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ORIGINAL RESEARCH

Intelligent agent for real-world applications on robotic edutainment and humanized co-learning

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Abstract
Dynamic assessment with an intelligent agent can differentiate the capabilities and proficiency of students. It can therefore be advocated as an interactive approach to conduct assessments on students in learning systems. Facebook AI Research proposed ELF OpenGo, an open-source reimplementation of the AlphaZero algorithm. They also developed Darkforest, which displays the competence and skills of high-level amateur Go players. To enable these open-source AI bots to assist humans at different levels in learning Go, this paper proposes an intelligent agent for real-world applications in robotic edutainment and humanized co-learning. To achieve this, we successfully constructed an OpenGo Darkforest (OGD) cloud platform using these AI bots and further combined the brain computer interface with the OGD cloud platform to observe the relationship between the brainwaves and win rates of human Go players. The intelligent agent also converted human brainwaves into physiological indices and reflected these in the robot to express human feelings or emotions in real-time. For future educational applications, this paper also presents intelligent robot teachers learning together with students in Taiwan and Japan. More than 200 students have been co-learning with intelligent robot teachers in Tainan, Kaohsiung, Taipei, and Tokyo from 2018 to 2019. The learning performance and feedback from students and teachers has been extremely positive, especially from remedial students.

Keywords Intelligent agent · Dynamic assessment · Humanized co-learning · Robot edutainment · Brain–computer-interface

1 Introduction

The AlphaGo algorithm provides a remarkable demonstration of the deep reinforcement of learning capabilities and exhibits outstanding performance in the abstract strategy board game Go (Silver et al. 2017). Facebook AI Research (FAIR) proposed using ELF OpenGo, an open-source reimplementation of the AlphaZero algorithm (Silver et al. 2017), to convincingly demonstrate keen competition against global top professionals (Tian et al. 2019). In addition to ELF OpenGo, FAIR developed Darkforest (Tian and Zhu 2016), which displays the competence and skills of high-level amateur Go players. Using these two open-source AI bots, we successfully constructed an OpenGo Darkforest (OGD) cloud platform to assist humans at different levels in playing and learning Go. In 2018, we then combined the brain computer interface (BCI) with the OGD cloud platform to observe variances in human Go players' brainwaves during play (Lee et al. 2018a, 2019a, b). The BCI is a bridge between human brainwaves and the machine that can activate signals produced (Tiwari et al. 2018). Over the past few decades, electroencephalography (EEG), an electrophysiological monitoring method used to record electrical activity in the human brain, has proven to be a robust indicator in the assessment of human

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physiological states (Chuang et al. 2015; Sanders 2018). The Go game is a highly competitive and time-consuming activity. Each right or wrong step can strongly affect the probability of winning or losing the game. In this research, we adopted a commercial EEG headset with eight channels to collect EEG signals from a Go player when he/she was playing. Our aim was to observe the relationship between his/her physiological indicators, including attention, stress, fatigue, left-brain activation, and right-brain activation, and the win rate of the game. We also believed that listening to music or singing is relatively more relaxed than playing Go. Hence, we developed an intelligent agent to infer a person's feelings based on his/her physiological states and then communicate these emotions to the robot when the person is listening to music.

Dynamic assessment (Stemberg and Grigorenko 2001) can differentiate the capabilities and proficiency of students. Therefore, dynamic assessment has been advocated as an interactive approach toward conducting assessments on students in learning systems. Computational tools can deduce a student's strengths and weaknesses. Intelligent tutoring systems have begun to show effects equivalent to those of expert human tutors in providing tailored or adaptive learning experiences, especially those in well-defined cognitive domains. Instructional systems can also assess a student's learning, and instructions can be adapted to change accordingly. Although technology cannot entirely replace educational activities conducted by human teachers, it plays an indispensable role in a complex adaptive system that involves domain knowledge, pedagogy, and the environment that students, instructors, and technology co-create. In item response theory (IRT)-based models (Embretson and Reise 2000), estimating the parameters of items for a specific student group is a crucial task. Based on parameterized probabilistic models, a message might be sent to the tutor controller to assign the most appropriate task; for example, selecting an easier or harder exercise as an item response model (Lee et al. 2018b).

In recent years, researchers have been making efforts to develop and explore a model of an intelligent robot teacher that can learn with humans. This will be useful for future educational applications. One of the most obvious benefits that AI education can offer is the personalized learning model (Rogers 2017). Students and teachers play the most important roles in the traditional classroom. What will the future classroom be like with intelligent robot teachers? To create a classroom with intelligent robot teachers, equipment such as iPads/notebooks and the Internet will be necessary in addition to different types of intelligent robots. Various types of robots have been applied to the fields of education combined with entertainment (Edutainment). The objectives of Edutainment for students are *Learning on Robots*, *Learning through Robots*, and *Learning with Robots* (Takase et al. 2015; Yorita et al. 2009, 2011). These are described in detail below.

1. *Learning on Robots:* Develop the knowledge and skills of students through project-based learning. Students can learn basic/fundamental knowledge on robotics by competing with a robot.
2. *Learning through Robots:* Acquire interdisciplinary knowledge on mechanics, electronics, dynamics, biology, and informatics using robots. Numerous types of educational materials using robots have been developed thus far.
3. *Learning with Robots:* Apply human-like robots with a friendly disposition for computer-assisted instruction. A student learns along with a robot who can help teachers teach students and monitor their learning. For example, a robot partner can be used for team teaching. When a human teacher teaches a foreign language, a robot partner can be used as a linguistics teacher.

Since 2017, we have introduced intelligent robot teachers to elementary schools in Taiwan and Japan (Lee et al. 2018c). The robot teachers co-learn mathematics and language along with students in the classroom. Over 200 students participated in the human and machine co-learning class to learn mathematics and English alongside robots. For mathematical teaching, the social constructivist paradigm informs the teaching–learning process. Marked changes from traditional approaches to teaching are needed as the role of a teacher changes from "showing and telling" to responsive guidance in stimulating pupils' thinking. In the developed learning model, we found that students are able to access learning content that aligns with their ability and learning progress. Teachers have more time to take care of slow learners because AI robot teachers can assist teachers by explaining concepts repeatedly to students without feeling tired or becoming impatient. Quick learners can challenge advanced knowledge, whereas low-performing students can learn at the level that suits them best to gradually boost their confidence. Based on the learning performance of students involved, we found that the proposed model is the most helpful for remedial students.

The remainder of this paper is structured as follows: Sect. 2 describes the Go robot agent used for humanized edutainment with BCI applications. In Sect. 3, we introduce the intelligent agent for robotic edutainment that infers a person's feelings according to his/her physiological indicators. An ontology-based intelligent agent for future educational applications in mathematical and language learning is presented in Sect. 4. Experimental results are shown in Sect. 5, and final conclusions are presented in Sect. 6.

2 Go robot agent for humanized edutainment with BCI application

In this section, the structure of an OGD cloud platform with a BCI application is presented. This is followed by the introduction of a brainwave preprocessing module and a Go robot agent.

2.1 Structure for OGD cloud platform with BCI application

Figure 1 shows the OGD cloud platform with a BCI application, which operates as follows: (1) The team members of Black and White are composed of a human Go player and a robot Palro. The human player wears a wireless EEG brainwave headset and plays Go against his/her competitor on the OGD cloud platform. OGD prediction agents, including a FAIR dynamic Darkforest (DDF) AI bot prediction mechanism and a FAIR ELF OpenGo AI bot prediction mechanism, predict the top five selections for the next move better than the human player. The robot Palro with the intelligent agent infers variances in the game situation and subsequently predicts and reports the top moves to its team member. (2) The brainwave preprocessing module collects a human's brainwaves to estimate his/her psychological indicators, such as the attention level, left-brain activation level, right-brain activation level, stress level, and fatigue level, while they are playing the game. The Go robot agent provides real-time information regarding situation, win rate, simulation numbers, and the top matching rate of the game on the OGD cloud platform by using WebSocket techniques. (3) The collected data are preprocessed, analyzed, and learned using fuzzy markup language (FML) (IEEE CIS 2016) to construct the personalized knowledge base and rule base of the fuzzy inference system and predict the likelihood of winning the game for either side. The goal of the machine learning mechanism is to make the win rate predicted by the Darkforest AI bot closer to the win rate predicted by the ELF OpenGo AI bot.

2.2 Brainwaves preprocessing module

Figure 2 shows the location of eight channels, the international 10–20 systems, and the adopted wireless headset called BR8 (Brain Rhythm INC 2018). The letters "F, P, and O" of each EEG channel identify the frontal, parietal, and occipital lobes, respectively. After collecting EEG signals, we performed a time–frequency analysis to transfer time domain EEG signals to different frequency brain waveforms. Brain waveforms can normally be subdivided into bandwidths known as gamma, beta, alpha, theta, and delta, descriptions of which are as follows: (1) gamma waves (30–80 Hz) have been linked to states of high attention; (2)

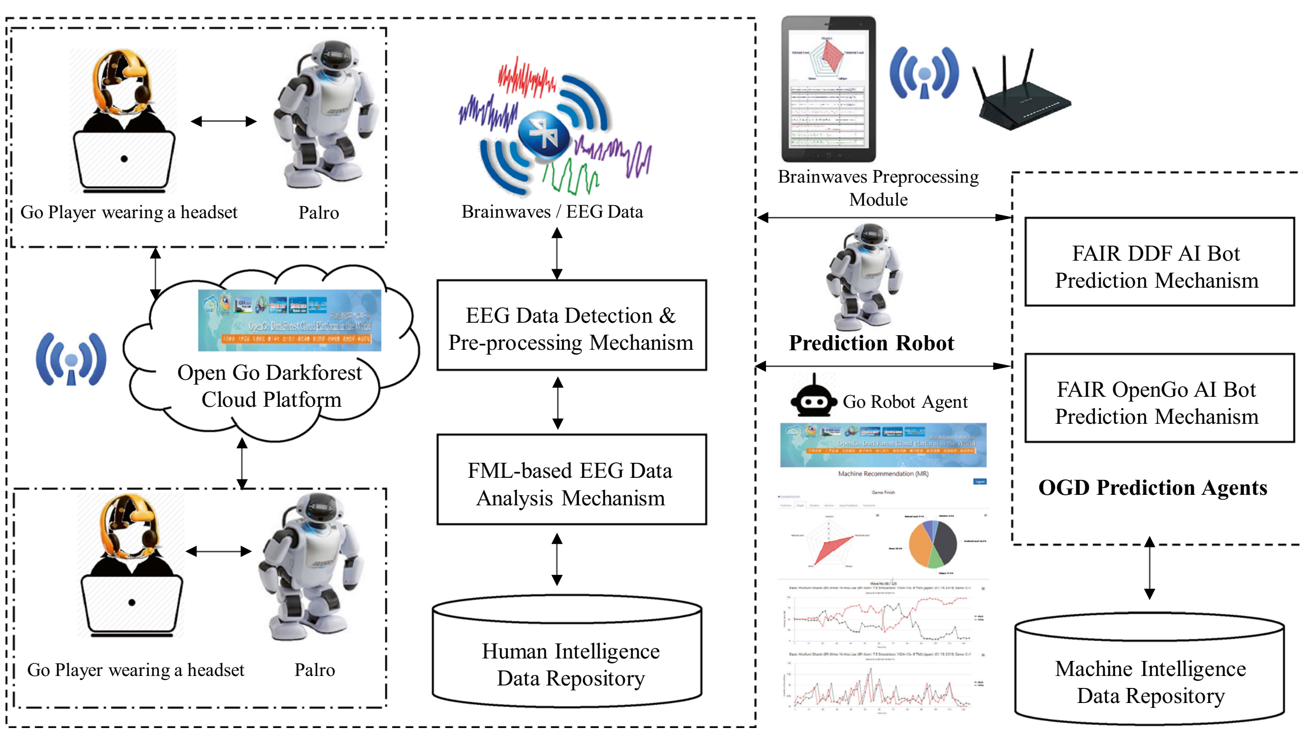

Fig. 1 OpenGo Darkforest (OGD) cloud platform with a BCI application

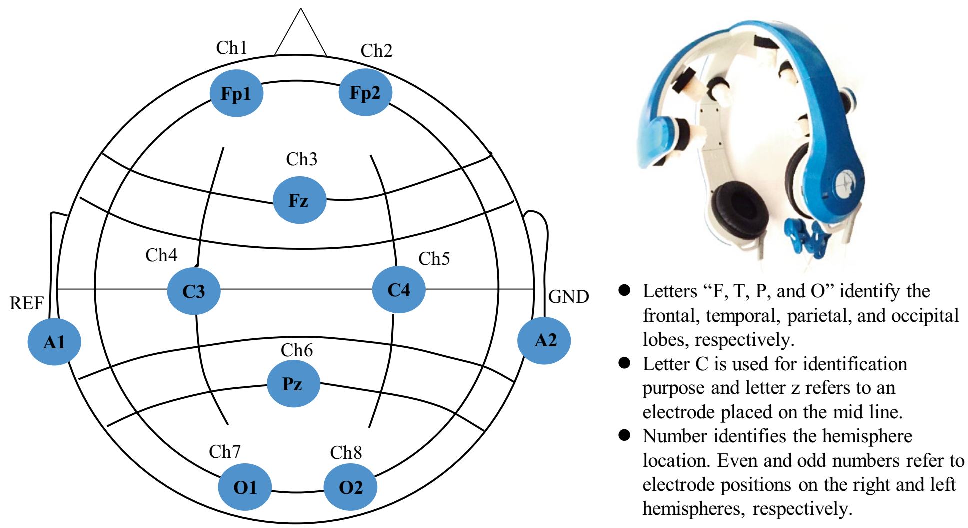

Fig. 2 Location of the eight channels and picture of the adopted wireless headset (Brain Rhythm INC. 2018; Lee et al. 2019b)

beta waves (12–30 Hz) may be involved in movement and complex tasks, such as memory and decision making; (3) alpha waves (8–12 Hz) appear when a relaxed person closes his eyes; (4) theta waves (4–8 Hz) may help the brain sort information essential for navigation; and (5) delta waves (1.5–4 Hz) indicate deep sleep and anesthesia (Mayfield Brain and Spine 2018; Sanders 2018; Lee et al. 2019b).

The brainwave preprocessing module is responsible for analyzing brainwaves from the eight channels of the wireless headset and transferring them into five indicators: *attention level*, *left-brain activation level*, *right-brain activation level*, *stress level*, and *fatigue level*. (1) *Attention level*: The alpha-band energy of the frontal lobe significantly decreases when a person is engaged in deep concentration, which is in contrast to the rest state. In this paper, we analyzed the alpha waves of the channels Fp1, Fp2, and Fz to evaluate the attention level of the Go player. (2) *Left-brain activation level* and *right-brain activation level*: When the left brain is activated, the right brain will be negatively correlated with the left brain. We used the brainwaves of the channels C3, C4, and Pz to measure these two corresponding indicators. (3) *Stress level*: We evaluated a person's stress level by measuring changes in the theta and alpha bands of the frontal lobe, including the channels Fp1, Fp2, and Fz. (4) *Fatigue level*: As shown in past EEG studies (Lin et al. 2014; Ko et al. 2017; Lee et al. 2019b), fatigue is strongly associated with energy from the occipital alpha and theta bands of the channels O1 and O2. When the level of fatigue increases, the corresponding EEG power in the occipital area also increases.

2.3 Go robot agent for humanized co-learning

Figure 3 shows the structure of the developed Go robot agent, including intelligent agents with a Go game server and learning agents with a Go learning server. Intelligent

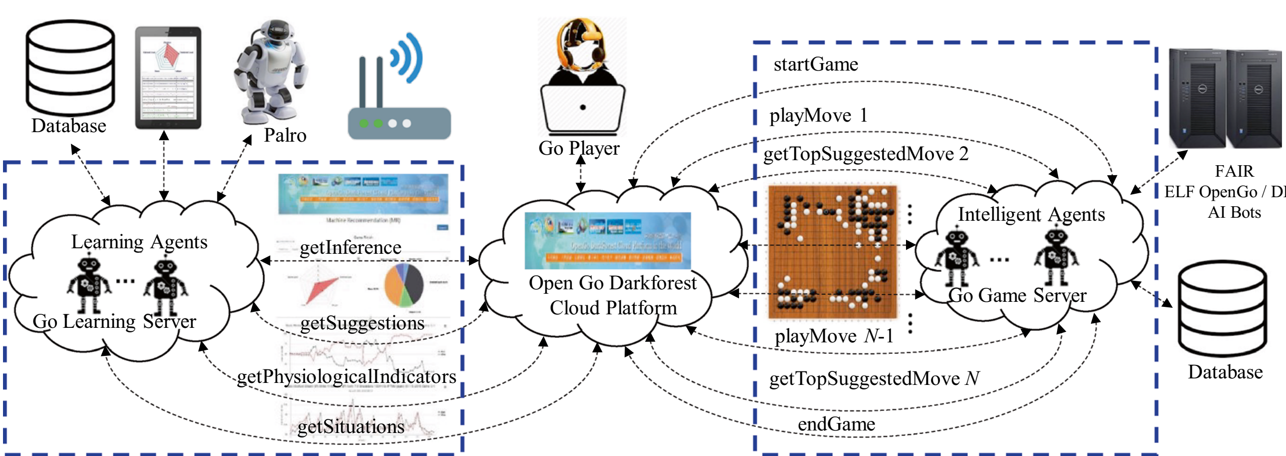

Fig. 3 Go robot agent with intelligent agents on Go game server and learning agents on Go learning server

agents with the Go game server act as a bridge between the OGD cloud platform and FAIR ELF OpenGo/DDF AI bots. The agent responds to four types of commands: *startGame*, *playMove*, *getTopSuggestedMove*, and *endGame*. If we assume the human Go player is Black and the AI bot is White, we can briefly describe these four commands as follows: (1) *startGame*: When a human plays Go against the AI bot, the first command given is to activate the AI bot, including clearing the current board, setting the parameters of the game for the AI bot, and obtaining the predicted top five selections for the first move. (2) *playMove*: After starting the game, he/she plays a stone on the game board by himself/herself. The intelligent agents with a Go game server then send out a command to obtain the top five selections for the second move predicted by the AI bot and then stores these in the database. (3) *getTopSuggestedMove*: The intelligent agents with a Go game server query the top suggested moves that are stored, and the OGD cloud platform plays the second move on the game board for the AI bot. (4) endGame: The *playMove* and *getTopSuggestedMove* commands are executed alternately until the last move of the game. Finally, the human Go player sends out an *endGame* command to ask the AI bot to end the game. The learning agents with the Go learning server act as a bridge between the OGD cloud platform and the human Go player, the robot Palro, and the brainwave preprocessing module. The four types of commands are as follows: the commands *getSuggestions*, *getInference*, and *getPhysiologicalIndicators* allow people who watch the game to acquire the following real-time variances: (1) win rate/simulations/matching rate, (2) current game situation, and (3) physiological indicators of the human Go player when the human Go player or the AI bot plays a stone on the game board. The command *getSituation* allows the robot Palro to report the real-time game situation and the top suggested move to the Go player as a reference.

3 Intelligent agent for robotic edutainment and humanized co-learning

In this section, the structure for an intelligent agent on entertainment is proposed. We then introduce the knowledge base and rule base of the *feeling fuzzy inference agent* for robotic edutainment. Finally, the *feeling fuzzy inference agent* for humanized co-learning is presented to predict a human's real-time feelings or emotions when having fun.

3.1 Structure for intelligent agents on robotic edutainment

Figure 4 shows the structure of an intelligent agent for entertainment, including a *physiological indices agent* and a *feeling fuzzy inference agent*, that can be applied to fields of robotic edutainment such as singing or listening to music for fun. We combined the BCI and FML-based inference mechanism with developed intelligent agents to communicate with the robot so that it understands human thinking from detected brainwaves. The proposed structure operates as follows:

1. A human wearing a wireless EEG brainwave headset holds a smart device to listen to a popular song. The brainwave preprocessing module receives and analyzes humans' brainwaves while they are listening to acquire five physiological indices. These are then stored in the physiological indices repository.
2. The domain expert constructs the knowledge base and rule base of the *feeling fuzzy inference agent* according to the stored physiological indices.
3. The *physiological indices agent* communicates with the brainwave preprocessing module to receive real-time physiological indices from the repository. At the same time, the *physiological indices agent* broadcasts the analyzed physiological indices to the *feeling fuzzy inference agent* and TMU robots, which display real-time variances in these indices on their screen.
4. The *feeling fuzzy inference agent* infers humans' feelings, such as being exhausted, tired, worried, or doubting, based on the constructed knowledge base and rule base as well as the received physiological indices. Simultaneously, the inferred feeling is broadcast to the robots Zenbo (Asus.com 2019) and Palro to report humans' feelings and display them on the robots' face. In this paper, the inferred feeling is composed of eleven different types of facial expression: "*exhausted*, *tired*, *impatient*, *innocent*, *worried*, *normal*, *shocked*, *questioning*, *doubting*, *confident*, and *happy*." Additionally, the e-book website receives broadcast packages to show the real-time fuzzy inference process on the smart device.

