A study on the Impact of AI-Driven STEAM Curricula on Computational Thinking Development in the Chinese Elementary School

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Abstract: *This study investigates integrating artificial intelligence (AI) into computational thinking (CT) curricula for primary school students in China. A 9-week after-school course was designed for 15 Grade 4-6 students, combining STEAM education, project-based learning (PBL), and co-design methodologies. Students used the Machine Learning for Kids platform to build and train models, integrating them into Scratch to create AI-powered applications. Pre- and post-surveys were designed based on the Computational Thinking Scale (CTS) to measure students' CT dimensions, while the Bebras Challenge test was adopted to evaluate students' performance in CT test, both showing significant improvement. Additionally, focus groups were conducted to collect students' feedback on this learning experience. Students reported significant improvement in engagement, problem-solving skills, and awareness of AI applications, despite some challenges about technology and language. These findings demonstrate the potential of integrating AI education into primary school curricula to enhance students' CT skills, contributing to the development of AI and CT education frameworks while providing practical implications for implementing AI education in K-12 schools.*
Keywords: AI Education, Computational Thinking, Co-design, Project-based Learning, STEAM Education

1. Introduction

Computational Thinking (CT), as defined by Wing (2006), emphasizes representing and solving problems using computer science concepts. With AI's growing role in daily life, understanding and leveraging AI to address complex problems is essential (Brynjolfsson & McAfee, 2017). Recognizing this need, China has established CT and AI literacy as core competencies in its K-9 Information Technology curriculum, providing a strong foundation for students to succeed in the digital age (Ministry of Education of China, 2022). Early exposure to CT and AI is crucial, because children's cognitive abilities are highly malleable, making it easier to cultivate strong problem-solving skills (Bers et al., 2019). This study examines how AI education impacts CT skill development among Chinese primary school students, highlighting the intersection of CT and AI in early education.

2. Literature Review

Integrating AI education with STEAM and project-based learning (PBL) offers a multidisciplinary framework that promotes computational thinking (CT) more effectively than traditional methods by connecting learning to real-world problems and encouraging iterative solution refinement (Huang & Qiao, 2024; Shin et al., 2021). Moreover, co-design, as a collaborative learning approach, further enhances CT by positioning students as creators and innovators, emphasizing active participation and hands-on engagement to foster creativity, critical thinking, and problem-solving skills (Sunday et al., 2024). However, assessing CT remains a challenge, with qualitative methods like interviews being underutilized compared to traditional tests, portfolios, and surveys, which often focus narrowly on algorithmic thinking and problem decomposition while overlooking creativity, collaboration, and reflection (Cutumisu et al., 2019; Tang et al., 2020; Brennan & Resnick, 2012).

3. Research Questions

Existing research underscores the potential of pedagogical approaches in fostering computational thinking (CT) yet critical gaps remain. These include understanding how AI education can be integrated into STEAM through PBL and co-design, as well as the prevailing reliance on quantitative methods that fail to capture qualitative insights and the interplay between CT assessment tools. To address these gaps, this study explores the following research questions:

RQ1: How does the AI-machine learning curriculum impact pupils' CT skills？

RQ2: What are the relationships between CT dimensions measured through scale surveys, and students' performance on CT tests?

RQ3: What are students' experiences and perceptions of this AI-integrated STEAM curriculum?

4. Methodology

4.1. Course Design

In this 9-week course, students explored the fundamentals of ML through PBL. Projects were developed on the ML for Kids platform teaching students to build ML models which can be exported to Scratch, allowing students to build AI-powered applications. The course began in Week 1 with a pre-test to assess students' prior knowledge, followed by an introduction to the basic syntax of Scratch. In Week 2, students learned the basics of supervised learning, while Weeks 3-7 guided them through ML projects like text recognition ("Make me Happy"), image recognition ("Pokemon Images"), and chatbot creation ("Owls Chatbots"). Week 8 encouraged creativity and collaboration through co-designing individualized chatbots, and Week 9 concluded with a review and post-test to measure learning outcomes.

4.2. Data Collection

4.2.1. Survey (scales)

The Computational Thinking Scale (CTS) developed by Korkmaz and Bai (2019) was adopted in this study as it has been validated in the Chinese context. This reliable tool assessed five key dimensions: creativity, algorithmic thinking, cooperativity, critical thinking, and problem-solving, aligning well with the objectives of this AI-ML course. Participants completed the CTS both before (pre-test) and after (post-test) the course to evaluate the impact of the course on their CT development.

4.2.2. Bebras tests

A set of pre- and post-tests consisting of six CT questions was used to evaluate students CT skills, such as algorithmic thinking and pattern recognition abilities. These questions were selected from Bebras Challenge tests. Question 1 and Question 6 are shown as examples in Figure 1. Question 1 assesses students’ pattern recognition by requiring students to identify the most often borrowed book through analyzing patterns and frequencies in records, while Question 6 examines encryption algorithm analysis based on a provided example.

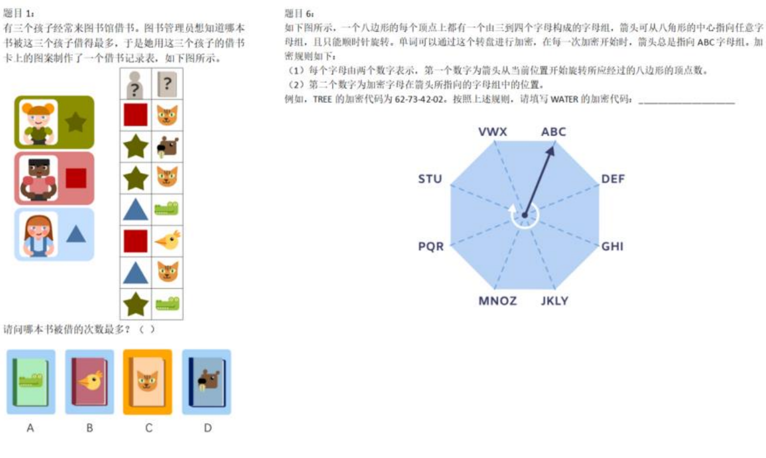

Fig.1 Question 1 and question 6 of CT test from Bebras Challenge

4.2.3. Interviews

The interviews, conducted in focus groups each involving 4-5 students, explored participants' experiences and perspectives regarding their ML projects, while also examined their CT skills. It began by investigating participants' favorite aspects of working on projects, including what they found most engaging. Next, they were asked to explain ML in simple terms to assess their communication skills. The discussion then shifted to real-world ML applications, focusing on its practical benefits. Finally, participants shared how they tackled project challenges, revealing their problem-solving strategies and resilience—key elements of computational thinking.

4.3. Data Analysis

This study employed multiple analyses to evaluate the learning program's impact. Paired t-test was used to compare pre- and post-survey data of Computational Thinking Scales (CTS) and test scores to identify significant changes. Additionally, thematic analysis was implemented to explore students' perceptions of a STEAM curriculum integrating ML, project-based learning, and co-design, revealing insights into their learning experiences. