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Improving student learning performance in machine learning curricula: A comparative study of online problem-solving competitions in Chinese and English-medium instruction settings

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Abstract

Background: Numerous higher education institutions worldwide have adopted English-language-medium computer science courses and integrated online problem-solving competitions to bridge gaps in theory and practice (Alhamami *Education and Information Technologies*, 2021; 26: 6549–6562).

Objectives: This study aimed to investigate the factors influencing the use of online competitions in machine learning courses and their impact on student learning. We also analyse disparities in learning outcomes and instructional language effects (Chinese vs. English).

Methods: Among 123 participants at northern Taiwan university, 74 chose Chinese instruction (CMI), and 49 opted for English instruction (EMI). The course spanned 18 weeks: team formation in week one, data analysis, machine learning, and deep learning from week 2 to 8, draft proposals and oral presentations by week 9, instructor guidance in weeks 9–17, followed by off-campus competitions. In week 18, students presented projects for evaluation by judges.

Results: The results showed improved scores in competition proposal writing and oral presentations, especially for CMI students, who excelled in these areas and in terms of creativity. CMI students emphasized domain knowledge, implementation completeness, and technical depth in proposals. The EMI students focused on implementation completeness and artificial intelligence model accuracy, along with creativity.

Conclusion: CMI students achieved superior outcomes in machine learning courses, particularly in terms of competition proposals, oral presentations, and increased creativity. Instructional language choice significantly influenced learning trajectories, leading to distinct knowledge development focuses for CMI and EMI.

KEYWORDS
competition learning, English-medium instruction (EMI), learning performance, machine learning, online problem-solving competition

1 | INTRODUCTION

Artificial intelligence (AI) started the fourth industrial revolution; it has replaced many roles and become the centre of many industries. Humans could collaborate with AI to enhance production efficiency and determine optimal solutions (Shin, 2021). The USA, China, South Korea, and several other countries have been preparing AI education to adapt to changes worldwide (Bhutoria, 2022; Ng, Luo, et al., 2022). AI education inspires students' computational thinking and AI thinking competencies, which further cultivates their ability to react to the rapid development of technology and become smart interdisciplinary learners (Huang & Qiao, 2022). Previously, AI education focused mainly on teaching AI knowledge and skills to students (Dohn et al., 2022), but there were fewer exercises applying AI techniques to solve real-world problems. Industries frequently host extensive online problem-solving competitions cantered on AI, enabling students to assemble interdisciplinary teams and collaborate on addressing real-world challenges (AIdea, 2023). Competition-based learning could link school and industry, allowing students to implement the theory learned in class. Students could show their creativity in competition, and companies could discover outstanding talent that meets their needs, making job searching and talent acquisition easier than before (Abou-Warda & Roberts, 2016).

Online problem-solving competitions primarily offer industry-generated questions and authentic data to foster the formation of cross-disciplinary teams among students. The objective of these teams is to utilize industry-provided data to develop AI models that address real-world challenges (AIdea, 2023). Throughout the competition, student teams engage with experts globally, providing them with the opportunity to refine their thinking on algorithm enhancement, AI model improvements, and innovative solutions (Kaggle, 2023). Among various information competitions, online problem-solving competitions are the most popular among students. Students believe that optimizing AI model accuracy from a data analytics perspective alone is enough for them to participate in competitions, which are easier than other types of competitions (Chang & Lin, 2024). Nevertheless, they often underestimate the importance of comprehending and extracting data features from interdisciplinary viewpoints, which can impede the effectiveness of a creative solution. Therefore, this study investigated whether integrating online problem-solving competitions with machine learning courses can enhance students' practical experience in building AI models effectively and utilizing industry-provided data to address real-world challenges. The aim is to validate the effectiveness of this course design in fostering students' domain knowledge, enhancing their ability to craft competition proposals, refining oral presentation skills, and bolstering their proficiency in implementing AI solutions (Angeli & Giannakos, 2020).

Moreover, educational institutions in non-English-speaking countries have recently promoted the adoption of English as a medium of instruction (EMI) in computer education (Alhamami, 2021). EMI is crucial for nurturing international talent and bolstering the global competitiveness of higher education institutions (Richards & Pun, 2023). However, this policy has faced widespread criticism primarily because of its inefficiency in delivering course content and the lack of evidence supporting its effectiveness as a teaching language in computer science courses. Its success is significantly influenced by the English proficiency of both teachers and students as well as their level of computer science knowledge (Alhamami, 2021). Currently, research related to EMI predominantly concentrates on policy shortcomings (Alhamami, 2021), variations in programs across countries (Richards & Pun, 2023), and the impact of student characteristics on EMI learning efficacy (Alhamami, 2021; Peng & Xie, 2021). Conversely, studies investigating how EMI can be effectively integrated with teaching strategies to enhance student learning efficiency are relatively scarce (Lee, 2022), especially in the field of computer science. Therefore, this study additionally examines whether the introduction of a competition learning strategy (online problem-solving competition) into machine learning courses with EMI and CMI (Chinese-medium instruction) results in similar learning effects and paths for the two student groups following the intervention.

2 | LITERATURE REVIEW

2.1 | Curriculum design for AI education

AI education delves into the realms of computer capabilities, encompassing sensing, perceiving, decision-making, acting, comprehending, reasoning, learning, and creating (Chiu, 2022). The position of AI education within the professional landscape of computer science (Zawacki-Richter et al., 2019) mandates that students acquire proficiency in AI knowledge and technology (Ng et al., 2023). AI education employs three primary teaching methods: project / problem-based learning, which establishes a tangible context to inspire AI learning; collaborative learning, which fosters communication and teamwork among students for the acquisition of AI knowledge and skills; and experiential learning, which incorporates interactive activities to enhance students' practical experience in AI (Ng et al., 2023). Notably, 'competitive learning' synergizes the benefits of the aforementioned methods, encouraging students to form cross-disciplinary teams to collaboratively tackle complex, real-world problems (Jiea et al., 2019).

AI education concentrates on cultivating student expertise in AI methods and research capabilities. Courses aim to provide a comprehensive understanding of the theoretical foundations of AI, modelling technology, model architecture, and existing limitations in the field while also exploring the potential for future methodological advancements (Ng et al., 2023). To assess the attainment of learning objectives, educators and researchers commonly employ quantitative methods, such as attitude questionnaires and knowledge tests (Chiu, 2021), qualitative assessments, including assignments and actual observations (Druga et al., 2019), and mixed methods, such as triangulation (Ng et al., 2023).

