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Game-Based Learning of AI Image Recognition on Computational Thinking and Self-Efficacy of Undergraduates

Hui-Wen HSUEH, Ting-Chia HSU *
Department of Technology Application and Human Resource Development, National Taiwan Normal University, Taiwan, ROC
* ckhsu@ntnu.edu.tw

Abstract: With the rise of artificial intelligence (AI), cultivating the AI abilities of the new generation of learners has become crucial. However, currently, there is a lack of tools in education found to effectively enhance students' AI abilities. To discover effective ways to foster students' understanding of AI concepts and skills, this research developed an Artificial Intelligence Image Recognition Robot unit, which was conducted through a series of AI courses in conjunction with educational robots. There are total of 41 undergraduates participating the instructional experiment. The first half of the experiment focused on introducing AI concepts and implementing image recognition models, while the second half involved robot programming and a robot board game competition. At the beginning and the end of the nit, students completed the AI Learning Achievement Test, the Programming-Oriented Computational Thinking scale and the Robot Self-Efficacy Scale to assess differences before and after the unit. The research found that by taking the AI Image Recognition Robot unit, students' AI learning achievements, programming-oriented computational thinking, and robot self-efficacy were significantly enhanced. This suggests that students will be better equipped to evaluate and understand the effectiveness of algorithms in programming and problem solving in the future. It is recommended that robots be incorporated as educational tools when engaging in AI learning.

Keywords: Artificial Intelligence, Educational Robot, self-efficacy, Computational Thinking

1. Introduction

With the rise of artificial intelligence (AI), it is being widely used in various fields and industries, bringing great changes to people's lives. With its rapid development, the demand for personnel with AI skills is gradually increasing, and it is crucial to cultivate the ability of AI for the new generation of learners (Su et al., 2022). However, how to effectively train students to learn AI concepts and technologies is lack of empirical study evidences. Relevant studies have mentioned that learning the CT concept and implementation from learning by doing of educational robots plays a key role in AI education, and allowing students to participate in the development and production of robots can effectively promote their interest and understanding in the field of AI (Dodds et al., 2006). Therefore, this study used educational robots with the hope of improving students' learning achievements in learning AI.

Self-efficacy is a theoretically and empirically robust motivational belief, and people with high self-efficacy put in more effort and persist for longer than those with low self-efficacy (Klassen & Klassen, 2018). This study used the Robot Self-Efficacy Scale to test whether this unit can improve students' robot self-efficacy and enable them to explore robot learning more actively, so as to help them obtain deeper help and inspiration in the field of AI in the future. Computational thinking, a way of solving problems and understanding computational processes, plays an important role in the modern digital generation (Witherspoon et al., 2017). There is a close relationship between computational thinking and

programming. Writing programs helps to improve students' computational thinking ability, so that they can solve real-life problems using this ability (Selby, 2015). This unit used the Programming-Oriented Computing Thinking scale to test whether the writing of robot programs can improve the performance of students' computing thinking, which will help students to effectively solve problems in AI or everyday life in the future.

Both aspects play an important role in learning to apply AI technology. Therefore, through robot self-efficacy and programming-oriented computational thinking, we wanted to detect the influence of students' mental state when learning about AI, and thus we proposed the following two research questions:

- Does the artificial intelligence image recognition robot unit affect students' programming-oriented computing thinking?
- Does the artificial intelligence image recognition robot unit affect students' robot self-efficacy?

2. Literature review

2.1 Educational robots

In Papert's constructivism, it is mentioned that if learners can engage in hands-on learning themselves, it will be more effective for understanding knowledge (Papert, 1980). Integrating educational robots into the classroom allows students to have complete control over the entire learning process, engaging them in hands-on activities that enhance their active participation and focus. This approach makes the teaching content more meaningful and interesting (Chaidi et al., 2021). Additionally, involving students in the development and creation of robots can effectively stimulate their interest and understanding in the field of artificial intelligence (Dodds et al., 2006). It not only improves learners' motivation to learn and their ability to collaborate in teams, but also enables them to learn from mistakes. Various studies have shown that educational robots indeed have a positive impact on students (Castro et al., 2018). Through constructing and programming robots, students' computational thinking is significantly enhanced, making educational robots a highly effective teaching tool for promoting computational thinking development (Chaidi et al., 2021; Ioannou & Makridou, 2018; Qu & Fok, 2021).

2.2 Computational Thinking

Computational thinking is an important concept that is of great interest to the international education community, and cultivating students' computational thinking has become an important task to promote the development of IT talents (Yang et al., 2020). Wing (2006) mentioned that computational thinking is the ability to solve problems, construct systems and understand human behavior based on computer science. Computational thinking emphasizes thinking at different levels and in different fields, and can cultivate learners' critical thinking skills so that they can be applied to solve other daily life problems. Computational thinking has also been identified as an indispensable and important skill in learning AI knowledge (Kim et al., 2021).

2.3 Self-efficacy

Self-efficacy refers to an individual's estimation of or belief about his or her own ability in a specific situation or task. It is one of the factors that affect human activities. It directly or indirectly affects human behavior, such as personal motivation, thinking mode, and the amount and time of personal effort to complete an activity (Bandura, 2006). Self-efficacy is a theoretically and empirically robust motivational belief that has been shown to play an important role in learning and developing new skills (Klassen & Klassen, 2018). This study measures students' robot self-efficacy, which is used to evaluate learners' self-efficacy in

learning robotics, that is, learners' motivational beliefs when learning about robots (Tsai et al., 2021).

3. Method

3.1 The Artificial Intelligence Image Recognition Robot Unit

For this study, we designed an artificial intelligence image recognition robot unit. The topics include the concept of artificial intelligence and machine learning, the implementation of image recognition model training and robot programming, and so on. We used the Teachable Machine platform launched by Google for image recognition implementation, as it is easy to operate and does not require programming or any professional knowledge. (Figure 1). In this study, each student was assigned the task of utilizing the platform, teachable machine, to implement image recognition. The students were given specific assignments to hone their skills in training image recognition models comprehensively. Upon completion of recognition, learners could import the trained image recognition model into the robot program.

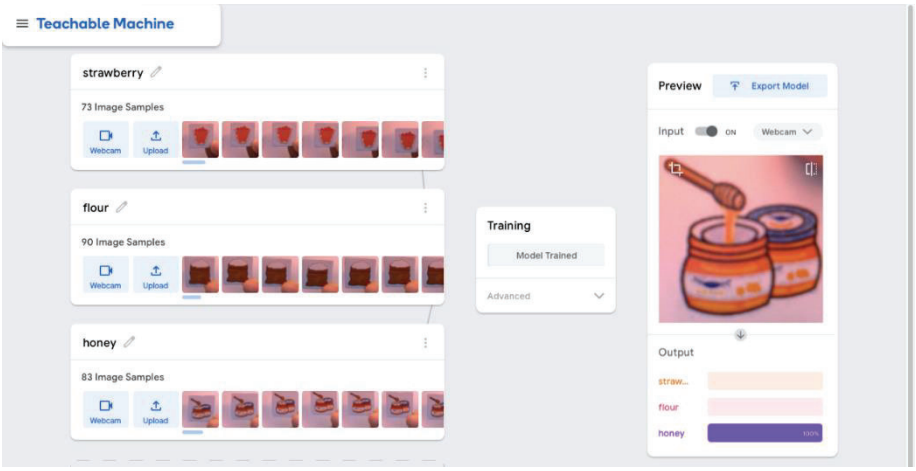

Figure 1. The Interface of the Teachable Machine Image Recognition Platform

The programming unit utilizes the BlocklyDuino platform, through which students learned how to write robot programs online. The platform allowed them to experiment with importing code into the robots and successfully operating the robots (as shown in Figure 2).

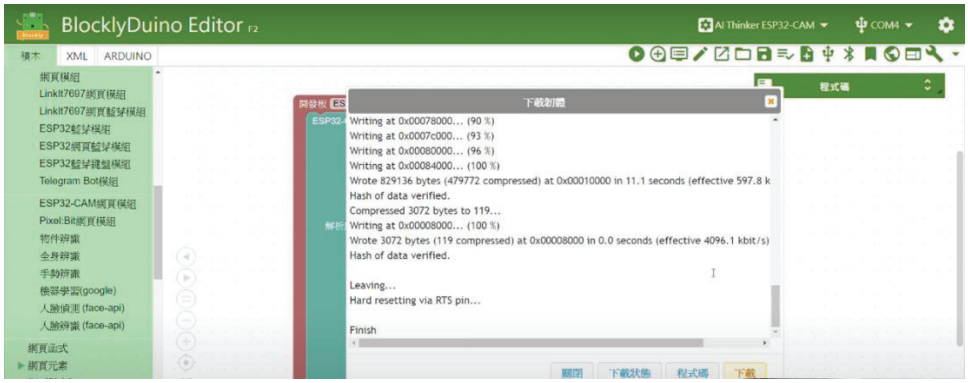

Figure 2. The Interface of the BlocklyDuino Programming Platform

The post-competition used the "Shopping Robot Game" developed by Professor Ting-Chia HSU's team from National Taiwan Normal University. This board game combines the concepts of artificial intelligence and the Internet of Things. Players can control the robots in the game using their own trained image recognition models and programmed code.

