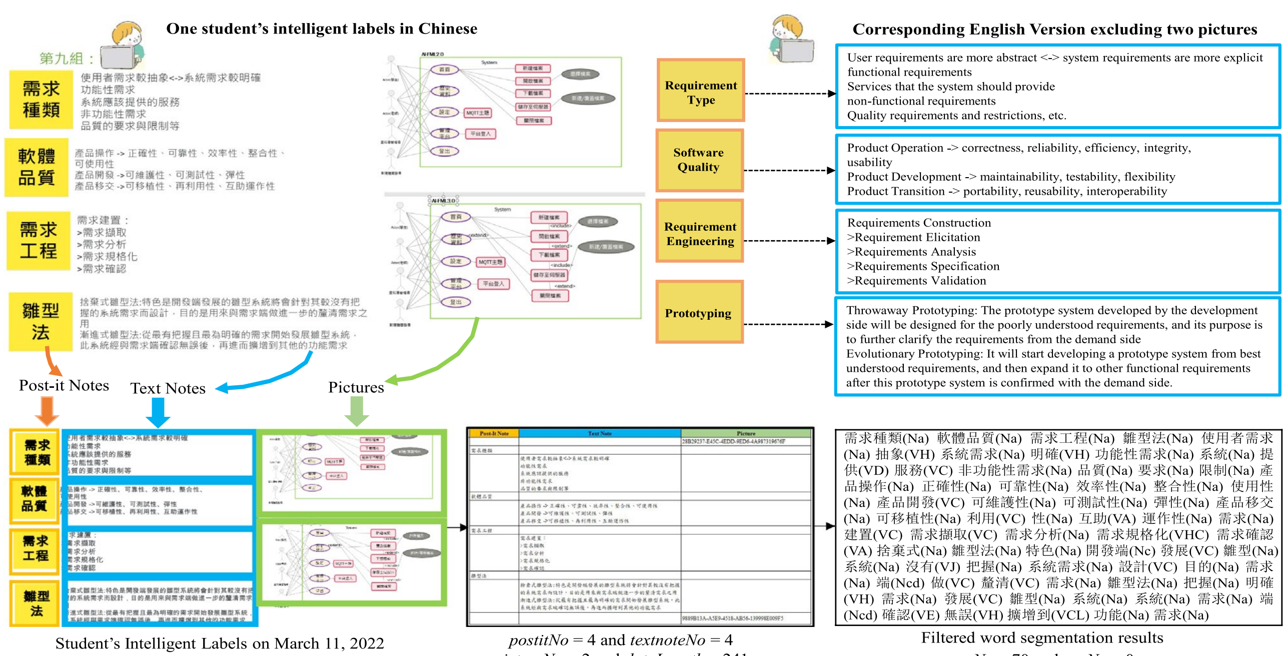


Fig. 13 An example of a student's intelligent labels on Software Engineering

outputs the quantity score $v_{sum}=101$ based on the parameters $w_{postit}=0.6$, $w_{textnote}=0.3$, $w_{picture}=0.1$, $w_{datalength}=0.2$, $w_{ckipws}=0.7$, and $w_{ckipner}=0.1$. The 8-quantile *QuanQ* of this student is 0.8 so his quantification result $QuanS=80$.

6.2 Qualitative evaluation for CI&AI-FML Metaverse on software engineering applications

In this subsection, we show the performance of the learned fastText-based model using the similarity of some selected concepts which are grouped according to *CI&AI-FML* Metaverse *V(HI, FO, AI, MI, HS)* and *Software Engineering* (SE). The training data contain Chinese Wikipedia, important SE-related learning concepts, and students' intelligent labels in the courses of *Software Engineering* and *Software Project Planning* from Feb. to Jun. 2022. Table 4 shows the *CI&AI-FML*-related and SE-related concepts in both Chinese and English.

To measure the system's performance on the qualitative evaluation, we take the series of 模糊變數(*Fuzzy Variable*) as an example. Figure 14a shows the similarity between a given concept and *CI&AI-FML*-related concepts and it indicates that the series of 模糊變數(*Fuzzy Variable*) has the highest similarity with all *CI&AI-FML*-related concepts except for *sim* (類神經網路(*Neural Network*), 知識庫(*Knowledge Base*)). Figure 14b shows the similarity between a given concept and SE-related concepts. Observe Fig. 14b that the series of 專案規劃(*Project Planning*), 軟體設計(*Software Design*), and 軟體工程(*Software Engineering*) have a higher similarity with the SE-related concepts than the other *CI&AI-FML*-related series, including模糊邏輯(*Fuzzy Logic*), 模糊變數(*Fuzzy Variable*), and 類神經網路(*Neural Network*).

Next, we use principal component analysis (PCA) to explore and visualize the performance of the learned model. Figure 15 shows the cosine similarity of the selected *CI&AI-FML*-related concepts and SE-related ones, respectively. Observe Fig. 15 that the SE-related concepts cluster together but *CI&AI-FML*-related concepts cluster into three groups surrounded by red, orange, and blue circles.

6.3 Evaluated learning level for CI&AI-FML Metaverse on software engineering applications

To measure the system's performance, this paper adopts human intelligence (*TMI*) as a golden standard, where *TMI* is the students' learning level, i.e. students' learning thermometer, evaluated by their teachers. Table 5 shows the acquired results of quantitative and qualitative analysis, where the learning performance for episode 3 on Mar. 11 is calculated when $w_{avgsum}=0.1$, $w_{avgavg}=0.9$, $w_{QuanS}=0.1$, and $w_{QualS}=0.9$. Three students (G2.1, G3.1, and G7.3) with an asterisk (*) superscript were absent on that day so their human intelligence (*THI*) and machine intelligence (*TMI*) are both 0C, where *THI* and *TMI* denote the evaluated results done by the on-line NUTN teachers and the proposed methods in this paper.