Learning outcomes are categorized into affective, behavioural, and cognitive dimensions (Ng et al., 2023). The affective dimension delves into how students enhance their inner feelings and physiological changes toward AI (Rogaten et al., 2019). The behavioural dimension scrutinizes students' external activities during the learning process and associated psychological activities, including active learning, behavioural intentions, cooperation, and participation (Priya et al., 2022). The cognitive dimension assesses learners' perceived AI knowledge, aligning with the cognitive goals in Bloom's taxonomy and focusing on three levels: (1) knowing and understanding, involving the ability to explain, specify, and comprehend concepts (Zhang et al., 2022); (2) using and applying, encompassing the ability to apply prior knowledge and develop AI drivers and algorithms (Williams et al., 2022); and (3) evaluating and creating, enabling students to design and implement AI-driven solutions for problem solving (Ng, Lee, et al., 2022). By measuring these objectives, teachers and researchers can gauge the effectiveness of AI course design and pinpoint areas that require improvement (Zhang et al., 2022).

2.2 | Utilizing online problem-solving competitions to enhance students' AI learning

Online problem-solving competitions are based on the concept of competition-based learning (Liu et al., 2017). Competition-based learning is fundamentally project-oriented education that encompasses problem solving, decision making, research skills, and reflection (Jiea et al., 2019). According to social interdependence theory, a competition mindset arises when a group competes with other groups (Sung, 2022). During competition, team members collaboratively analyse the possible strategies of opposing teams and then develop solutions or alternate methods after collecting meaningful information (Johnson, 2016). This collaboration stimulates new perspectives and creations, and the process of problem solving also encourages individuals to provide personal knowledge, skills, resources, experience, or thoughts (Kim & Shin, 2015) to enhance team progress and encourage their peers to learn more (Johnson, 2016).

Online problem-solving competitions serve as the cornerstone of computer programming contests, necessitating teams to engage in critical thinking and craft solutions for unpredictable problems rooted in their experiences. Both of these requirements are fundamental aspects of human intelligence and prove challenging to replicate through machine learning methods (Li et al., 2022). Conquering competitive programming problems represents a significant leap for participating teams, demanding a deep understanding of algorithms, mathematics, and data structures (Wirawan et al., 2017). With each competition, fresh and demanding problems emerge, allowing teams to draw inspiration from solutions and algorithms from prior contests. The world of competitive programming has enjoyed widespread popularity, with events such as the International Collegiate Programming Competition and the International Olympiad in Informatics, which have been prestigious fixtures in computer science since the 1970s, attracting hundreds of thousands of participants globally (Li et al., 2022). A recent online problem-solving competition, organized by the Kaggle (2023) and Aidea (2023) platforms, also involved the participation of experts from various corners of the world.

Currently, a few studies have discussed the instructional application of online problem-solving competitions in machine learning or information science courses (Chow, 2019), including competition experiences (Cabellos-Aparicio et al., 2021; Salta et al., 2020), and postcompetition outcomes (Cañada et al., 2015; Yuen et al., 2023). For instance, based on his experience teaching machine learning, Chow (2019) suggested that the Kaggle competition teaching model effectively heightened students' motivation and improved learning outcomes. Cabellos-Aparicio et al. (2021) detailed the 'ITU AI/ML in 5G Challenge' competition, encompassing competition questions, available tools and resources, organizational aspects, competition statistics, solutions from the top three winners, and the authors' experiences in the competition. Salta et al. (2020) introduced a cooperative physics puzzle game on an online platform called Geometry Friends and discussed the associated competition challenges and prevailing solutions. Cañada et al. (2015) and Yuen et al. (2023) delved into students' competition rankings, opinions, and academic progress postcompetition. Their findings indicated that participation in competitions could enhance students' intrinsic learning motivation, reduce absences, and improve proficiency in new programming languages (Cañada et al., 2015). Furthermore, competitions also foster independent learning, innovative thinking, and problem-solving skills (Yuen et al., 2023). Nevertheless, existing studies have not thoroughly investigated how the intervention of teaching strategies and variations in teaching languages affect students' performance throughout the competition process. Therefore, the primary objective of this study was to examine the improvement in the learning outcomes of students in machine learning courses taught in both Chinese and English before and after their participation in online problem-solving competitions under the guidance of instructors.

2.3 | Factors influencing learning outcomes in online problem-solving competitions

Success in computer programming competitions relies heavily on the seamless integration of domain knowledge and information technology (Dash et al., 2022). Domain knowledge encompasses the type of knowledge associated with a specific domain or topic and is often referred to as background knowledge. The context of information technology encompasses relevant information related to the problem, which can take various forms, such as features, concepts, rules of thumb, distributions, or causality. Domain knowledge plays a critical role in human-robot collaboration (Dash et al., 2022). Recent research on machine learning (Murdock et al., 2020), deep learning (She et al., 2021), and neural networks (Shui et al., 2022) has demonstrated the benefits of integrating domain knowledge and AI in enhancing model prediction performance. In situations with limited data availability, the incorporation of domain knowledge into models can help maintain model performance and expedite solution development (Yamamura et al., 2022). However, domain knowledge is crucial in the realms of computer science and competitive learning (Dash et al., 2022). Nevertheless, there is a notable absence of empirical studies that adequately integrate assessments of domain knowledge to gain insights into students' actual learning experiences in computer science and competitive learning.

In computer programming competitions, students develop a set of essential skills. First, they acquire "competition proposal writing," aimed at showcasing their comprehensive grasp of interdisciplinary knowledge for problem-solving deployment (Han & Liu, 2018). In addition to classroom instruction, students are expected to engage in self-directed learning, integrate interdisciplinary knowledge and collaborate with teammates from diverse backgrounds. By the competition's conclusion, students must devise innovative solutions to address intricate problems (Chen, 2022). Second, students acquire "oral presentation" skills, enabling them to transform and comprehend knowledge or information from diverse domains and employ both linguistic and nonlinguistic techniques (Sondakh et al., 2020). They are encouraged to express their viewpoints while engaging in constructive challenges, thereby fostering collaborative problem solving (Chen, 2019). This teaching approach has proven effective in cultivating students' communication and expressive abilities in multisubject, multicultural, and multilingual environments (Chen, 2019). Finally, the competitive environment in the course fosters the development of "AI model accuracy." This setting encourages students to apply AI knowledge and algorithms acquired in their coursework to tackle real-world problems (Song et al., 2022). Through continuous practice, students become adept at resolving complex information technology challenges, enhancing their problem-solving abilities and hands-on skills (Jiao et al., 2020). While guiding students in crafting creative solutions and creating competition projects, teachers have progressively honed students' skills in competition proposal writing, oral presentation, and AI domain knowledge. Nevertheless, there is a dearth of studies that thoroughly investigate the influence of student participation in competitions on the development of these skills.