3.2 Knowledge base and rule base

The *feeling fuzzy inference agent* is based on the Takagi–Sugeno–Kang (TSK) fuzzy inference mechanism. The input fuzzy variables *Attention*, *Left-Brain Activation Level* (*LBAL*), *Right-Brain Activation Level* (*RBAL*), *Fatigue*, and *Stress* represent a person's physiological state in relation to his/her attentional level, left-brain activation level, right-brain activation level, fatigue level, and stress level, respectively. We utilized the trapezoidal membership function shown in Eq. (1) for fuzzy set *FS*, specified by four parameters expressed as *BS*, *BC*, *EC*, and *ES*. Table 1 shows the parameters of defined fuzzy sets. The fuzzy output variable is *Feeling*, which comprises eleven linguistic terms: *Exhausted*, *Tired*, *Impatient*, *Innocent*, *Worried*, *Normal*, *Shocked*, *Questioning*, *Doubting*, *Confident*, and *Happy*. The weighted average (WA) method computes the overall output μ as Eq. (2). There were 32 fuzzy rules in total. Table 2 lists partial adopted fuzzy rules, the criteria for which are as follows: (1) Exhausted: five physiological indices are all low, (2) Tired: *Stress* or *Fatigue* is high, (3) Impatient: *RBAL*,

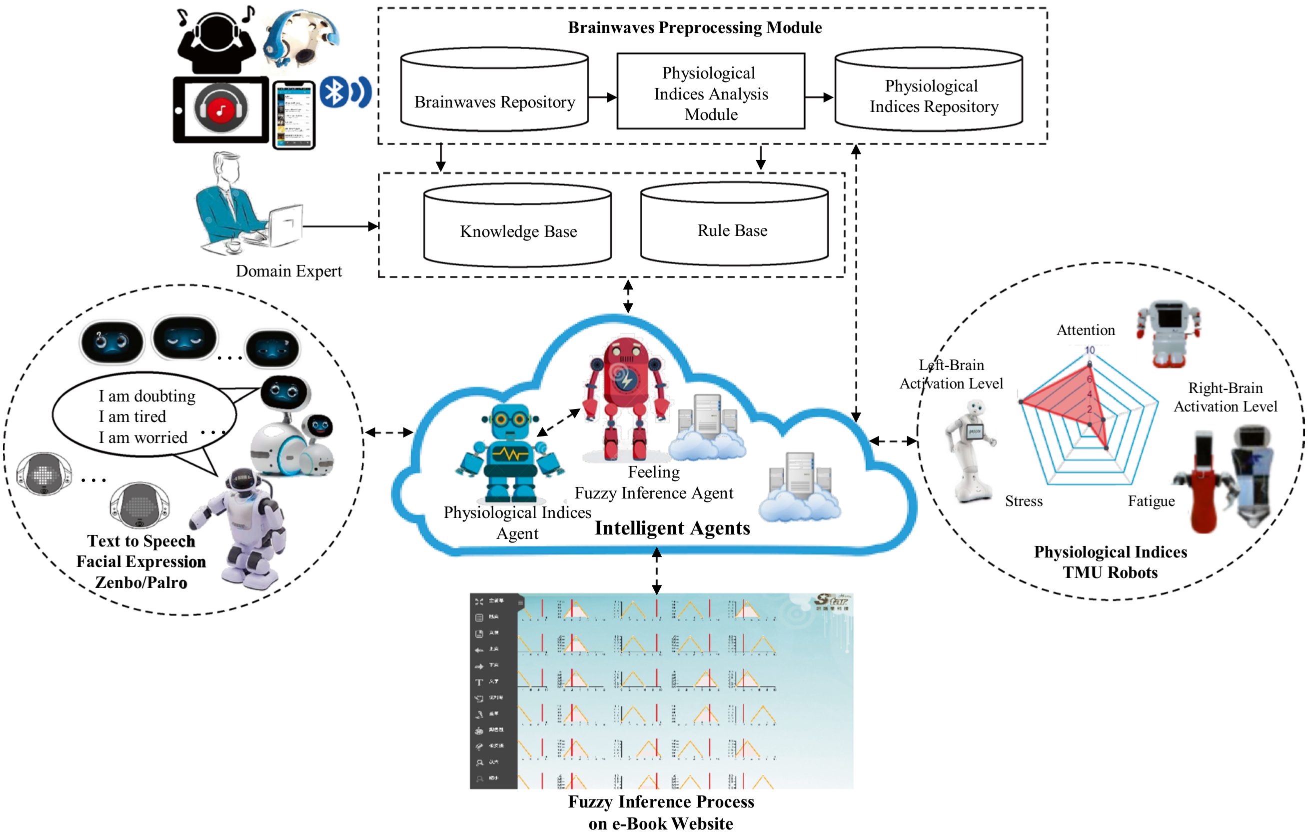

Fig. 4 Structure of intelligent agents on robotic edutainment

Table 1 Parameters of the defined fuzzy sets

Fuzzy sets	Input fuzzy variables				
	Attention	*LBAL*	*RBAL*	*Fatigue*	*Stress*
Low	[0, 3, 3, 6]	[0, 3, 3, 6]	[0, 3, 3, 6]	[0, 3, 3, 6]	[0, 3, 3, 6]
High	[4, 7, 7, 10]	[4, 7, 7, 10]	[4, 7, 7, 10]	[4, 7, 7, 10]	[4, 7, 7, 10]

Table 2 Partial adopted fuzzy rules

No	Attention	*LBAL*	*RBAL*	Fatigue	Stress	Feeling	No	Attention	*LBAL*	*RBAL*	Fatigue	Stress	Feeling
1	Low	Low	Low	Low	Low	Exhausted	17	High	Low	Low	Low	Low	Confident
2	Low	Low	Low	Low	High	Shocked	18	High	Low	Low	Low	High	Confident
3	Low	Low	Low	High	Low	Tired	19	High	Low	Low	High	Low	Questioning
4	Low	Low	Low	High	High	Impatient	20	High	Low	Low	High	High	Normal
5	Low	Low	High	Low	Low	Doubting	21	High	Low	High	Low	Low	Happy
6	Low	Low	High	Low	High	Doubting	22	High	Low	High	Low	High	Confident
				⋮						⋮			
15	Low	High	High	High	Low	Confident	31	High	High	High	High	Low	Tired
16	Low	High	High	High	High	Worried	32	High	High	High	High	High	Innocent

Stress, and *Fatigue* are all high, (4) Innocent: five physiological indices are all high, (5) Worried: *LBAL* and *Stress* are both high, (6) Normal: *Attention* is high, (7) Shocked: *Stress* is high, (8) Questioning: *Attention* or *LBAL* is high, (9) Doubting: *Attention* or R*BAL* is high, (10) Confident: *Attention* is high and *Fatigue* is low, and (11) Happy: *Attention* is high, *LBAL* is high, *Stress* is low, and *Fatigue* is low. Table 3 shows the partial FML code for the feeling fuzzy inference agent.

$$FS(x\colon BS, BC, EC, ES) = \begin{cases} 0, & x < BS \\ \frac{x-BS}{BC-BS}, & BS \le x < BC \\ 1, & BC \le x < EC \\ \frac{ES-x}{ES-EC}, & EC \le x < ES \\ 0, & x \ge ES \end{cases} \tag{1}$$

where *BS*, *BC*, *EC*, and *ES* denote the *Begin Support*, *Begin Core*, *End Core*, and *End Support*, respectively, of the trapezoidal-shape fuzzy set *FS*.

$$\mu = \frac{\sum_{i=1}^{N} z_i \times w_i}{\sum_{i=1}^{N} w_i} \tag{2}$$

where N is the number of rules, z_i is the output of the *ith* rule, and w_i is the firing strength of the *ith* rule.

3.3 Feeling fuzzy inference agent

Figure 5 presents the flowchart for the *feeling fuzzy inference agent*. First, the *physiological indices agent* broadcasts the analyzed physiological indices per second to the *feeling fuzzy inference agent*. This then synchronizes to accumulate the received physiological indices separately until the time interval (T) is up, where T could be 1, 15, or 30 s (s), depending on the actual situation. Second, the agent calculates the average of each physiological index, which then forms the input data of the TSK-based fuzzy inference mechanism. The value of the fuzzy output variable *Feeling* is then calculated by the WA method. Third, the crisp output value is mapped into semantics as shown in Table 4: these represent the real-time feelings of the subject. Finally, the robot displays the inferred semantics on its face and states how the subject feels in this situation. In this paper, we used the commercial robot Zenbo/Zenbo Junior with 24 different types of facial expression to reflect the feelings of the man/woman. We selected 11 out of 24 facial expressions shown in Fig. 5 to express the human's feelings on the face of the robot Zenbo. In this way, both the human participant and human non-participants non-subjects were able to understand how the participant is feeling through the robot Zenbo's expression and speech. Thus, the goal of co-learning between the human and the robot was achieved.

4 Ontology-based intelligent agent for future educational applications

This section describes an ontology-based intelligent agent that can be used for future educational applications. We first introduce the domain ontology-based future educational ecosystem. This is followed by presentation of the *Item_Bank ontology*, *Student_Group ontology*, and *item parameters mapping mechanism* between the *Item_Bank ontology* and the *Student_Group ontology*. Finally, the robot agents based on domain ontology are introduced.

4.1 Domain ontology-based future educational ecosystem

Figure 6 shows the domain ontology-based future educational ecosystem for agent-based robot teachers that can learn various domains of knowledge such as mathematics, languages such as English and FML, and the Go game domain along with students in the classroom (Lee et al. 2018c). It operates as follows:

1. *Phases 1 and 2:* Domain experts and senior teachers define the curriculum guide for each subject. Publishers then invite human experts to plan and set out the course outlines by following the curriculum guide. The publishers then invite other human experts to create learning contents, such as textbooks, electronic books (e-Books), supplementary materials, or social media materials.
2. *Phase 3:* The *ontology agent* and the *teaching assistant agent* construct the domain ontology for robot teachers' learning in mathematics, English, FML (IEEE CIS 2016), and Go.
3. *Phase 4:* The proposed model is introduced into teaching fields to allow robot teachers and students to learn together in classrooms based on the adaptive learning schedule. The robots, for example, Palro and Zenbo, serve as teaching assistants who interact with students in the classroom to stimulate their learning, motivate them, and help them make progress.
4. *Phases 5 and 6:* The agent-based robot teachers are composed of four agents: an *IRT agent*, an *assessment agent*, a *recommendation agent*, and a *learning agent*. Each student in the classroom uses a handheld device, such as an iPad, to make a response on the test paper. The robot teachers with an *IRT agent* and an *assessment agent* then select suitable items for students based on their real-time responses and assess each student's level of ability, for example, *below-basic*, *basic*, *proficient*, or *advanced* level (Lee et al. 2018b).

Table 3 Partial FML code for the feeling fuzzy inference agent

```
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<fuzzySystem xmlns="http://www.ieee1855.org" networkAddress="127.0.0.1">
    <knowledgeBase networkAddress="127.0.0.1">
        <fuzzyVariable name="Attention" domainleft="0" domainright="10" scale="" type="input">
            <fuzzyTerm name="Low" complement="false">
                <trapezoidShape param1="0" param2="3" param3="3" param4="6"/>
            </fuzzyTerm>
            <fuzzyTerm name="High" complement="false">
                <trapezoidShape param1="4" param2="7" param3="7" param4="10"/>
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        </fuzzyVariable>
                                    ⋮
        <tskVariable name="Feeling" scale="null" combination="WA" type="output">
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            </tskTerm>
            <tskTerm name="Tired" order="0">
                <tskValue>10</tskValue>
            </tskTerm>
            <tskTerm name="Impatient" order="0">
                <tskValue>20</tskValue>
            </tskTerm>
                                    ⋮
        </tskVariable>
    </knowledgeBase>
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<tskRule name="Rule1" connector="and" andMethod="MIN"
weight="1.0">
    <antecedent>
        <clause>
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        <clause>
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                <term>Exhausted</term>
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    <tskConsequent>
        <tskThen>
            <tskClause>
                <variable>Feeling</variable>
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        </then>
    </tskConsequent>
</tskRule>
                    ⋮
    </tskRuleBase>
</fuzzySystem>
```

Fig. 5 Feeling fuzzy inference agent flowchart

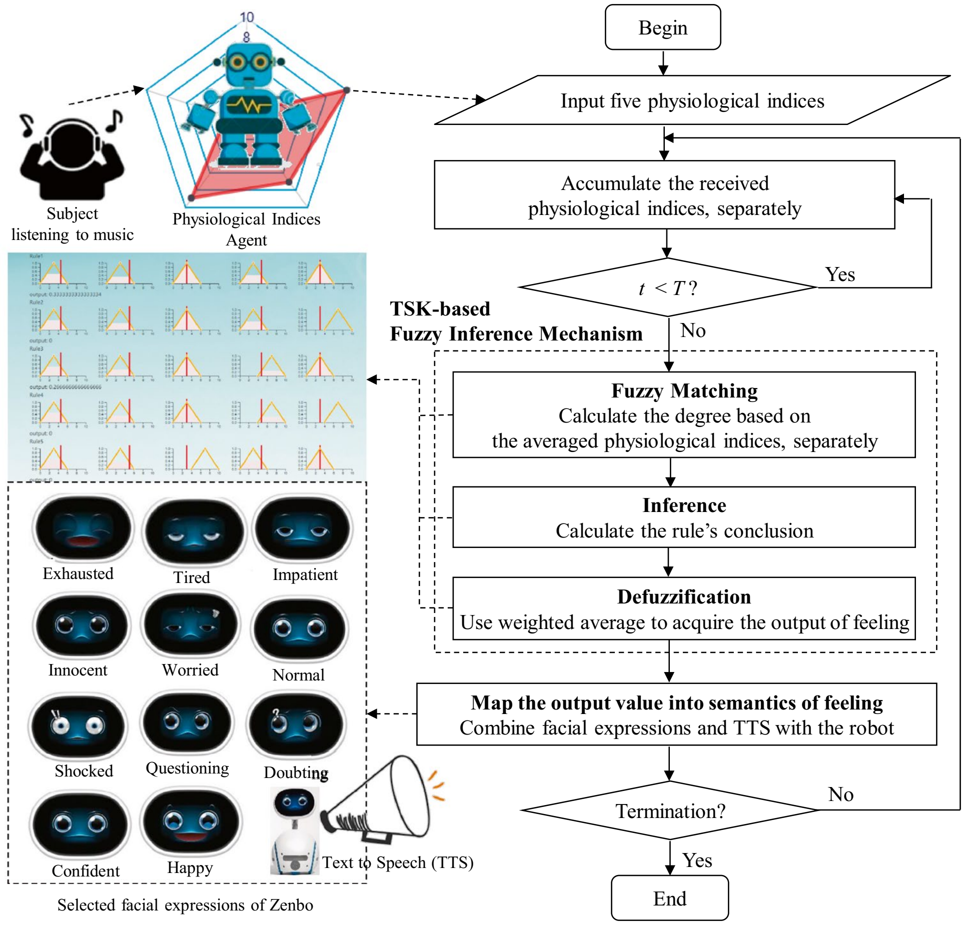


Table 4 Mapping among output range, semantics of feeling, and text to speech

Semantics of feeling	Text to speech	
	Chinese	English
Happy: (0.9, 1]	太棒了	Wonderful!
Confident: (0.8, 0.9]	我很有信心	I have confidence in myself
Doubting: (0.7, 0.8]	我正在思考	I am thinking
Questioning: (0.6, 0.7]	我很認真專注	I am focusing now
Shocked: (0.55, 0.6]	怎麼會這樣呢	Why this happened?
Normal: (0.5, 0.55]	加油	Cheer up
Worried: (0.4, 0.5]	我有點緊張	I am a little nervous
Innocent: (0.3, 0.4]	提起精神振作點吧	Cheer up again!
Impatient: (0.2, 0.3]	加油再撐會兒	Cheer up and hang in there for a while
Tired: (0.1, 0.2]	我累了	I am tired
Exhausted: (0, 0.1]	我撐不住了	I am exhausted

5. *Phases 7 and 8:* The personalized, time-saving, and interactive classroom models all rely on the effective use of data (Rogers 2017). The specific data are then collected and analyzed by the established platform in Taiwan and Japan. Robot teachers with a *recommendation agent* offer individual feedback to students by selecting suitable teaching materials for their next session of adaptive learning. The robot teachers with a *learning agent* assess each student's actual ability for the next teaching and learning session as well as organizing the learning process based on their learning history. All of the analyzed results are fed back to the teaching field to refine the robot teachers in the classroom further.

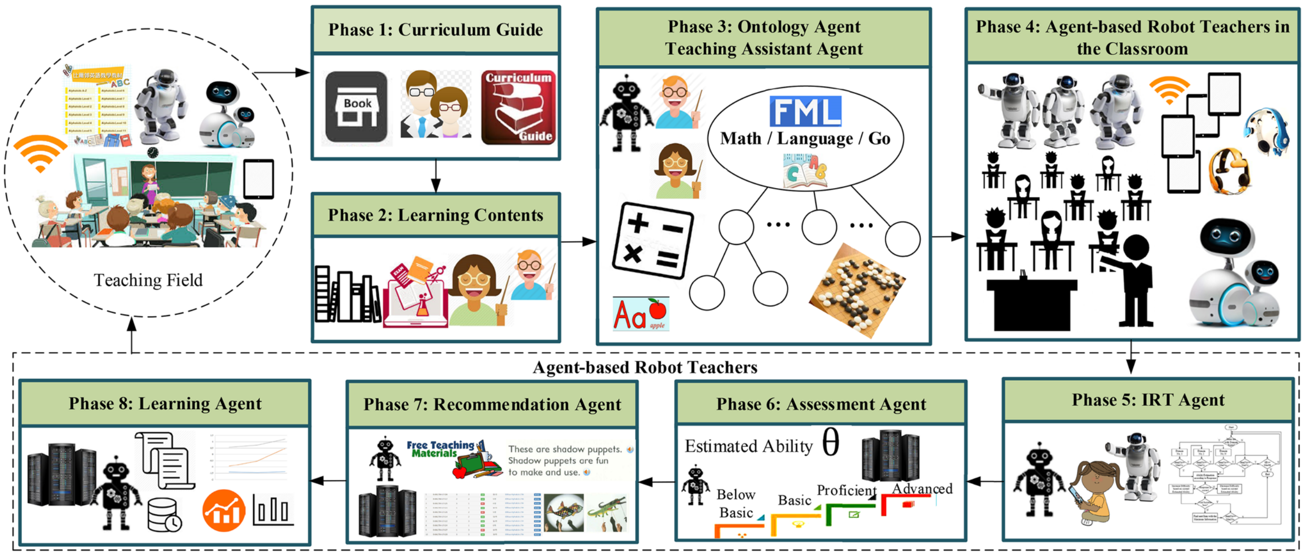


Fig. 6 Domain ontology-based future educational ecosystem

4.2 Item parameter mapping mechanism between Item_Bank ontology and Student_Group ontology

Figure 7 shows the item parameter mapping mechanism between the *Item_Bank ontology* and the *Student_Group ontology*. The left-hand side of Fig. 7 is the *Item_Bank ontology*, which includes teaching materials for mathematics, English, and FML. Clear differences exist in the ability levels of students, whether they are in Asia, Europe, or America. Thus, the abilities of students vary within each continent, country, city, school, grade, or even class. In this paper, we used English as the subject for the student and robot co-learning in the classroom. Teaching materials were obtained from the Boyo Social Welfare Foundation and BillKuo Languages & Technology Co., Ltd. Teaching materials provided by Boyo contained 1500 words, whereas those provided by Billkuo comprised Levels 1 through to 11, with six books for each level. The learning contents are suitable for elementary-school and junior high-school students. We computerized these teaching materials to be the item banks of agent-based robot teachers. The robot teachers

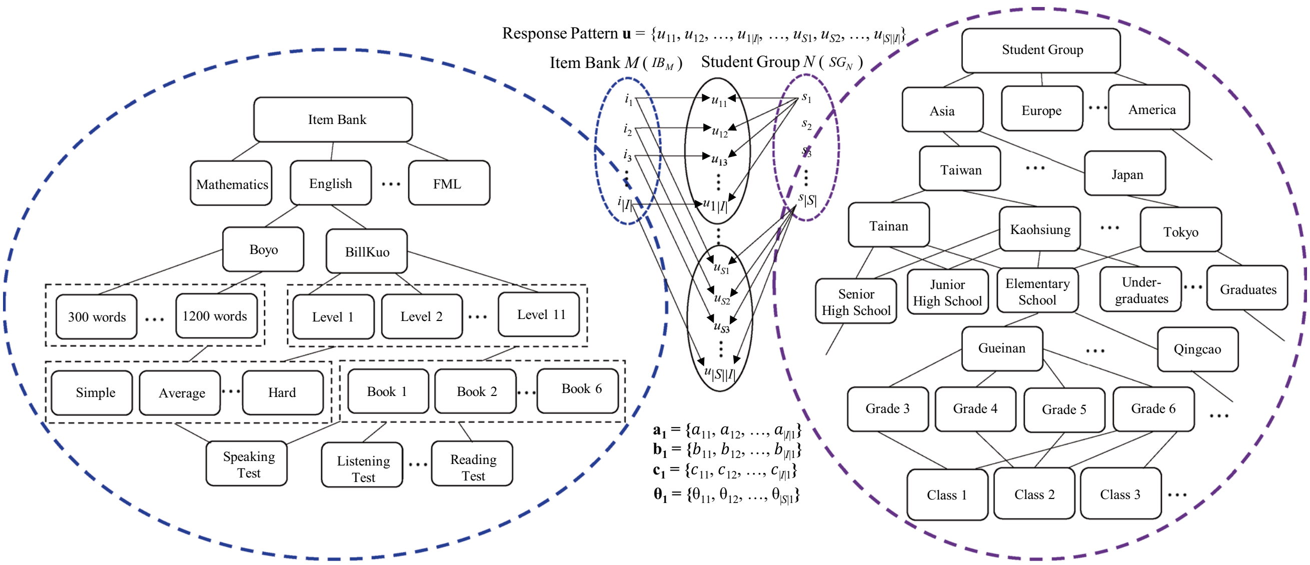


Fig. 7 Item parameters mapping mechanism between *Item_Bank ontology* and the *Student_Group ontology*

therefore learned how to speak, listen to, and read English along with students in the classroom. The right-hand side is the *Student_Group ontology*. From March to May in 2019, we introduced robot teachers into six classes from grade 3 to grade 6 of the Gueinan elementary school in Tainan, Taiwan, to co-learn English with students. Additionally, three-grade students of Qingcao elementary school also participated in this research project. The middle of Fig. 7 represents the item parameter mapping mechanism between the *Item_Bank ontology* and the *Student_Group ontology*, where (1) $\mathbf{u} = \{u_{11}, u_{12}, \ldots, u_{1|I|}, \ldots, u_{S1}, u_{S2}, \ldots, u_{|S||I|}\}$ denotes the response pattern made by students $s_1, s_2, s_3, \ldots$, and $s_{|S|}$ in Student Group No. 1 (SG_1) to items $i_1, i_2, i_3, \ldots$, and $i_{|I|}$; (2) $\mathbf{a}_1 = \{a_{11}, a_{12}, \ldots, a_{|I|1}\}$, $\mathbf{b}_1 = \{b_{11}, b_{12}, \ldots, b_{|I|1}\}$, and $\mathbf{c}_1 = \{c_{11}, c_{12}, \ldots, c_{|I|1}\}$ denote the parameters of the discrimination, difficulty, and guessing of the items $i_1, i_2, i_3, \ldots$, and $i_{|I|}$ for students $s_1, s_2, s_3, \ldots$, and $s_{|S|}$ in SG_1, respectively; and (3) $\theta_1 = \{\theta_{11}, \theta_{12}, \ldots, \theta_{|S|1}\}$ denotes the estimated ability of the students in SG_1 (Lee et al. 2018b).

4.3 Robot agents based on domain ontology in various robotic applications

A robot partner for educational purposes can teach by interacting with students in everyday situations. Furthermore, the robot can observe the state of friendship among students. This is very useful information for teachers who may find it extremely difficult to obtain such information from daily communication and interactions between students. Hence, virtual robots (i.e., smart machines in Taiwan and Japan) learn about students' learning behavior and their personalized parameters, whereas physical robots (i.e., Palro and Zenbo) not only teach students in the classroom but also achieve the goal of intelligent robot learning with humans in the classroom.

Figure 8 shows *robot agents* based on domain ontology in various robotic applications (Lee et al. 2019a). Our idea was to construct the domain ontology, such as mathematics, English, Go, and FML, required for *robot agents* to communicate with various robots. In this way, physical robots can serve as teaching assistants in the classroom. Figure 9 shows the flowchart for the *IRT agent* and the *assessment agent*. Each student has to login on the IRT challenge system and then choose the test paper from the item bank. If this chosen test paper is for adaptive testing, the *IRT agent* adaptively chooses the next item from the established item bank based on real-time responses until the total number of items (*ItemNo*) has reached $ItemNo_{Max}$ or the standard deviation (SD) is less than or equal to minimum (SD_{min}) (Wang et al. 2014; Lee et al. 2018b). If he/she correctly answers the item, the *IRT agent* chooses a more difficult item next time. By contrast, if he/she gives a wrong answer, the *IRT agent* chooses an easier item next time. The *assessment agent* estimates the student's ability (θ), for example, *below-basic*, *basic*, *proficient*, or *advanced level* (Lee et al. 2018b) until the end of the challenge.

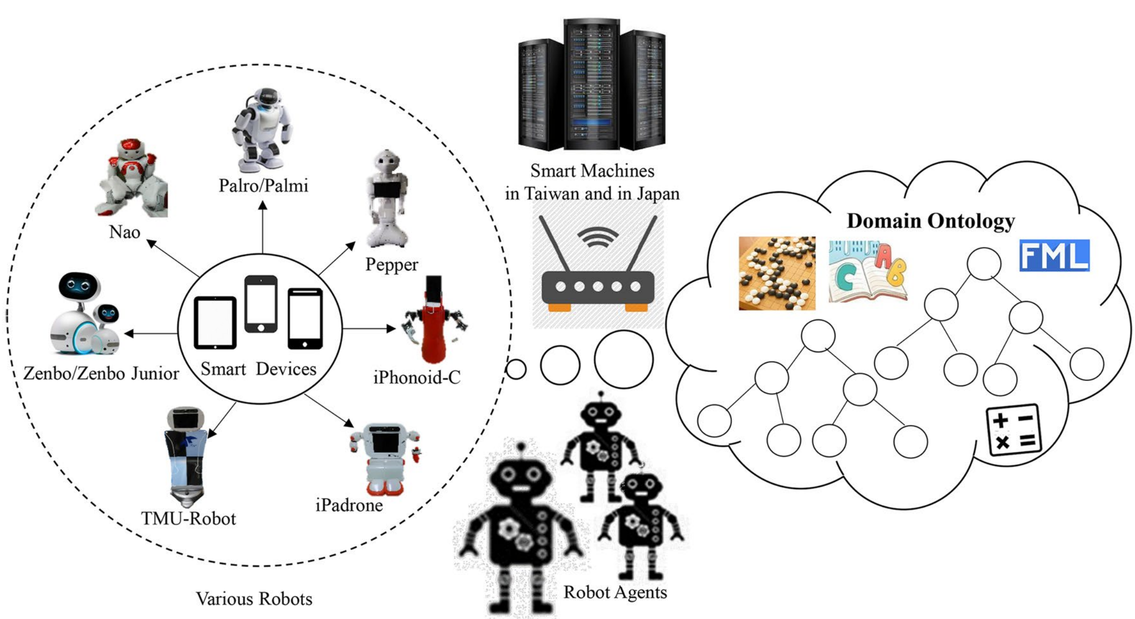


Fig. 8 Robot agents based on domain ontology in various robotic applications (Lee et al. 2019a)

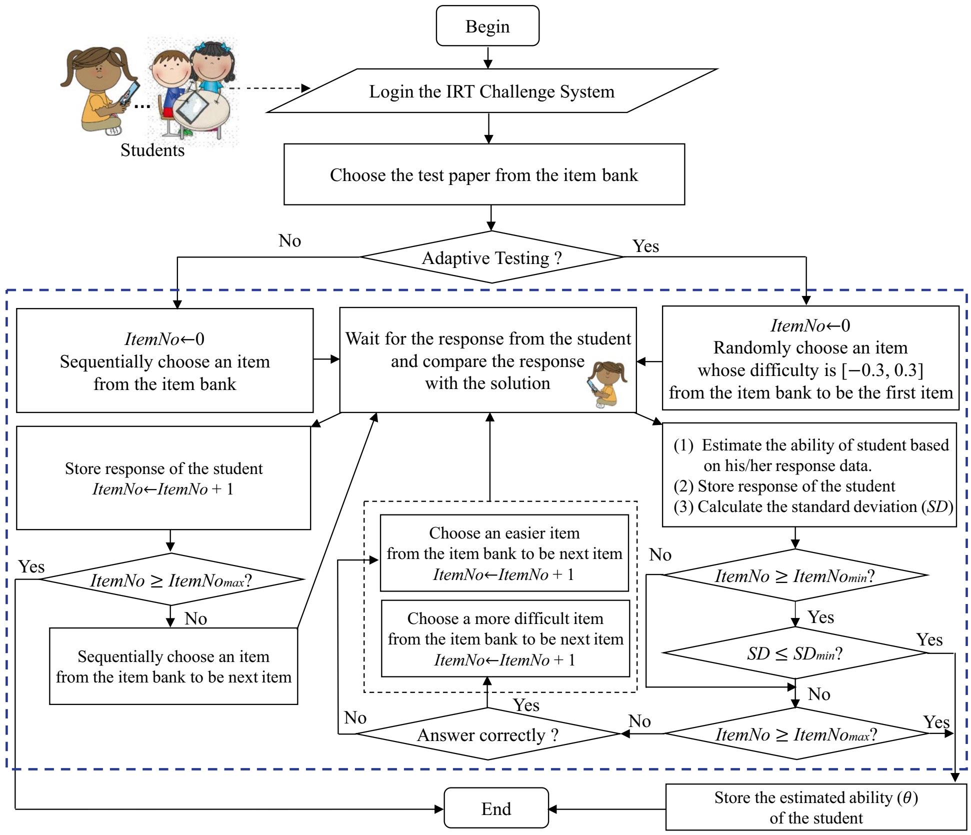


Fig. 9 Flowchart of the IRT agent and assessment agent

5 Experimental results

In this section, we present a series of experimental results, including robotic edutainment and humanized co-learning performance evaluations for Go game learning applications, entertainment in the form of listening to music, mathematical learning, and English language learning. Finally, we offer some opinions and comments on the robot teacher from Lu-An Lin, a Go player who participated in the research.

5.1 Applications to go game learning based on BCI

To observe the variance in the brainwaves of human Go players while engaged in play, we invited three Go players, Yi-Hsiu Lee (8P, Japan), Hirofumi Ohashi (6P, Japan), and Lu-An Lin (7D, Taiwan), to participate in this experiment in 2018 and in 2019. To denote proficiency in playing Go, 1P-9P is deemed as the professional level and 1D-7D is deemed as the amateur level. The higher the level of a Go player, the more competent he/she is supposed to be. Figure 10a shows that Lin cooperated with the robot Palro to play Go against FAIR ELF OpenGo in November 2018 while wearing a headset to measure her brainwaves. These were then displayed on the screen of the iPad. Figure 10b shows that Lee and Ohashi played Go against each other in January 2019 on the OGD cloud platform. Their brainwaves were displayed on the screen of the robot Pepper. Figure 11a shows Lee's psychological indicators when he cooperated with the robot Palro as Black and played against

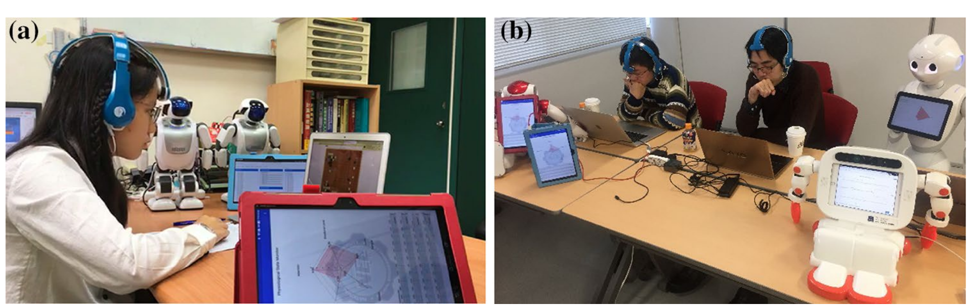


Fig. 10 Go players, including (**a**) Lu-An Lin (7D) and (**b**) Yi-Hsiu Lee (8P, left) and Hirofumi Ohashi (6P, right) played Go with ELF OpenGo while wearing headsets to measure their brainwaves displayed on the screen of the iPad and robot Pepper

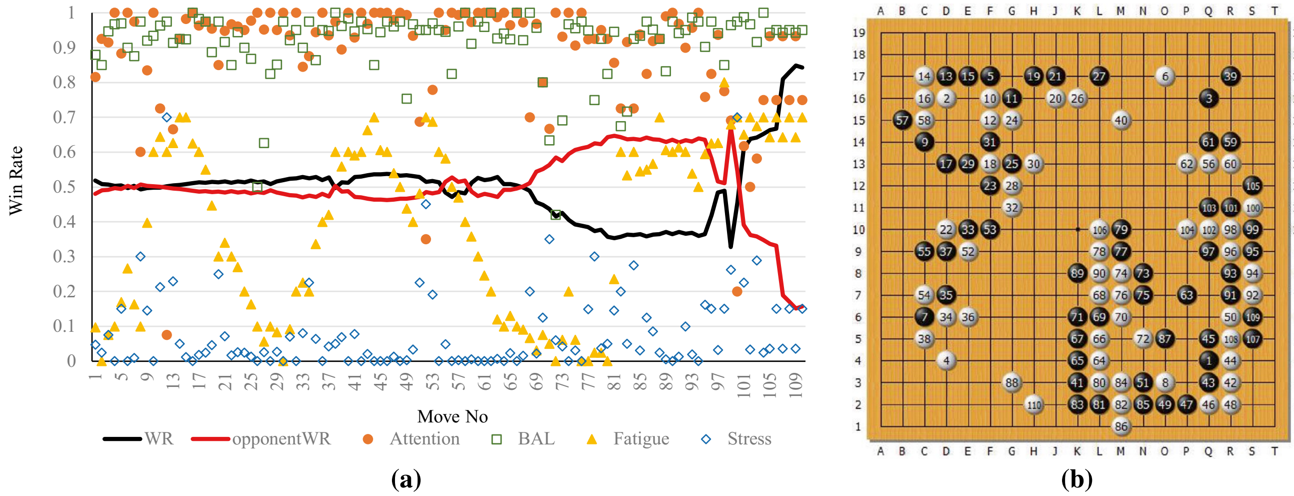


Fig. 11 **a** Lee's psychological indicators, win rate, and the win rate of his opponent. **b** Game record

FAIR ELF OpenGo as White in November 2018. Lee and the robot Palro won the game (Lee et al. 2019b). The robot Palro reported the most top moves predicted by the FAIR OpenGo AI bot and showed the position of this top move on its face to Lee. Additionally, we set FAIR ELF OpenGo's simulations to 1024. As shown in Fig. 11a, Lee's fatigue level fluctuated a great deal prior to Move 80. However, he experienced the intensity of fatigue only in the last few moves before he won the game. Figure 11b shows the game record. Lee commented as follows on this game: "I took the Palro's suggestions to play for the first few moves so the situation was a draw. W64 is an over-played move so I launched a counter-attack but failed. Additionally, I played B73 at N8 instead of O9 because I misheard from the Palro. The win rate of Black started decreasing since B73. Finally, Black won the game because White made a mistake from Moves 91 to 94."

Figure 12a shows Ohashi's psychological indicators, win rate, and the win rate of his opponent. In the game, Ohashi as Black played against FAIR ELF OpenGo as White in November 2018. White won the game (Lee et al. 2019b). The figure indicates that Ohashi experienced high levels of stress and left-brain activation throughout the entire game; however, his attention level was not high. Figure 12b shows the game record. Ohashi commented as follows on this game: "I lost my concentration because I needed to watch the Palro's five suggested moves listed on the screen of the iPad and then found the corresponding position in the board." Figure 13a shows Lin's psychological indicators in a game where Lin cooperated with the robot Palro (FAIR Darkforest) as Black and played against FAIR Darkforest as White in November 2018. White won the game (Lee et al. 2019b). Lin's fatigue level was also high throughout the game because her partner FAIR Darkforest put her at

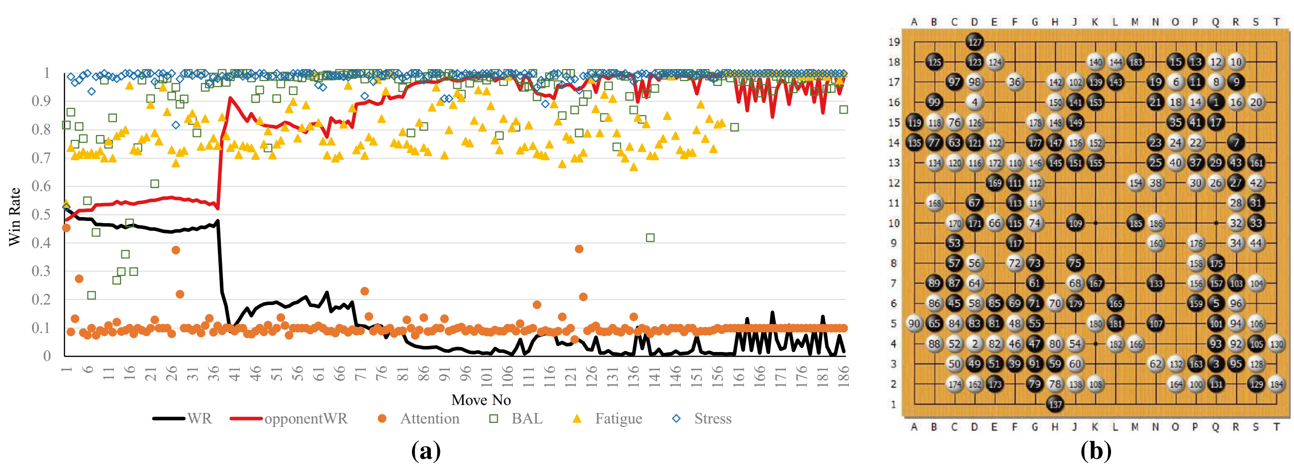
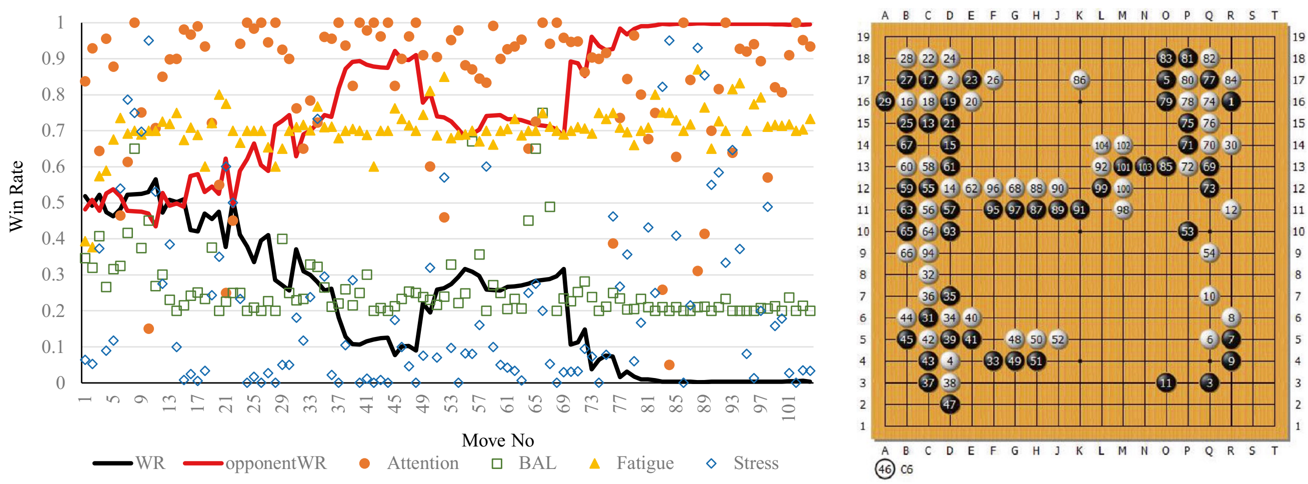


Fig. 12 **a** Ohashi's psychological indicators, win rate, and the win rate of his opponent. **b** Game record



(a) (b)

Fig. 13 **a** Lin's psychological indicators, win rate, and the win rate of her opponent. **b** Game record

a disadvantage, and she tried her best to turn the tables. Both had paid tremendous attention to the game. Figure 13b shows the game record, and Lin made the following comments on this game: "I once played against Darkforest 3 years ago. At first, to defeat Darkforest was a dream, but now beating Darkforest was a breeze after a few rounds of practice. I was in partnership with Darkforest as Black. Sometimes I ignored its suggested moves but sometimes I had to follow the suggestions due to our partnership. Once my partner put me at a disadvantage and I tried my best to turn the tables. Since Move 73, the game situation was not favorable for Black. Indeed, it was another kind of learning experience."

5.2 Applications to entertainment on listening to music based on BCI

This section presents experimental results for entertainment applications based on the BCI. On April 23, 2019, we invited two human Go players, Yu-Lin Lin (7D, Taiwan) and Yu-Hao Huang (2D, Taiwan), both of whom were studying at Tainan First Senior High School (TNFSH) in Taiwan, to wear a wireless headset and give their comments on the game played by Huang on December 19, 2018. Additionally, we invited the principal of TNFSH, Tien-Tang Chang, to wear a wireless headset and sing a song to Lin and Huang. Table 5 shows the scenarios for these three activities. Figure 14a shows the percentage of eleven feelings experienced by Lin that were inferred using the proposed method during activities 1, 2, and 3, respectively. As shown, the percentages of *Questioning* and *Doubting* are relatively higher than the others. Figure 14b shows similar information for Huang.

Table 5 Scenarios of the three activities on Apr. 23, 2019

Activity no	Descriptions
1	Lin and Huang each worn their own wireless headset while they were watching the game move by move to give a comment through selecting "Black has an obvious advantage," "Black has a possible advantage," "White has an obvious advantage," "White has a possible advantage," or "both are in an uncertain situation." The game was played by Huang as White against FAIR Darkforest as Black on Dec. 19, 2018 and finally Black won the game.
2	Lin and Huang each worn their own wireless headset to give comments on the game while they were listening Chang to sing "Well-intentioned (用心良苦)" released in 1993.
	Song "Well-intentioned" is about older 10 years old than Lin and Huang.
	Video Link: https://youtu.be/kJny2aT-y3E
3	Lin and Huang each worn their own wireless headset to listen Chang to sing "Clown (小丑)" released in 1980. That is, they did not give comments on the game when they listened to "Clown".
	Song "Clown" is about older 20 years old than Lin and Huang. Lin and Huang have never listened to song "Clown" before.
	Video Link: https://youtu.be/cKNIWLbDA-w

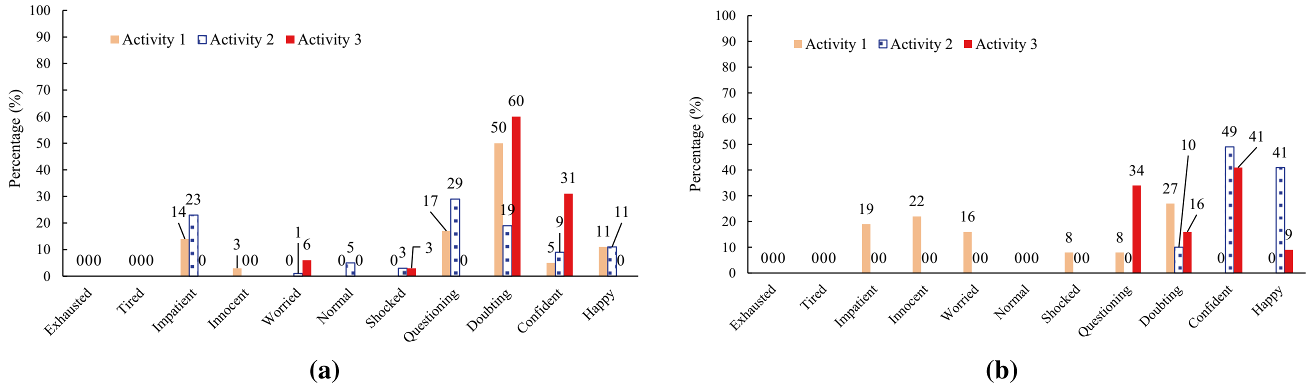


Fig. 14 Bar chart showing the percentage by eleven inferred feelings for **a** Lin and **b** Huang

Notably, the total percentage of *Impatient*, *Innocent*, and *worried* felt by Huang (57%) in activity 1 is higher than that of Lin (17%). This is because Lin's Go level is 7D, which is higher than the FAIR Darkforest AI bot with only 1000 simulations; however, Huang's is 2D, which is lower than the FAIR Darkforest AI bot. Hence, Huang needed to spend much more effort deciding on his comment for each move. Lin and Huang are both more familiar with the song "*Well-intentioned* (用心良苦)" than the song "*Clown* (小丑)." When they first listened to *Clown*, they tried to understand what Chang was singing and the mood of the song, which may have caused the total percentage of *Questioning* and *Doubting* in activity 3 to be higher than in activity 2.

Figure 15 shows Lin and Huang's changes in mood, inferred by the proposed method over time. One-time unit for activity 1 is 30 s; therefore, the total time Lin and Huang spent commenting on the game was approximately 18–20 min. One-time unit for activities 2 and 3 was 1 s; thus, the total time Lin and Huang spent listening Chang to sing the songs "*Well-intentioned* (用心良苦)" and "*Clown* (小丑)" was approximately 75 s and 64 s, respectively. Figure 15 shows that they both experienced a sharp change in feelings when they carried out activity 1 (dashed line) and focused on thinking during the second half of the time unit when they carried out activity 3 (solid line). Figure 15b shows that Huang carried out activity 2 (dotted line) with concentration and happiness. We then obtained the average of all the inferred feelings. Lin and Huang's main feelings when carrying out activities 1-3 were ("*I am focusing now*," "*I am focusing now*," and "*I am thinking*") and ("*Cheer up*," "*Wonderful*," and "*I have confidence in myself*"), respectively.

5.3 Applications to mathematical learning

Intelligent robot teachers learning mathematics alongside elementary-school students have been introduced into the classroom in Taiwan since 2018. We designed one class as an experimental group and another as a control group. In the learning mathematics model, we divided the experimental group into different groups based on their competence in math, thereby applying heterogeneous grouping in the classroom. Each group was accompanied by a robot Palro to co-learn the mathematical concepts of "*number line*" and "*groups of numbers*" through the developed game-playing teaching platform. The human teacher first reviewed the

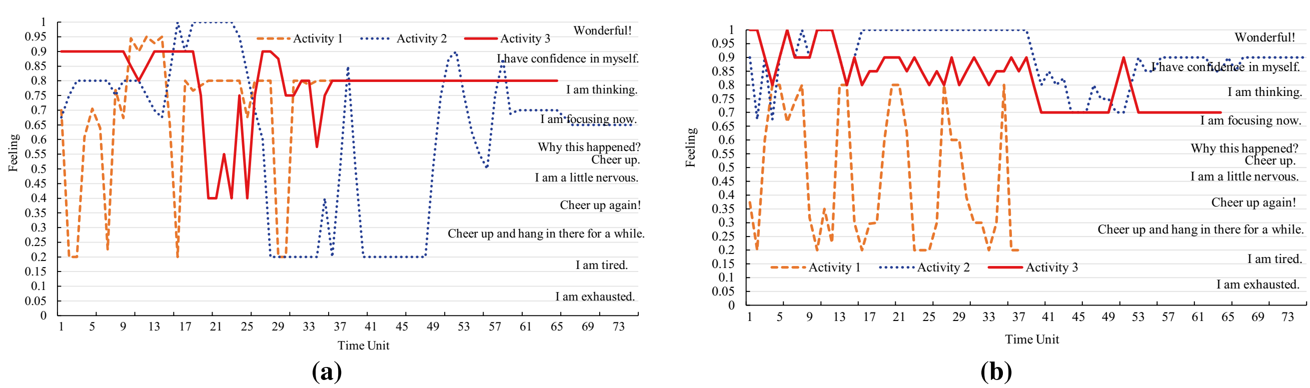


Fig. 15 Line chart of the inferred feeling vs. time unit for **a** Lin and **b** Huang

previous knowledge possessed by students regarding mathematical challenges they would later encounter. The students then used handheld devices, such as iPads, to take on these challenges by cooperating with robot Palro. If they passed a challenge, it meant they understood this mathematical concept. In this playing-and-learning model, robot Palro cheered when a challenge was passed. At the same time, robot Palro with an *intelligent agent* helped students overcome this challenge by providing different levels of hints. Finally, the human teacher assigned homework to each group to test whether students really understood these mathematical concepts. In such an interactive classroom, all children cannot wait for the next class. Students in the control group did not join the game-playing teaching class and were taught mathematics in the traditional way by the human teacher. Figure 16 shows the performance progress curve for students in experimental and control groups. Values marked with a star (*), circle (o), and cross (+) on the top denote students' estimated ability in the pretest, immediate posttest, and delayed posttest, respectively. Figure 16 shows that the slope of low- and medium-ability students in the experimental group is the steepest, which showed that these students had made the most obvious learning progress. By contrast, students in the control group had not made any obvious progress.

5.4 Applications to english language learning

For English learning, we introduced teacher robots into one 3-grade class (grade 3A), one 4-grade class (grade 4A), one 5-grade class (grade 5A), and three 6-grade classes (grade 6A, grade 6B, and grade 6C) at Gueinan elementary school in Taiwan from March to May in 2019. We cooperated with BillKuo Languages & Technology Co., Ltd. to create English teaching materials in the form of e-Books and then integrated these with the robots Palro, Zenbo, and Zenbo Junior. Additionally, we include listening test items, that is, questions, in the constructed adaptive challenge

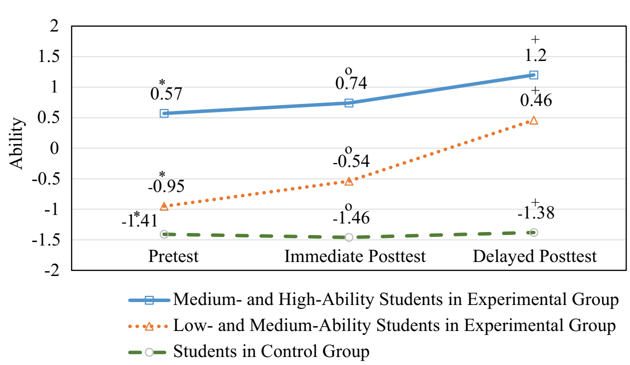


Fig. 16 Performance progress curve for experimental group and control group

platform, Android app, and iOS app. The English words and sentences of each book were also incorporated into the developed speaking test Android app based on the concepts of the flashcard. Our model of the robot English teachers was as follows: The human teacher helped categorize students based on their English competence, for example, (1) grade 3A and grade 4A: There were five groups and all were heterogeneous; (2) grade 5A: There were four groups including group 1 (advanced), groups 2 and 3 (basic), and group 4 (remedial); (3) grade 6A, grade 6B, and grade 6C: There were five groups, and all were heterogeneous except for remedial group 5. The English robot teachers joined the English class on March 12, 2019, and co-learned with the students biweekly. However, the English robot teachers did not join the grade-5A English class until April 30, 2019. Table 6 shows the learning content for each co-learning English class based on the English competence of students. We included the contents of the next one or two books in the test paper each time. For example, the challenge contents of the Grade-6 students on March 26 were Books 1 to 3 of Level 7 but the ones on April 9 were Books 1 to 4 of Level 7.

Our scenario for the English co-learning class with students was as follows: At the beginning of the class, robot teachers first performed a dance to attract students' attention and motivate learning. The students then surfed the adaptive challenge platform to execute the listening challenge as many times as they could. They were able to view all questions they had attempted until they had finished the challenge. Third, robot teachers learned with the students by reading aloud the English vocabulary and sentences in e-Books or embedded teaching materials in the robot. The students could also touch the screens of robot teachers to interact with theme while learning. To refine the model, we collected students' feedback on this new-style English teaching curriculum through an online questionnaire. Finally, robot teachers performed once again and the class was left feeling happy. Figure 17a shows the rate of correct answers in each English class for the six classes involved. Figure 17a shows that the lowest correct rate was obtained on the pretest on March 12; however, the most obvious progress had taken place on the immediate posttest on March 26. This is because the human teacher had helped students to review their answers in the English class on March 19. After March 26, the correct rate sometimes decreased and sometimes increased. The varying content of each challenge may be the reason for this result. Nevertheless, the final correct answer rate on May 14 was higher than the first one on March 12. Figure 17b shows the correct answer rate given by the remedial group for three grade-6 classes. The trend lines in Fig. 17b indicate that low-performing students exhibited an upward trend in their learning performance.

Figure 18 shows a simple stacked bar graph comparing the total number of items answered correctly and the total

Table 6 Learning contents on each co-learning English class

Grade	Date	Challenge range	Grade	Date	Challenge range
3	03/12/2019	BillKuo Books 1 to 6 of Level 1	4	03/12/2019	BillKuo Books 1 to 6 of Level 1
	03/26/2019	BillKuo Books 1 to 6 of Level 1		03/26/2019	BillKuo Books 1 to 6 of Level 1
	04/09/2019	BillKuo Books 1 to 6 of Level 1 and BillKuo Books 1 to 2 of Level 2		04/09/2019	BillKuo Books 1 to 6 of Level 1 and BillKuo Books 1 to 3 of Level 3
	04/30/2019	BillKuo Books 1 to 6 of Level 1 and BillKuo Books 1 to 4 of Level 2		04/30/2019	BillKuo Books 1 to 6 of Level 1 and BillKuo Books 1 to 5 of Level 3
	05/14/2019	BillKuo Books 1 to 6 of Level 1 and BillKuo Books 1 to 6 of Level 2		05/14/2019	BillKuo Books 1 to 6 of Level 1 and BillKuo Books 1 to 6 of Level 2
5	03/12/2019	None	6	03/12/2019	BillKuo Books 1 to 6 of Level 7
	03/26/2019	None		03/26/2019	BillKuo Books 1 to 3 of Level 7
	04/09/2019	None		04/09/2019	BillKuo Books 1 to 4 of Level 7
	04/30/2019	BillKuo Books 1 to 5 of Level 7		04/30/2019	BillKuo Books 1 to 5 of Level 7
	05/14/2019	BillKuo Books 1 to 6 of Level 7		05/14/2019	BillKuo Books 1 to 6 of Level 7

The main learning contents of grade-3A and grade-4A students are BillKuo Levels 1 to 2

The main learning contents of grade-5A and grade-6 students are BillKuo Level 7

The main learning contents of grade-5A and grade-6 remedial group are BillKuo Levels 1 to 2

number of items answered incorrectly. The dashed line shows the total number of items attempted. For example, the grade-3A students attempted 6477 items, of which 4907 were correctly answered and 1570 incorrectly answered. Additionally, a secondary axis is included in Fig. 18 to plot the average correct answer rate in a solid line. This shows that the grade-3A students have almost the same strength in English as grade-4A students and that grade-6B students exhibit better competence in English than the other two grade-6 classes. Although grade-5 students only joined twice, their competence in English was higher than the three grade-6 classes. The feedback received and the data collected showed that the robot teachers were welcomed by most of the students, irrespective of whichever grade they were in.

5.5 Opinions and comments for the robot teacher from Lu-An Lin

Lu-An Lin is a high-performing first-grade junior high-school student. She experienced the constructed OGD cloud platform for Go learning and the adaptive challenge system for mathematical and English learning in 2018 and in 2019. The following is her opinions and comments for the robot teacher: (1) Go learning: "For me, the experimental test was an exciting and refreshing experience. When I was doing the Go testing, the Mindo, i.e., a wireless headset, on my head could detect the brainwaves, read them, or precisely to say, translate them into certain meaningful information, such as the level of fatigue and how I felt about the test." Lin says "Even the AI Go learning support system could provide me with suggestions, most of which amazed me and helped me turn the table around. (2) Mathematical learning: The math test wasn't as difficult as I supposed it should be. Still, I made some errors. Although the questions were not that challenging, there were two or three questions worth thinking for a while. The test comprised the questions of basic, intermediate, high-intermediate, and advanced levels. The AI math learning support system can not only help the low-performing students work out basic questions but also challenge the high-performing students. Indeed, it is an adaptive learning support system." (3) English learning: "To be frank, before the test I took it lightly. That wasn't going to be a hard task. But when I finished it, I realized there was something I really didn't know (e.g., Do tadpoles grow front legs or back legs first?). So I consulted the science textbook, trying to get every detail in the book. Afterwards, I did the test again and I got higher grades. Additionally, in the listening section the speaker spoke quickly and thus it wasn't that easy to answer all the questions correctly. I had to listen carefully; I had to pay attention to such grammatical details as tense and regular/irregular plural nouns. Doubtless, the AI English learning support system is instrumental to English learners."

6 Conclusion and discussions on future education

An intelligent agent for real-world applications in the field of robotic edutainment and humanized co-learning was presented in this paper. Three main applications were focused upon: (1) Go game: Through playing games between humans and the machines, the proposed approach combines the BCI and the robot with learning Go and listening to music for entertainment. We analyzed collected brainwaves to generate five real-time physiological indices to illustrate variances in

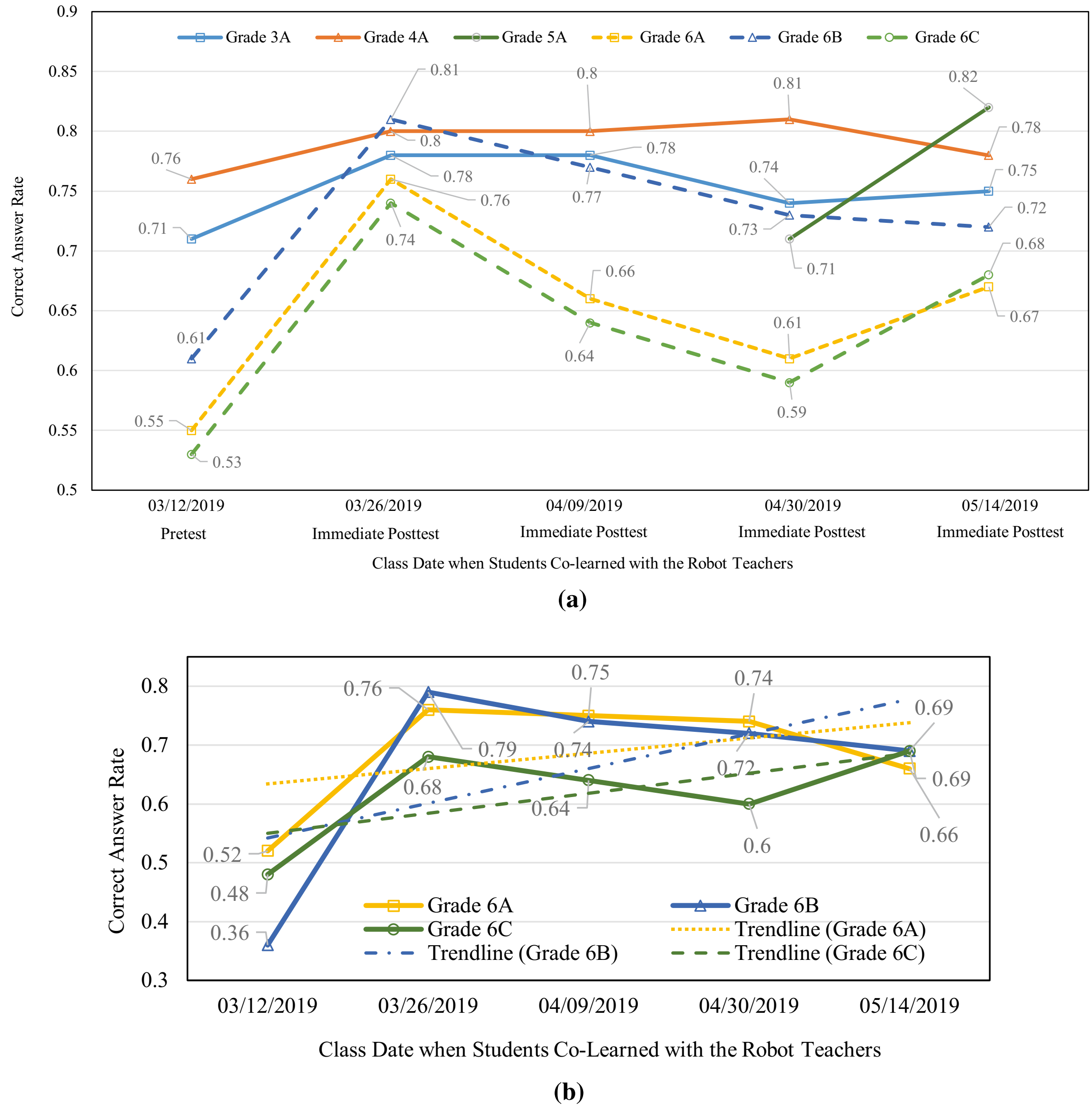


Fig. 17 Correct answer rate of **a** six classes and **b** remedial group of three grade-6 classes on five English classes

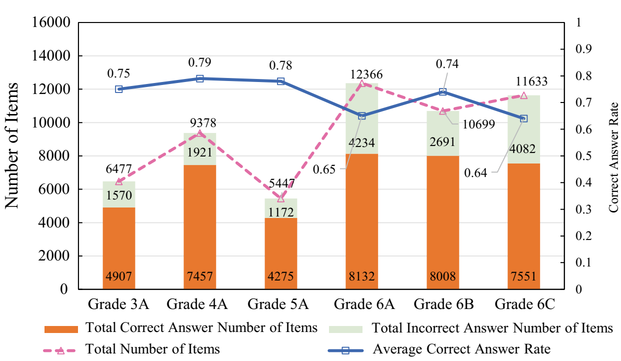


Fig. 18 The total correct/incorrect answer number of items and average correct answer rate for six classes

the win rate between the human Go player and his/her opponent (a man/woman or a machine). (2) Listening to music for entertainment: The real-time feelings of a man/woman who is singing/listening to a song/giving comments on the Go game were inferred according to the developed TSK-based fuzzy inference mechanism. Moreover, we combined this with the robot Zenbo to reflect the human's feelings on the face of the robot Zenbo through the SDK package developed by ASUSTek Computer Inc., Taiwan. (3) Mathematical and English language learning: Through playing games, we introduced robot teachers to elementary schools in Taiwan in 2018 and 2019. The robot teachers were welcomed by most of the students. The experimental results showed that low- and medium-ability students had made the most progress in mathematical learning. Low-performing students had also re-built their confidence and interest in learning English.

The main applications in this paper were for Go game, listening to music for entertainment, mathematical, and English language learning. However, future research can certainly be extended to other learning domains. We therefore propose the following to improve the performance of the approach adopted in this research: (1) adopt other humanized inference models and machine learning models to generate more comparisons and analysis for intelligent agents, (2) try using different BCI devices to collect more brainwaves to generate more accurate physiological indices, (3) develop different types of intelligent agents to enable robots to co-learn with students in the classroom, and (4) distribute the robot-teaching model to other teaching and learning fields to collect useful data for a more precise machine learning mechanism that will contribute to a future human–robot co-learning model.

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References

Asus.com, Zenbo (2019) https://zenbo.asus.com/. Accessed 21 May 2019

Brain Rhythm Inc. (2018) http://www.bri.com.tw/product_br8plus.html. Accessed 21 May 2019

Chuang CH, Huang CS, Ko LW, Lin CT (2015) An EEG-based perceptual function integration network for application to drowsy driving. Knowl Based Syst 80:143–152

Embretson SE, Reise SP (2000) Item Response Theory. Taylor & Francis

IEEE CIS (2016) 1855-2016-IEEE standard for fuzzy markup language. https://ieeexplore.ieee.org/document/7479441. Accessed 21 May 2019

Ko LW, Komarov O, Hairston WD, Jung TP, Lin CT (2017) Sustained attention in real classroom settings: an EEG study. Front Hum Neurosci 11:388

Lee CS, Wang MH, Ko LW, Kubota N, Lin LA, Kitaoka S, Wang YT, Su SF (2018a) Human and smart machine co-learning: brain–computer interaction at the 2017 IEEE International Conference on Systems, Man, and Cybernetics. IEEE Syst Man Cybern Magz 4(2):6–13

Lee CS, Wang MH, Wang CS, Teytaud O, Liu JL, Lin SW, Hung PH (2018b) PSO-based fuzzy markup language for student learning performance evaluation and educational application. IEEE Trans Fuzzy Syst 26(3):2618–2633

Lee CS, Wang MH, Huang TX., Chen LC, Huang YC, Yang SC, Tseng CH, Hung PH, Kubota N (2018c) Ontology-based fuzzy markup language agent for student and robot co-learning. In: 2018 World Congress on computational intelligence (IEEE WCCI 2018), Rio de Janeiro, Brazil, pp 8–13

Lee CS, Wang MH, Chen LC, Nojima Y, Huang TX, Woo J, Kubota N, Sato-Shimokawara E, Yamaguchi T (2019a) A GFML-based robot agent for human and machine cooperative learning on game of Go. In: 2019 IEEE Congress on Evolutionary Computation (IEEE CEC 2019), Wellington, New Zealand, pp 10–13

Lee CS, Wang MH, Ko LW, Tsai BY, Yang SC, Lin LA, Lee YH, Ohashi O, Kubota N, Shuo N (2019b) PFML-based semantic BCI agent for game of Go learning and prediction. https://arxiv.org/abs/1901.02999

Lin CT, Chuang CH, Huang CS, Tsai SF, Lu SW, Chen YH, Ko LW (2014) Wireless and wearable EEG system for evaluating driver vigilance. IEEE Trans Biomed Circ Syst 8(2):165–175

Mayfield Brain & Spine (2018) Anatomy of the brain. http://www.mayfieldclinic.com/PE-AnatBrain.htm. Accessed 21 May 2019

Rogers C (2017) Me, myself and AI: are robot teachers in our future. https://edtechnology.co.uk/Article/me-myself-and-ai-are-robot-teachers-in-our-future/. Accessed 21 May 2019

Sanders L (2018) Brain waves may focus attention and keep information flowing. https://www.sciencenews.org/article/brain-waves-may-focus-attention-and-keep-information-flowing. Accessed 21 May 2019

Silver D, Schrittwieser J, Simonyan K, Antonoglou I, Huang A, Guez A, Hubert T, Baker L, Lai M, Bolton A, Chen Y, Lillicrap T, Fan H, Sifre L, Driessche G, van den Graepel T, Hassabis D (2017) Mastering the game of go without human knowledge. Master 550:354–359

Stemberg RJ, Grigorenko EL (2001) Practical intelligence and the principal. https://eric.ed.gov/?id=ED483040 (2001)

Takase N, Takeda T, Botzheim J, Kubota N (2015) Interaction, communication, and experience design in robot edutainment. In: 6th International Conference on Advanced Mechatronics (ICAM2015), Waseda University, Tokyo, Japan, December 5–8, pp 159–160

Tian Y, Zhu Y (2016) Better computer Go player with neural network and long-term prediction. https://arxiv.org/abs/1511.06410

Tian Y, Ma J, Gong Q, Sengupta S, Chen Z, Pinkerton J, Zitnick CL (2019) ELF OpengGo: An analysis and open reimplementation of AlphaZero. https://arxiv.org/abs/1902.04522

Tiwari N, Edla DR, Dodia S, Bablani A (2018) Brain computer interface: a comprehensive survey. Biol Inspir Cognit Architect 26:118–129

Wang MH, Wang CS, Lee CS, Lin SW, Hung PH (2014) Type-2 fuzzy set construction and application for adaptive student assessment system. 2014 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE 2014), Beijing, July 6-11

Yorita A, Kubota N (2011) Mutual learning for second language education and language acquisition of robots. In: Proceedings of the 6th international symposium on autonomous minirobots for research and edutainment, S32, Bielefeld, Germany, May 23-25

Yorita A, Hashimoto T, Kobayashi H, Kubota N (2009) Remote education based on robot edutainment. In: Proceedings of the 5th international symposium on autonomous minirobots for research and edutainment, Incheon, Korea, August 16–18, pp 204–213