


## Article

# Is It Possible for Young Students to Learn the AI-STEAM Application with Experiential Learning?

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**Abstract:** This study attempted to evaluate the learning effectiveness of using the MIT App Inventor platform and its Personal Image Classifier (PIC) tool in the interdisciplinary application. The instructional design was focused on applying PIC in the integration of STEAM (i.e., Science, Technology, Engineering, Art, and Mathematics) interdisciplinary learning, so as to provide sustainable and suitable teaching content based on the experiential learning theory for 7th grader students. Accordingly, the sustainable AI-STEAM course with the experiential learning framework has been implemented and verified, so as to confirm that the AI-STEAM course is not too difficult for young students. Many basic concepts involved in the AI-STEAM course, regarding programming logic, electromechanical concepts, interface design, and the application of image recognition, were measured in this study. The results showed that the students not only made significant progress in learning effectiveness, but also in particular made significant improvements in two parts: electromechanical concepts and image recognition knowledge. In the end, this study further provides some advice on the sustainable AI-STEAM course based on the survey of some important factors including active learning, and self-efficacy after confirming that it is not a barrier for the young students to learn the sustainable AI-STEAM course developed in this study.

**Keywords:** artificial intelligence education; STEAM; experiential learning; personal image classifier



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## 1. Introduction

With the progress of science and technology, it is important for young students to gain computational thinking (CT), and to cultivate insights about artificial intelligence (AI) technology [1], such that they can develop CT literacy and experience AI application at the same time. In addition, working with AI applications requires the cooperation and co-creation of people with different professional backgrounds, so as to allow the students to gain high-quality education emphasized on the fourth sustainable development goal (i.e., SDGs) proposed by United Nations [2]. Therefore, in the development of the sustainable AI interdisciplinary course, there are many related AI teaching content or education policies attached. However, previous studies have reminded and shown that language and mathematical barriers would prevent young students from learning to program and AI [1,3]; meanwhile, the formal learning site is lack of learning tools or platforms which is suitable for young students to easily learn AI integrated with STEAM application (AI-STEAM) at present [4]. To allow the young students to learn program, block-based programming (BBP), such as Scratch, MIT App Inventor, and so on, was proposed [3]. To allow the young students to reserve technical knowledge and skills related to AI application without those barriers, the Personal Image Classifier (PIC) website was proposed and evaluated in the current study.

Most applications of AI sit behind the interfaces of applications and are not so obvious. AI becomes fully evident or visualized in the specialized training of neural networks or in robotics or the control afforded by AI. Therefore, PIC, which visualized the process of neural networks, was used as the entrance of AI learning for novices in the current study. In order to cultivate the students to adapt to the changes of the technology and times when facing the future, the interdisciplinary learning content integrated the AI technology with the STEAM learning content was developed in the current study, named as the sustainable-development AI-STEAM courses. As the application of AI in different domains will require the cooperation of people with talents in different subjects, the STEAM learning content developed for the students to learn in the tasks realistically matching to what they will experience in society or in the workplace [2]. In sum, the current study directly used AI for specific purposes to do with STEAM education.

However, AI technology has always given people an impression of being difficult and hard to understand, which forms a challenge when implementing on-site teaching for young students [5]. Therefore, it is very important to develop the sustainable teaching content and innovatively interdisciplinary direction, and to decide which learning approach to use. Scholars have noted that project-based active learning techniques have a remarkable potential and sustainability to enhance students' learning experience in the introductory computer programming courses [6]. Experiential learning connects real-life experiences to learning objectives, and also motivates students to learn. Experiential learning is suitable for this complex professional field because it lets students construct knowledge through a continuously strengthened way, which can help students learn [7]. When facing digital native students, it is necessary to choose appropriate learning approaches to arouse motivation and increase interest [8]. Therefore, this study attempted to provide an effective cross-disciplinary teaching model in AI education (AI-STEAM courses) through experiential learning for hand-on activates, and to verify whether it can help students improve their learning effectiveness.

In order to verify that experiential learning integrated into the AI-STEAM courses enables students to make significant progress in their learning effectiveness, this research will explore and further discuss the following aspects. Firstly, whether there was a significant difference between the pre-test and post-test of those students who take AI-STEAM courses integrated into experiential learning. Specially, in programming learning, the scholars found that those students who regularly attended each active learning session were able to conceptualize programming principles better than their peers [9], and other scholars indicated that self-efficacy was an effective predictor of students' academic persistence and sustainable to their career decision-making [6]. Therefore, in the evaluation of the AI-STEAM course, this study would further explore student's self-efficacy and active learning when they adopted different IT courses (the conventional course vs. the sustainable AI-STEAM course).

## 2. Literature Review

### 2.1. Artificial Intelligence Education

AI has been recognized as a non-human intelligent programming technology that can perform specific tasks while there is a growing field of general AI that is accelerating. It can mimic human cognitive models to perform computational processing, and also learn and apply new data to improve processing results [10–12]. With the development and maturity of technology, the influence of AI may extend to many levels and industries, such as finance, healthcare, manufacturing, retail, industrial supply chain, etc., and many industries may change a lot due to the rise of AI technology [10]. Therefore, how to cultivate the knowledge of AI technology and establish foresight for future changes becomes very important.

