Computers and Education: Artificial Intelligence 2 (2021) 100012

Contents lists available at ScienceDirect

Computers and Education: Artificial Intelligence

journal homepage: www.elsevier.com/locate/caeai

Behavioral-pattern exploration and development of an instructional tool for young children to learn AI

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ARTICLE INFO

Keywords:
Artificial intelligence education
Interdisciplinary instructional tool
Behavioral patterns

ABSTRACT

This study aimed at developing an instructional tool for the artificial intelligence education of young students, and used learning analytics to identify the sequential learning behavioral patterns of students during the process of learning with the instructional tool. The instructional experiment took 9 weeks. The first stage of the course was 5 weeks spent on individual learning of MIT App Inventor and Personal Image Classifier. The second stage was 4 weeks spent on cooperative learning to make a robot car and play a computational thinking board game. In the second stage, the students worked in pairs to make the robot car. Finally, they played the computational thinking board game with the personal image classification application they developed in the first stage and the robot car they made in the second stage. The innovative studies found meaningful behavioral patterns when the young students learned the application of artificial intelligence with the instructional tool developed and proposed in the study.

1. Introduction

In response to the development and demand for artificial intelligence (AI) technology in society in recent years, and the related knowledge on which the technology field of 12-year compulsory education focuses, this research aimed to design a set of innovative AI teaching materials. Elementary school high-grade students were recruited as the research subjects, and AI, science, technology, engineering and mathematics (STEM) education, were combined with computational thinking (CT) to explore the implementation results of the teaching material and students' learning portfolios.

With the rapid development of technology, many AI applications can be seen in our daily life. Also, many problems can be solved via AI. Therefore, in addition to knowing how to use related products and services appropriately, learning how to make and apply AI has become more important (Sakulkueakulsuk et al., 2018). The Ministry of Education of Taiwan proposed the "AI teaching & AI education-the overall education strategy of artificial intelligence and emerging technology" in 2019. It is based on the information technology of 12-year compulsory education, and promotes emerging technology and AI education from elementary school to university. For elementary and junior high schools, it emphasizes CT as the foundation, and aims to cultivate students' interest and correct concepts. According to past studies, students at higher educational levels generally have basic programming skills, so the current AI education usually targets students in elementary school (Williams et al., 2019).

The information technology of 12-year compulsory education belongs to the field of science and technology, which emphasizes the cultivation of students' knowledge in "design thinking" and "computational thinking," and strengthens students' knowledge integration capabilities of STEM through hands-on practice and interdisciplinary courses. Since the field of technology and information covers a wide range of content and changes quickly, it causes increasing difficulty and complexity in the interdisciplinary nature of curriculum design, which is a challenge for teachers and researchers with different disciplinary backgrounds (Hwang et al., 2020a,b; Yang et al., 2020).

The teaching materials developed in this study aimed to arouse students' learning interests and help them understand the basic concepts of AI integrated with interdisciplinary knowledge. The development projects included the teaching materials for the whole course and self-developed modular teaching aids. In addition, the case study method was adopted. The learning process data before, during, and after the class were collected to explore the meaningful learning behavior patterns of the participants and to ensure the feasibility of the teaching materials.

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https://doi.org/10.1016/j.caeai.2021.100012
Received 1 January 2021; Received in revised form 26 January 2021; Accepted 26 January 2021
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2. Literature review

2.1. AI education

AI-related technologies such as smart appliances, Google, Siri, and AI computer games have become common in our daily life. Most people know about the existence of these services and products, but only a few understand the technology and principles behind them. Therefore, scholars have stated that the education of AI knowledge and technology should be emphasized. For example, Burgsteiner et al. (2016) believed that, with the development of AI and computer science, the younger generation should be equipped with related knowledge and technologies (such as basic concepts of algorithms, data structures, and programs).

AI technology and knowledge fall within the field of engineering and science, which aims to construct human intelligence. The research scope is wide, such as planning, decision-making, visual processing, machine learning, knowledge representation, and reasoning through computers, so that it is not the development of a single subject but rather interdisciplinary research (Russell et al., 2010). Research also shows that the development of technology in recent years has promoted the upgrading of computer software and hardware, allowing many teachers to conduct courses of AI knowledge and applications via computers. However, due to its complexity, the teaching subjects were mostly students in higher education and those with programming skills (Williams et al., 2019). Besides, its various content also troubles many teachers when they design introductory courses, as introductory courses include many topics which are seemingly unrelated to specific AI technology teaching (Markov et al., 2005). Shamma indicated that introductory courses often require students to read classic theories and articles to understand basic concepts, but many technologies are difficult to explain only through textbooks (Shamma and Turner, 1998). To solve these problems, many educators have tried to transform such courses from theoretical explanation to practical application, such as making robots with algorithm and machine learning applications (Burgsteiner et al., 2016; Kumar, 2001), or using course content developed by mobile applications to make students think about and practice different technologies of machine learning (Zhu, 2019).

With the increase in children's contact with emerging technology products and even learning through AI systems, children's AI education has gradually been emphasized. For example, Williams et al. (2019) designed related robot teaching materials, hoping to cultivate children aged from 4 to 7 to have the correct concept of AI technology and to build an appropriate relationship. Some scholars also stated that, in addition to focusing on the convenience and applications of AI technology, safety and privacy were also an important issue. For example, the research by Druga et al. (2018) pointed out that children seemed to trust smart robots too much (telling the robots their personal information). Due to the increasing demand for children's AI education, many online platforms overseas have created development environments integrated with programming blocks, such as Machine Learning for Kids, eCraft2Learn, Cognimates, etc., providing many AI experiences and learning activities for children, so that users could try to make a personalized AI project to understand its applications. As for the teaching strategy (Fig. 1) for emerging technology proposed by Taiwan's Ministry of Education in recent years, the importance and future of AI education from elementary schools to colleges were also mentioned. For the stage of primary and secondary schools, it is hoped to combine the technology course syllabus of 12-year compulsory education with the overall development project of technology education.

Among all AI technologies, machine learning (ML) is one of the important technologies that has created rapid AI development in the past 2 decades. It mainly explores how computer systems can achieve self-improvement through the learning experience, and summarizes all of the principles in the learning systems. Many practical technologies for commercial purposes, such as image recognition, speech recognition, language processing, and self-driving, are all applications of machine learning in our life (Jordan and Mitchell, 2015). For course design that shifts to application, many educators have also used image recognition, voice assistants, and other technical experiences and construction as the starting point for guiding students to learn AI (Van Brummelen, 2019).

2.2. Computational thinking

Computational thinking (CT) is a "method which uses basic computer science to solve problems, design systems, and understand human behavior, and is a basic ability everyone should be equipped with, rather than being limited to engineers. Also, it is not a set of procedures or a skill that needs to be learned by memorization, but a thinking strategy that can be applied to various fields and daily life (Wing, 2006). The process (which varies slightly due to different applications and fields for different types of research) usually includes decomposing and defining problems, logically organizing and analyzing data, abstracting, automating solutions through algorithms (a series of steps), analyzing and selecting possible solutions, and applying the solution to other problems. Since the following abilities and attitudes play a key role in CT, learners using CT could enhance their confidence in handling complex things, their

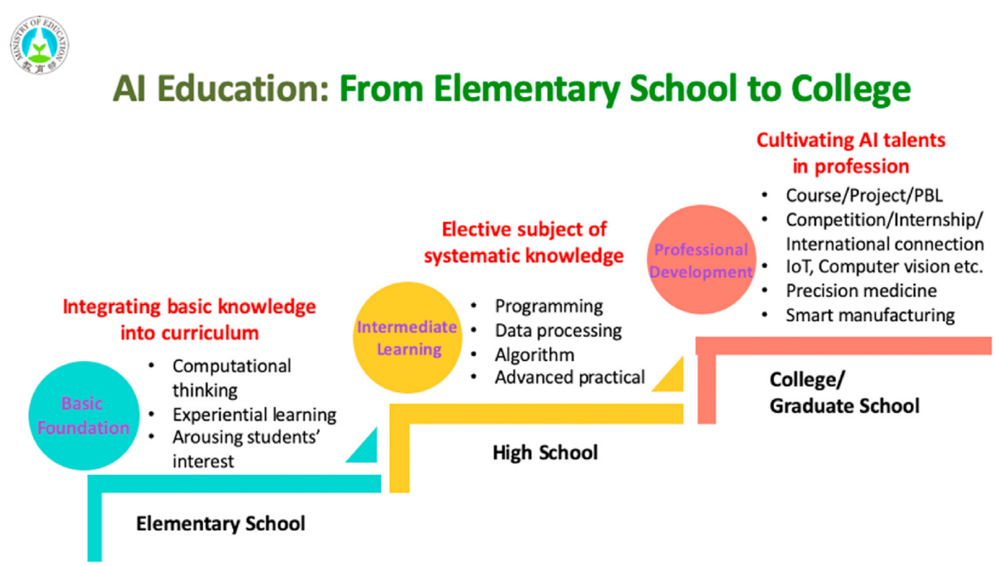


Fig. 1. Key strategies of AI education at different stages.

persistence in solving difficult problems, their tolerance of uncertainty, their ability to deal with open problems, and their ability to achieve common goals through communication and collaboration with others (Barr et al., 2011).

