Applying Competition-Based Learning to Stimulate Students' Practical and Competitive AI Ability in a Machine Learning Curriculum

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***Abstract*—*Contribution:* This study incorporates competition-based learning (CBL) into machine learning courses. By engaging students in innovative problem-solving challenges within information competitions, revealing that students' participation in online problem-solving competitions can improve their information technology, and showcase competitions can enhance their competition ability.**

***Background:* The CBL model seamlessly integrates project-based learning and competition, placing a strong emphasis on both collective learning and outcomes. This approach cultivates motivation among team members, driving them to enhance their learning and translate knowledge into practical experience.**

***Research Questions:* The objective is to examine the disparities in the development of theoretical knowledge, information technology, AI practical ability, and competition ability among students participating in online problem-solving competitions and showcase competitions, and discusses the potential moderating effect of competition type on the relationships between variables in the hypothetical model.**

***Methodology:* The study involved 74 students enrolled in machine learning course at a university. The students were given theoretical knowledge and information technology pretests and posttests in the 2nd and 17th weeks, respectively. In the 18th week, the students presented their projects using slideshows and were graded by judges while also submitting their final competition proposal and slides.**

***Findings:* Students in online problem-solving competitions can enhance their information technology, while those participating in showcase competitions can improve their competitive ability. Moreover, the competition type was found to moderate the relationships among theoretical knowledge, information technology, and AI model accuracy. The findings suggest that incorporating CBL into machine learning courses effectively cultivates students' AI practical and competitive abilities.**

***Index Terms*—Competition-based learning (CBL), competitive ability, machine learning, practical ability.**

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Ethnical Standard of Research Ethics Committee for Human Subject Protection, National Yang Ming Chiao Tung University under Application No. NYCU-REC-111-025F.

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I. Introduction

Digital technology has changed rapidly in the 21st century, with innovations in cloud computing, big data, data science, AI, and blockchain, and these technologies have had a great impact on society and the economy. Enterprises have also devoted resources and advanced technology to industrial upgrading [1]. To meet the needs of the industry and to train talent with AI knowledge and techniques, higher education institutions have proactively designed AI-related courses, minor credit courses, and secondary specialty courses. However, the majority of higher education institutes provide AI education to teach AI knowledge and techniques [2]. This type of education lacks real-world application opportunities, which results in an education–job mismatch. In addition, there is a weak connection between universities and enterprises, with a lack of programs cultivating relative talent. Competitions play a crucial role in bridging the divide between industry and academia [3]. By offering a competitive platform and inspiring students to devise creative solutions, they contribute to addressing human challenges in both the environmental and industrial sectors. Empirical evidence supports the notion that engagement in competitions learning effectively nurtures students' diverse hard and soft skills [4].

Previous competition-related research has focused on group competitions in courses, online competitions, or startup competitions to discuss the skills and results students gain during these courses [4]. As of now, there is no study investigating the relationship between various types of competitions within a given field and the development of students' abilities, hindering teachers in the more effective design of course activities. Using information competitions as an illustrative example, these can be categorized into online problem-solving competitions and showcase competitions. The former emphasizes the precision of AI models, fostering students' information technology and AI implementation capabilities [21], [29]. In contrast, the latter requires students to propose inventive solutions to industrial problems, practicing and presenting their work at the competition site while responding to judges' questions. Despite the somewhat intricate procedures of the latter competition, it significantly aids students in cultivating profound information knowledge and diverse competition abilities [17].

Due to the continual evolution of the machine learning field, competitions consistently present the most recent challenges and topics. Courses incorporating competition-based learning (CBL) can dynamically adjust their content, ensuring alignment with industry trends and facilitating the acquisition of the latest knowledge and technology by students. Consequently, this study concentrates on integrating diverse competitive learning activities into machine learning courses. This approach enables students to directly engage with industrial data and challenges through competitions, effectively applying AI models or conceptualizing innovative solutions for various industrial problems. Through the collection of student competition learning materials, the study aims to investigate the influence of online problem-solving competitions on students' information technology and AI implementation capabilities. Additionally, it examines the inspirational impact of showcase competitions on students' information knowledge and competition aptitudes. Concurrently, the study explores whether the type of competition moderates the influence of the interrelatedness of students' abilities within the hypothesis model. The study outcomes offer a novel set of perspectives for curriculum design, serving as a valuable reference for related fields.

II. Review

A. Competition-Based Learning

CBL is a type of teaching method in which real-world tasks are assigned to student teams, and then these teams are encouraged to compete against each other on the final product performance [5]. CBL is based on project-based learning (PBL) [6], and PBL involves challenging problem-solving tasks, including decision making, investigation skills, and reflection [7]. CBL encourages students to join open-ended projects, while the goal of integrating competition into PBL is to stimulate the activeness of students, making them plan projects thoroughly and devote themselves to competition [6].

For enterprises, competition is the driving force for raising product competitiveness and pushing state-of-the-art technique development. Thus, CBL could also stimulate students' ability to develop different strategies to enhance product performance [8]. Based on social independence theory, when a group competes against other groups, they constantly compare themselves to others [9], analyze the strategies from other teams, perform recursive thinking, organize information, and generate alternate solutions [9]. Presently, the common beliefs of group members can often stimulate the group to generate new ideas and creativity, and in the process of helping each other solve problems, participants will also be encouraged to contribute personal knowledge, resources, experiences, and ideas to promote group progress and inspire peer learning [10].

B. Competition-Based Learning, Practical and Competitive Ability

Practical ability strengthens the connection between students' real-life experience, learning content, and interdisciplinary knowledge through hands-on tasks [11]. To cultivate students' creativity, numerous courses have combined hands-on experience with competition, making students feel pressure during competition and construct relative abilities to perform better than others. This teaching method is considered effective in cultivating university students' hands-on and competitive abilities [10]. The overall learning structure of information technology competition is the cycle of code reading, code composing, designing, creating, and data source sharing. Through practice, students can learn how to solve complex information technology problems and improve their hands-on and problem-solving abilities [10]. To achieve this goal, lecturer created a competitive environment or encouraged students to participate in off-campus competitions. These methods could encourage students to combine AI techniques, AI knowledge, algorithms, and real-world problem solving [9].

Competition ability is a critical ability students cultivate during information technology competitions. In the initial stage of the competition, teams would need to compose competition proposals, which is an opportunity to cultivate students' ability of creative solution and presentation of critical points of the solutions they have created, which help demonstrate their competition proposal ability [12]. Students must demonstrate the creativity, highlights, and practicality of their project to the judge using slideshows, and they must also show the judges the commercial value of their project. Project presentation could help cultivate students' project presentation ability [13]. Under the peer learning environment, CBL also encourages students to share their thoughts, challenge others, and come up with solutions collaboratively, which could help cultivate students' communication and deliverance abilities [14]. Competition-based teaching methods have been proven to have a positive influence on students' learning outcomes [12], [13], [14].

C. Theoretical Knowledge, Information Technology, Practical and Competitive Ability

The definition of theoretical knowledge and information technology ability is the hands-on and comprehensive ability to apply knowledge to solve real-world problems [15]. One with this ability is usually equipped with information technology knowledge and hands-on skills, including programming, data structure, software design, or operation systems, and then integrates these skills to develop a new product with a certain level of performance [16]. During information technology competitions, AI practical ability and competitive ability are critical factors in victory [17]. CBL could organize learning activities through specific projects, transforming knowledge learned in class to interaction problem-solving and task completion. Students apply their knowledge to deconstruct the task and plan a thorough solution for it, which is beneficial for the development of their project proposal ability [13].

CBL could also enhance students' hands-on AI ability. Abichandani et al. [18] and Abushakra et al. [4] found that students gained hands-on skills, hands-on experiences, and a positive mindset after participating in these competitions. They believed that competition encourages students to develop new skills and discover development possibilities.

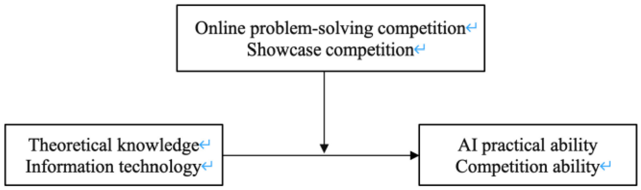

Fig. 1. Hypothetical model.

Lei et al. [19] stated that CBL could help students become team players and have a better understanding of knowledge learned in class, which raised their learning outcomes and relative skills. When students complete AI projects using the AI knowledge and technique they have, their inner potential and interest in learning are enhanced through the process of project prototype showcasing and competitor interaction [15]. Markandan et al. [20] also found that CBL is being implemented correctly, which could enhance students' knowledge/technique sharing and transformation, and CBL could also raise their high-level cognitive technique, learning outcome, collaborating ability, and communication ability.

III. Method

A. Purpose and Hypothesis

This study investigates the implementation of CBL in machine learning courses while promoting active student engagement in global information technology competitions. The primary objective is to examine the discrepancies in the development of diverse abilities between the online problem-solving competition group and the showcase competition group. Furthermore, the study explores the potential moderating effect of competition type on the relationships between variables in the hypothetical model. Fig. 1 illustrates the study structure, and the hypotheses are as follows.

Hypothesis 1: The online problem-solving competition group is experiencing faster growth in its practical ability in information technology and AI compared to the showcase competition group.

Hypothesis 2: The showcase competition group is experiencing faster growth in its theoretical knowledge and competitive ability compared to the online problem-solving competition group.

Hypothesis 3: Competition type moderates the relationships among theoretical knowledge, information technology, AI practical ability, and competitive ability.