International demand of AI talents continues to increase [13]. Realizing that AI occupies an important position in the future development of society, investing in AI from the primary education level is an issue that needs urgent attention [14]. Many countries have listed AI application as the essential part in information technology (IT) curriculums

of primary and secondary schools [14]. Presently, there are many studies devoted to the development of AI learning content. For example, the scholars worked with high school students to teach common algorithm concepts in AI through Scratch [8], and there was also basic AI concept learning combined with robots [15].

However, AI knowledge is extensive in content and wide in scope. From various definitions, AI technology covers the concept of automation to more complex neural networks. AI brings people convenience in particular for the dangerous workplace but also had a possible controversy like violating social ethics or causing higher unemployment rate and so on. In sum, AI technology often integrates many aspects of knowledge that involve complex mathematical theory or logical reasoning, such as statistics or probability [16], which will cause excessive learning thresholds, especially for young students. Therefore, how to integrate this extensive knowledge into the current stage of information education of secondary school is a big challenge and critical starting point. In the early days of AI education, people focus more on understanding the potential and limitations of AI technology [8], to help students have a better understanding of real-life applications of AI and the potential of future AI development.

In order to design teaching content and courses that are consistent with primary and secondary schools, this study uses image recognition technology as the entry point for AI technology learning and utilizes Personal Image Classifier (PIC) as a web tool for training image recognition (<https://classifier.appinventor.mit.edu/>, accessed on 10 November 2019), which enables students to have more realistic display and interactive feedback. The platform can train its own image recognition model through machine learning [17] and can connect to MIT App Inventor which is a BBP learning platform [18], through which students can design practical and interactive APPs through the graphical interface. This study further integrated the interactive AI platform with STEAM learning, so as to achieve the AI-STEAM courses.

## 2.2. STEM and STEAM Education

STEM education emphasizes the integration of interdisciplinary knowledge, covering the four major fields of science, technology, engineering, and mathematics. The newly added art part in STEAM is not limited to painting or music subjects but extends to humanities and social fields such as literature and society [19]. Besides emphasizing the spirit of interdisciplinary learning, creativity, cooperation, communication, and critical thinking are also gradually valued, so the scholar has changed from STEM to the concept of STEAM [20]. Expanding the combination of artistic and humanistic concepts, STEAM has become a new concept of interdisciplinary discipline learning [21].

CT is regarded as an important skill in STEAM courses in elementary and middle schools [22]. Zeng (2013) believed that CT is the foundation of AI technology, emphasizing solving problems with the concepts of deep learning and cognitive computing, putting forward the concept of AI thinking [23]. In addition, some studies have proposed that hands-on practice combined with STEAM cross-domain can let learners learn AI concepts and application [24]; there are also studies that use machine learning to teach content and use visual textbooks and interactive teaching methods to allow learners from art and creative backgrounds to understand relevant knowledge, so that students can apply AI technology and concepts to different domains [25]. This shows that AI technology does not have the background restrictions of learners. If AI can be effectively integrated in the STEAM cross-domain teaching mode, students can obtain interdisciplinary knowledge and learn related AI application, which is useful for connecting future information trends.

Accordingly, both AI and STEAM education emphasize the integration of knowledge in different subject areas (i.e., AI-STEAM courses), allowing students to increase practical knowledge by participating in real-life practical applications [26]. In addition to planning the use of image recognition technology for teaching, this study will also cooperate with the application design of the Internet of Things (IOT) to enable students to integrate with real-life situations and combine AI image recognition, programming, basic circuit concepts,

graphic card design and other cross-fields integration and learning, to strengthen the AI application and CT literacy of the young students.

### 2.3. Experiential Learning

In order to combine the knowledge learned in the classroom with authentic situations, the integration of experiential education is a good medium. The concept of experiential learning was proposed by Kolb (1984), which includes concrete experience, reflective observation, abstract conceptualization, and active experimentation [27]. These four steps serve as a cycle and emphasize the core positioning of “experience” in the learning process [28,29].

Presently, there are many different disciplines that integrate the concept of experiential learning in teaching and have proven its effectiveness, such as the field of art and machine learning [25] and robot education that emphasizes STEAM [1,30], etc. Therefore, it can be found that the structure of the experiential teaching process can help students to think step by step, so that students can more logically construct the teaching concepts and actively think about what they have learned, and finally be able to connect to everyday real situations.

Experiential learning emphasizes practical experience in learning, learning by doing, and can be combined with practical applications in real-life situations, where the reflection process is regarded as the key to learning guidance [31]. Therefore, in addition to strengthening the relevance to daily life applications in the curriculum planning stage, we must also pay attention to the process of guiding reflection in the classroom, so that when students are learning new content, they will not be passive information receivers but are able to actively acquire and implement knowledge. This active learning model can improve learning effectiveness in cross-disciplinary courses [25], helping students develop a more complete and profound thinking and learning process.

Although AI is not a novel concept and discipline, this part of education is gradually gaining attention. When facing complex subject content, if there is no structural pedagogy to support it, it may be difficult to construct students’ knowledge acquisition to achieve good learning results. Therefore, for AI teaching, this research hopes to be able to focus more on interdisciplinary integration (i.e., AI-STEAM), and guide with a structured experiential teaching method to help students recognize and construct AI-related learning concepts through the process of learning by doing.

The research questions of this study are organized and listed as follows:

- (1) What is the learning effectiveness of students adopting the sustainable AI-STEAM courses?
- (2) How were the investigation results of the students enrolling in the sustainable AI-STEAM course and the investigation results of those enrolling in the conventional BBP course, in terms of self-efficacy?
- (3) How were the investigation results of the students enrolling in the sustainable AI-STEAM course and the investigation results of those enrolling in the conventional BBP course, in terms of active learning?

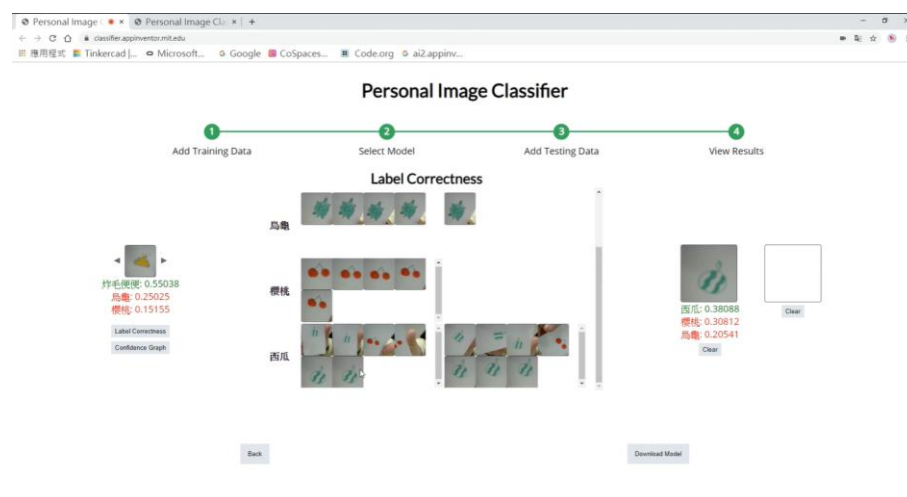
## 3. Method

This study proposed the PIC learning platform and developed the AI-STEAM curriculum for secondary school students, then conducted an instructional experiment to examine the learning results of the participants. This study proposed the PIC learning platform and developed the AI-STEAM curriculum for secondary school students, then conducted an instructional experiment to examine the learning results of the participants.

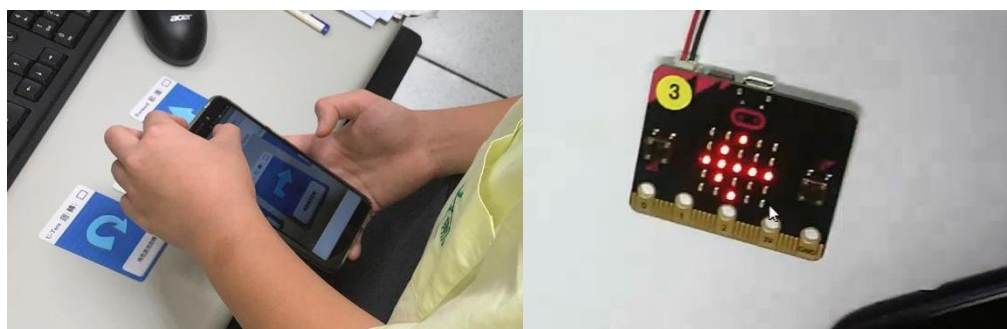
### 3.1. System Structure

This study uses the MIT App Inventor programming platform and the Personal Image Classifier (PIC) web tool to conduct the instructional experiment with experiential learning of the AI-STEAM courses. The content of the course includes teaching basic concepts of machine learning through image recognition, training image recognition models, and oper-

ating and applying these models to MIT App Inventor and basic IOT applications. Students trained their own image recognition model through PIC in the classroom (Figure 1). At the end of the class, they uploaded their image recognition model to MIT App Inventor and used the mobile platform to connect their machine learning model with the microcomputer control board (Micro: bit) (Figure 2).



**Figure 1.** Personal Image Classifier (PIC) image recognition training platform [14].



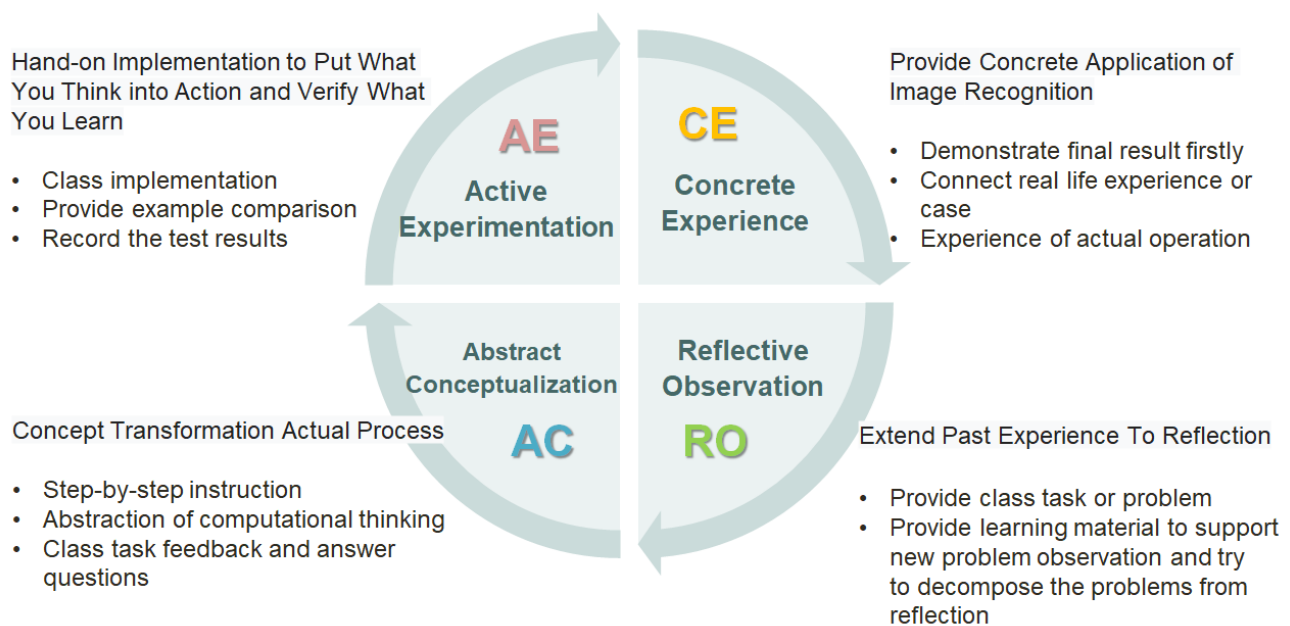
**Figure 2.** Identify images via mobile phone and interact with micro:bit control board.

### 3.2. Instructional Design with Experiential Learning Cycle

The experiential learning process includes four steps: concrete experience, reflective observation, abstract conceptualization, and active experimentation, as shown in Figure 3. The key items of the AI-STEAM course are also listed in each phase of the experiential learning cycle in Figure 3.

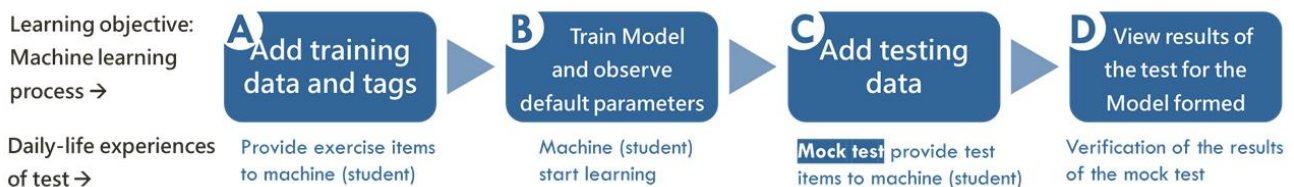
This study will focus on the teaching content, following this cycle for detailed arrangements and planning. A total of six courses are planned, and each class is 45 min. The weekly themes are: (1) App Inventor Introduction and Logic Application, (2) Machine Learning Introduction and Experience, (3) Image Training Recognition Model, (4) Image Training and Adjustment Recognition Model, (5) Model Application and Light Design, and (6) App Inventor IOT Application.





**Figure 3.** The cycles of experiential learning in the AI-STEAM curriculum.

The overall curriculum structure conforms to the experiential learning cycle, which is used to provide the students with the experience and practice of applying the main steps of machine learning for an image recognition application. Figure 4 shows four parts on PIC from step A to step D [18]. The students do not need to know the complex mathematics and command-line-based programs when the students use PIC of MIT App inventor [18].



**Figure 4.** The students experience the process of machine learning without complex mathematics in the experimental group.

There was a total of six weeks of experiential learning of AI-STEAM courses in the experimental group, as shown in Table 1. In every cycle, the students had a learning objective and experienced the whole process of CT in one period of each week. To connect the four stages of the experiential learning cycle (Figure 3) and the 6 week course periods (Table 1): first, the concrete experience (CE) stage connects to students' past experiences in their daily lives, which is used to compare to the process of machine learning or the concept of real-world AI applications. Second, the reflective observation (RO) stage encourages the students to reflect on what they observed and found. The teachers provide a worksheet for the students to help them discover the main point of the task from observation and analysis. The students have to provide feedback for their experience and current task. Third, in the abstract conceptualization (AC) stage, the students have to practice abstraction and pattern recognition of CT for the current task. They also decompose the problem to find possible solutions for each subproblem. The step-by-step process of experiential learning allows the students to deliberate and link the related concepts and practices of the curriculum. Fourth, the active experimentation (AE) stage asks the students to implement the training model or BBP so as to test what they considered in the previous stage. The overall results echo the information and demonstration provided in the original concrete experience stage, so that the students can verify what they have learned.