CT can be applied in various fields, including AI technology. Zeng (2013) proposed the conceptualization of "AI thinking" for the recent application development trend of AI technology in various fields, and believed that AI thinking and CT had many similarities, but AI was more advanced. Also, it is hard for students to live without computers and related products nowadays, and they might be engaged in related industries in the future. Therefore, some educators believe that it would be too late to teach related concepts in college. Instead, teachers have to start cultivating students' CT competence from elementary school or even kindergarten (K-12) (Barr and Stephenson, 2011). The science and technology field of Taiwan's 12-year compulsory education also designated CT as the core course of the information technology courses, hoping to cultivate students' ability to use information technology tools to solve problems, cooperate, interact, and communicate with others. As mentioned in this chapter, cultivating CT abilities as the basis for learning AI knowledge and skills in the future is Taiwan's education strategy for elementary and middle school students.

CT ability training courses for elementary and middle school students have been implemented in many countries, and were integrated into various subjects, combined with various teaching methods and teaching materials, but not limited to programming and solving computer-related problems. Examples include training students' CT abilities, teamwork, and project management skills through Lego robots (Chaudhary et al., 2016), social studies classes to explore children's lives in ancient Rome and modern children's life, music classes that combine the concepts of scale and pitch with the Scratch platform (Barr et al., 2011), training children's CT ability through board games and cooperation strategies, and so on (Apostolellis et al., 2014; Berland and Lee, 2011), all of which can be used as references for this research.

2.3. Trends of science, technology, engineering and mathematics (STEM) education

STEM represents the four fields of science, technology, engineering, and mathematics, and the training of related talents benefits the development of technology and economy. STEM education is now mostly used to describe the interdisciplinary courses including the four fields, emphasizing that students should learn knowledge in the four fields and apply the knowledge acquired to solve problems in their daily life, including the process of inquiry, design, and analysis (Watson and Watson, 2013). True STEM education should let students understand how things work and improve their operation of technology. The engineering component involves problem-solving and innovation capabilities, so introducing engineering concepts in class is also very important (Bybee, 2010). The scholars noted that a maker activity, which is a playful exploration of tools and materials for meaningful hands-on creation, provided an impactful entry point for the students in science, technology, engineering, and mathematics (STEM) (Keune et al., 2019).

The technology field of Taiwan's 12-year compulsory education includes two parts: life technology and information technology, and it also mentions the teaching concept of STEM education. Through the establishment of the technology field, students can integrate the knowledge of science, technology, engineering, and mathematics through hands-on practice and interdisciplinary curricula (the course syllabus of 12-year compulsory education). As mentioned in the previous paragraph, AI technology is interdisciplinary research. In addition to science and engineering, the logic and calculations behind AI comprise many mathematical concepts, finally becoming a practical technology to help users solve problems (Russell et al., 2010). That is, AI technology covers the four major fields mentioned in STEM. Therefore, in recent years, educators have combined AI topics with technologies in STEM education, using the characteristics of STEM education to have students learn the application of AI technology (Sakulkueakulsuk et al., 2018). Also, some scholars believe that relevant professions in the STEM field should learn AI knowledge. Through understanding the thinking mode, they could integrate knowledge and humanistic ideas into various fields, transform it into an understandable input form of AI technology, and get output to help them solve the problems in their fields (How and Hung, 2019). To sum up, the variety of AI technology is in many ways consistent with the spirit of STEM education, and AI education is a part of STEM education.

Many studies have proposed effective teaching directions and curriculum design principles for STEM education. For example, Kennedy and Odell (2014) emphasized the need to promote the process of students' inquiry, and teachers should guide students to discover problems and observe. Park and Ko (2012) stated that the course content should include practice and reality, emphasizing the linking of life issues to science and engineering to stimulate students to systematically predict future development. The teaching materials suitable for learners, hands-on practice, thinking, and cooperative learning can all be used as a reference for AI teaching materials in this research. The purpose of this study is to provide game-based learning tools and materials for young students to achieve meaningful learning with the hand-on activities.

3. Methods

3.1. Participants

There were eight subjects (students A to H) who took part in this study, all of whom were gifted students in the fifth grade of a public elementary school in Taipei City. Students A to G are boys and student H is a girl. The first 5 weeks of the course were not conducted in groups, while the last 4 weeks were conducted in pairs.

3.2. Measuring tools

This study collected qualitative and quantitative data from each student during the teaching experiment. The students took the learning effectiveness tests after finishing the course. The whole course was recorded for behavior sequential analysis with the codes of Table 1 to understand the students' learning behavior. The learning behaviors and their operational actions were both recorded by video and screenshots.

The learning effectiveness test comprised 20 multiple-choice questions about the concepts and knowledge taught in the course. For example, item 18 asks, "*If people train the three categories of fruits which are orange, apple and watermelon in PIC, which one is an impossible answer when you test the trained model with the image of a guava? (A) Apple (B) Watermelon (C) Guava (D) Orange.*" The test was used to understand the students' learning and understanding of the related knowledge after completing the course developed in this study.

3.3. Experimental procedure

Fig. 2 shows the process of the research. One week before the experiment, an investigation was conducted to know the students' condition and level related to the course. Then the 9-week course started, during which every student's learning behaviors were recorded. Since the teaching materials developed for this study were integrated applications of innovative content, design-based research was adopted. After each class, the participating experimenters (1 teacher, 3 teaching assistants, and 1 homeroom teacher of the gifted class) had a reflective discussion. They then revised the course plan based on the discussion results and implemented it in the next class. A learning effectiveness test was conducted 1 week after the course ended.

3.4. Development of the instructional materials and tools: AI 2 Robot City

The purpose of designing the teaching materials of this study was to promote AI education and cultivate the required technology knowledge,

Table 1
The schema of behaviors.

Code	Meaning	Example
TH	Being taught by teachers	Listen to teacher talking about the course Guided by teacher
PP	Talking to peers about the course content	Have a discussion with a peer about the course content (but not asking for help) Teach a peer what to do
AT	Ask teachers for help	Ask the teacher a question directly
AP	Ask peers for help	Ask a peer what to do in the next step
P	Operating teaching materials individually	Look for some information in the pdf file on the laptop Code for MIT App Inventor or micro:bit Write the worksheets Assemble the robot car
TE	Testing and execution	Test the app on the cellphone Test the program on micro:bit Execute the instruction of the robot car on the map
PO	Expressing individual opinions to unspecified people	Speak out what he/she observes or feels during the hands-on activity
N	Doing something irrelevant to the course content	Chat with peers Watch something that has nothing to do with the course on the laptop
S	Setting and inputting data to train a model	Set the labels of the model Adjust some hyperparameters of the model
TD	Collecting the training data	Take pictures of direction cards
AM	Analyzing the result of the model	Observe the recognition results of the training model Compare the pictures of testing data
SR	Simulating the result of execution	Use gestures, sentences, or body language to simulate the route of the robot car before actually moving it
O	Observing the situation without actual acts	Focus on the movement of another team's robot car Use sentences or gestures to observe how many material cards are left on the map
F	Correcting or fixing the operation	Take the robot car apart after finding wrong assembly

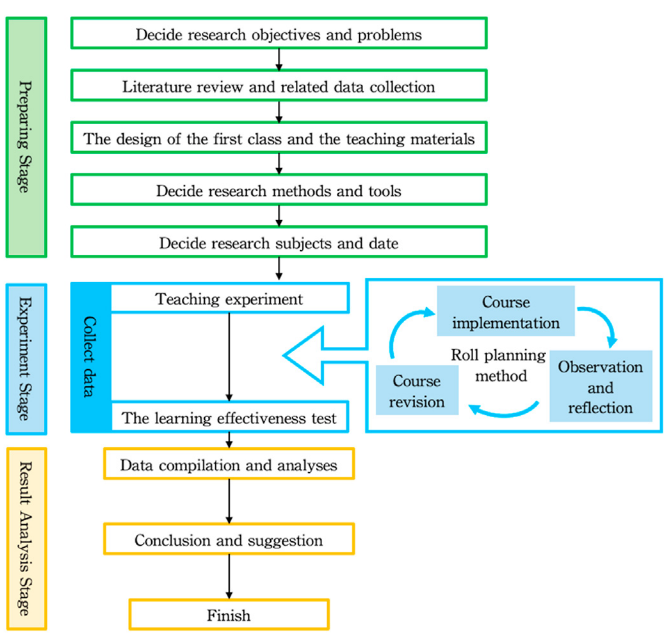


Fig. 2. Research flow chart.

which integrated three core concepts, namely computational thinking, AI education, and STEM education. This instructional tool cultivated the students to develop the image recognition app to read the cards of the boardgame, so as to control the robot cars for competing the computational thinking board game. The teaching material and instructional tools developed by this study are called "AI 2 Robot City." This version was modified from the unplugged educational board game, Robot City (Kuo & Hsu, 2020), and allowed the players to control the robot car they made by recognizing the direction cards through the mobile app. Fig. 3 shows the framework of its system, including software, hardware, and a game mechanism.

The students in the study had to learn to develop a smart phone app with MIT App Inventor to recognize control cards in order and convert them into the car's movements. The interface of the image recognition application is shown as Fig. 4.

In addition, the app had to provide the players with a loop function to help them familiarize themselves with the repetition concepts while using the app to play the board game, shown as Fig. 5.