The game aims to apply the knowledge learned in the unit and enhance learners' motivation through gameplay. Following the principles of the Internet of Things, players roll the dice on the webpage to move the robots on the map (Figure 3) and collect materials. By utilizing image recognition, players add the collected materials to their shopping carts strategically, aiming to gather the required items from the shopping list in the board game.

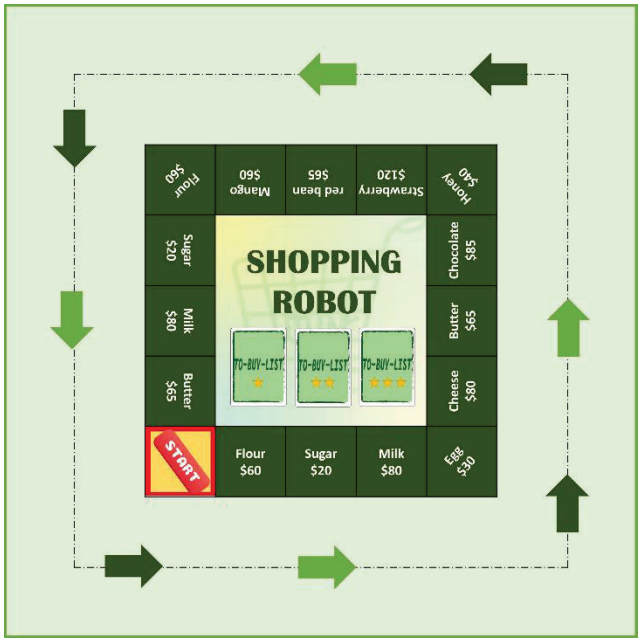

Figure 3. The Map of the Shopping Robot Game

3.2 Research Framework

In this study, the research framework was divided into independent and dependent variables. The independent variable was the artificial intelligence image recognition robot course, while the dependent variables were learning achievement, programming-oriented computational thinking, and robot self-efficacy, as shown in Figure 4.

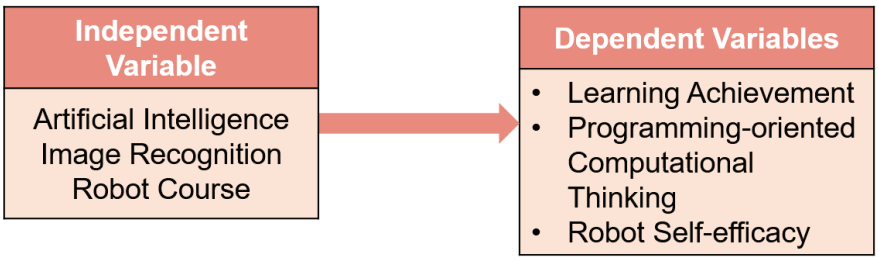

Figure 4. Research Framework

3.3 Experimental Design

In this study, the curriculum was divided into two parts, with the first part focusing on introducing the concepts of artificial intelligence, machine learning, and the implementation of image recognition. The second part emphasized robot programming and the implementation of a board game involving image recognition robots. Figure 5 illustrates the unit design.

	First half of the lesson	Second half of the lesson
Topic	1. AI and Machine Learning Concepts 2. Image Recognition Model Implementation and Testing	1. Robot Programming 2. AI Image Recognition Shopping Robot Game

Figure 5. Instructional Design

The first part of the course introduced the fundamentals of artificial intelligence and machine learning. Participants were assigned the tasks of implementing and testing image recognition models. In the second part, hands-on learning was emphasized. Learners were introduced to the concept of robot motor movement and provided with partially completed programming code in a block-based format. Participants were responsible for completing the missing sections in the code. After finishing the code, they used BlocklyDuino to write the robot board game program and subsequently tested the written program.

Towards the end of the curriculum, participants were grouped as necessary to engage in an educational board game titled "Shopping Robot Game." Following a brief introduction from the teacher, the game commenced, accommodating students in pairs or groups of four. They utilized the programs and models they had developed earlier to manipulate the robots within the board game. After the game concluded, a summary session was held to recap the experience.