B. Curriculum Design and Teaching

The curriculum aims to encourage students to integrate knowledge and skills learned in the classroom, apply them in information competitions, and solve real-world industrial problems. The curriculum concept emphasizes the significance of competition and cooperation, both of which foster students' learning interests, enhance their AI implementation ability, and improve their competitiveness [10], [15]. To ensure the smooth flow of course activities, the selection and training of teaching assistants (TAs) are conducted before the start of the school term. Six students who possess a solid grasp of the courses units, have a basic understanding of AI technology, exhibit a positive attitude, and are willing to assist others who are chosen as TAs. These TAs are required to attend a comprehensive three-day training course to ensure their familiarity with the course content and to equip them with the necessary skills to lead group discussions, provide guidance and support, grade assignments, and aid lecturer in creating effective learning environments.

Fig. 2. Design thinking activities.

The syllabus is designed following a student competition preparation procedure. In the first week, lecturer introduce various information competitions, share award-winning works of seniors, and provide guidance for future studies or employment to ignite students' learning motivation. Weeks 2–8 will be dedicated to introducing and implementing various AI models, laying a solid foundation for students' AI abilities ahead of the competition. From the 9th to the 17th week, the competition preparation stage begins. lecturer will use design thinking teaching to guide students in each group through the steps of empathizing, defining, ideating, prototyping, and testing, leading them to gradually complete their competition work (Fig. 2). In this stage, lecturer acts as guides, teaching advanced AI models relevant to the competition theme and assisting students in writing competition proposals, creating slideshows, and honing oral expression skills. Each TA will also take responsibility for leading 3–4 groups, facilitating discussions, and problem solving. During the official competition, lecturer and TAs will provide supervision and guidance, ensuring that participants are reminded of the necessary precautions.

C. Participants and Procedure

The research subjects consisted of 74 students who enrolled in a machine learning course for the first time during the first semester of 2021 at a university in Northern Taiwan (59 undergraduate students and 15 graduate students; 62 students from the Department of Computer Science and Information Engineering, 11 from the Department of Electrical Engineering, and 1 from the Department of Biomedical Science and Engineering; 45 men and 29 women). The research team explained the research objective, research process, disclaimer, and participant agreement to the students in the first week of the course. Lecturer introduced the course syllabus and information technology competition for students to refer to.

The students had to follow the course schedule by participating in the theoretical knowledge and information technology pretest in week 2 and the posttest in week 17. The pretest's purpose was to assess the students' learning initial abilities, while the pre- and post-test comparison provided an understanding of the enhancement in abilities of the two groups of students following their learning experiences. Theory and AI modeling were taught during weeks 2–8 with the goal of equipping students with foundational knowledge and skills in AI for competitions. Each group was mandated to finalize the competition theme, a three- to four-person competition team, and submit a preliminary concept by the 9th week. In the online problem-solving competition, 18 teams and 60 students participated, while in the showcase competition, 4 teams and 14 students took part. Lecturer and TAs provided tailored guidance to assist each group in developing their competition projects during weeks 9–17. For instance, for the online problem-solving competition, the emphasis was on tasks, such as data preprocessing, AI model refinement, and the mastery of advanced models. In contrast, the guidance for the showcase competition centered on crafting innovative problem solutions, utilizing AI models for creating competition entries, and enhancing presentation skills.

Irrespective of the type of competition in which students participated, each group was required to present their competition projects in class in the 18th week. This practice served the dual purpose of enabling all students to gain insights into diverse creative concepts and problem-solving techniques through the presentation and sharing of their peers' projects. Simultaneously, lecturer, external experts, TAs, and peers utilized a rubric for evaluating each group's competition proposal, slideshow production, and oral presentation. Informed consent was submitted after their grades were finalized, and the study data were obtained from only those students who agreed to participate.

D. Competition Types

There are two types of competitions that students join.

Online Problem-Solving Competition: The organizer posted the questions and data for the competition, and the contestants then built AI models for prediction and uploaded their results. They had to continually optimize their algorithms and models to compete against others. Since the competition was fully online and the model prediction performance leaderboard was updated in real time, the contestants could compete with people worldwide. This competition also helped the students increase their sense of data, algorithms, and models in a high-pressure environment. The contestants could access the relevant information through Kaggle, the largest community of data science in the world. There are always many data analysis competitions underway on Kaggle; since these competitions offer great prizes, they attract many talented data scientists to join in the contest and share their thoughts or tactics on tackling these problems, enabling others to learn from the best [21]. For example, the students in this study took part in the 2021 AIdea competition for orchid species identification and classification [29]. The Aidea platform is similar to the Kaggle platform and was developed in collaboration with the Industrial Technology Research Institute in Taiwan. It offers industry-provided data that enables students to engage in AI model practice and training. The students applied normalization to the provided orchid images from AIdea and subsequently utilized transfer learning technology to train the classification model (Fig. 3).

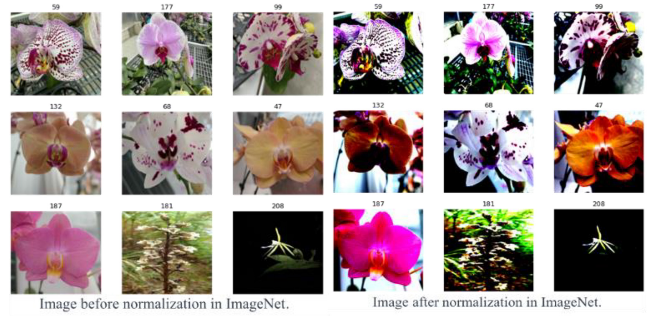

Fig. 3. In 2021, students participated in the orchid species identification and classification competition [29], which was hosted by AIdea. First, they performed normalization on the orchid images and subsequently utilized transfer learning technology to train the model.