MIT App Inventor has added functions related to machine learning, and packaged the complex processes into modules, making users focus on how to apply machine learning technology to solve specific problems of individuals or groups (Tang, 2019; Van Brummelen, 2019; Zhu, 2019). This research employed the Personal Image Classifier (PIC) webtool, which simplifies the training process of image recognition models, allowing users to set the model labels and providing training data to train a personal image recognition model without coding. Fig. 6 was the first version of PIC. Currently, the second version has been deployed. The model can be applied to the self-designed applications.

Hardware: STEM robot car and the map of the CT board game.

To achieve "learning by doing," the structure of the robot car was drawn and then made with a laser-cutting machine. The components of the robot-car are shown in Fig. 7. This study provided the students with the components to create their own robot-car.

The robot car can be controlled through Bluetooth, which allows practice with the Internet of Things. The main control board used in this study is the micro:bit which is a micro-controller for children developed by the British Broadcasting Corporation. The firmware inside the micro-controller can be written by the students with MakeCode. The micro:bit carries the Bluetooth function for receiving signals transmitted by mobile apps.

Fig. 8 not only presents the control board used but also the robot-car created by the students. Therefore, the students could learn the connection between the program and the hardware, which would strengthen their mechatronic integration abilities.

Finally, students could control their cars to move on the map shown as Fig. 9, to complete the game tasks.

3.5. Game mechanism: gameplay of Robot City

Robot City is the unplugged version of a structured programming board game. Players can practice their computational thinking during the game: decomposition, pattern recognition, abstraction, and algorithms, cultivating logical thinking and problem solving. The instructional tool named "AI 2 Robot City" proposed in this study was the plugged and new version. The basic gameplay is as follows:

Step 1

Arrange the game venue: The complete game venue is composed of four small maps, which can be arranged freely to increase the game variability and prevent players from remembering specific solutions.

Step2

Before the game, each team should have three control cards (forward, left-turn, and right-turn), a robot car, and a mobile phone with the image recognition app installed.

Step 3

Draw task cards and place them on the table. The players can only draw new cards after the task cards on the table are all completed. This limitation makes the players think about how to get higher scores in their condition.

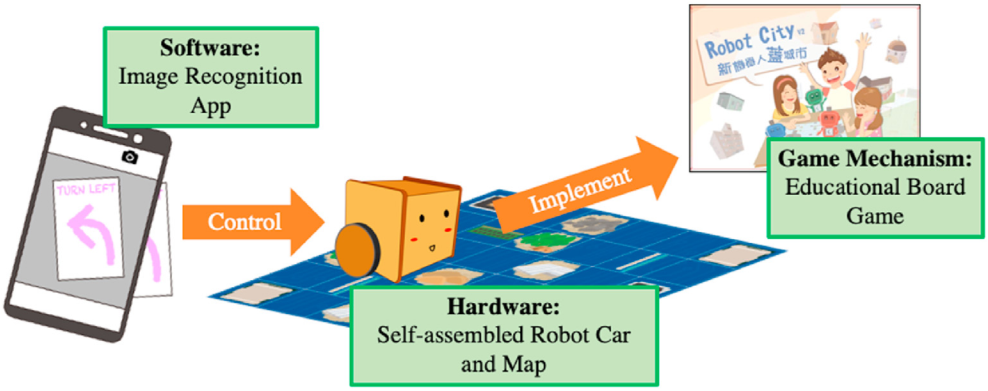


Fig. 3. The schematic diagram of the main system.

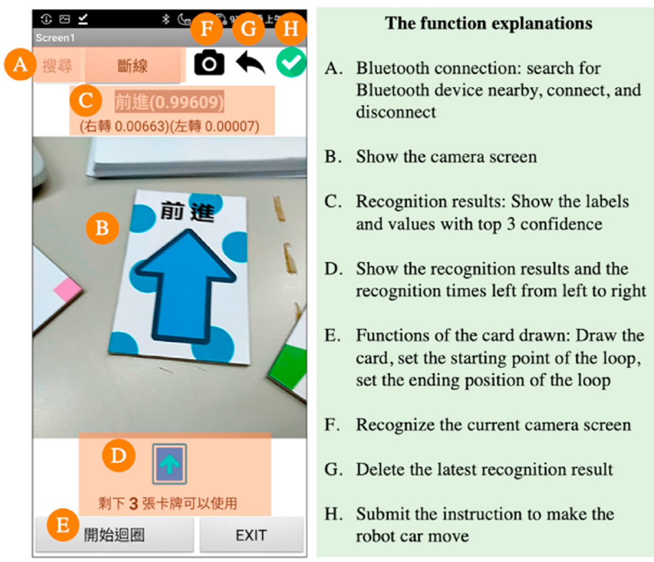


Fig. 4. Main screen explanations of the mobile app.

Step 4

The players are divided into two teams to play the game. Before the game starts, players play rock-paper-scissors, and the winning team can choose the starting point first and be the first to start.

2.5.5. Step 5

When it is the team's turn, they should first decide on the car's destination, use the app to draw the loop function, and then recognize its direction cards to control the car's movement.

Step 6

When all the raw materials on the map are taken, the game ends and the team gaining the highest scores wins.

The purpose of this research was for students to understand the integration and application of different technologies, rather than learning to operate new technology, so this study utilized teaching materials that the students were familiar with. According to the analyses of the learners, it was found that all the subjects had a foundation in programming blocks, so MIT App Inventor was introduced for mobile app development. Since all the subjects had experience of using micro:bit, the robot car was selected as the main control board in the study. As for the image recognition application, the students had to experience the Teachable Machine webpage and the PIC webpage from the instructional experiment in this study. Both can train personalized image recognition

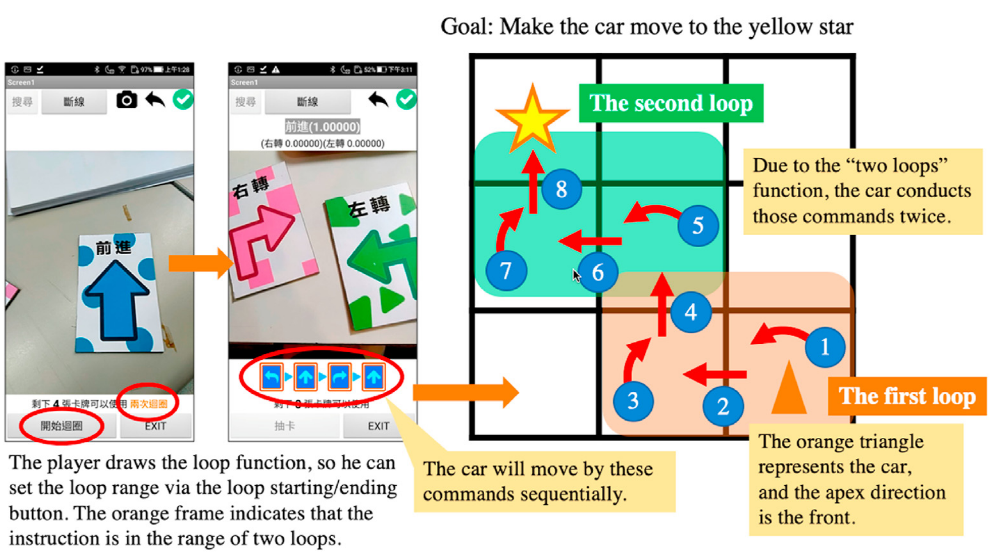


Fig. 5. Operating explanations: have the car make a two-loop movement for example.

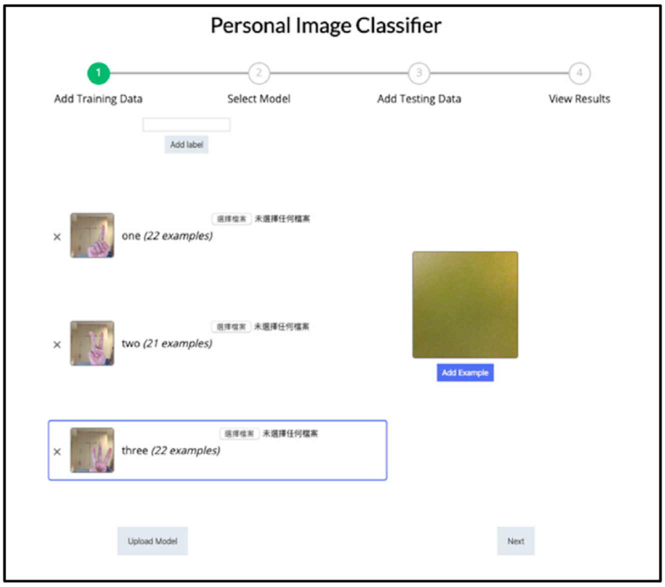


Fig. 6. The interface of the Personal Image Classifier (PIC) webtool.

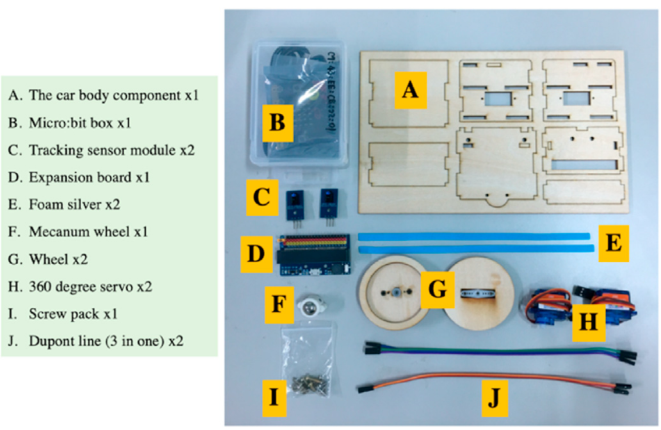


Fig. 7. Components of the robot car.

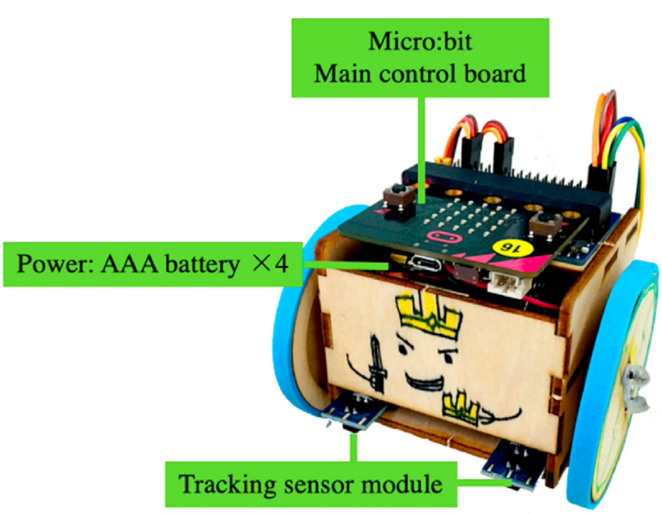


Fig. 8. The creation of the robot car (from a student's work).

models without writing code. The latter can be applied to personalized mobile apps, and can therefore control the robot car's actions via Bluetooth connection.

To sum up, the integration of this board game made the course more in line with the strategy of the MOE for primary and secondary schools. That is, through computational thinking, experiential learning, and interest arousal, the students could gain a foundation in cognition.

4. Results

4.1. The behavioral patterns of the individual learning in the course

The first 5 weeks of the course involved individual learning which covered two topics: MIT App Inventor and Personal Image Classifier. In order to ensure consistency during encoding, the recorded videos were coded by two researchers (Kappa = 0.71). The adjusted residuals table of Z values in the serial behavior analysis were turned into behavior transition diagrams to explore the students' learning behaviors in the first 5 weeks.

During the course, the eight students displayed eight different behavior patterns of learning, while they all had a pattern of S and TD (e.g., the red circle part in the behavior transition diagram, Figs. 10–17), which means they all had a significant behavior transition between setting the model and collecting the training data on the PIC webtool.

Fig. 10 shows the behavior transfer of student A during the first 5 weeks of the course, in which there are four learning patterns, including the first pattern of P, PO, the second pattern of AT, PP, the third pattern of AM, AP, and the last one of S, TD. First, the transition between P and PO is significant as it shows that student A had some personal opinions during the hands-on activities and tended to speak them out to others. In the second pattern, AT and PP had an influence on each other because student A usually asked the teacher questions when discussing the course with peers. This behavior could help him solve his problems instantly during discussion. In terms of the third pattern, he might have some trouble analyzing the result of the training model on the PIC webtool as he tended to ask peers for help (AM→AP).

Fig. 11 shows the behavior transfer of student B during the first 5 weeks of the course. There are three learning patterns, including the first pattern of S, AT, the second pattern of TD, PO, AM, and the third pattern of S, TD. In the first pattern, student B might have had some problems while setting hyperparameters to train the image recognition model because he usually asked teachers for help when setting the model (S, AT). In terms of the second pattern, he was more likely to have some ideas after collecting training data (TD→PO), and tended to analyze the training model after expressing his personal opinions (PO→AM).

Fig. 12 shows the behavior transfer of student C during the first 5 weeks of the course, in which there are three learning patterns, including the first pattern of N, PP, AM, S, the second pattern of AP, P, and the third pattern of TD, S. First, we found that after setting the model or observing the result of the model, student C was motivated to discuss with peers (S→PP, AM→PP). However, he often did something that had nothing to do with the course after discussion (PP→N). In the second pattern, it was found that he did hands-on activities after asking his peer for help (AP→P) to check whether he was on the right track.

Fig. 13 shows the behavior transfer of student D during the first 5 weeks of the course, in which there is a learning pattern consisting of PO, PP, AM, S, TD. We found that student D was easily motivated to discuss with peers after expressing his personal opinions or analyzing the model he trained (PO→PP, AM→PP). In addition, he tended to check the result of his training model after collecting the training data for the model which he was going to train (TD→AM), so he could adjust the way of taking pictures of the training data for the new model.

Fig. 14 shows the behavior transfer of student E during the first 5 weeks of the course, in which there are two learning patterns, including one of PO, PP, and the other of TD, S. Student E tended to express his own opinions after discussing the course content with his peer. According to

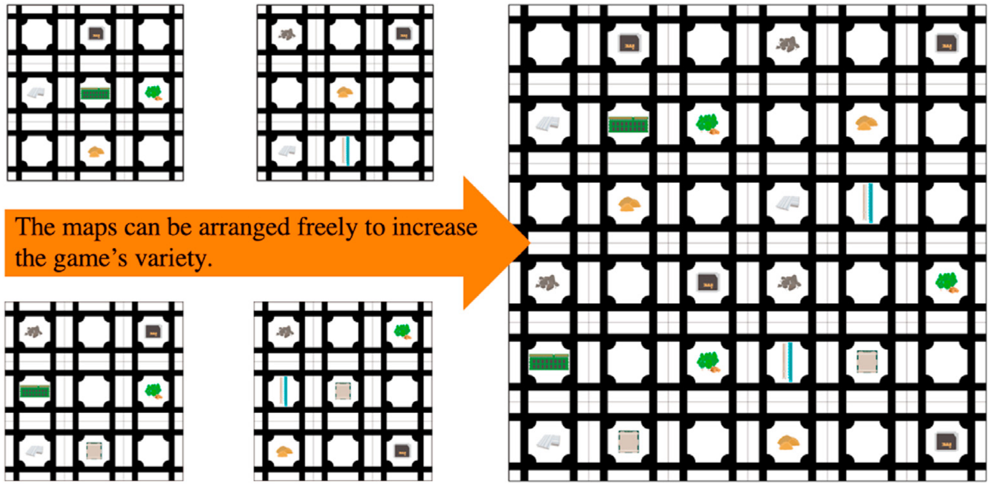


Fig. 9. Explanation of the whole map.

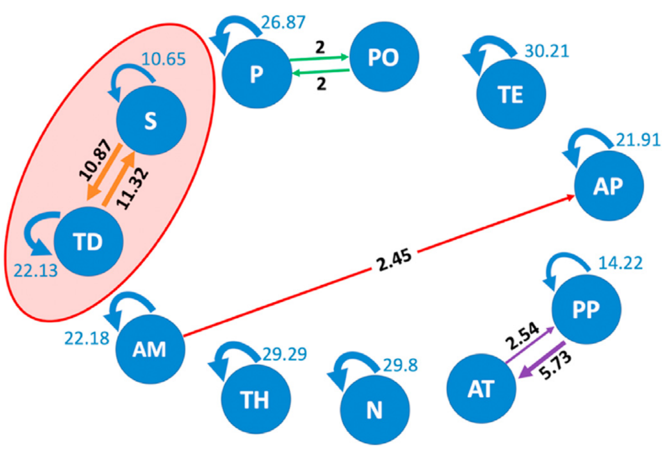


Fig. 10. Behavior transition diagram of the individual learning of student A. NOTE. P: individual operation, PO: expression of personal opinions, TE: testing and execution, AP: asking peers for help, PP: discussion with peers, AT: asking teachers for help, N: irrelevant behaviors, TH: being taught by teachers, AM: analyzing the training model, TD: collecting training data, S: setting the model. Arrow direction: causal relationship between behaviors; Number: the significant Z value.

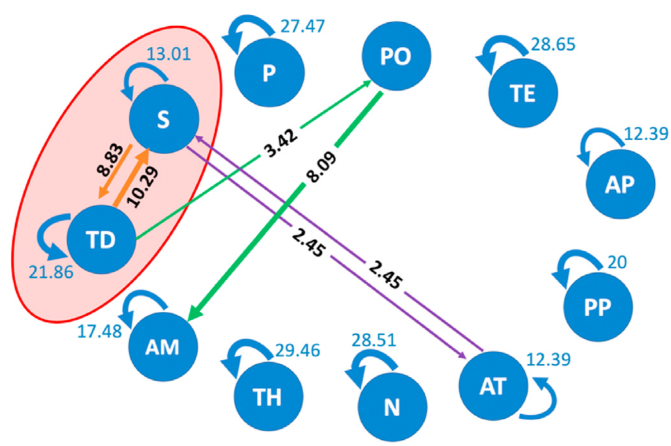


Fig. 11. Behavior transition diagram of the individual learning of student B. NOTE. P: individual operation, PO: expression of personal opinions, TE: testing and execution, AP: asking peers for help, PP: discussion with peers, AT: asking teachers for help, N: irrelevant behaviors, TH: being taught by teachers, AM: analyzing the training model, TD: collecting training data, S: setting the model. Arrow direction: causal relationship between behaviors; Number: the significant Z value.

his limited learning behavior and only speaking out his personal opinions after discussion, student E might be a more passive learner.

Fig. 15 shows the behavior transfer of student F during the first 5 weeks of the course, in which there is a learning pattern (N, AM, PO, TD, S) consisting of four parts. In the first part, student F tended to analyze the result of his model after doing something that was not relevant to the course, so he could focus on his process of training the model again and know how to adjust the setting (N→AM). After analyzing the model, he was more likely to speak out about what he had found (AM→PO), then he continued his training process about setting the model (PO→S).

Fig. 16 shows the behavior transfer of student G during the first 5 weeks of the course, in which there are two learning patterns, including one of AP, PP, and the other of S, TD. It was found that student G was easily motivated to ask his peer questions or to ask for help after discussing the course content with peers. Moreover, because he tended to discuss and share his opinions with one particular peer, he did not express personal comments to unspecified people (PO) during the learning activities.

Fig. 17 shows the behavior transfer of student H during the first 5 weeks of the course. There is a learning pattern consisting of three parts. In the first part, it was found that after collecting the training data, student H was more likely to speak out or ask her peer for help after expressing her personal opinions (TD→PO, TD→AP). In addition, she also asked the teacher for help or did something that was irrelevant to the course content after expressing her own opinion (PO→AT, PO→N). She might have had more problems with collecting training data because she usually asked the others questions or asked for help after that behavior (TD→AP, TD→PO→AT).

4.2. The behavioral patterns of the cooperative learning in the course

The last 4 weeks of the course, which covered two topics, the robot car and the Robot City board game, involved cooperative learning. In order to ensure consistency during encoding, the recorded videos were coded by two researchers (Kappa = 0.72). The adjusted residuals table of Z values in the serial behavior analysis were tuned into behavior transition diagrams, to explore students' learning behaviors in the last 4 weeks.

The results showed that the eight students' learning behaviors displayed four different types of behavior patterns. Moreover, all students had a pattern of SR and O (the red circle part in the behavior transition diagram), which means that all students had significant behavior

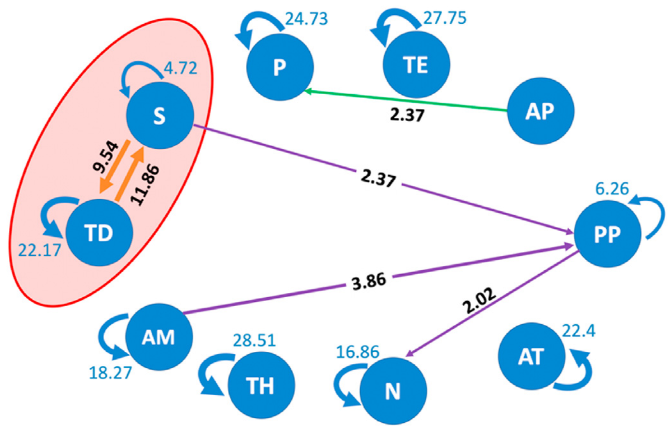


Fig. 12. Behavior transition diagram of the individual learning of student C. NOTE. P: individual operation, TE: testing and execution, AP: asking peers for help, PP: discussion with peers, AT: asking teachers for help, N: irrelevant behaviors, TH: being taught by teachers, AM: analyzing the training model, TD: collecting training data, S: setting the model. Arrow direction: causal relationship between behaviors; Number: the significant Z value.

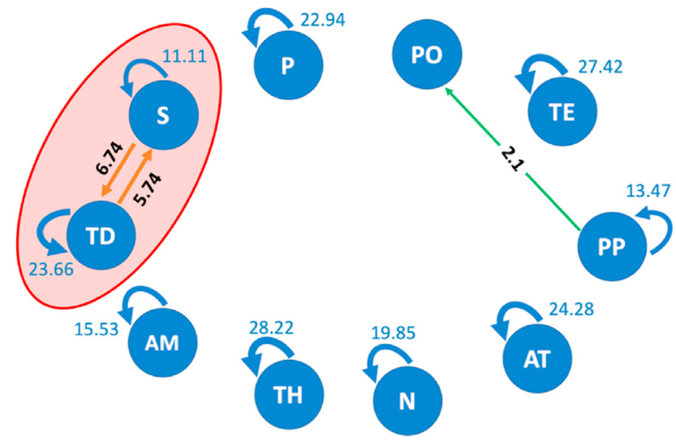


Fig. 14. Behavior transition diagram of the individual learning of student E. NOTE. P: individual operation, PO: expression of personal opinions, TE: testing and execution, PP: discussion with peers, AT: asking teachers for help, N: irrelevant behaviors, TH: being taught by teachers, AM: analyzing the training model, TD: collecting training data, S: setting the model. Arrow direction: causal relationship between behaviors; Number: the significant Z value.

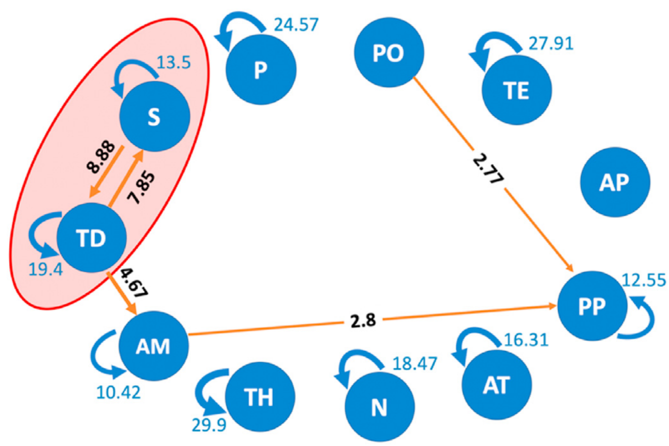


Fig. 13. Behavior transition diagram of the individual learning of student D. NOTE. P: individual operation, PO: expression of personal opinions, TE: testing and execution, AP: asking peers for help, PP: discussion with peers, AT: asking teachers for help, N: irrelevant behaviors, TH: being taught by teachers, AM: analyzing the training model, TD: collecting training data, S: setting the model. Arrow direction: causal relationship between behaviors; Number: the significant Z value.

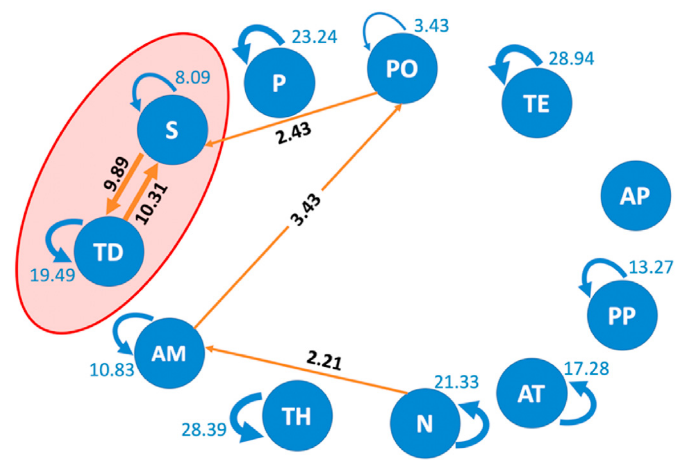


Fig. 15. Behavior transition diagram of the individual learning of student F. NOTE. P: individual operation, PO: expression of personal opinions, TE: testing and execution, AP: asking peers for help, PP: discussion with peers, AT: asking teachers for help, N: irrelevant behaviors, TH: being taught by teachers, AM: analyzing the training model, TD: collecting training data, S: setting the model. Arrow direction: causal relationship between behaviors; Number: the significant Z value.

transitions between simulating the result of execution (SR) and observing the situation (O) when they played the board game and did hands-on activities with their peers.

According to Table 2, Students A, B, C, and E had the same learning pattern during the last 4 weeks of the course, which consists of SR and O. This behavior transition also showed in the learning patterns of other students. It was found that the students usually decided what to do in the next step by simulating the movement of the robot car (SR) and observing the situation of the game play (O).

Fig. 18 shows the behavior transfer of student D during the last 4 weeks of the course, in which there is a learning pattern consisting of three parts. In the first part, TE and SR had an influence on each other because student D predicted the result by simulating the movement of the robot car (SR→TE), and tested the program on Micro:bit or moved the robot car on the map to verify his prediction (TE→SR). Secondly, student D also implemented the program to move the robot car directly after observing the situation of the game play (O→TE).

Fig. 19 shows the behavior transfer of student F during the last 4 weeks of the course, in which there is a learning pattern consisting of TE, SR, O. It was found that testing and execution (TE) was able to trigger student F's behavior of simulating the result of execution (SR) because he tended to move the robot car first and then use the actual result of execution to adjust his prediction.

According to Table 3, Students G and H had the same learning pattern during the last 4 weeks of the course, which consists of SR, O, and TE. It was concluded that SR was more likely to result in students' behaviors of TE. They tested their program for Micro:bit or executed the movement of their robot cars after simulating and predicting the result (SR→TE). This behavior could help them verify whether their speculation was right, and also gave them the opportunity to correct their action before actually testing.