The aforementioned skills contribute to achieving competitive outcomes, including creativity, technical proficiency, comprehensiveness, and feasibility (Aldea, 2023; Kaggle, 2023). Research indicates that students who engage in competitions exhibit greater activity and positivity, along with improved creative, hands-on problem-solving, and teamwork abilities. In a competitive milieu, students increase their technical skills, fostering the development of more innovative designs (Chen et al., 2016). The solutions proposed by these students tend to be more practical and thorough than those generated in noncompetitive settings (Watson & McGowan, 2019). Competition-based learning facilitates effective communication among team members, enabling them to surmount challenges and promote information gathering from diverse sources. This collaborative approach encourages greater dedication to optimizing models, ultimately leading to superior solutions (Chen & Chang, 2020). Although international information competitions employ standardized scoring indicators, including creativity, technical proficiency, comprehensiveness, and feasibility, it is surprising that few studies have utilized these indicators to assess students' performance in competitions.

Furthermore, given the prevalence of English as the primary language in international information competitions, non-English-speaking countries have increasingly advocated for using English as the main teaching language, especially in computer science (Alhamami, 2021). However, no studies have scrutinized whether incorporating competitive learning into EMI computer science courses can yield learning outcomes comparable to those for students whose native language aligns with the language of instruction. To address these gaps, the second objective of this study is to compare differences in domain knowledge, competition proposal writing, oral presentation, AI model accuracy, and competition outcomes among students in machine learning classes taught in Chinese and English before and after the competition. This comparison aimed to verify the effectiveness of instructional interventions employed by teachers in integrating competitive learning into the curriculum.

2.4 | The influence of instructional language (Chinese vs. English) on students' learning trajectories in online problem-solving competitions

Since the advent of computers, computer science education has been closely associated with the English language, which is widely recognized as the language of science and technology. Most higher education institutions globally, even in non-English-speaking nations, offer computer science courses in English (Alhamami, 2021). Alhamami (2021) observed that students with a strong command of English tend to attain higher levels of academic success. Similarly, Gu and Ren (2017) noted that students perform better when they possess professional-level English proficiency prior to enrolling in engineering-related courses. However, Raj et al. (2017) found that implementing an EMI policy in university-level computer science programs can be challenging, particularly for students who are new to programming languages and whose native language is not English. Furthermore, Pal and Iyer (2015) discovered that students in programming language courses tend to achieve superior results when taught in their native language compared to those taught in English.

Numerous discussions within the relevant literature have explored the implementation of EMI policies in higher education. However, research pertaining to computer science courses remains relatively limited. The emerging trend of utilizing computer science to address intricate real-world challenges underscores the necessity for students to acquire diverse knowledge from various fields and effectively integrate it into information technology to devise efficient solutions (She et al., 2021). Constructing machine-based models has the potential to enhance programming language accuracy by incorporating precise and in-depth domain knowledge (Dash et al., 2022). Furthermore, leveraging domain knowledge for ongoing refinement and deepening of algorithms can lead to more precise and efficient prediction models (She et al., 2021). This approach enables students to cultivate creativity, practical skills, and a deeper understanding of information technology for addressing complex problems (Chang & Lin, 2024). Conversely, limitations in language proficiency among students studying computer science may result in a decline in domain knowledge, comprehension of information concepts, and proficiency in technology (Pal & Iyer, 2015). These language-related challenges can indirectly impede students' problem-solving abilities.

Studies consistently highlight that students with robust English proficiency demonstrate superior performance in both academic achievements and career outcomes (Alhamami, 2021). However, divergent perspectives exist around the resulting student proficiency in subject content or the effectiveness of EMI courses (Peng & Xie, 2021). Particularly within the context of information competitions, students are required to possess a profound understanding of diverse information, technologies, and domain-specific knowledge. Subsequently, they are expected to formulate innovative solutions in response to the competition theme. During this process, students' professional learning abilities play a pivotal role in influencing competition proposal writing, oral presentations, and the accuracy of AI models used in implementing creative solutions. Ultimately, the various skills cultivated by students in the competition preparation stage will impact their performance in terms of creativity, implementation completeness, and technical depth during formal competition. As such, the third objective of this study is to test a mediating moderation hypothesis for competition learning based on theoretical foundations, aiming to ascertain whether instructional language (Chinese vs. English) interferes with students' learning trajectories.

2.5 | Purpose and questions

The objective of this study is to explore the factors that influence machine learning courses within online problem-solving competitions and their influence on student competition outcomes. Furthermore, this study also examines variations in student learning outcomes and the effects of instructional models between CMI and EMI. The hypotheses are as follows:

> **Hypothesis 1.** Participation in an online problem-solving competition by students in both CMI and EMI machine learning classes is expected to result in higher scores for posttest competition proposal writing and oral presentations compared to their pretest scores.

> **Hypothesis 2.** The domain knowledge, competition proposal writing, oral presentation skills, AI model accuracy, and competition outcomes of students in CMI machine learning classes are hypothesized to be significantly superior to those of students in EMI classes.

> **Hypothesis 3.** CMI and EMI in machine learning classes moderate the relationships among domain knowledge, competition proposal writing, oral presentations, AI model accuracy, and competition outcomes.

3 | RESEARCH DESIGN

3.1 | Curriculum design and teaching

The curriculum is designed with the goal of encouraging students to integrate the knowledge and skills acquired in the classroom, apply them to information competitions, and address real-world industrial challenges. This curriculum concept places a strong emphasis on the importance of both competition and cooperation, which collectively stimulate students' interest in learning, enhance their proficiency in implementing AI solutions, and boost their competitiveness (Huang & Qiao, 2022; Jiao et al., 2020). To ensure the seamless execution of course activities, the selection and training of teaching assistants (TAs) are carried out prior to the start of the academic term. Six students who possessed a firm grasp of the course material, outstanding proficiency in English, possessed a fundamental understanding of AI technology, demonstrated a positive attitude and were willing to assist their peers were chosen as TAs. These TAs need to complete a comprehensive three-day training program to familiarize themselves with the course content and equip themselves with the necessary skills to lead group discussions, provide guidance and support, assess assignments, and collaborate with instructors to create effective learning environments.