Showcase Competition: The organizers set the topics of the competition, and the contesting teams had to develop products using their creativity along with advanced technology based on the given topic. The competition encouraged the contestants to utilize the data to implement creative and practical products or services through data mining or manipulation [17]. For example, the students in this study participated in the International ICT Innovative Services Award 2021 [30]. They built a prediction model of flower blooming based on the blossom season and weather information. Then, the model is integrated into a tourism application. They were honored with an award in the Information Application category (Fig. 4). There are two stages in the competition: 1) in the "project proposal" stage, the contestants draft a proposal describing the creativity, features, technical specifications, target audience, and business model of the project and 2) in the "presentation" stage, the contestants show the motivation, main features, creative ideas, and business models of their project to the judges. This competition applied developmental pressures on students, while lecturer taught machine learning, data analysis, slideshow composition, and oral presentation techniques. Competition could raise students' hands-on ability, proposal composition ability, project slideshow preparation ability, and project presentation ability.

E. Measures

Theoretical Knowledge Test: Theoretical knowledge is the basis of AI implementation, and the objective of the test is to determine whether one has basic AI knowledge. This study utilizes the questions from the Ministry of Education's series of course plans in the field of artificial intelligence technology and applications in Taiwan. Both the pretest and posttest consist of two types, and they are identical [24].

Fig. 4. Status of students attending the finals of International ICT Innovative Services Award 2021 [30].

Which description is incorrect?
(A) We don't need to predetermine the number of clusters when using K-means algorithm.
(B) Support Vector Machine can support multicategory classification using one-versus-one or one-versus-rest structure.
(C) Decision trees work by selecting the rules with the largest information gain.
(D) There is one generator and one discriminator in a Generative Adversarial Network.

Fig. 5. Theoretical knowledge question.

There are four scenarios when you unlock your phone using your fingerprint; how do place the scenarios into the confusion matrix?

1. The smartphone is unlocked with your fingerprint.
2. The smartphone can't be unlocked with your friend's fingerprint.
3. The smartphone can't be unlocked with your fingerprint.
4. The smartphone is unlocked with your friend's fingerprint.

A.

	Actual Yes	Actual No
Predicted Yes	1	2
Predicted No	3	4

B.

	Actual Yes	Actual No
Predicted Yes	1	4
Predicted No	3	2

C.

	Actual Yes	Actual No
Predicted Yes	2	1
Predicted No	4	3

D.

	Actual Yes	Actual No
Predicted Yes	4	2
Predicted No	1	3

Fig. 6. Situation question.

1) Theoretical knowledge is measured with multiple choice questions with correct and incorrect concepts in each question to test the basic AI knowledge of the students. An example is shown in Fig. 5. There are eight questions, and ten points are awarded for each correct answer.
2) Situational questions measured the students' AI knowledge and concepts in various scenarios, and the students had to demonstrate a full understanding of the concepts to obtain the correct answer. An example is shown in Fig. 6. There are two questions, with ten points awarded for each correct answer.

Information Technology Test: The students completed an information technology test and constructed an AI model based on the provided questions in a computer classroom without Internet access or any other outside resources. AI practice includes data preprocessing, data visualization, and AI model construction. In addition to scoring them on model performance, the lecturer could also determine the difficulties students faced in model construction by reading the code they wrote to identify which step of the information technology test they struggled with the most. This study also incorporated questions from of Taiwan's Ministry of Education AI project, with only one question type being the same in both the pretest and posttest [24]. The single question is shown in Fig. 7. The grading formula is as follows: model accuracy 30%, data

Predict each passenger on the Titanic will survive or not with the given data. The data include training data (train.csv), test data (test.csv) and an example of the submission format (gender_submission.csv). There is lots of information about the passengers in the training data, for example, the passenger's sex, name, port of embarkation, room number, age, number of siblings (Sibsp), fare, and ticket number. Predict whether the passenger will survive the sinking of the Titanic with this information.

- Training data (train.csv) as follows:

PassengerId	Survived	Sex	Age	Sibsp	Ticket	fare	Embarked
1	0	male	22	1	A/5 21171	7.25	S
2	1	female	38	1	PC 17599	71.2833	C
3	1	female	26	0	STON/O2.	7.925	S
4	1	female	35	1	113803	53.1	S

- Test data (test.csv) as follows:

PassengerId	Sex	Age	Sibsp	Ticket	fare	Embarked
892	male	47	1	363272	7.8292	Q
893	female	62	0	240276	7	S
894	male	27	0	315154	9.6875	Q
895	male	22	1	3101298	8.6625	S

- Format of submission (gender_submission.csv) as follows:

PassengerId	Survived
892	1
893	0
894	0
895	1

- The score for the prediction result is calculated as what percentage of your predicted survival outcomes are correct, that is, accuracy. Accuracy = (TP + TN)/(TP + TN + FP + FN). Accuracy accounts for 30%.
- In addition to prediction result, there three steps need to be presented during the implementation: "data preprocessing (30%)", "data visualization(20%)" and "AI model building(20%)". Each step has its own percentage of score.

Fig. 7. Information technology question.

preprocessing 30%, data visualization 20%, and AI model construction 20%. Based on the scores the students obtained in each part, the lecturer could further analyze weaknesses in their practical abilities.

AI Model Accuracy: The accuracy counting formula is Accuracy $=$ [true positive (TP) $+$ true negative (TN)]/[TP $+$ TN $+$ false positive (FP) $+$ false negative (FN)], which counts the proportion of correct predictions. Lecturer asks student to evaluate the model on "test data," which is inaccessible to the model during its training phase. The model accuracy on test data indicate the performance of the model and the AI practical ability of the students. Thus, the model accuracy on test data will be used for grading.

Competition Proposal: The competition proposal is one of the most important items for review. The students who joined the course were required to compose a competition proposal based on the topic of the competition. The proposal is constructed of the following five parts: 1) *background and question:* stating the problem and the state-of-the-art solutions, along with their downsides; 2) *objective:* stating the goal of the proposed solution; 3) *data and model building:* stating the proposed method and its structure, including each step of the analysis; 4) *contributions:* stating the creativeness, innovativeness, feasibility, application environment, and field of application; and 5) *expected results:* anticipating the potential of the proposed method and its benefits. Lecturer helped the students modify their competition proposals after they submitted the first version, and the modification continued until the competition ended. This study used a rubric scale to evaluate the proposal quality, with ratings of outstanding (16–20 points), good (11–15), and needs improvement (under 10 points). The maximum score for each item is 20 points, and the total maximum score is 100 points. Lecturer, TAs, professionals, and peers scored the proposals based on this standard. All scorers completed the scale independently. Scorer reliability was calculated using SPSS 26, with Krippendorff $\alpha = 0.79$.

TABLE I
DESCRIPTIVE STATISTICS FOR THE MEANS OF VARIABLES

Variables	Online problem-solving competition (N = 60)				Showcase competition (N = 14)				*df*	*t*	*Cohen's d*
	Mean(*SD*)	Std. Error	95% Confidence Interval		Mean(*SD*)	Std. Error	95% Confidence Interval				
			Lower Bound	Upper Bound			Lower Bound	Upper Bound			
Theoretical knowledge											
Pretest	63.28(20.98)	2.80	56.93	68.16	70.00(13.48)	4.72	56.64	77.21	70	-.69	-.38
Posttest	64.83(19.30)	2.54	59.75	69.90	70.00(7.39)	2.11	66.18	75.36	69	-1.80	-.35
Information technology											
Pretest	13.57(13.81)	1.81	9.88	17.14	24.29(26.52)	7.09	8.97	39.60	69	-1.47	-.51
Posttest	65.98(23.32)	2.98	60.72	72.67	57.86(25.17)	6.73	43.32	72.39	71	1.27	.33
Practical ability											
AI model accuracy	88.53(6.83)	.92	86.68	90.37	85.17(6.10)	1.76	81.29	89.04	65	1.57	.52
Competition ability											
Competition proposal	80.28(4.52)	.58	79.12	81.45	84.57(5.04)	1.34	81.66	87.48	72	3.13**	.90
Slideshow production	77.12(13.01)	1.69	73.73	80.51	88.33(12.67)	3.66	80.28	96.39	69	2.73**	.87
Oral presentation	88.11(2.54)	.33	87.46	88.77	91.43(2.74)	.73	89.85	93.01	72	4.33**	1.27

Note. $^{**}p$ <.01

Slideshow Production: Slides were used for the contestants to express the content and value of their project, as the logic explanations explained for when composing and presenting the slides is extremely important for their careers. The scoring is based on the rubric scale, and the five items being evaluated are as follows: 1) *background and question:* stating the problem and the state-of-the-art solutions, along with their downsides; 2) *objective:* stating the goal of the proposed solution; 3) *results:* stating the main results, such as the accuracy of the model; 4) *the business model and potential benefits of the project:* evaluate the possible business models that the project could have and the corresponding financial and social benefits; and 5) *innovativeness of the project:* demonstrate the contributions and uniqueness of the project. The maximum score of each item is 20 points, and the maximum total score is 100. Scorer reliability was calculated as Krippendorff $\alpha = 0.81$.

Oral Presentation: In the intermediary stage, the students prepared slides and presented their project to the judges, and they had to demonstrate the contributions of their project. To deliver a good presentation, the students required much practice. Oral presentation is an important skill that students need, and this skill is useful for both competition and their future careers. This study also used the rubric scale to evaluate the students' oral presentation performance. The five levels were excellent (90–100), great (80–90), good (70–80), average (60–70), and not good (under 60). Lecturer, TAs, professionals, and peers scored the presentations based on this standard. Scorer reliability was calculated as Krippendorff $\alpha = 0.87$.

IV. RESULTS

In this study, an independent sample *t*-test was initially employed to compare the mean differences in various abilities between two groups of students participating in online problem solving and showcase competitions (Table I). Before proceeding with the formal analysis, the study conducted an assessment of the data's normal distribution and homogeneity. The kurtosis values for each variable ranged from −0.69 to 2.43, and the skewness ranged from −1.04 to 6.33. All variables fell within the acceptable normal distribution range of kurtosis (±3) and skewness (±10) [23]. Additionally, the results of Levene's homogeneity test confirmed that the data met the assumption of homogeneity ($F = 0.38$–2.68, $p > 0.05$), making it suitable for further analysis.

The *t*-test results indicated that there were no significant differences in students' theoretical knowledge ($t = -0.69$, $p > 0.05$, *Cohen's* $d = -0.38$) and information technology ($t = -1.47$, $p > 0.05$, *Cohen's* $d = -0.35$) between the participants of the online problem-solving competition and the showcase competition before the course commenced. This suggests that the initial learning abilities of the two groups of students are comparable. After the competition, it was found that the average scores of competition proposal ($t = 3.13$, $df = 72$, *Cohen's* $d = 0.90$), slideshow production ($t = 2.73$, $df = 69$, *Cohen's* $d = 0.87$), and oral presentation ($t = 4.33$, $df = 72$, *Cohen's* $d = 1.27$) from the students who participated in the showcase competition were obviously higher than those who participated in the online problem-solving competition. This implies that for students who opt to engage in the showcase competition, the guidance from lecturer and TAs will be centered on fostering their skills in developing creative problem solutions, using AI models to craft competition projects, and enhancing their presentation abilities. Consequently, students' competitive abilities after participating in the showcase competition will surpass those of students involved in online problem-solving competitions.

The study also examined disparities in students' theoretical knowledge and information technology performance before and after their engagement in the competition (Table II). In order to assess the differences between the pre- and post-test scores of the two groups of students, a repeated-measures analysis of variance (ANOVA) was employed, with a 2 (competition type) × 2 (pretest/posttest) design. The dataset comprised paired samples and met the fundamental assumptions of normal distribution (kurtosis = −0.69–2.43, skewness = −1.04–6.33) and homogeneity ($F = 0.38$–2.68, $p > 0.05$) [23]. Following the adjustment groups, the findings revealed a significant improvement in students' posttest scores within the realm of information technology ($F = 127.61$, $df = 1$, $\eta_p^2 = 0.65$), surpassing their respective pretest

TABLE II
REPEATED MEASURES ANOVA RESULTS FOR THE COMPETITION TYPES

Source	*SS*	*df*	*MS*	*F*	*P*	η_p^2
Theoretical knowledge						
Group (online problem-solving competition, showcase competition)	703.60	1	703.60	1.39	.24	.02
Error	34445.69	68	506.55			
Test time (pre- and posttest)	57.86	1	57.86	.28	.60	.00
Group * Test time	11.97	1	11.97	.06	.81	.00
Error	14480.17	68	212.94			
Information technology						
Group (online problem-solving competition, showcase competition)	37.55	1	37.55	.07	.79	.00
Error	35724.78	68	525.36			
Test time (pre- and posttest)	41400.40	1	41400.40	127.61***	.00 After adjusted groups: posttest > pretest	.65
Group * Test time	1987.55	1	1987.55	6.13*	.02 The interaction effect is evident.	.08
Error	22060.49	68	324.42			

Note. $^{*}p$ <.05, $^{***}p$ <.001

scores. This suggests that the application of pedagogical strategies and engagement in information competitions can result in enhancements in students' proficiency in the field of information technology.

By analyzing the interaction of competition types with time, this study finds that information technology achieves statistical significance, and its interaction is shown in Fig 8. The information technology pretest score is the average score and was higher for the students who participated in the showcase competition ($M = 24.29$, $SD = 26.52$) than for those who participated in an online problem-solving competition ($M = 13.57$, $SD = 13.81$). For the information technology posttest, the average score of the students who participated in an online problem-solving competition ($M = 65.98$, $SD = 23.32$) was higher than that of the students who participated in the showcase competition ($M = 57.86$, $SD = 25.17$). This implies that the online problem-solving competition places its primary emphasis on the effectiveness of the AI model. When students engage in this competition, lecturer and TAs concentrate on instructing students in data preprocessing, AI model adjustments, and the utilization of advanced models. As a result, the participants in online problem-solving competitions excel in their information technology skills compared to students involved in showcase competitions.

The results also revealed that there was minimal to no improvement in the average scores of the theoretical knowledge pre- and post-tests for the two groups of students ($p > 0.05$). This observation might be attributed to the fact that the 74 subjects had no prior experience with a machine learning course, while they had previously completed data analytics courses. Since the content covered in a machine learning course often overlaps with that of a data analytics course, students' pretest scores in theoretical knowledge were already relatively high, and this contributed to the lack of a significant difference between pretest and posttest scores. Moreover, the machine learning course placed a strong emphasis on hands-on practical learning, which is also reflected in the information technology test scores.

Finally, to examine whether the competition type can moderate the relationship between variables, this study adopted the

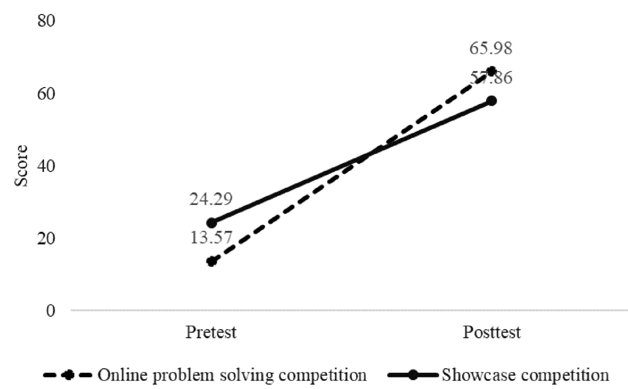

Fig. 8. Interaction effect of the competition types and information technology pretest/posttest scores.

moderating effect analysis proposed by Baron and Kenny [22]. Prior to commencing the formal analysis, checks were conducted to assess the normal distribution, homogeneity, and the presentation of the correlation matrix for both sets of data. The analysis results indicate that the data conforms to the assumptions of normal distribution (kurtosis $= -0.69$–2.43, skewness $= -1.04$–6.33) and homogeneity ($F = 0.38$–2.68, $p > 0.05$) [23]. In the correlation matrix of the online problem-solving competition group, the positive relationships among theoretical knowledge, information technology, and competition ability ($r = 0.35$–0.70, $p < 0.05$). Practical ability was negatively related to theoretical knowledge and competition ability ($r = -0.27$ to -0.44, $p < 0.05$). The results indicate that as students' theoretical knowledge and information technology proficiency increase, their competitive abilities also exhibit improved performance. Nevertheless, when students prioritize enhancing their practical skills, their theoretical knowledge and competitive abilities may diminish. In the correlation matrix of the showcase competition group, the theoretical knowledge pretest was positively related to the posttest ($r = 0.61$, $p < 0.05$), and there were positive relationships among practical ability and competition ability ($r = 0.61$–0.90, $p < 0.05$). The results indicate that as students' theoretical knowledge proficiency increase, their practical skills and competitive abilities also exhibit improved performance.

TABLE III
MODERATED REGRESSION ANALYSIS

Variables	Practical ability	
	AI model accuracy	
	M1	M2
	β	β
Control variables		
Theoretical knowledge pretest	-.26*	
Information technology pretest		-.08
$\triangle R^2$	.07	.01
Predictor variable		
Theoretical knowledge posttest	-.33*	
Information technology posttest		-.12
Theoretical knowledge posttest × Competition types	-.31*	
Information technology posttest × Competition types		.30*
$\triangle R^2$	.08	.09
Total $\triangle R^2$	.15	.10
F value	3.46*	2.33
df	63	63

Note. $^*p < .05$, $^{**}p < .01$; Prediction results that lack significance are excluded from Table III

Knowledge and technology models were treated separately when performing regression analysis. The theoretical knowledge pretest was included in the first layer of the knowledge model, and the theoretical knowledge posttest and the moderator variable (theoretical knowledge posttest × competition types) were included in the second layer. The control variables in the information technology pretest were included in the first layer of the technology model, and the information technology posttest and the moderator variable (information technology posttest × competition types) were included in the second layer to predict practical and competitive ability. Since the correlation coefficient of some variables was above 0.5, collinearity issues were checked for regression analysis. The regression analysis tolerance of this study was between 0.17 and 0.78, the variance inflation factor (VIF) was between 1.28 and 6.03, the tolerance was not less than 0.1, and a VIF greater than 10 may have collinearity, as Hair et al. [23] proposed. The analysis results are shown in Table III. This study found that the theoretical knowledge posttest negatively predicted AI model accuracy ($\beta = -0.33$, $p < 0.05$). In other words, as students' scores on the theoretical knowledge posttest increase, the accuracy of the AI model tends to decrease. The competition type negatively moderated the relationship between the theoretical knowledge posttest and AI model accuracy ($\beta = -0.31$, $p < 0.05$). This indicates that the competition type influences the connection between the theoretical knowledge posttest and AI model accuracy, potentially exacerbating this negative association. The competition type positively moderated the relationship between the information technology pretest and AI model accuracy ($\beta = 0.30$, $p < 0.05$). This suggests that the competition type can strengthen the positive association between the information technology pretest and AI model accuracy.

V. CONCLUSION

This study integrates CBL into machine learning courses, encouraging active student engagement in global information technology competitions. The study examines disparities in the development of theoretical knowledge, information technology, AI practical ability, and competition readiness between two groups of students participating in online problem-solving competitions and showcase competitions, and evaluates the progress in students' theoretical knowledge and information technology skills before and after their participation in the competition. Additionally, the study explores the potential moderating effect of competition type on the relationships between variables in the hypothetical model.