4.3. Results of the learning effectiveness test

The full credit of the learning effectiveness test was 100 points, and it was used to understand the students' integrated understanding of the

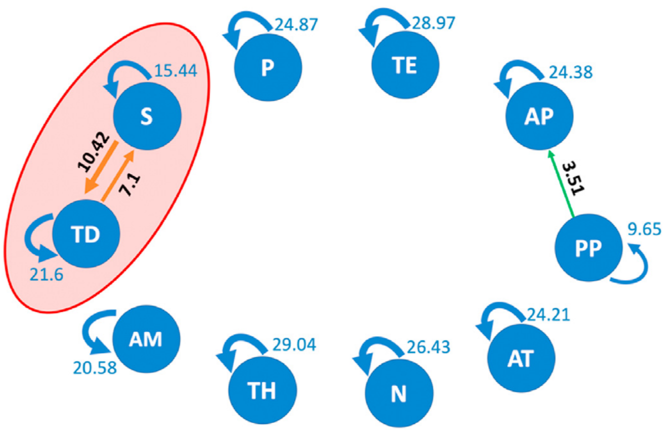


Fig. 16. Behavior transition diagram of the individual learning of student G. NOTE. P: individual operation, TE: testing and execution, AP: asking peers for help, PP: discussion with peers, AT: asking teachers for help, N: irrelevant behaviors, TH: being taught by teachers, AM: analyzing the training model, TD: collecting training data, S: setting the model/Arrow direction: causal relationship between behaviors; Number: the significant Z value.

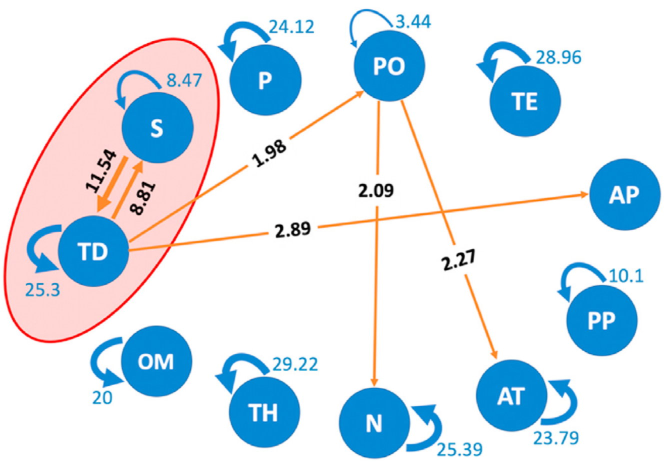


Fig. 17. Behavior transition diagram of the individual learning of student H. NOTE. P: individual operation, PO: expression of personal opinions, TE: testing and execution, AP: asking peers for help, PP: discussion with peers, AT: asking teachers for help, N: irrelevant behaviors, TH: being taught by teachers, AM: analyzing the training model, TD: collecting training data, S: setting the model. Arrow direction: causal relationship between behaviors; Number: the significant Z value.

knowledge related to the course. According to Table 4, the results revealed that students A, B, E, and F were low achievers on the test, while students G and H performed well. It was found that those students who had similar learning effectiveness (e.g., AB, CD, EF, GH) in Table 4 revealed similar learning behaviors in the cooperative learning stage.

5. Discussion

5.1. What were the learning behaviors of the students when they learned individually in the course?

All of the students (Figs. 10–17) had a significant behavioral pattern showing their repeated behaviors of collecting the training data and setting the image recognition model (TD ⇆ S) when they individually used the PIC webtool to train their models. To get a good image recognition model, the students experienced the process of trial and error. Trial and error is a necessary process for AI development, and it is also a critical feature to measure innovation in the AI field (Tang et al., 2020). Therefore, in terms of learning the basic procedures of AI and machine learning, the PIC webtool encouraged the students to experience this process and knew how it worked.

One of the important concepts of learning machine learning is that "computers can learn from data" (Touretzky et al., 2019). In the case of the image recognition we taught in the course, the quality of the training data could affect the performance of the image recognition model. According to the current study, the students used their own way to take pictures of the training data (the self-drawn cards) at the beginning of using the PIC webtool to train their model, but after the teacher's explanation and their personal experiences of getting bad results, they started to adjust their way of collecting the training data. For example, some students took the pictures from different angles to make the model learn more about the images; some students moved their cards closer to the camera to fill the scene with the image that they wanted to recognize, so they could decrease the effect of the background when the computer learned from their training data; they also tried different amounts of training data to train their model. In addition, we also mentioned how hyperparameters affect the performance of the model, and gave them time to try different hyperparameter settings.

However, although every student experienced the process of trial and error during individual learning, they still had different results in the learning effectiveness test. The students seemed to gain benefits from the trial and error behaviors, such as TE and SR, during collaborative learning. It is inferred that just trial and error is not enough for students in interdisciplinary learning; there are other behavioral patterns which affected their learning in the course.

5.2. What were the differences in the behavioral patterns of the low achiever and high achiever students when they learned individually?

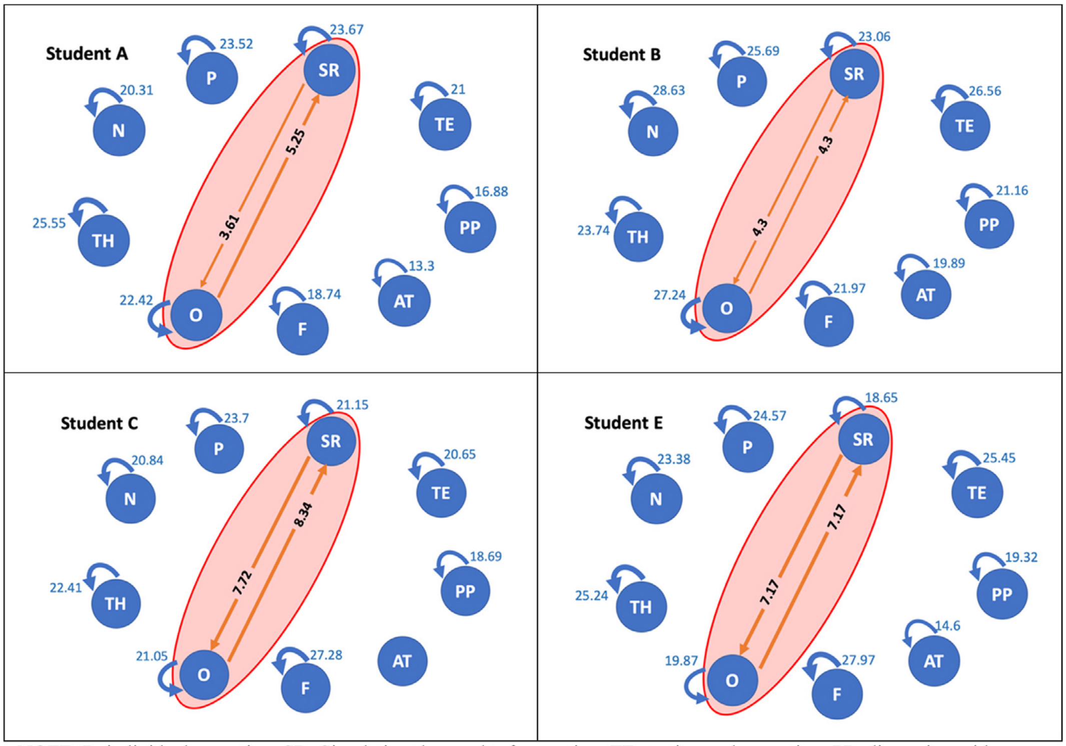
As mentioned above, there were other learning behaviors which influenced the students' learning effect, so we explored the relation between the students' scores on the learning effectiveness test and their learning behavioral patterns. Table 5 reveals that the students A, B, E, and F were low achiever students, while student H got the highest score on the learning effectiveness test.

The current study found that the key difference between student H and the other students was the relation between behaviors PO and AT, shown as Table 5. Student H usually spoke out her own opinions or questions during the hands-on activities, and then asked the teacher to verify her thoughts (TD→PO→AT). This behavior allowed her to know if what she had learned was right, and then she corrected her wrong operation instantly. Analyzing the content of her opinions and questions, we found that they corresponded to wonderment questions, which is a type of student-generated question that motivates students to think more deeply, and leads to meaningful construction of knowledge (Chin and Brown, 2002).

In terms of students A and B, they also had the behavior of expressing personal opinions (PO) and asking the teacher for help (AT) during the course, but they were independent behaviors. Student A usually spoke out his comments while doing the hands-on activities by himself (PO ⇆ P), but he did not ask the teacher to verify his thoughts or operation. Instead of asking the teacher questions during the learning activities, he tended to ask the teacher questions when he discussed with peers (AT ⇆ PP). This made it hard for him to instantly correct his wrong steps, and so he might have had some misunderstandings while operating the teaching materials. Student B usually asked the teacher for help when he set the model on the PIC webtool (AT ⇆ S) because the hyperparameters part was harder than the collecting and adjusting training data part for the students. He liked to speak out his opinions when he collected training data and analyzed his model (TD→PO→AM), but he did not ask the teacher to check his comments.

On the other hand, Students E and F seldom asked others questions or helped during the hands-on activities. Student E expressed personal

Table 2
The first pattern of behavior transition diagram of cooperative learning.



NOTE. P: individual operation, SR: Simulating the result of execution, TE: testing and execution, PP: discussion with peers, AT: asking teachers for help, N: irrelevant behaviors, TH: being taught by teachers, O: Observing the situation, F: correcting or fixing the operation. Arrow direction: causal relationship between behaviors; Number: the significant Z value.