**Table 1.** Learning process of the sustainable AI-STEAM courses.

Week	Topic	EL	Example of Learning Contents
1	Introduction To MIT App Inventor	CE RO AC AE AC AE	Operating an App in person to see the demonstration of the design and function of the App. e.g., A simple mobile game. Reflecting step by step according to the guidance of an example connecting what they see to what they will learn. e.g., Reflecting on the function of the components on the screen of the mobile game. Understanding the block-based programming instructions. e.g., Basic operation of condition with if . . . else . . . blocks. The students implement a small App by themselves with MIT App Inventor. Understanding how to install the App onto their smart phone. Testing the results and trying to revise or debug.
2	Introduction to machine learning	CE RO AC AE	Experiencing the application of machine learning. e.g., Watching a video of self-driving cars, discussing Facebook asking students to tag themselves when a student's photo is uploaded. Operating image recognition programs: 1. An App for fruit classification written by the instructor 2. Teachable machine 3. Quick draw Sharing what they see after operating an image recognition application. e.g., Reflecting on how the system reacts when a new fruit that was not included in the classification tags is shown. Explaining the results of machine recognition and the concept of machine learning. Revising the input data to Teachable machine and examining the operational results.
3	Using PIC to built the first personal classification model	CE RO AC AE	Review and explain machine learning platform activities. Reflecting on experiences of using the fruit classification App and connecting to the PIC platform. e.g., Can the classification be enhanced? Understanding the four steps in the Personal Image Classifier of MIT App Inventor. Using PIC to train a fruit classification model in person.
4	Adjust and train the image recognition model	CE RO AC AE	Reviewing and exploring the operation of the PIC platform. Reflecting on how to judge whether the model is good or not e.g., Trying to recognize the same fruit with a different background, different angles, or different brightness and reflecting on why the recognition results are different. Understanding how to adjust the model. Implementation of model training and parameter adjustment.
5	The application of trained model and Introduce to the Micro:bit	CE RO AC AE CE RO AC AE	Experiencing the PIC process with self-drawn arrow cards. Discussing how to improve the trained model and reflecting the components required in the recognition App, to correctly recognize the arrow of forward, turn right, and turn left. Understanding the instructions to import the model into an App. Actual implementation with MIT App inventor and confirmation of the recognition results. Experiencing that the Micro:bit arrow light changes according to different actions. Reflecting on what IoT applications image recognition technology can be used for. Understanding why the image recognition model can be connected to control the Micro:bit light. Implementing the control of the micro:bit lights with block-based programming.

Table 1. Cont.

Week	Topic	EL	Example of Learning Contents
6	IoT Application with MIT App Inventor and PIC	CE	Further experiencing the results of Micro:bit light design and the application of image recognition.
		RO	Reflecting on how to map the card recognition result to the light display on micro:bit.
		AC	Understanding the instructions to write a blocks-based program to show different arrow light signals on micro:bit.
		AE	Implementing the design of the light signals on Micro:bit with block-based programming.
		CE	Experiencing the connections between the smartphone and the micro:bit.
		RO	Reflecting on how the image recognition application of arrow cards affects the signals showing on the micro:bit.
		AC	Understanding the instructions to the Bluetooth connection between MIT App Inventor and micro:bit.
		AE	Implementing and examining the IoT application with MIT App Inventor and PIC.

In addition to carry out the image classification of the AI application, the students experienced the physics concept about electronical science (S), how to write the block-based program (T), how to implement electromechanical reaction (E), the design and drawing of the cards or images which they used for training, classification, and recognition (A), and calculation of the steps or loops to move in the mission (M).

### 3.3. Participants

The students participating in this experiment were students in the seventh grade of a junior high school in northern Taiwan. Thirty-eight students were valid samples. There were twenty people in the experimental group (10 girls and 10 boys), eighteen in control groups (10 girls and 8 boys). All participants have learned the basic concepts of BBP in the original IT class, which is a formal class in the junior high school. The experimental group conducted an AI-STEAM course that integrates experiential learning. In order to compare the perspectives of the students in the experimental group with those in the control group which did not adopt the AI-STEAM course, this study used the same questionnaire to investigate the attitudes of the students learning the original science and technology curriculum in the control group.

### 3.4. Measurement Tools

This was an instructional experiment research after the PIC learning system was developed. In order to evaluate the results of the instructional experiment, the test sheets and questionnaires are the research tool in this study. The two classes learned the BBP for six weeks and had similar prior knowledge before the treatment. This study compared the progress which the experimental group made in the learning effectiveness. The learning effectiveness test of the AI-STEAM course includes the basic concepts of BBP, basic electromechanical concepts, platform interface design, and principles of image recognition, adding to a total of 20 items. The items are all multiple-choice questions. Each question is worth 5 points and twenty items add up to full marks of 100 points.

The active learning scale have five items [32]. The reliability of the original questionnaire is 0.789. The five items are all started from the first-person pronouns, and then the following content: “learned many factual materials”; “improved ability to communicate clearly”; “became more interested in the subject”; “participated actively”; “assignments aided the student’s learning”. The Cronbach’s  $\alpha$  value of the retest reliability of the active learning was 0.847. While active learning has recently received a great deal of attention [33], this study explored the active learning of the participants before and after the experiment. The self-efficacy for learning and performance scale was proposed by Pintrich based on



Albert Bandura's definition [34]. There were eight items, for instance, "I believe I will receive an excellent grade in this class", "I'm confident I can understand the basic concepts taught in this course", "I'm confident I can do an excellent job on the assignments and tests in this course", and so on. The Cronbach's  $\alpha$  value of the reliability of the self-efficacy was 0.930.

### 3.5. Experiment Process

This research experiment was conducted in a formal class of seventh-grade students. The students in the control group learned conventional BBP from the first week to the sixth week. After the first mid-term examination week (seventh week), six treatment sessions of the AI-STEAM lessons were conducted in the experimental group while the control group continued their original BBP learning content. The program includes six formal learning weeks, and one week for preparation before the instrument and one week for evaluation after the instrument, as shown in Figure 5. The conventional class teaching methods were based on the original textbook content, which is BBP during the experimental weeks. The experimental group carries out the AI-STEAM courses and continues to extend and create the proficiency of the BBP learned in the first six weeks.