The results of this study partially support hypothesis 1. Students who participated in online problem-solving competitions had lower preclass information technology grades than students who participated in showcase competitions. Through practicing AI techniques and building optimal models [9], students who participated in online problem-solving competitions would have higher after-class information technology grades than students who participated in showcase competitions. The explanation of this phenomenon is that the online problem-solving competition required the teams to build an AI model with high accuracy; thus, the students had to understand and properly design a model to obtain the best results, which increased their information technology and practical abilities. The results are in line with the concept proposed by Jiao et al. [10], who suggested that students could enhance information techniques by continuously practicing the cycle of code reading, programming, designing, and creating.

The results of this study also partially support hypothesis 2. Those who joined the showcase competition were better in competition proposal, slideshow production, and oral presentation than those who joined the online problem-solving competition. The results are in line with the concepts proposed by Chen [12], Chang [13], and Chen [14]. The showcase competition demands student teams to generate a range of creative solutions before the event [12]. Once the project successfully clears the preliminary competition, the team must collaboratively refine the project content and present a final product [14]. During the final round, they are required to demonstrate project creativity, highlights, practicability, and commercial value to the judges using slides [13]. The study has shown that this learning process significantly contributes to the development of various competitive abilities in students.

In addition, the results of this study also partially support hypothesis 3. Competition type negatively moderates the relationship between theoretical knowledge and AI model accuracy. This may be caused by the fact that teams were required to propose a model with great prediction performance within a short amount of time; when they dedicated more time to understanding relative knowledge, the less time they would have for model training and tuning, making these two factors negatively correlated. Finally, competition type positively moderates the relationship between information technology and AI model accuracy, indicating that those who are better in information technology build AI models with higher accuracy. In particular, students who engage in online problem-solving competitions exhibit superior proficiency in various information technologies, including programming, data structure, software design, and operation systems. Through the effective integration of these skills, they successfully develop predictive models that achieve a commendable level of performance [16]. The study's overall findings indicate that various competition types enhance the development of different abilities in students. Online problem-solving competitions accelerate the growth of students' information technology abilities, while showcase competitions effectively promote the development of their competitive abilities.

VI. Contributions, Limitations, and Future Work

Current information technology courses have been fully integrated into education, and the teaching method proposed by this study could be applied to other information technology courses to help students construct relative abilities. The teaching model differs by competition type; each group has its own project, which helps students earn real-world project experience, and enterprises, which can recruit them based on the results from the competition. Finally, this study proposed an evaluation method suitable for competition learning. This study applied a standard test to evaluate students' theoretical knowledge and information technology ability and used a rubric scale to allow lecturer, TAs, professionals, and peers to evaluate the competition proposal, slideshow production, and oral presentation performance of each group, making the evaluation more complete.

There are some limitations to this study. First, students may choose competitions based on curiosity about new technology or topics or even based on peer preference, resulting in an unbalanced situation between the online problem-solving competition (60 students) and the showcase competition (14 students). Unbalanced data can significantly impact the outcomes of statistical analysis. Typically, statistical results derived from a group with many samples tend to be more robust than those from a group with a small number of samples, leading to biased judgments [25]. Previous approaches to handling unbalanced data primarily involved imposing balance, such as random data selection or deletion. While these methods were statistically effective, they failed to represent the true distribution of the data accurately [26]. In this study, the authors refer to Szucs and Ioannidis [27] and review more than 1000 journals on functional magnetic resonance imaging (fMRI) from 1990 to 2018. The findings reveal that 96% of the highly cited FMRI experimental papers had a median sample size of 12. Additionally, the majority of these small-sample studies utilized t-tests, correlation analysis, and repeated-measures ANOVA for data processing, providing the advantage of accurately representing the true state of the research data. To address the issue of unbalanced data in future related studies, it is advisable to begin by conducting interviews to gain insights into the rationale behind students' selection of competition projects, including personal preferences, strengths, and weaknesses, or future career plans, which could help lecturer lead students based on the student's expectations.

Finally, in the CBL environment, "competition" plays a crucial role, with two distinct types, anonymous and nonanonymous, each having a profound impact on students' learning outcomes and psychological development [28]. Anonymous competitions foster learning by generating positive motivation and promoting meaningful cognitive engagement. Conversely, nonanonymous competitions often lead to peer rivalry, potentially eroding students' confidence and interest in learning when faced with failures [28]. In this study, the online problem-solving competition adopts an anonymous format, while the showcase competition follows a nonanonymous approach. The study revealed that students participating in the former were more inclined to share their problem-solving skills within the group, among peers, or on the website while preparing for the competition. However, the latter tended to face conflicts of views during the proposal preparation stage, disagreements on function, interest, aesthetics, or work quality during the implementation of work, and intense competition for opportunities to give oral presentations in the final stage. To gain a more comprehensive understanding of students' performance goals, learning strategies, and responses to different competition modes, future studies are recommended to collect student competition diary data.

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