The syllabus was structured in accordance with a student competition preparation framework. One class is conducted in Chinese, while the other is conducted in English. During the initial week, instructors introduce students to various information competitions, showcase award-winning projects from previous students, and offer guidance on future academic or career pursuits to inspire and motivate their learning. Weeks 2–8 will focus on teaching data analysis principles, various machine learning algorithms, and deep learning models, establishing a robust foundation for AI skills in preparation for the competition. The competition preparation phase officially commences from the 9th to the 17th week. Online problem-solving competition places a strong emphasis on devising efficient AI solutions for industrial challenges. As a result, instructors employ problem-oriented teaching techniques to assist each group of students in utilizing the provided materials to construct AI models (Figures 1, 2). In cases where the model's predictive performance is subpar, teachers and teaching assistants offer guidance to students in adapting both the data and AI models according to the data's characteristics or in utilizing more advanced AI models to enhance prediction accuracy.

FIGURE 1 Illustrates group-based problem-oriented teaching.

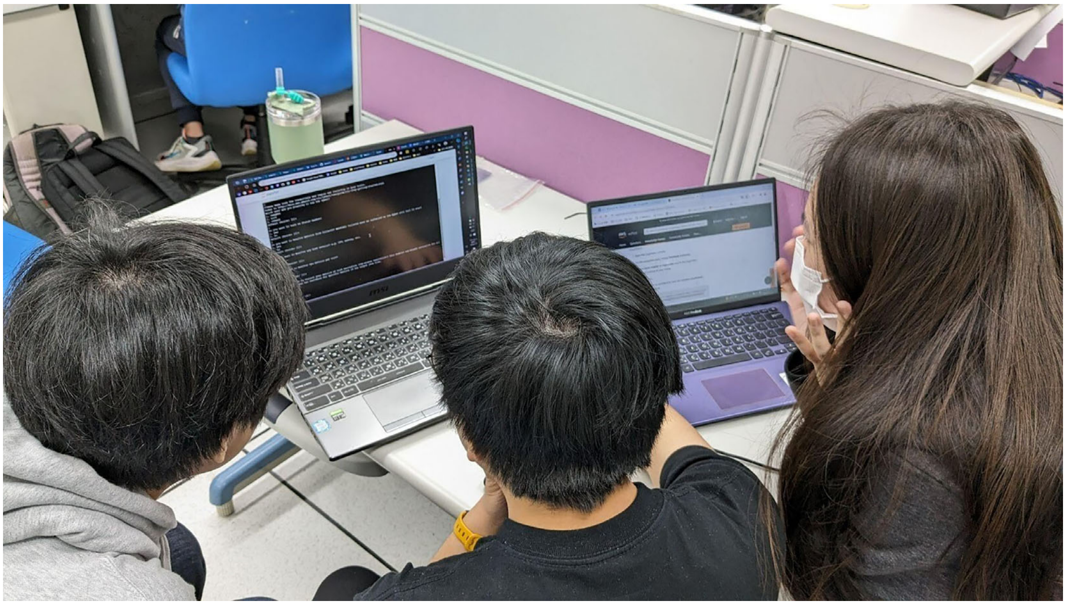

FIGURE 2 Online discussions for student after-school groups.

3.2 | Participants and procedure

In 2022, at a university in northern Taiwan, the participants in this study were students enrolled in machine learning courses provided by the Department of Information Engineering. The study included a total of 123 students, 74 of whom opted for CMI (comprising 59 undergraduates and 15 graduates) and 49 of whom chose EMI (comprising 39 undergraduates and 10 graduates). In the first week of the course, the research team explained the research objectives and procedures and obtained participant consent from the students. The instructor provided an overview of the syllabus and discussed the available online problem-solving competitions. Subsequently, she encouraged students to create teams of 2–4 members and initiate the planning process for the competition content. In the second to eighth weeks of the course, lecturers taught data analysis principles, various machine learning algorithms, and deep learning models in class. During the ninth week, each group was required to submit a draft of their competition proposal and an oral presentation video file. These submissions will enable the instructor and teaching assistants to gain insight into the competition's theme and each group's initial planning. Simultaneously, a rubric will be employed to assess the initial proficiency of each group's competition proposal writing and oral presentation skills. Between weeks 9 and 17, the instructor and teaching assistants guided each group in developing optimal solutions aligned with the competition theme, refining or replacing AI models and enhancing teamwork skills based on the respective group's competition plan and oral presentation draft. Throughout this timeframe, each group is expected to participate in various competitions according to specified schedules. In the 18th week, each student group must deliver their presentations in class, submit the final iteration of their competition proposal, and answer questions from the judges, which includes external experts, tutors, teaching assistants, and classmates. Judges will employ a rubric to evaluate the students' competition proposals, work, and oral presentations, as well as to gauge their progress in domain knowledge, competition proposal composition, oral presentation proficiency, and competition outcomes (creativity, implementation completeness, and technical depth) achieved through their participation in competition learning. Prior to grading, the instructor clarified the rubric of grading criteria for all judges.

3.3 | Online problem-solving competition

In an online problem-solving competition, the organizers would come up with questions and relative data for the competitors to solve with predictions using AI models. The competitors continue optimizing their algorithm and AI models and upload the prediction results every day, and the platform updates the rankings in real time. Students could compete with competitors worldwide since the competition is completely online, which places pressure on students to increase their understanding of AI models and sharpen their sense of assigned data. Relative information could be obtained from the largest data science community, Kaggle, where outstanding data scientists and enthusiasts share their thoughts on how to address these problems. Kaggle competitions often come with a high prize, which attracts the best talent to participate in these events. Students can also learn from others by studying their thought processes and coding logic (Kaggle, 2023). In addition to Kaggle, the AIdea AI collaboration platform is another platform that pursues effective AI solutions by attracting talent to participate in tasks and problems provided by corporations in Taiwan. The AIdea platform is supported by the technology development program in the Department of Industrial Technology, Ministry of Economic Affairs, and developed and implemented by both the Computational Intelligence Technology Center and the Industry, Science and Technology International Strategy Center in the Industrial Technology Research Institute (AIdea, 2023).