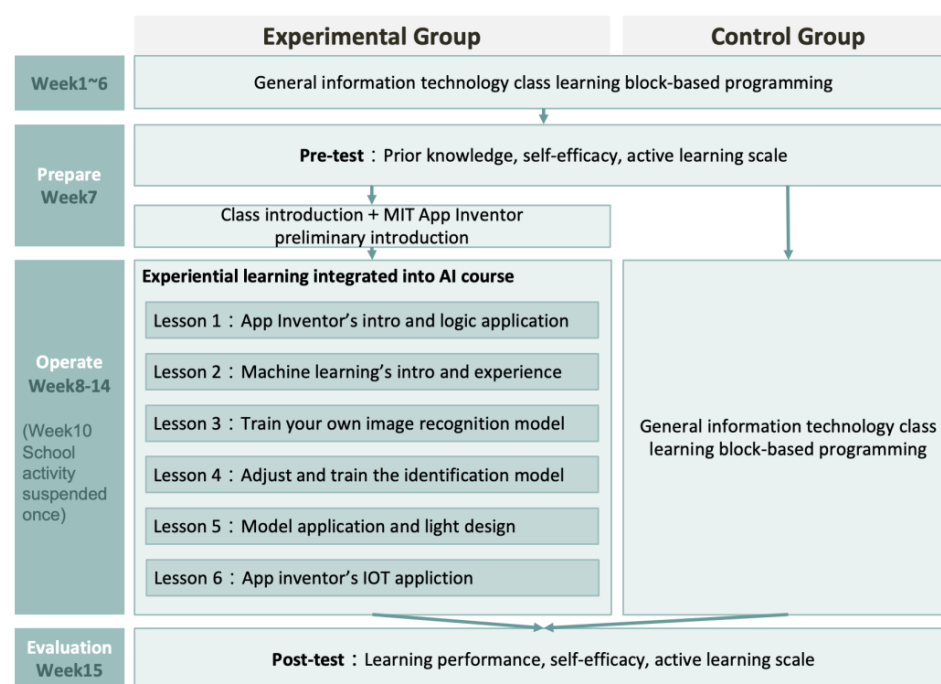


Figure 5. Experimental flow chart.

From the first week to the sixth week, the conventional class method was maintained both in the experimental group and the control group. The learning content includes the basic concepts of programming and BBP, so that both the control group and the experimental group had similar BBP proficiency before the formal experiment. The seventh week is a pre-test of the prior knowledge and learning attitude of the experimental group and the control group. The 8th to 14th weeks were the formal courses, but the tenth week was suspended for school activities. The formal courses ran for 6 weeks, with one 45 min period per week. The experimental group conducted AI-STEAM courses that integrated experiential learning, while the control group maintained the conventional class teaching methods and content in the field of science and technology. The fifteenth week was the evaluation week. Students in the experimental group were tested for learning effectiveness in logic, basic electromechanical with micro: bit, and Personal Image Classifier (PIC) in MIT App Inventor, and students in both groups were measured for active learning and self-efficacy. This study adopted paired-sample *t*-test to check whether the students made

significant progress when they learned the AI-STEAM curriculum. The analysis of variance (ANCOVA) was used to compare whether the self-efficacy of the students in the AI-STEAM course was different from that of those in the BBP course without involving AI application. This study also employed ANCOVA into comparing the active learning presented by the students in the AI-STEAM curriculum and the active learning reported by the students in the BBP course without involving AI application.

## 4. Results

### 4.1. Learning Effectiveness of the AI-STEAM Course

Firstly, according to the results of the pre- and post-tests of the experimental group, a single-group pre- and post-test paired sample *t*-test analysis was conducted, and the effective samples of the experimental group were 20 students in one class. The results showed that the learning effectiveness of the students made significant progress ( $T(19) = -2.891^{**}$ ,  $p < 0.01$ ). The learning effectiveness of the experimental group is shown in Table 2. This study confirmed that the students made significant progress in the course of AI-STEAM.

**Table 2.** Learning effectiveness pre- and post-tests (paired sample *t*-test).

AI-STEAM	N	Mean	SD	t	df	p
Pre-test	20	39.50	17.46	−2.891 **	19	0.009
Post-test	20	53.25	24.46			

\*\*  $p < 0.01$ .

### 4.2. Results of Self-Efficacy Survey

People are afraid that the AI-STEAM courses may be too difficult for the young students to learn. This study attempted to confirm that the students were able to make progress in the AI-STEAM courses, and the different conditions of active learning and self-efficacy would cause different results of the AI-STEAM courses. The students have filled out the questionnaires before and after the treatment, so this study employed ANCOVA into comparing the investigation results of the students enrolling in the AI-STEAM course with the investigation results of the students enrolling in the original BBP.

This study adopted pre-survey self-efficacy as the covariance, the courses as the independent variable, and the post-survey self-efficacy as the dependent variable when the ANCOVA (analysis of covariance) was conducted. The Levene's test was not violated ( $F = 2.285$ ,  $p = 0.139 > 0.050$ ), referring that the prerequisite of the data homogeneity was confirmed. However, the regression between pre-survey self-efficacy and different courses achieved significant interaction ( $F = 4.587^{*}$ ;  $p = 0.039 < 0.05$ ). Therefore, the Johnson-Neyman analysis had to be further conducted. The Johnson-Neyman levels could represent the values of pre-survey self-efficacy below which (for the lower level) there was a significant ( $p < 0.05$ ) effect of AI-STEAM vs. BBP on the post-survey self-efficacy.