Observe Table 5 that the average learning thermometer difference between *THI* and *TMI* is about 3.19C. The first two big differences between *THI* and *TMI* are students G3.2 and G3.4 with a cross (+) superscript. This is because students G3.2 and G3.4 directly took a screenshot and uploaded their classmate's intelligent labels to their own Google Jamboard. Under this situation, the proposed agent can correctly catch the cheating but the human cannot. Student G10.3 with a hashtag (#) superscript got the highest *TMI*. Figure 16a shows the average *THI* and *TMI* values of each student (G1.1 to G11.3) from Feb. to Jun. 2022. Observe that student G8.2 has the best performance from the viewpoint of both humans and machines. Figure 16b shows the average performance of each group.

Table 4 Selected *CI&AI-FML*-related and SE-related concepts

Concepts type	*CI&AI-FML*-related	SE-related
Concepts of categories	模糊集合 (Fuzzy set) 隸屬函數 (Membership function) 知識庫 (Knowledge base) 規則庫 (Rule base) 智慧計算 (Computational intelligence) 函數 (Function)	需求管理 (Requirement management) 需救發展 (Requirement development) 使用案例 (Usecase) 分工結構圖 (Work breakdown structure) 里程碑 (Milestone) 甘特圖 (Gantt chart)
Concepts of series	模糊邏輯 (Fuzzy logic) 模糊變數 (Fuzzy variable) 類神經網路 (Neural network)	專案規劃 (Project planning) 軟體設計 (Software design) 軟體工程 (Software engineering)

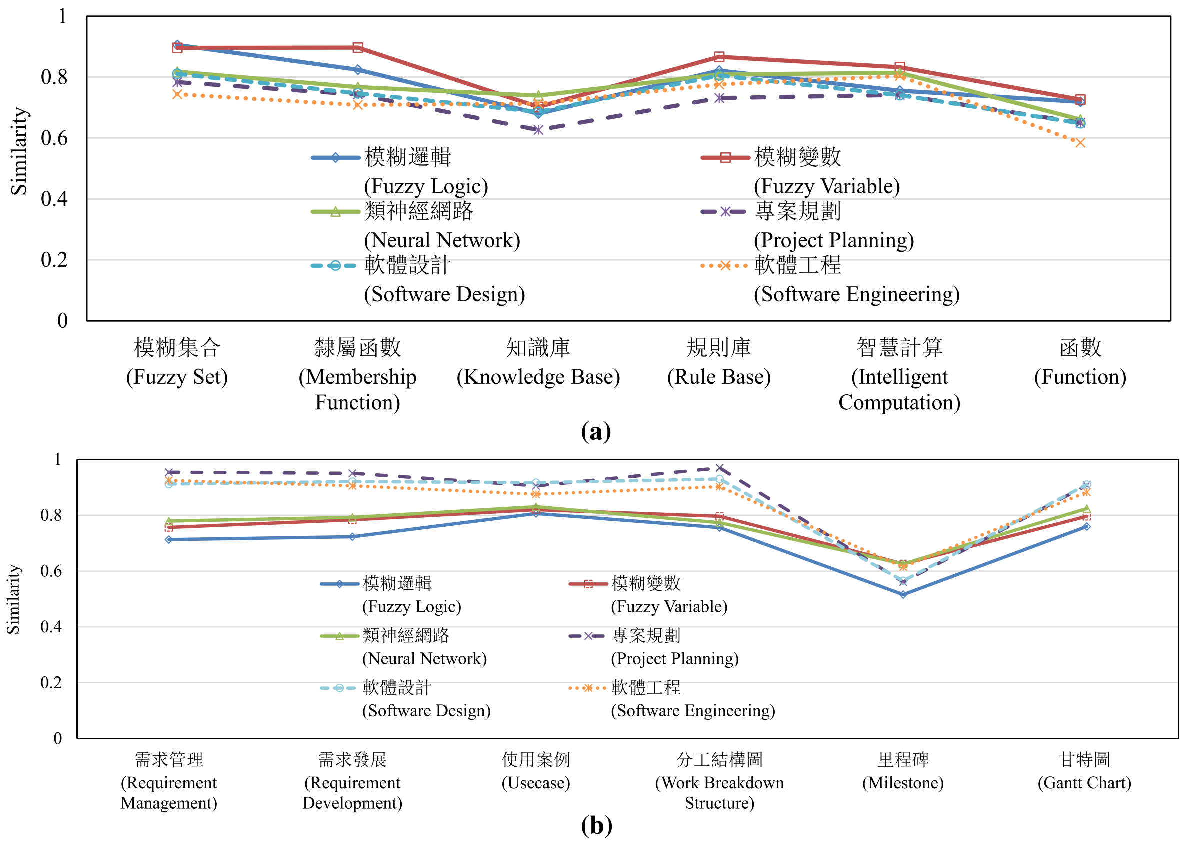
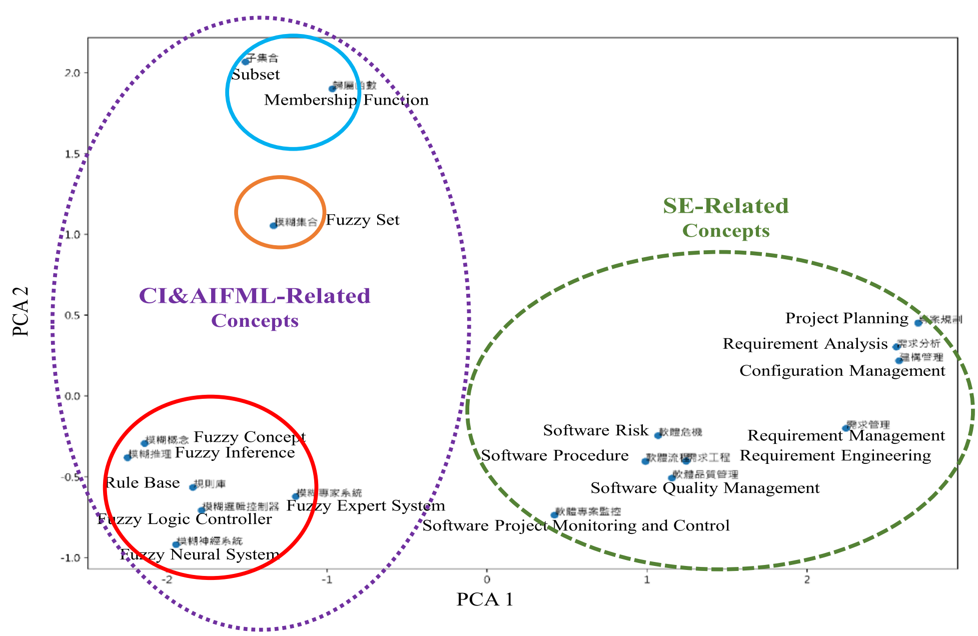


Fig. 14 Grouped line charts on the similarity for the **a** CI&AI-FML-related and **b** SE-related categories

Fig. 15 Scatter plot of cosine similarity between concepts



The learning thermometer of group G2 is the lowest from the viewpoint of both humans and machines. The biggest and smallest difference between *THI* and *TMI* happens in groups G1 (6.8C) and G11 (0.7C), respectively.

Table 5 Learning thermometer of students on Mar. 11, 2022

Student no.	Quantitative results			Qualitative results					*THI*	*TMI*	|*THI-TMI*|
	v_{sum}	*QuanR*	*QuanS*	v_{avgsum}	v_{avgsum_R}	v_{avgsum_Q}	v_{avgavg}	*QualS*			
G1.1	51.3	0.53	75	18.23	0.63	0.7	0.7	70.11	44	70.60	26.60
G1.2	28.7	0.87	55	11.11	0.93	0.55	0.74	72.17	65	70.45	5.45
G1.3	123	0.09	80	54.57	0.1	0.8	0.64	65.78	65	67.20	2.20
G1.4	71.9	0.37	75	28.08	0.43	0.75	0.72	72.3	65	72.57	7.57
G2.1*	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0	0	0
G2.2	31.8	0.75	65	11.59	0.86	0.55	0.77	75.04	60	74.04	14.04
G2.3	73.5	0.31	80	19.21	0.6	0.7	0.73	73.5	56	74.15	18.15
G2.4	31.7	0.78	60	11.59	0.86	0.55	0.77	75.04	65	73.54	8.54
G3.1*	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0	0	0
G3.2+	0.2	0.96	50	N/A	N/A	N/A	N/A	N/A	66	5.00	61.00
G3.3	57.9	0.46	75	20.91	0.56	0.7	0.72	71.92	57	72.23	15.23
G3.4+	0.2	0.96	50	N/A	N/A	N/A	N/A	N/A	61	5.00	56.00
⋮											
G7.1	25.7	0.9	55	9.2	0.96	0.5	0.76	74.06	57	72.15	15.15
G7.2	37.2	0.68	65	15.49	0.7	0.65	0.67	67.12	57	66.91	9.91
G7.3*	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0	0	0
G8.1	90.9	0.28	80	38.88	0.3	0.8	0.63	65.37	71	66.83	4.17
G8.2	209.8	0.03	85	102.26	0.03	0.85	0.65	67.12	83	68.90	14.10
G8.3	37.8	0.65	65	13.97	0.8	0.6	0.73	72.17	65	71.45	6.45
G9.1	101	0.18	80	47.01	0.2	0.8	0.67	68.44	74	69.60	4.40
G9.2	49.4	0.56	70	23.24	0.5	0.75	0.66	67.27	52	67.54	15.54
G10.1	32	0.71	65	12.52	0.83	0.6	0.73	72.32	44	71.58	27.58
G10.2	43.3	0.59	70	21.91	0.53	0.75	0.73	73.25	66	72.92	6.92
G10.3#	72.9	0.34	80	28.71	0.4	0.75	0.73	73.77	66	74.39	8.39
G11.1	58	0.43	75	25.15	0.46	0.75	0.67	68.69	61	69.32	8.32
G11.2	109.9	0.15	80	49.19	0.16	0.8	0.66	67.82	74	69.04	4.96
G11.3	93.8	0.21	80	40.89	0.23	0.8	0.63	65.5	71	66.95	4.05
Average	64.55	0.51	70.31	29.89	0.51	0.7	0.69	70.13	57.34	60.53	3.19

When all cells of column *Qualitative* are N/A, it denotes that this student did not use a post-it or text note to label the learned important concepts. Hence, there are no qualitative results

6.4 Learning data evaluation for CI&AI-FML Metaverse on software engineering applications

In this subsection, we show students' learning performance in *V(HI, FO, AI, MI, HS)* with all episodes. Based on the concept of the derived measure, we categorize sixteen episodes into four main episodes: $EpisodeQ_1$, $EpisodeQ_2$, $EpisodeQ_3$, and $EpisodeQ_4$. Each *EpisodeQ* is composed of four episodes. Hence, the number of episodes from $EpisodeQ_1$ to $EpisodeQ_4$ (i.e. $NEpisodeQ_1$, …, and $NEpisodeQ_4$) equals 4, respectively. We create a derived measure from the existing learning thermometer values evaluated by machine intelligence (*TMI*) of episodes 1 to 16 by accumulating the *TMI* value of the previous *EpisodeQ* to create a new derived measure called accumulated *TMI*, including $ATMIQ_1$, $ATMIQ_2$, $ATMIQ_3$, and $ATMIQ_4$ calculated by Eq. (3).

$$ATMIQ_k = ATMIQ_{k-1} + \frac{\sum TMI_{ij}}{NEpisodeQ_k} \tag{3}$$

where 1) $1 \le k \le 4$, 2) $1 \le i \le S$, 3) $ATMIQ_0 = 0$, 4) $NEpisodeQ_0 = 0$, 5) range of j is bounded in $[(k-1) \times NEpisodeQ_{k-1} + 1, (k-1) \times NEpisodeQ_{k-1} + NEpisodeQ_k]$, and 6) TMI_{ij} denotes the learning thermometer done by machines of the ith student in the jth episode.

Figure 17 shows the accumulated learning thermometers *ATMIQ* of each student from $EpisodeQ_1$ to $EpisodeQ_4$. It indicates that the students G1.1–G1.3 and G8.2 perform well because all their *ATMIQ* values on the solid lines are higher than the corresponding values on the trendlines (dotted line) and these four students tend to keep a good performance

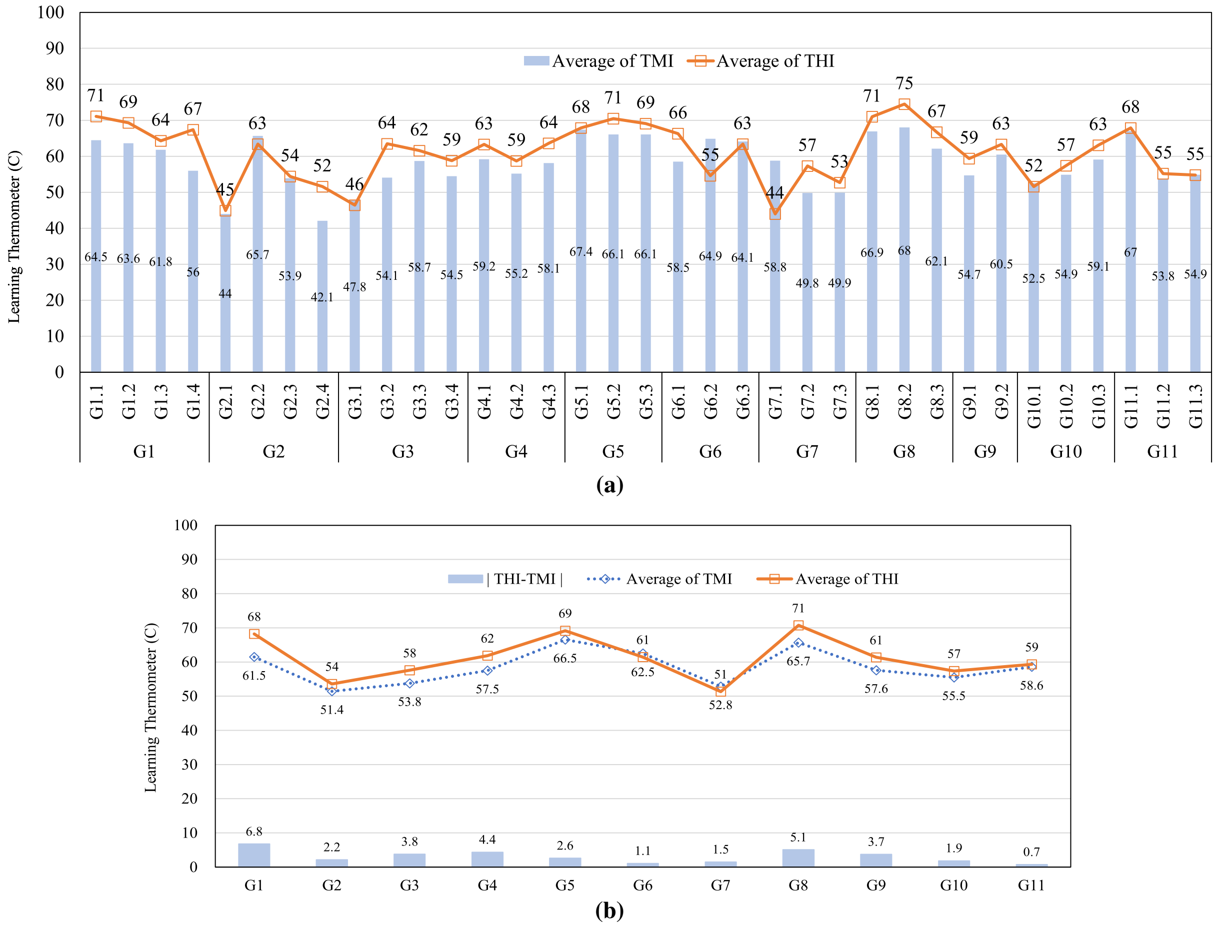


Fig. 16 *THI* and *TMI* average values of **a** each student and **b** each group for all episodes

because the values of "EpisodeQ$_1$–Q$_4$" curves are higher than the ones of "Trendline (EpisodeQ$_1$–Q$_4$)".

Since episode 9, that is, the start of $EpisodeQ_3$, the *TMI* values were immediately announced to the students within five hours after class. Therefore, we separate the whole semester into the first-half semester ($EpisodeQ_1$–Q_2) and the latter-half one ($EpisodeQ_3$–Q_4) to validate if this taken action will help increase the learning performance of the students. Figure 18 shows the stacked bar chart of the normalized learning performance of each student for the 2022 spring semester, where the *y*-axis value denotes the normalized distance between *TMI* and the value on the trendline.

This paper adopts the Min–Max normalization method to bound all *TMI* values to [0, 1] for a particular period, including the first-half semester, the latter-half one, and the whole semester. Then, we convert 0 into 0.5 using a liner function $y = 0.5 \times x + 0.5$, where y is the normalized reward and x is the result of Min–Max Normalization. We can see that over half of the students (63%), the performance in the latter-half semester is better than in the first-half one which validates our assumption: Taking this action "real-time announcing the result of the learning performance to the students" can stimulate their learning motivation, especially for student G2.1.

6.5 Evaluation of CI&AI-FML Metaverse for high-school students learning english

6.5.1 Profile of students and information of ten episodes

In this subsection, the high-school students' English learning data of *CI&AI-FML* Metaverse *V(HI, FO, AI, MI, HS)* are analyzed. There are thirty-one students at FJHS in Taiwan involved in the *CI&AI-FML* Metaverse to learn English. The involved students are two grade-8 classes (Classes 8A and 8B) and each week is 45 min. The students of each class are categorized into four groups (G1 to G4) according to homogenous grouping, that is, Group 1 (G1) is with the highest ability in English and G4 is the weakest. Ten episodes are grouped into three main episodes, including $EpisodeQ_1$, $EpisodeQ_2$, and $EpisodeQ_3$. The cut-off dates for $EpisodeQ_1$ to $EpsiodeQ_3$ are the dates of the first, second,

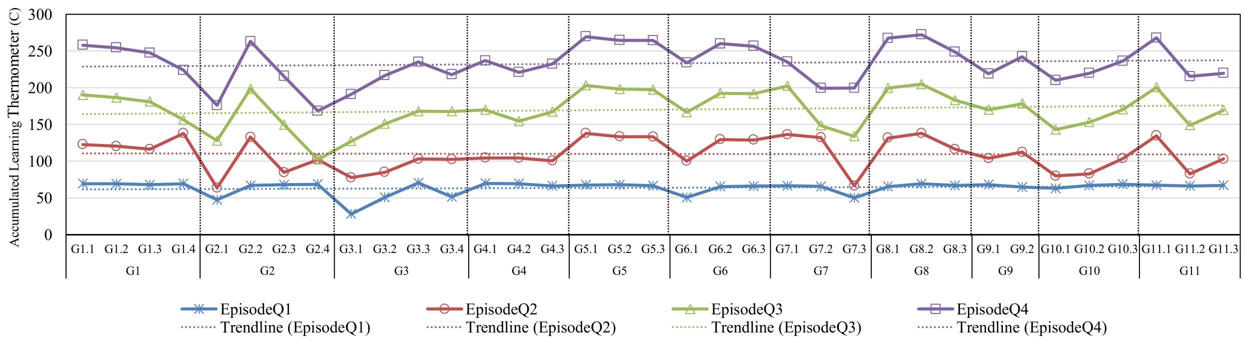


Fig. 17 Accumulated learning thermometers of $EpisodeQ_1$ to $EpisodeQ_4$

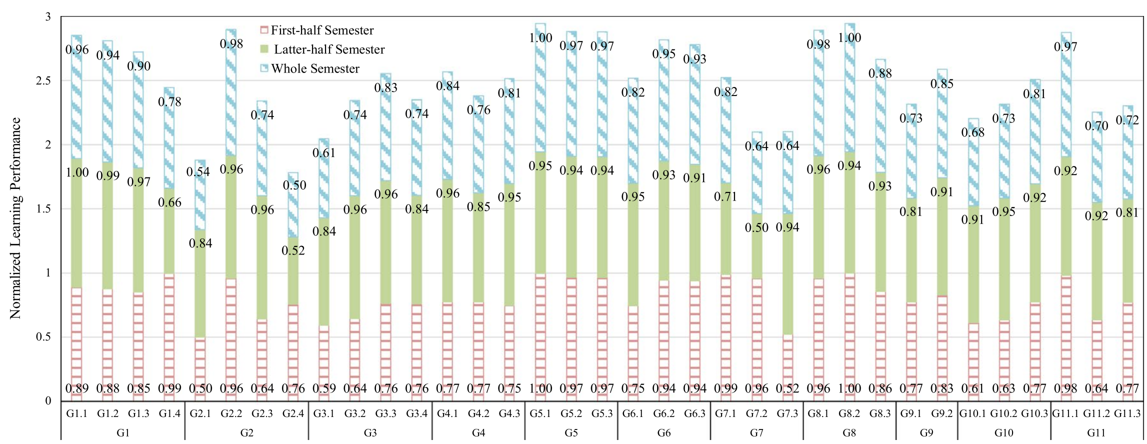


Fig. 18 Normalized learning performance of each student

and third periodic tests, respectively, at school. However, owing to the COVID-19 situation in Taiwan, the involved students have been forced to join English learning in a distance-learning way since May 25. Because of this, we only take the collected data during the period of $EpisodeQ_1$ and $EpisodeQ_2$ into consideration to analyze the students' learning performance.

6.5.2 Learning performance of students

In addition to doing the listening challenge and speaking practice (Lee et al. 2020), the involved students labeled learned English words or sentences with Chinese meanings from their textbooks using Google Jamboard in the class. Video 3 is provided in the Appendix to get more information about the situation in class. This paper first uses the CKIP library to segment Chinese and English. Next, the NLTK library (Steven et al. 2009) is applied to segment English to keep the words with meaningful POS to analyze the quantitative results. Finally, we adopt the pre-trained word vectors for English (Grave et al. 2018) released by Facebook to be the fastText-based model to analyze students' qualitative level of their intelligent labels.

Figure 19 shows the two-class whole students' learning thermometers, including the evaluated results (red and green curves) done by their teachers, i.e. human intelligence (*THI*), and the ones (red and green bar charts) done by machines, i.e. machine intelligence (*TMI*) during the period of $EpisodeQ_1$ and $EpisodeQ_2$. Figure 19 indicates that the Class 8B students perform better than the Class 8A no matter in the periodic tests (*THITeacher*, red & green solid curves) or the *CI&AI-FML* English learning (*TMITHIAvg*, red and green bar charts) at $EpisodeQ_1$ and $EpisodeQ_2$. The trend lines (red and green dashed lines) show that the learning thermometers of *TMITHIAvg* tend to keep decreasing from G1 to G4 owing to homogenous grouping.

However, observe Fig. 19a that the right-end point of the trend line ($THITMIAvgEpisodeQ_2$) is higher than the one of the trend line ($THITMIAvgEpisodeQ_1$). In other words, Class 8A students make good progress with English in $EpisodeQ_2$ compared to $EpisodQ_1$ in an average case. Figure 19b indicates that Class 8B keeps their learning performance balanced but G3 and G4 students have a good performance from the point of *THITMIAvg*, some of whom (for example students G3.4 and G3.5) are better than groups G1 and G2.

6.5.3 Analysis of students' feeback in various learning subspaces

The students provided their learning feedback weekly and at the end of the semester through the feedback system. We extract students' responses to five questions listed in Table 6 to make an analysis. The analyzed results for the whole involved students' responses to Questions 1 and 2 indicate that the percentage of positive growth in Question 1 and Question 2 from $EpisodeQ_1$ to $EpisdoeQ_2$ is about 83.9% and 77.4%, respectively. Therefore, more than three-quarters of the students liked this course and the AI-FML robot helps them learn English.

Figure 20 shows two-class students' responses to Questions 3, 4, and 5 of each group to understand the involved students' subjective thoughts on the improvement in their English ability at the end of the semester. The *Feedback_Analysis* computes the response to Questions 3 to 5 of each student calculated by Eq. (4) and then we acquire the average of each group. Figure 20 shows that the Class 8A students who considered their English ability to be improved are more than Class 8B students. To our surprise, the ratio of G3 students in both two classes is relatively higher than the one of the other groups; however, the ratio of Class 8B G1 students is the lowest.

$$Feedback_{Analysis} = \sum_{q=1}^{3} (u(s,q) \times 0.5) + 0.5 \tag{4}$$

where (1) u denotes the response to the questions where *Yes*, *Almost the same*, and *No* are converted into 1, 0.5, and 0, respectively, (2) s denotes the index of students, and $1 \le s \le 31$, and (3) q denotes the index of questions, and $3 \le q \le 5$.

Overall, most students provided positive feedback to the *CI&AI-FML* English learning course, indicating that grade eight students' motivation for *CI&AI-FML* English