The two platforms mentioned above update their questions periodically, resulting in varying topics and requiring AI techniques for online problem-solving competitions. Grading the quality of Irvin mangoes requires image recognition, and a competition involving doctor–patient communication requires natural language processing techniques to classify diagnoses and ensure privacy. The optic plate scheduling problem mainly focuses on production schedule optimization, and the objective is to generate the least amount of waste while increasing the production level at the same time. Students obtained access to real-world data provided by various companies and applied AI techniques to achieve the best results. For example, the instructor guided students in participating in the "Employee Resignation Prediction" competition hosted on the AIdea platform in this study. This competition offers a wide array of data concerning factors influencing employee turnover, including employee age, performance, education, business trips, and leaves, encompassing a total of 47 different feature values. Typically, an enterprise's human resources department relies on manual assessment based on past experiences and conditions to gauge the likelihood of employee turnover. However, this manual approach is disadvantaged by the complexity of employee data, making accurate turnover rate predictions challenging. Consequently, this competition team employed machine learning techniques to construct models for analysing and forecasting future employee turnover rates. The competition evaluated the participating teams' predictions using the Fbeta-score. Ultimately, the team achieved an Fbeta score of 0.192, securing the 16th position among 467 participants.

3.4 | Measures

3.4.1 | Domain knowledge rubric

To evaluate the understanding and application of domain knowledge on each competition topic (Dash et al., 2022), this study applied a rubric for quantitative evaluation. The details of the scale are as follows: Outstanding (9–10 points): The student fully understands the domain knowledge regarding the competition topic and then accurately applies the knowledge to enhance model prediction performance. Excellent (7–8 points): The student understands most of the domain knowledge regarding the competition topic and then applies it to enhance model prediction performance. Great (5–6 points): The student understands the domain knowledge regarding the competition topic to a certain extent and then applies it to enhance the prediction performance. Good (3–4 points): The student tried to understand the domain knowledge regarding the competition topic and then tried to apply it to enhance the prediction performance. Poor (1–2 points): The student is not aware of the domain knowledge needed for this competition and cannot apply it to enhance model prediction performance. An external expert, an instructor, and six TAs provided grades based on this scale to evaluate how students applied domain knowledge to the prediction model. All scorers completed the scale independently. Scorer reliability was calculated using SPSS 26, with a Krippendorff $\alpha = 0.74$. The scoring formula for domain knowledge equally allocates score results among an external expert, an instructor, and TAs, with each contributing one-third of the total value.

3.4.2 | Competition proposal writing rubric

The composition of competition proposals is an important element in the competition participation review, which evaluates students' ability to draft proposals based on a given topic. The proposal can be decomposed into five parts: (1) proposal background and current issues, including current methods used and issues faced; (2) proposal objectives, including the goals of the proposed method; (3) solution architecture and steps, including the architecture of the proposed method and an elaboration of each step of the process; (4) highlights of the proposed solution, including the creativity, innovativeness, feasibility, application scenarios, and application level of the proposed solution; and (5) expected outcomes and benefits, including the estimated results and benefits of the proposed solution. Instructors and teaching assistants supervise students in modifying competition proposals, AI models, and project presentation techniques. A rubric was set to evaluate the competition proposal design before and after participating in competitions, with three scales: excellent (8–10 points), good (5–7 points), and poor (under 4 points). An external expert, an instructor, and six TAs handed out grades based on this scale to evaluate students' competition proposal composition ability. Each scorer independently completed the scale, and scorer reliability was assessed using SPSS 26, resulting in a Krippendorff α coefficient of 0.81. The scoring formula for the competition proposal evenly distributed the score among an external expert, an instructor, and TAs, with each contributing one-third of the total value.

3.4.3 | Oral presentation rubric

To evaluate students' ability to clearly express the content and value of their project, an oral presentation rubric was used. During the intermediate round, students prepared a slideshow to demonstrate the content and value of their project. To clearly deliver the features of their project fluently in a short period, students needed to take time practicing, honing a presentation ability that is important to students for both competition and their careers. The rubric's scale for presentation ability is as follows: excellent (9–10 points), great (7–8 points), good (5–6 points), ordinary (3–4 points), and poor (lower than 2 points). An external expert, an instructor, six TAs, and fellow classmates handed out grades based on this scale to evaluate students' communication ability. Each scorer completed the scale independently, and scorer reliability was evaluated using SPSS 26, yielding a Krippendorff α coefficient of 0.79. The scoring formula for the oral presentation evenly allocated the score among an external expert, an instructor, TAs, and classmates, with each contributing one-fourth of the total value.

3.4.4 | AI model accuracy

The accuracy counting formula, accuracy = [true positive (TP) + true negative (TN)]/[true positive (TP) + true negative (TN) + false positive (FP) + false negative (FN)], calculates the proportion of correct predictions. The lecturer instructed students to assess the model on "test data," which was unavailable to the students during the training phase of the model. The model's accuracy on the provided test data reflects both its performance and the practical AI proficiency of the students. Thus, the model's accuracy on test data will be a key factor in determining grades.

3.4.5 | Competition outcomes rubric

To evaluate the quality of the project, this study referred to the grading standards of previous information technology competitions and applied these evaluation metrics. "Creativity" implied the influence and creativeness of the project; "Implementation completeness" implied the completeness of the backend system and frontend user interface. "Technical depth" would be the uniqueness and level of the technique used in the project, with better outcomes being harder to copy. This study designed a competition outcome rubric based on these metrics and classified the project as excellent (8–10 points), moderate (5–7 points), or poor (under 4 points). The maximum possible point value is 10 points. One external expert, an instructor, six TAs, and fellow classmates handed out grades based on this scale to evaluate students' projects. Each scorer completed the scale independently, and scorer reliability was evaluated using SPSS 26. The Krippendorff α coefficients for creativity, implementation completeness, and technical depth were determined to be 0.63, 0.68, and 0.82, respectively. The scoring formula for the competition outcomes evenly distributed the score among an external expert, an instructor, TAs, and classmates, with each contributing one-fourth of the total value.

4 | DATA ANALYSIS AND RESULTS

4.1 | Descriptive analysis

This study aimed to understand the differences in the performances of students participating in different taught languages before and

TABLE 1 Descriptive statistics for each variable.