When the students in the control (i.e., BBP course) and experimental group (i.e., AI-STEAM course) had low prior self-efficacy (i.e., pre-survey of self-efficacy  $< 2.401$ ), the students gain better self-efficacy by means of BBP in comparison with AI-STEAM, as shown in Figure 6. In other words, this study suggested the instructors consider the previous self-efficacy which the participants presented. The moderator value defining Johnson-Neyman significance region containing 18.421% of participants is below 2.401 presented in the pre-survey self-efficacy. Specifically, the low or high self-efficacy which the participants previously had resulted in relatively large effects on the self-efficacy which they would gain after learning the AI-STEAM course. The cross-over interaction occurred in the results of Johnson-Neyman analysis, as shown in Figure 6.

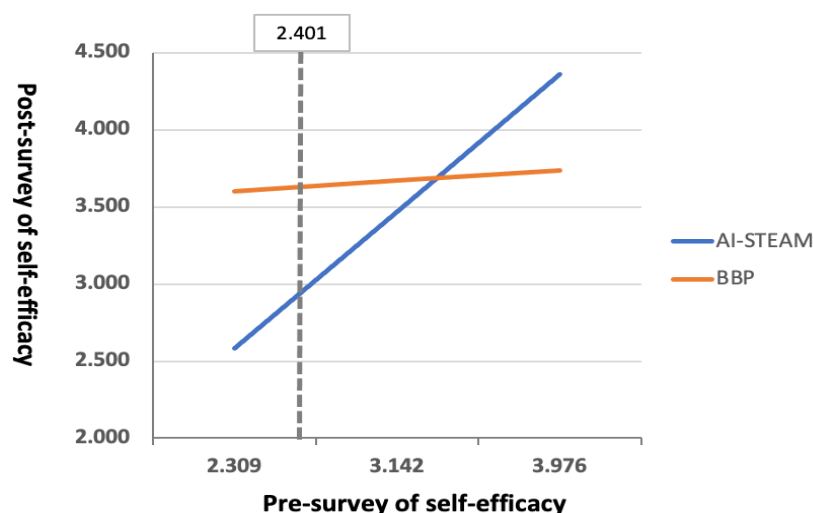


Figure 6. Results of Johnson-Neyman analysis in self-efficacy.

#### 4.3. Results of Active Learning Survey

This study adopted pre-survey active learning as the covariance, the courses as the independent variable, and the post-survey active learning as the dependent variable when the ANCOVA was conducted. Since the data did not conform to the assumption of homogeneity of the regression slope, this study converted the original score by the reciprocal ( $1/(N + 5)$ ), and after conversion, the homogeneity assumption of variance was met. Nevertheless, the regression between pre-survey active learning and the courses achieved significant interaction ( $F = 7.699^{**}$ ;  $p = 0.009 < 0.01$ ; effect size = 0.185). Therefore, the Johnson-Neyman analysis had to be further conducted. The AI-STEAM course did not increase the affordance of the seventh-grade students in comparison with conventional BBP, which was not as hard as some teachers and students' thought. However, this study suggested instructors pay attention to the students' prior survey of active learning due to the results of further analysis with Johnson-Neyman method. It was found that when the students in the control (i.e., BBP) and experimental group (i.e., AI-STEAM) had low prior active learning (i.e., pre-survey of active learning  $< 3.327$ ), the students show higher active learning by means of BBP in comparison with AI-STEAM, as shown in Figure 7. In the control group (i.e., BBP), it means that the students who originally had a high degree of active learning actually showed a decline or did not have higher degree in their attitudes of active learning, like the line with orange line in Figure 7.

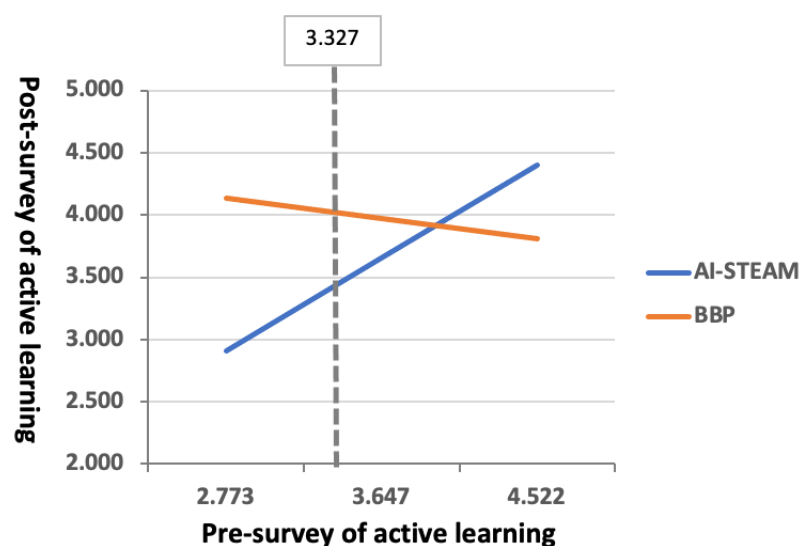


Figure 7. Results of Johnson-Neyman analysis in active learning.

## 5. Discussion

### 5.1. Learning Effectiveness

As AI education is now an important subject for teenager to master, this study made significant contribution to develop the innovative and sustainable AI-STEAM learning content for young students. From Table 2, it can be found that the use of experiential learning integrated with AI-STEAM courses has a significant improvement in the pre- and post-test; this indicates that the learning content and teaching methods incorporated in this study can help students learn to understand the basic concepts and applications of image recognition in the AI-STEAM course. In addition, the four aspects of programming logic, electromechanical concepts, App Inventor interface, and image recognition in the experimental group are further discussed in the following Table 3.