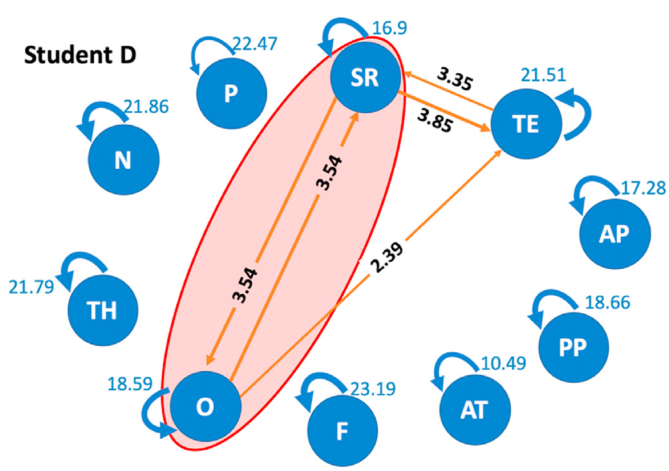


Fig. 18. The second pattern of behavior transition diagram of cooperative learning.
NOTE. P: individual operation, SR: Simulating the result of execution, TE: testing and execution, AP: asking peers for help, PP: discussion with peers, AT: asking teachers for help, N: irrelevant behaviors, TH: being taught by teachers, O: observing the situation, F: correcting or fixing the operation. Arrow direction: causal relationship between behaviors; Number: the significant Z value.

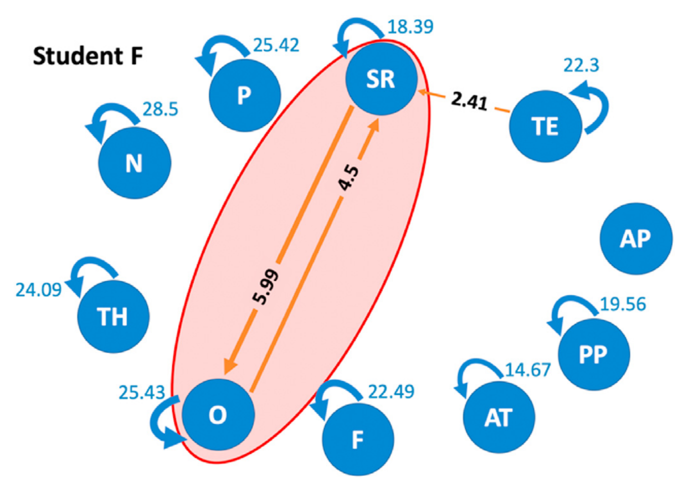
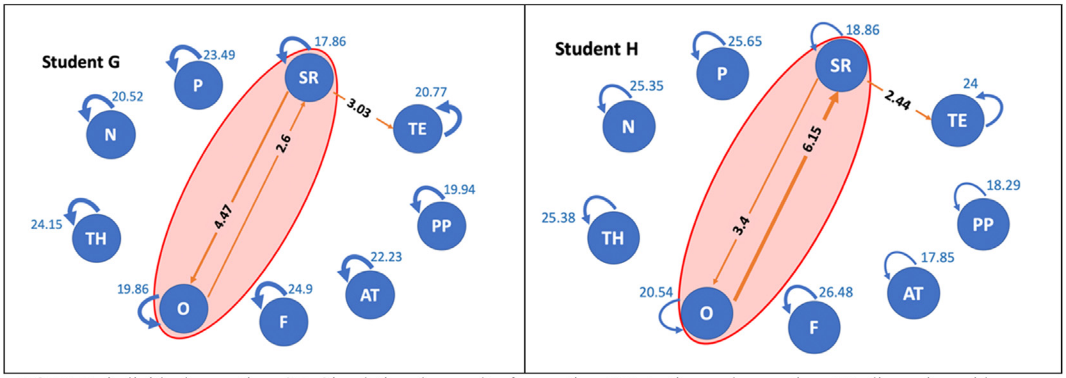


Fig. 19. The third pattern of behavior transition diagram of cooperative learning.
NOTE. P: individual operation, SR: Simulating the result of execution, TE: testing and execution, AP: asking peers for help, PP: discussion with peers, AT: asking teachers for help, N: irrelevant behaviors, TH: being taught by teachers, O: observing the situation, F: correcting or fixing the operation. Arrow direction: causal relationship between behaviors; Number: the significant Z value.

comments only when he discussed with peers, and he did not have many actions after that (PP→PO), indicating that he was a more passive learner. Student F tended to express his own opinions during the hands-on activities but did not ask the teacher to verify them, or discuss with his peers; he just kept trying on the PIC webtool to train his image recognition model by himself (AM→PO→S). The lack of asking questions might be one of the reasons why students E and F had lower achievement in the course because questioning plays an important role in the learning process (Chin and Osborne, 2008).

Table 3
The fourth pattern of behavior transition diagram of cooperative learning.



NOTE. P: individual operation, SR: Simulating the result of execution, TE: testing and execution, PP: discussion with peers, AT: asking teachers for help, N: irrelevant behaviors, TH: being taught by teachers, O: observing the situation, F: correcting or fixing the operation. Arrow direction: causal relationship between behaviors; Number: the significant Z value.

Table 4
Students' learning effectiveness test scores.

Group ID	Group 1		Group 2		Group 3		Group 4	
Student	A	B	C	G	D	F	E	H
Score	60	60	80	85	80	55	55	90

5.3. What were the learning behaviors of the students when they learned cooperatively in the course?

Compared to the behavioral patterns of the individual learning, the students did not speak out their personal opinions (OP) during the cooperative learning. Due to being divided into pairs, they tended to express their comments to their partner rather than to unspecified people. They usually talked to their partner while doing the hands-on activities in the course, which might have led to less behavior of asking the teacher for help and verification.

In addition, all the students had a significant behavioral pattern between simulating the result of execution and observing the situation (SR ⇆ O). This learning pattern helped them decide the next step or how to modify their operation. For example, they observed the distribution of resources on the board game map to think about how to move their robot cars when they played the board game. They decided what details they needed to deal with to complete the task and what details they could ignore. The behavior of observation and simulation made the students experience the process of abstraction, which is an essential part of computational thinking (Wing, 2008).

However, we found that although the behaviors of simulation and observation were helpful for the students to solve problems, it might not be enough for them in such an interdisciplinary course. There were only four students (students A, B, C, and E) who had this learning pattern during the cooperative learning, but students A, B and E were the low achievers in the learning effectiveness test. There were other learning behaviors which influenced the students' learning effect in the cooperative learning activities.

5.4. What were the differences in the behavioral patterns of the low achiever and high achiever students when they learned cooperatively?

The current study found that the behavior of testing and execution (TE) was important when the students were learning cooperatively in such an interdisciplinary course. According to Table 6, Students G and H, who were the top two in the learning effectiveness test, had the same behavioral pattern that they tended to test and execute their actions on the robot cars after simulating the result (SR→TE). This behavior indicated that they predicted before taking action, which helped them check whether their speculation was right so that they could modify their next step and understand the learning activities. It made the students experience the process of systematic testing and debugging in computational thinking (Shute et al., 2017). In terms of student D, who also performed well in the learning effectiveness test, behavior TE made his behavioral pattern more complicated than those of other students. Behavior TE connected the behavior O and SR, which indicated that student D used two different learning ways (O→SR→TE and O→TE→SR) during the class activities.

However, this study also found that student F, who was a low achiever in the learning effectiveness test, had similar behaviors to students G and H, but the sequence of behavior SR and TE was opposite. In other words, student F tended to carry out his actions directly and then checked the result by simulating the movement of the robot car (TE→SR), so he could adjust his action in the next testing. According to the video record, the behavior SR of student F was more similar to verification, because he usually expressed the simulation of the result when the robot car did not move as expected. This might have resulted in more unexpected results or mistakes during the learning activities.

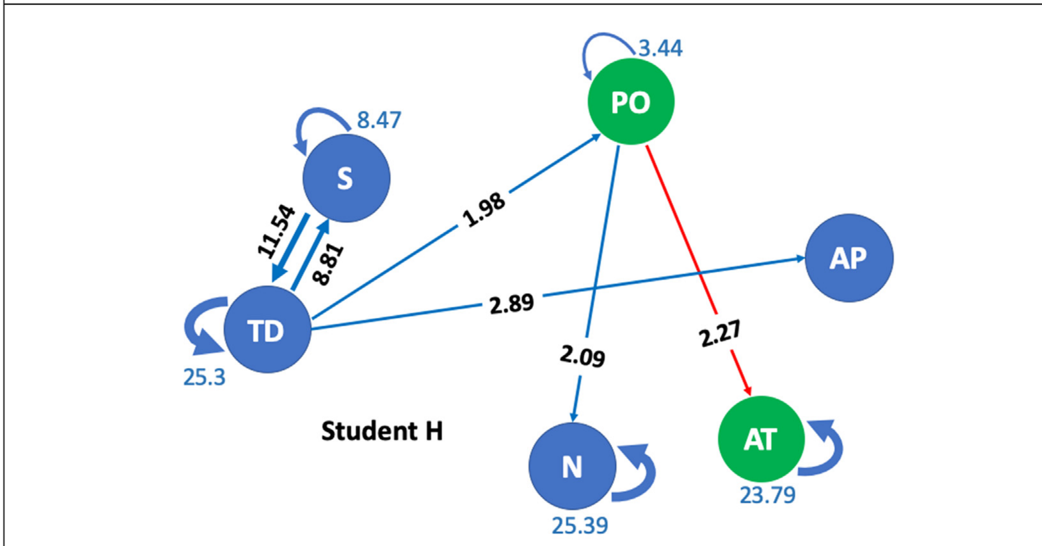
Accordingly, it is inferred that the sequence of SR and TE is important for students' learning in the course, particularly for cooperative learning. This study found that there were two positive effects when students expressed their prediction of the result before testing (SR→TE). First, their partner could understand what they thought more clearly and they reached an agreement more easily; secondly, they probably avoided making mistakes and getting results that they did not want, because they found potential errors before taking action and fixed them instantly, which was similar to the previous study which found that children who planned in advance produced more efficient ways to solve problems (Berland and Lee, 2011). On the other hand, if they tended to perform their actions before simulating the results (TE→SR) and adjusted their ways to test the next time, they experienced the process of debugging but were not able to prevent the potential errors; moreover, there was more dissension in the group.