	Machine learning curriculum									
	CMI					EMI				
				95% Confidence intervalflyer					95% Confidence interval	
Variables	*N*	Mean (SD)	Std. error	Lower Bound	Upper Bound	*N*	Mean (SD)	Std. Error	Lower Bound	Upper Bound
Domain knowledge	74	4.62 (2.58)	0.30	4.02	5.22	49	4.84 (2.68)	0.37	2.68	0.38
Competition proposal writing										
Pretest	74	5.93 (0.50)	0.06	5.82	6.05	49	5.84 (1.05)	0.14	1.05	0.15
Posttest	74	8.11 (0.49)	0.06	8.00	8.22	49	7.86 (1.42)	0.19	1.42	0.20
Oral presentation										
Pretest	74	7.69 (0.31)	0.04	7.62	7.76	49	7.41 (0.41)	0.06	0.43	0.06
Posttest	74	8.87 (0.29)	0.03	8.81	8.94	49	8.55 (0.57)	0.08	0.60	0.09
AI model accuracy	67	8.79 (0.68)	0.08	8.63	8.96	37	8.75 (1.57)	0.25	1.57	0.26
Competition outcomes										
Creativity	74	6.96 (0.70)	0.08	6.80	7.12	49	6.31 (1.09)	0.15	1.09	0.16
Implementation completeness	74	7.08 (0.78)	0.09	6.90	7.26	49	6.91 (0.81)	0.11	0.81	0.12
Technical depth	74	6.71 (0.70)	0.08	6.54	6.87	49	6.58 (1.08)	0.15	1.08	0.15

TABLE 2 Repeated measures ANOVA results for both the Chinese instruction (CMI) and English instruction (EMI) groups.

Source	SS	df	ms	*f*	*p*	η_p^2
Competition proposal writing						
Group (taught language types)	11346.51	1	11346.51	9417.75***	0.00	0.99
Error	145.78	121	1.21			
Test time (pre- and posttest)	259.47	1	259.47	795.76***	0.00	0.87
Group * Test time	0.38	1	0.38	1.17	0.28	0.01
Error	39.45	121	0.33			
Oral presentation						
Group (taught language types)	15590.55	1	15590.55	82248.81***	0.00	0.99
Error	22.94	121	0.190			
Test time (pre- and posttest)	79.10	1	79.10	706.83***	0.00	0.85
Group * Test time	0.04	1	0.04	0.35	0.56	0.00
Error	13.54	121	0.112			

***$p < 0.001$.

after the online team-based problem-solving competition by performing a 2 (taught language type) × 2 (pretest/posttest) repeated-measures ANOVA, and the statistical results are shown in Tables 1 and 2. After adjusting for the CMI and EMI groups, the competition proposal writing ($F = 9417.75$, $df = 1$, $\eta_p^2 = 0.99$) and oral presentation ($F = 82248.81$, $df = 1$, $\eta_p^2 = 0.99$) scores of the students were obviously greater for the CMI group than for the EMI group. After adjusting for the time of the pretest and posttest. The competition proposal writing ($F = 795.76$, $df = 1$, $\eta_p^2 = 0.87$) and oral presentation ($F = 706.83$, $df = 1$, $\eta_p^2 = 0.85$) scores of the students were obviously greater on the posttest than on the pretest. Upon analysing the interaction between the language types used for instruction and time, no significant interaction between the two was detected ($F = 1.17$, $df = 1$, $\eta_p^2 = 0.01$; $F = 0.35$, $df = 1$, $\eta_p^2 = 0.00$). This study also examined whether there were language type differences in domain knowledge, AI model accuracy and outcomes of online team-based problem competition (Table 3). The results showed that the average scores of creativity ($t = 3.69$, $df = 121$, Cohen's $d = 0.71$) for the students who participated in the CMI course were obviously greater than those for the students who participated in the EMI course.

TABLE 3 *T* test of domain knowledge, artificial intelligence (AI) model accuracy and competition outcomes between the Chinese instruction (CMI) and English instruction (EMI) groups.

	CMI		EMI					
Variables	*N*	Mean (SD)	*N*	Mean (SD)	*df*	*t*	*p*	Cohen's *d*
Domain knowledge	74	4.62 (2.58)	49	4.84 (2.68)	121	−0.46	0.65	−0.08
AI model accuracy	67	8.79 (0.68)	37	8.75 (1.57)	102	0.18	0.86	0.03
Competition outcomes								
Creativity	74	6.96 (0.70)	49	6.31 (1.09)	121	3.69***	0.00	0.71
Implementation completeness	74	7.08 (0.78)	49	6.91 (0.81)	121	1.19	0.24	0.21
Technical depth	74	6.71 (0.70)	49	6.58 (1.08)	121	0.81	0.42	0.14

***$p < 0.001$.

4.2 | Multiple group comparison

To examine whether the language of instruction in machine learning can moderate the relationship between variables, this study adopted the moderating effect analysis proposed by multiple group comparison. Before entering the formal model analysis, the study first examined the normal distribution of the data and bivariate correlations between all measured variables. The kurtosis of each variable ranged from $-2.34 \sim 0.85$, and the skewness ranged from -0.37 to 8.50. This means that each variable fell within the normal distribution range of kurtosis ±3 and skewness ±10 and thus was suitable for analysis (Hair et al., 2010). In the correlation matrix of the CMI group, the positive relationships among domain knowledge, competition proposal writing (pre- and posttest), oral presentation (pre- and posttest), and competition outcomes (creativity, implementation completeness, and technical depth) ($r = 0.35$–0.83, $p < 0.05$) and AI model accuracy were negatively related to creativity ($r = -0.44$, $p < 0.05$). In the correlation matrix of the EMI group, the positive relationships among domain knowledge and competition proposal writing (pre- and posttest) ($r = 0.29 \sim 0.61$, $p < 0.05$), competition proposal writing (pre- and posttest), oral presentation (pre- and posttest), competition outcomes (creativity, implementation completeness, and technical depth) ($r = 0.29 \sim 0.92$, $p < 0.05$), and AI model accuracy were negatively related to creativity ($r = -0.50$, $p < 0.05$).

To examine the moderating effect of the language of instruction on the mediation model, path modelling with Mplus software 7.0 was used to examine the proposed model (Muthén et al., 2017). The fit indices of the model include the root mean square error of approximation (RMSEA), the comparative fit index (CFI), and the standardized root mean square residual (SRMR). The model fitness is acceptable, with an RMSEA ≤0.08, a CFI >0.9, and an SRMR ≤0.08 (McDonald & Ho, 2002). In the proposed model, domain knowledge affected competition outcomes (creativity, implementation completeness, and technical depth) *through posttest* competition proposal writing, posttest oral presentation, and AI model accuracy. *In addition*, pretest competition proposal writing *and* pretest oral presentation *were controlled since there was an effect on* posttest competition proposal writing *and* posttest oral presentation.