The curriculum consisted of two parts: AI image recognition and robot programming, with each part lasting for 3 hours, for a total of 6 hours to complete this AI image recognition unit. After completing the learning unit, participants were asked to fill out the learning achievement test, the robot self-efficacy scale, and the programming-oriented computational thinking scale to assess the differences in participants' abilities before and after the unit. The experimental process is illustrated in Figure 6.

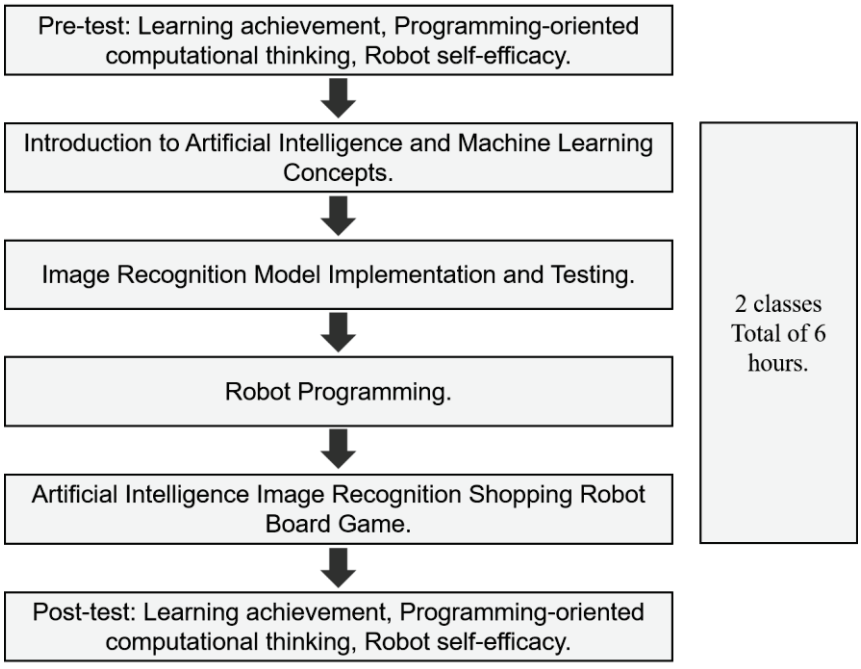

Figure 6. Experimental Process Flowchart

3.4 Experimental Participants.

The participants in this study were first-year students from an engineering-related department at a national university in the northern region of Taiwan. The study adopted a quasi-experimental research design and was conducted during the Computer Introduction

course offered by the department. The two-week instructional content focused on artificial intelligence image recognition. The total number of participants in the study was 41.

3.5 Experimental Tools.

3.5.1 Artificial Intelligence and Computational Thinking Test

To investigate whether there was a significant difference in learning achievement after completing this unit, the Artificial Intelligence and Computational Thinking Test was used to assess learners' performance. This test includes both multiple-choice questions and matching questions. There are 14 multiple-choice questions and three matching questions, totaling 17 questions, with a maximum score of 100 points.

3.5.2 Programming-Oriented Computational Thinking Scale

In this study, students completed the Programming-Oriented Computational Thinking Scale to understand whether their programming-oriented computational thinking was influenced after completing the artificial intelligence image recognition robot unit. This scale was adapted from the scale developed by Kılıç et al. (2021) and consisted of three dimensions: Conceptual Knowledge, Algorithmic Thinking, and Evaluation. The original scale had a Cronbach's alpha reliability coefficient of .97. For this study, the dimensions of Conceptual Knowledge and Algorithmic Thinking were used for measurement, comprising a total of 19 questions. The Cronbach's alpha reliability coefficients for these two dimensions were .89 and .94, respectively. The scale utilizes a Likert-type 5-point scale for evaluation, with higher scores indicating better programming-oriented computational thinking abilities. The example of the items are shown as follows. I am clear about the learning concepts of robotics. I can link robotics concepts with other learning subjects. I can evaluate several robotic solutions for solving a problem.