6. Conclusion

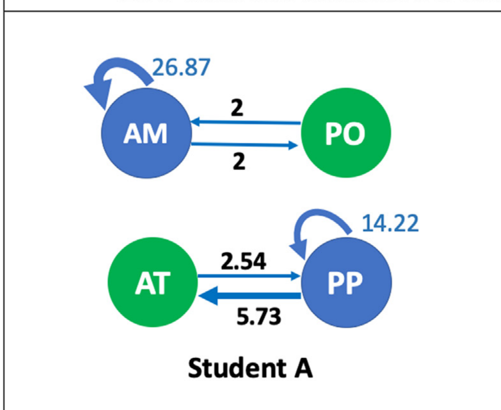
This study developed a creatively interdisciplinary course. The course integrated AI education and STEM, guiding students to apply all the

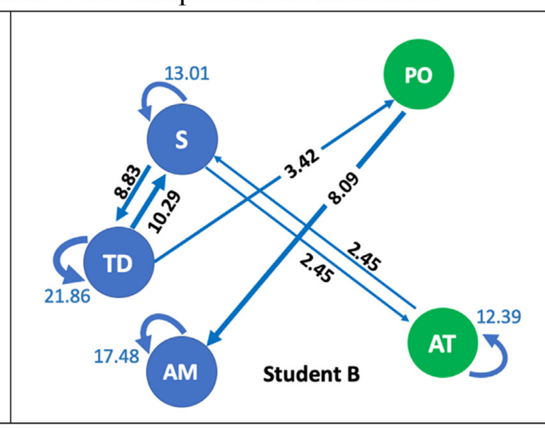
Table 5
A comparison of the behavioral patterns of the high achiever and low achiever students in individual learning.

High achiever: there was connection between behavior PO and AT

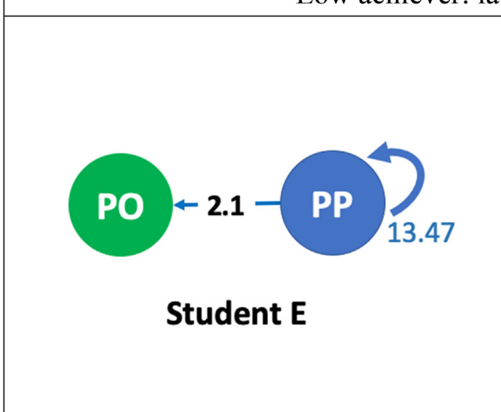


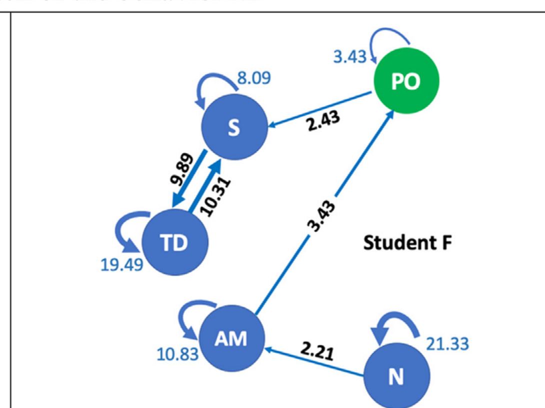
Low achiever: behavior PO and AT were independent of each other





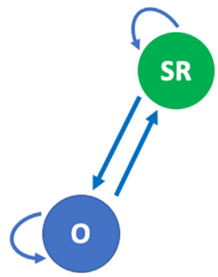
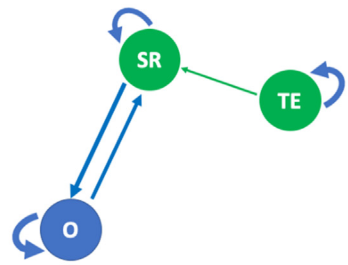
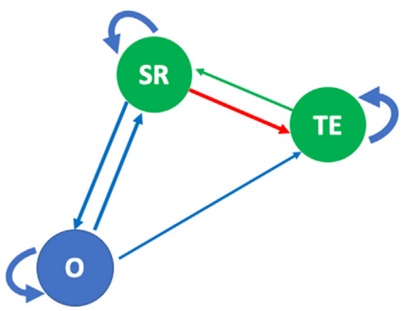
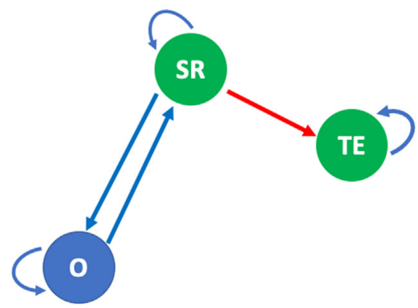
Low achiever: lack of the behavior AT





NOTE. PO: expression of personal opinions, AP: asking peers for help, PP: discussion with peers, AT: asking teachers for help, N: irrelevant behaviors, AM: analyzing the training model, TD: collecting training data, S: setting the model. Arrow direction: causal relationship between behaviors; Number: the significant Z value.

Table 6
A comparison of the behavioral patterns of high achiever and low achiever students in the cooperative learning.

The common behavioral pattern of all students in cooperative learning	Student F
	
Student D	Students G & H
	

NOTE. SR: Simulating the result of execution, TE: testing and execution, O: observing the situation. Arrow direction: causal relationship between behaviors.

knowledge into a computational thinking board game. It is a good demonstration of integrating teaching material. Moreover, the learning behaviors of students during the course have been collected to explore how they learned in the course. According to the sequence behavior analysis results, the design of the course and the hands-on activity using the PIC webtool was effective for the students to experience the process of training an image recognition model and learning the concept of machine learning, especially the process of trial and error. In terms of learning interdisciplinary knowledge individually, this study found that when students expressed personal opinions and asked the teacher to verify their comments, they performed better on the learning effectiveness test. Based on this result, it is suggested that teachers can guide their students to express more personal comments when they ask questions, or encourage them to talk about what they find and think before asking. This study also found that when students were learning cooperatively, if they predicted the result of the action before execution, they performed better on the learning effectiveness test. Therefore, it is recommended that when teachers design the learning activities of interdisciplinary courses with hands-on practice, how to encourage students to plan and predict before taking action is an important consideration.

In the current study, due to the time constraints and the number of research participants, we did not explore completely the learning effects of the course. The research limitation is the sample size, especially as there was only one girl among the gifted subjects. Therefore, in addition to her behavioral patterns which are inferred to be helpful for learning, we did not find any other factors contributing to sample H's outstanding performance. In addition, because such an interdisciplinary course consists of many topics and is more complicated than a single-object course, researchers need to keep exploring the learning performance. Moreover, this study only analyzed the students' sequential behaviors and integrated learning effectiveness. Future studies can consider collecting different data like affective factors (Hwang et al., 2020a,b) for further discussion on how students learn (Chen et al., 2020). The current study found that the individuals with the same level of learning effectiveness behaved similarly during the cooperative learning, although they were assigned to different groups. Future studies are strongly encouraged to explore the reasons which were not found in the current study. For example, this study did not assign group leaders. A previous study found that the students' interaction with group leadership in online collaborative learning can promote creative ideas and critical thinking, enhance reaching a consensus and making conclusions, and facilitate completion of the group learning tasks (Cheng et al., 2020). Therefore, it is valuable to explore different collaborative ways in STEM activities, and more evidence of the correlation between the learning effectiveness and behavioral patterns can be found.

Funding sources

The research is supported in part by the Ministry of Science and Technology under contract numbers MOST 108-2511-H-003 -056 -MY3.

CRediT authorship contribution statement

Ting-Chia Hsu: was responsible for conceptualization, Funding acquisition, Methodology, interpretation of data, Project administration, interpretation of data and, Writing - original draft, and review of the manuscript, and contributed to editing of the manuscript. **Hal Abelson:** was responsible for, Funding acquisition, Project administration, Supervision, and review of the manuscript. **Natalie Lao:** was responsible for software, Resources, review of the manuscript, and contributed to editing of the manuscript. **Yu-Han Tseng:** was responsible for instruction, Formal analysis, interpretation of data and, Writing - original draft, Visualization. **Yi-Ting Lin:** was responsible for data curation, Formal analysis, and investigation. All authors had full access to all data in the study and take responsibility for the integrity of the data and the accuracy of the data analysis, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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