The overall fit indices of the proposed model indicated a close fit to the data ($\chi^2 = 1015.30$, $df = 66$, $p < 0.01$, RMSEA $=0.08$, CFI $=0.96$, SRMR $=0.02$). As shown in Figure 3, the results indicated that in the CMI group, domain knowledge was positively related to posttest competition proposal writing ($\beta = 0.25$, $p < 0.001$) and AI model accuracy ($\beta = 0.55$, $p < 0.001$). Furthermore, posttest competition proposal writing was positively related to implementation completeness ($\beta = 0.86$, $p < 0.001$) *and* technical depth ($\beta = 0.80$, $p < 0.001$), posttest oral presentation was positively related to creativity ($\beta = 0.28$, $p < 0.01$), implementation completeness ($\beta = 0.16$, $p < 0.05$), *and* technical depth ($\beta = 0.27$, $p < 0.05$), *and* posttest AI model accuracy was negatively related to creativity ($\beta = -0.41$, $p < 0.05$) and was positively related to technical depth ($\beta = 0.32$, $p < 0.05$). *In the* EMI group, domain knowledge was positively related to posttest competition proposal writing ($\beta = 0.53$, $p < 0.001$) and AI model accuracy ($\beta = 0.48$, $p < 0.01$). Furthermore, posttest competition proposal writing was positively related to implementation completeness ($\beta = 0.17$, $p < 0.05$), posttest oral presentation was positively related to creativity ($\beta = 1.02$, $p < 0.001$), implementation completeness ($\beta = 1.13$, $p < 0.001$), *and* technical depth ($\beta = 1.03$, $p < 0.001$), *and* posttest AI model accuracy was negatively related to creativity ($\beta = -0.70$, $p < 0.001$) and was positively related to implementation completeness ($\beta = 0.25$, $p < 0.001$) *and* technical depth ($\beta = 0.20$, $p < 0.05$).

Subsequently, bootstrapping was employed using a 95% bias-corrected bootstrap confidence interval (CI) from 2000 resamples. This approach was used to examine the indirect impact of the language of instruction through domain knowledge on creativity, implementation completeness, and technical depth via posttest competition proposal writing and AI model accuracy. This study tested the model's indirect effect of CMI, and the results indicated that two paths had an indirect effect. The domain knowledge on implementation completeness was assessed by means of posttest competition proposal writing ($p < 0.05$, CI did include zero, $b = 0.14$, $SE = 0.04$, 95% CI [0.02,0.07]), and the domain knowledge on technical depth was assessed by means of posttest competition proposal writing ($p < 0.05$, CI did include zero, $b = 0.23$, $SE = 0.06$, 95% CI [0.04,0.09]). Then, the indirect effect of EMI was measured, and the results also indicated

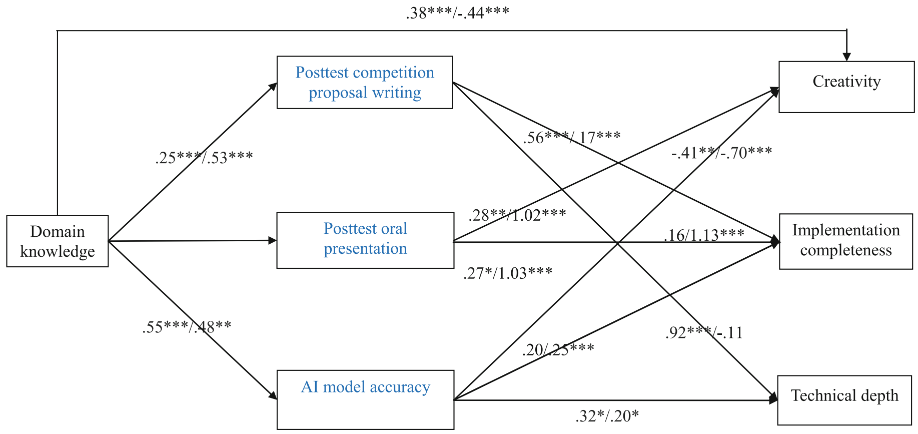

FIGURE 3 The indirect influence of domain knowledge on creativity, implementation completeness, and technical depth, mediated by machine learning in Chinese instruction (CMI) and English instruction (EMI), was examined through posttest competition proposal writing and AI model accuracy assessment ($n = 123$). The former path coefficient is CMI, and the latter is EMI. The black lines indicate significant paths, and nonsignificant paths were omitted. Path coefficients are standardized. χ^2 (66) = 1015.30, $p < 0.01$, CFI = 0.96, RMSEA = 0.08, SRMR = 0.02; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

that three paths had an indirect effect. The domain knowledge on implementation completeness was assessed by means of posttest competition proposal writing ($p < 0.05$, CI did include zero, $b = -0.09$, SE = 0.04, 95% CI [−0.05, −0.01]), the domain knowledge on creativity was assessed by means of AI model accuracy ($p < 0.05$, CI did include zero, $b = 0.33$, SE = 0.15, 95% CI [0.03,0.24]), and the domain knowledge on implementation completeness was assessed by means of AI model accuracy ($p < 0.05$, CI did include zero, $b = 0.12$, SE =0.05, 95% CI [0.01,0.06]). In these cases, the CI is more informative and considers possible nonsymmetry in the distribution of estimates (Muthén et al., 2017). Therefore, there was a significant indirect effect of domain knowledge on creativity, implementation completeness, and technical depth through posttest competition proposal writing and AI model accuracy, but through the posttest, the oral presentation did not have an indirect effect.

5 | CONCLUSIONS

The primary objective of this study is to explore the factors that influence machine learning courses within online problem-solving competitions and their effects on student learning outcomes. Furthermore, the study aimed to examine variations in student learning effectiveness and the moderating effects in the model with variations in CMI and EMI. This study's findings indicate a notable enhancement in the performance of students in machine learning CMI and EMI classes who engaged in an online problem-solving competition, particularly in the areas of competition proposal writing and oral presentations. Their performance shifted from good to excellent in both areas, which provides strong support for hypothesis 1. This demonstrates the success of the competition-learning model in enhancing student motivation to acquire AI knowledge, skills, and domain knowledge. It effectively harnesses their integration capabilities to amalgamate novel insights from diverse fields to secure victory in competition (Sondakh et al., 2020). The model not only furnishes a collection of innovative solutions aligned with the competition theme (Chen, 2022) but also affirms that competition learning propels students to explore diverse methods, employ advanced technologies to refine their solutions, and cultivate a profound understanding of applying learned concepts and algorithms to address real-world problems, while finding the experience both challenging and enjoyable. Furthermore, students demonstrate the ability to effectively communicate the creativity, commercial potential, and societal impact of their work within the constraints of competition regulations, as observed in their language use (Chen, 2019). This finding substantiates that the competition-learning model can serve as an effective method for teaching machine learning.