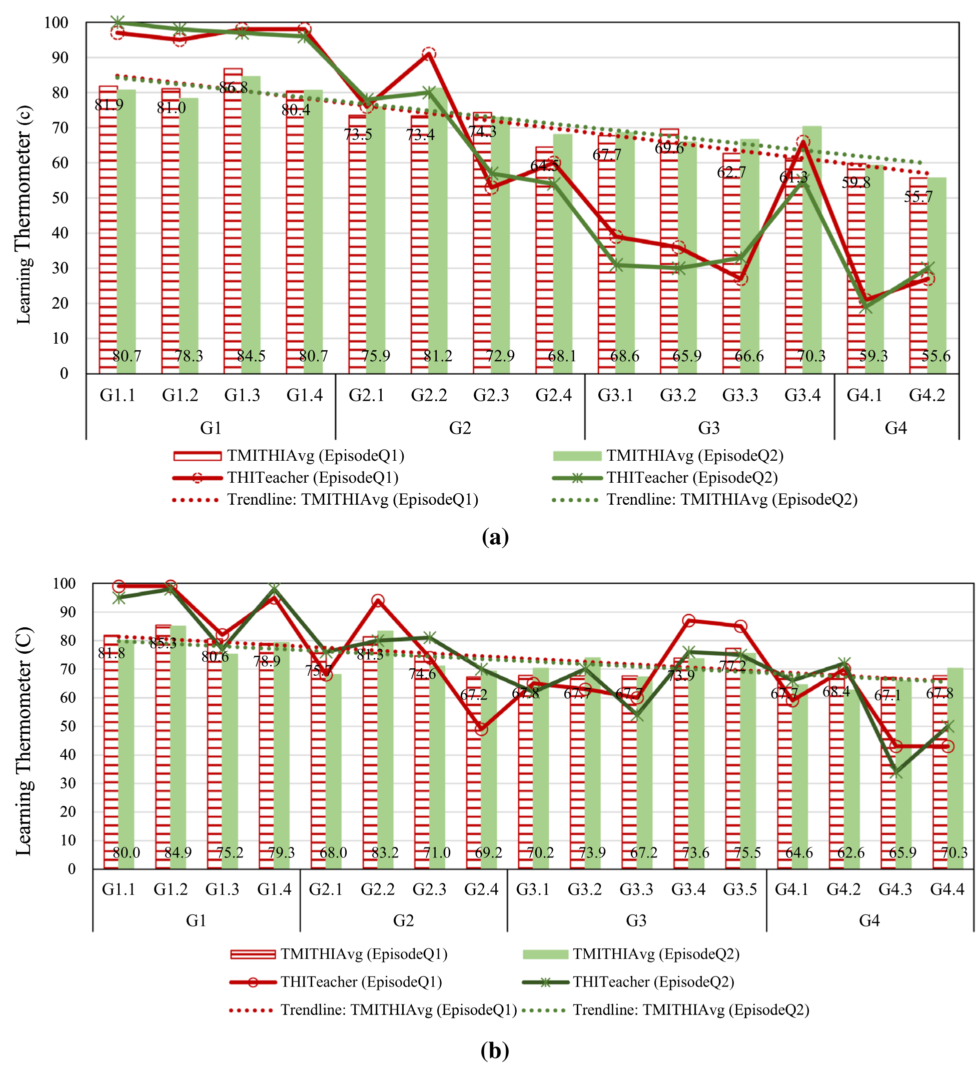


Fig. 19 Learning thermometers of Classes **a** 8A and **b** 8B

Table 6 Questions and choices

No.	Text		
	Feedback type	Questions	Single-choice options
1	Weekly	Do you like this course?	Yes/No
2		Does the AI-FML robot help you learn English?	
3	End of the semester	Do you think your English ability has improved?	Yes/ Almost the same/ No
4		Do you think your English listening ability has improved?	
5		Do you think your English speaking ability has improved?	

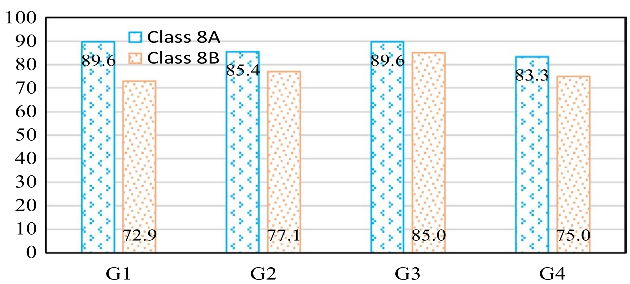


Fig. 20 Feedback analysis of Questions 3–5 in various learning subspaces

learning increased. For those students who provided negative feedback, we guessed that they may not be interested in English or their English ability is too excellent to make a self-challenge because the provided teaching materials are too easy for them.

6.6 Evaluation of CI&AI-FML Metaverse for elementary-school student learning CI&AI-FML

6.6.1 Profile of students and information of ten episodes

In Taiwan, we introduced the *CI&AI-FML* learning in a grade five computer science course (40 min once per week) at RDES during the 2022 spring semester. There are 133 students involved in the *CI&AI-FML* Metaverse *V(HI, FO, AI, MI, HS)* to learn *CI&AI-FML*. We divide the *CI&AI-FML* learning course at RDES from Mar. 2022 to Jun. 2022 into four defined intervals based on the stages of the human–machine co-learning model, including *EpisodeQ*$_1$, Q_2, Q_3, and Q_4. The *CI&AI-FML* learning in *EpisodeQ*$_1$, Q_2, Q_3, and Q$_4$ mainly focuses on concept-based plus experience-based, operation-based, and expression-based learning, respectively. The classes in *EpisodeQ*$_1$, Q_2, and Q_3 are classes in person but the ones in *EpisodeQ*$_4$ are online classes because of the COVID-19 situation in Taiwan. Therefore, this paper only considers the collection of data from *EpisodeQ*$_1$ to *EpisodeQ*$_3$. Video 4 is provided in the Appendix to get more information about the learning situation at RDES.

6.6.2 Learning performance of students

Figure 21 shows the average *THI* and *TMI* of six grade five classes, indicating that Class 5B gets the highest *THI* and *TMI* and the lowest *THI* and *TMI* happen in Classes 5A and 5C, respectively. Besides, we can see that there are different views between the point of HI and MI.

Figure 22 shows the normalized learning performance of six grade five classes for the 2022 spring semester. We can see that Classes 5B and 5D are of comparable performance in the 2022 spring semester and the performance of Class 5C is the last one of six grade five classes. Figure 22 illustrates that the learning performance in *EpisodeQ*$_3$ of Classes 5A, 5E, and 5F decreased when compared with that in *EpisodeQ*$_2$. Maybe, students considered the teaching content of *EpisodeQ*$_3$ more difficult than that of *EpisodeQ*$_2$.

7 Conclusion

The *HI-based CI&AI-FML Metaverse* with the *Heart Sutra*-inspired human intelligence, fuzzy ontology, artificial intelligence, and machine intelligence, is presented in this paper. The six-step educational process created using the ideas from the *Heart Sutra* has been proposed and described. Further, the *Metaverse* operations divided into four stages have been presented and discussed.

This paper is the advanced version of the previously published one (Lee et al. 2022). The distinguishing features, research gap we are trying to address, and the advancements of this paper are as follows: This paper.

- combines the principles of the *Heart Sutra* with the core technologies of CI&AI-FML and Metaverse,
- integrates the *Heart Sutra* with CI and AI technologies to design and implement a novel software/hardware environment—the *Metaverse*—for e-learning,
- develops the *HI-based CI&AI-FM) Metaverse* for student and smart machine co-learning,