3.5.3 Robot Self-Efficacy Scale

In this study, students completed the Robot Self-Efficacy Scale to understand their level of robot self-efficacy after completing the artificial intelligence image recognition robot unit. The scale used in this study is based on the one developed by Tsai et al. (2021), which consists of five dimensions: Conceptual Understanding, Technical Skills, Application, Analysis, and Collaboration. The full scale contains a total of 16 items, and has a Cronbach's alpha reliability coefficient of .97. Each item is evaluated using a Likert-type 5-point scale, with higher scores indicating higher levels of robot self-efficacy. The example of the items are shown as follows. I can use the loop structures (for,while, etc.) appropriately. I can write a program that can do more than one operation at the same time. I can create simple algorithms without using unnecessary codes in the program.

4. Research results

4.1 Learning Achievement in Artificial Intelligence and Computational Thinking

As shown in Table 1, the paired-samples *t* test was used as the statistical method to examine the difference in students' learning achievements in artificial intelligence and computational thinking concepts before and after the course. The research results revealed a significant difference between students' pretest (M = 73.22, SD = 9.13) and posttest (M = 83.29, SD = 7.48) scores in artificial intelligence and computational thinking learning achievements (t = -7.11***, p < .001). This indicates a noticeable improvement in students' learning achievements after taking the artificial intelligence image recognition robot course.

Table 1. *Paired Samples t Test for Learning Achievement in Artificial Intelligence and Computational Thinking Concepts*

Mean(SD)		*t*	*N*
Pretest	Posttest		
73.22(9.13)	83.29(7.48)	-7.11***	41

***$p < .001$

4.2 Programming-Oriented Computational Thinking

As shown in Table 2, paired-samples *t* tests were conducted to examine the difference in students' programming-oriented computational thinking before and after the course. The results revealed significant improvements in both dimensions, namely Conceptual Knowledge (t = -5.44***, $p < .001$) and Algorithmic Thinking (t = -6.89***, $p < .001$). This indicates that students' programming-oriented computational thinking showed a noticeable improvement after completing the artificial intelligence image recognition robot unit.

Table 2. *Paired Samples t Test for Programming-Oriented Computational Thinking*

Factors	*N*	Mean(*SD*)		*t*
		Pre-test	Post-test	
Conceptual knowledge	41	2.93 (0.81)	3.46 (0.58)	-5.44***
Algorithmic thinking	41	2.54 (0.82)	3.22 (0.67)	-6.89***

***$p < .001$

4.3 Robot Self-Efficacy Scale

As shown in Table 3, the paired samples *t*-test was used to detect the difference in the robot self-efficacy of the students before and after the unit. The results showed that practice, cooperation, comprehension and analysis all reached significant levels: practice (t = -3.52***, $p < .001$), collaboration (t = -2.55*, $p < .05$), comprehension (t = -3.61***, $p < .001$), and analysis (t = -3.56***, $p < .001$). It means that after the students took the artificial intelligence image recognition robot unit, the practice, cooperation, understanding and analysis of the robot self-efficacy of the students showed a clear trend of improvement.

Table 3. *Paired Samples t Test for Robot Self-Efficacy*

Factors	*N*	Mean(*SD*)		*t*
		Pre-test	Post-test	
Practice	41	2.73 (0.92)	3.16 (0.76)	-3.52***
Collaboration	41	2.93 (0.94)	3.30 (0.78)	-2.55*
Comprehension	41	2.75 (0.86)	3.23 (0.76)	-3.61***
Analysis	41	2.81 (0.82)	3.36 (0.74)	-3.56***

*$p < .05$, ***$p < .001$

5. Discussion and conclusions

The research findings indicate that after the two-week artificial intelligence image recognition robot unit, students' artificial intelligence learning achievement, programming-oriented computational thinking, and robot self-efficacy were significantly improved. Their performance after the unit was superior to their performance before the unit. The results demonstrate that integrating educational robots into the artificial intelligence image recognition classroom effectively enhances students' programming-oriented computational thinking. This suggests that students who learned artificial intelligence through educational robots were more effective in evaluating and understanding the effectiveness of algorithms when programming and problem solving.

Furthermore, concerning robot self-efficacy, the unit indeed boosted students' belief in their own abilities when working with robots. This means that students who participated in this unit had higher levels of self-efficacy in learning about robots, leading them to set more challenging goals for themselves and to strive to achieve them. Therefore, if educational robots can effectively enhance students' self-efficacy in learning, it will greatly benefit their personal motivation, thought processes, and effort levels when acquiring artificial intelligence skills.

Therefore, if educational robots can effectively enhance students' self-efficacy in learning, it will greatly benefit their personal motivation, thought processes, and effort levels when acquiring artificial intelligence skills.

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