**Table 3.** All aspects of learning effectiveness (paired sample *t*-test) of the AI-STEAM course.

Tests	Pre-Test		Post-Test		T	df	p
Phases	Mean	SD	Mean	SD			
Programming logic	8.62	4.33	11.09	7.27	1.51	19	0.147
Electromechanical concepts	12.91	7.87	19.38	6.99	3.84 **	19	0.001
Interface design	11.25	6.91	9.58	7.78	−1.12	19	0.278
Personal Image Classifier	9.17	7.10	14.25	7.12	2.58 *	19	0.019

\*\*  $p < 0.01$ , \*  $p < 0.05$ .

It was found that there are significant improvements in the electromechanical concept and image recognition. Although the programming logic is not significant, the overall post-test average has also improved, and there is especially good learning effectiveness in these two aspects. This result also reflects that in the process of experiential learning cycle for the AI-SATEAM course, the completeness of the entire cycle of knowledge construction and the actual learning senecios as well as interdisciplinary learning content did not cause a barrier for the young students to learn. Therefore, young students can learn AI-STEAM course when the instructors well design the learning platform, tools, and content.

### 5.2. Questionnaires Result Discussion

It was found that the prior active learning and prior self-efficacy of the students toward the AI-STEAM course play critical roles, implying that the young students who originally had high active learning and self-efficacy had relatively positive performance after experiencing the AI-STEAM courses. On the contrary, the students who had previously actively studied at a high level experienced a decline for continuously conventional BBP instruction. However, for those who originally had poor active learning and poor self-efficacy, they were recommended to stay in the stage of conventional BBP for longer time. This study has confirmed that there was interaction between pre-survey results and different courses. The previous study also indicated that among cross-disciplinary courses, active learning had the advantage of normalizing students from different backgrounds and can improve students' self-efficacy [5]. The AI-STEAM course had a complete interdisciplinary and sustainable framework based on experiential learning. The lack of connection with daily experience and hands-on activities also makes it impossible to cause the students with highly prior active learning to keep in the conventional BBP. Connecting young students' daily-life experience with the sustainable cross-disciplines are important to the active learning process [4]. This study found that there was a positively significant correlation between self-efficacy and active learning. Pintrich (1991), who proposed the scale of self-efficacy, has defined self-efficacy as a self-appraisal of one's ability to master a task: "Self-efficacy includes judgments about one's ability to accomplish a task as well as one's confidence in one's skills to perform that task" [34]. In summary, the young students had a positive attitude toward the innovative and sustainable AI-STEAM course, which is similar with Lin's finding that it is feasible for young students to learn the AI application [35].

## 6. Conclusions

This study developed a sustainable AI-STEAM course and found that the young students were able to make significant progress in the AI-STEAM courses. This study suggested the instructors take the prior active learning and self-efficacy situation of the young students into consideration. This research conformed to the previous study which indicated that students directly connect the instructional design and the past background knowledge and experience [36,37]. This study was the starting point of making AI+X come true. AI+X here refers that people in any domain (i.e., X) can learn the application of artificial intelligent (i.e., AI). It is imperative to develop the sustainable learning tool and curriculum for those people who do not come from the department of computer science when it is possible for people to experience AI application in their daily lives in near future. This study has tried to provide the young students who are not experts for learning the application of image recognition easily with the supportive platform and tools. From the results of the instructional experiment, it was sure that the learning tools did reform the difficulties of image recognition and programming to the acceptable level of the young students.

In recent future, how to design and integrate AI concepts and application in different cognitively developmental stages from young ages to undergraduates needs further efforts and exploration. This research confirmed the AI-STEAM course using experiential learning would not have barriers for the young students to make progress from learning although they have not learned complicated and advanced mathematics or algorithms such as the content in the universities. The research limitation includes the AI application scope and the sample size. Future work can examine additional aspects such as cognitive loads and learning motivations for the sustainable AI-STEAM courses. Due to the limitation of the number of subjects in this study, future studies can aim to increase the number of subjects and conduct experiments for different educational stages to further evaluate whether different subjects have different gains in using the AI-STEAM course. It is suggested that localized learning content can be continuously added in the AI-STEAM course so as to sustainably extend and develop some textbooks and content based on the background of the learners and the characteristics of the learning environment. This study also shed light of the feasibility and importance to incorporate AI with other disciplines. Facing the information explosion generation, the concepts of information education and cross-disciplinary education are indispensable, which is also essential for SDGs of United Nations [38]. More research and verification are required to see if there is a better way to help students when facing life, employment, and other situations in the future.

**Author Contributions:** T.-C.H. designed the work and interpreted the data, and writing the manuscript. H.A. supervised the team and led N.L. to develop the system. N.L. was a major contributor in the creation of PIC platform used in the work. S.-C.C. conducted the experiments in the junior high school and did initial statistics. All authors have read and agreed to the published version of the manuscript.

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**Institutional Review Board Statement:** The study was conducted according to the guidelines of the Declaration of Helsinki, and approved by the Research Ethics Committee of National Taiwan Normal University (REC Number: 201906HS021; date of approval: 23 August 2019).

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## Abbreviations

AI	Artificial Intelligence
STEAM	Science, Technology, Engineering, Art, Mathematics
AI-STEAM	AI integrated with STEAM application
PIC	Personal Image Classifier
MIT	Massachusetts Institute of Technology
BBP	Block-Based Programming

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