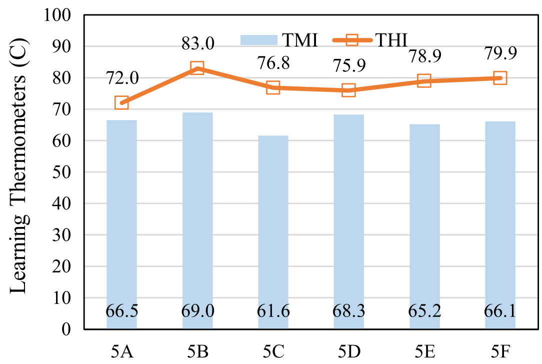


Fig. 21 Average *THI* and *TMI*

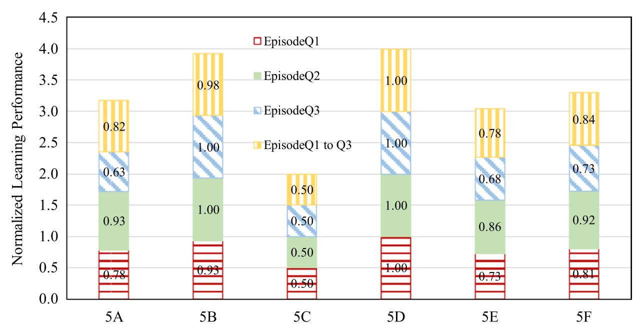


Fig. 22 Normalized learning performance of six grade five classes

- supports teachers and educators to prepare learning materials, identify concepts required by students to learn, provide evaluation criteria, and observe students' learning progress,
- utilizes the CI/AI techniques to enable teachers and students to interact with machines naturally and benefit from their intelligence,
- adopts the educational process inspired by the *Heart Sutra* combined with NLP tools and the developed intelligent agents to communicate with the variety of AI-FML tools to make young students enjoy, play, and learn with the machines and gain knowledge of CI applications,
- applies fuzzy logic and fuzzy set to the IRT learning system combined with the AI-FML tools to assist students who meet real-time remedial teaching,
- develops a *knowledge concept retrieval agent* that retrieves personalized information from students' intelligent labels,
- develops a *quantitative analysis agent* that (1) processes Chinese knowledge information to filter meaningless student-labeled data based on the results of word segmentation and part of speech analysis, and (2) quantifies students' learning situation using a ranking system with eight fuzzy sets, designated as Q_1 *to* Q_8,
- develops a qualitative analysis agent that (1) trains a fastText-based model using data collected and concepts relevant to the course domains, and (2) determines the similarity between pre-constructed concepts and student-labeled data using a ranking system with eight fuzzy sets, designated as Q_1 *to* Q_8,
- develops a *learning performance evaluation agent* evaluate the students' learning situation by combining the *quantitative* with *qualitative* results,
- develops a learning performance evaluation agent to evaluate the students' learning situation by combining quantitative and qualitative results, and
- expands the validation of the learning model from elementary and high schools to include universities such as software engineering course.

The NUTN team members first observe the students' HI at various subspaces of the *CI&AI-FML* Metaverse. Then, they prepare deep learning content based on their HI and go there to teach them while collecting data on HI and MI in the period of various episodes. In the virtual and physical *CI&AI-FML* Metaverse with different subspaces, the teacher, students, and the *CI&AI-FML* tools co-learn together through eyes (observing), ears (listening), nose (testing), tongue (speaking), body (exploring), and mind (thinking), to acquire top-level knowledge and intelligence in CI applications. To evaluate whether the involved students in various subspaces understand the knowledge of the *CI&AI-FML* applications, the proposed agents with the machine intelligence of CKIP Tagger, fastText deep learning model, and NLTK make the quantitative and qualitative analysis of the learning data. The higher the learning thermometer of the students is, the more knowledge of the *CI&AI-FML* applications the students understand. In this way, they can explain and speak to the other new teachers or learners in different subspaces through expression-based learning.

The experimental results revealed that the proposed HI-based *CI&AI-FML* Metaverse is an effective and feasible tool for e-learning in Taiwan. The involved students can understand the *CI&AI-FML* applications in the real world. However, we still encountered some difficulties in introducing the proposed *HI-based CI&AI-FML Metaverse* to the learning fields, especially in elementary schools. At the elementary-school level, children still learn through play—so no fun no learning. They have difficulties keeping their concentration on learning for too long and are easily influenced by their peers. Moreover, they do not fully understand what they label in their Google Jamboard after the concept-based learning steps. In the future, we plan to improve the performance of the proposed approach as follows:

- design the learning content that attracts children more than their games to make them enjoy learning through play,
- propose some questions for students to think about before learning to make them focus on finding the answers to these questions during learning,
- move students to the traditional computer classroom for concept-based learning to reduce the teachers' workload related to troubleshooting students' devices,
- plan to further incorporate reinforcement learning into the *HI-based CI&AI- FML Metaverse* to train a learning model to fit different learning subspaces by inputting collected data from different age groups, and
- promote the proposed *HI-based CI&AI-FML Metaverse* for student and smart machine co-learning to other counties to help more high-school and elementary-school students learn about computational intelligence and *CI&AI-FML*.

Appendix

In this Appendix, the short textual descriptions of the videos are given listed in Table 7.

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Table 7 Short textual descriptions of the videos

No	Short Textual Descriptions
1	**Topic: 2022 IEEE EAB meritorious achievement award in pre-university education** **Link:** https://youtu.be/ddequzADzC0, https://youtu.be/15nSpaz-m_4, and https://youtu.be/64Nr0vSCZIE
2	**Topic: Heart Sutra-inspired AI-FML Metaverse platform for student learning and experiencing CI** **Link:** For Heart Sutra-inspired AI-FML Metaverse: https://youtu.be/ETfYQknqFJw For elementary-school students: https://youtu.be/MhLFEtLUqPc For high-school students: https://youtu.be/gThJkTHCamE and https://youtu.be/EEOUGrLEh5Q For university students: https://youtu.be/FhMK1CHBThw These five videos describe the human-understandable explanations for Heart-Sutra-inspired AI-FML Metaverse to meet the needs of different ages
3	**Topic: CI&AI-FML english learning at FSJH on Feb. 23, 2022** **Links:** https://youtu.be/GyR6oq0P6DE / https://youtu.be/gHD3ySEeQpk
4	**Topic: CI&AI-FML learning at RDES on Apr. 6, 2022** **Links:** Grade five computer science course from Mar. 2 to Apr. 6, 2022: https://youtu.be/rN5ocqtpW80 AI-FML Club on Apr. 6, 2022: https://youtu.be/FqPfb6ZFTTA

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