The findings of this study partially support hypothesis 2. Compared with their counterparts in EMI classes, students enrolled in CMI machine learning classes demonstrated superior performance in terms of competition proposal writing, oral presentation, and creativity. This aligns with the findings of Pal and Iyer (2015), who asserted that students learning computer science in their native language experience enhanced learning outcomes. Similarly, Raj et al. (2017) argued that EMI is less advantageous for novice computer science students and those with lower proficiency in English. One possible explanation is that students in CMI classes are spared language challenges in the learning environment (Chen, 2022), affording them ample time to analyse problems, clarify ideas, and stimulate creativity through collaborative efforts. This empowers learners to effectively construct content knowledge and devise solutions related to the competition topic, leveraging the advantages of their mother tongue to articulate the distinctive features of their competition works. Conversely, students in EMI classes, particularly those with limited English proficiency, may encounter challenges in reading, discussing, listening, writing science-related reports, or posing field-specific questions to teachers in

English during class, thereby diminishing teacher–student interaction (Pun et al., 2024). Nevertheless, language-related hurdles may impact classroom dynamics, which play a crucial role in students' construction of scientific knowledge and language development (Pun et al., 2024). Particularly noteworthy is the online problem-solving competition's goal of proposing industry solutions, a task that demands a deep comprehension of algorithms, mathematics, and data structures (Wirawan et al., 2017). Coupled with domain-specific knowledge relevant to the competition theme (Dash et al., 2022), students can effectively address industrial challenges. However, students enrolled in EMI programs may contend with cognitive overload, stemming from the use of a second language to learn computer science, which could impact their performance in the competition.

The findings of this study partially corroborate hypothesis 3. Through a multigroup comparative analysis of the mediated moderation model in competitive learning, it was observed that there are slight variations in the learning trajectories of students in CMI and EMI classes. Overall, domain knowledge in both classes fosters implementation and technical depth through competition proposal writing and AI model accuracy. However, competition proposal writing and technical depth appear to hinder the development of creativity. This finding aligns with the findings of Chen (2019) and Yamamura et al. (2022). It is suggested that students with a deeper understanding of the subject matter are better equipped to leverage their domain knowledge to enhance the AI model and contribute to the team's ability to propose creative solutions that exhibit creativity, implementation integrity, and technical depth in their work. Notably, the students in CMI classes can simultaneously contribute positively to their technical depth performance through both competition proposal writing and AI model accuracy. Conversely, students in EMI classes can only exert a positive influence through the accuracy of the AI model. Given the emphasis on the precision of AI models in online problem-solving competitions, participating teams must possess a profound comprehension of algorithms, mathematics, and data structures (Wirawan et al., 2017). This study's findings suggest that students instructed in Chinese may possess a more in-depth understanding of academic fundamentals, enabling them to plan appropriate models when proposing solutions. In contrast, EMI students might have to wait until the model training phase to identify a suitable approach. Moreover, the domain knowledge of students in CMI and EMI negatively impacts creativity through AI model accuracy, contradicting previous research. This discrepancy might be attributed to the simultaneous challenges of language proficiency and project time constraints faced by this group of students. They may have prioritized optimizing the AI model within the limited learning time, inadvertently neglecting the creative aspects of the project.

6 | CONTRIBUTIONS, LIMITATIONS, AND FUTURE WORK

This study employs a one-semester-long experiment to assess the learning outcomes of students engaged in machine learning courses conducted in both Chinese and English. This contributes not only to the advancement of teaching practices and the design of instructional material but also to the development of valuable intervention strategies across various teaching languages. Consequently, the findings from this study significantly contribute to the methodologies employed in research focusing on CMI and EMI contexts. Moreover, individualized tutoring was provided to each team, tailored to their chosen competition topic in the study, ensuring the uniqueness of every subject. This approach enabled students to gain practical problem-solving experience and fostered authentic interactions between the academic institution and industry partners. Students may earn internships or full-time job opportunities from enterprises after the competition. Finally, an evaluation via competition-based learning outcomes using portfolio assessment was proposed. A rubric was developed to let off-campus experts, the instructor, the TA, and fellow classmates evaluate the domain knowledge, competition proposal writing, oral presentation, AI model accuracy, and competition outcomes of each team. These methods helped learning outcome evaluation become more thorough.

This study has several limitations. First, this study spanned one semester, which was possibly insufficient in length to grasp the enduring impact of CMI or EMI on student experiences and academic achievements. Notably, language proficiency might not singularly determine CMI or EMI success. Additional elements, including familiarity with academic principles, experience in learning participation, group dynamics, peer support, and the application of effective learning strategies, also prove pivotal (Aizawa, 2024). Future research should consider extending the study duration to garner a more comprehensive understanding. Second, students were not randomly assigned to either the CMI or EMI class. This was primarily because the participants belonged to the same computer science department at the university, and their math and English scores on the university entrance examination were comparable. Additionally, students were allowed to select their preferred language of instruction based on their individual learning needs. In future research, it would be beneficial to employ random assignment, conduct English proficiency and programming language assessments prior to the classes, and control for participants' initial learning abilities to minimize potential confounding variables. Finally, students were encouraged to participate in numerous online problem-solving competitions during the course, and students mostly selected Kaggle, AIdea, or TBrain competitions due to time limitations, which resulted in competition topic overlaps. This may be caused by the preference for competition type, curiosity about new techniques or technology, or even peer effects. Future studies could focus on investigating the reasons behind competition selection, such as personal interest, ability limitations, or career planning, which could help lecturers guide students in selecting topics based on their expectations.

AUTHOR CONTRIBUTIONS

Hui-Tzu Chang: Conceptualization; formal analysis; funding acquisition; writing – original draft; project administration; data curation.

Chia-Yu Lin: Investigation; supervision; funding acquisition; methodology; writing – review and editing.

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DATA AVAILABILITY STATEMENT

Research data are not shared.

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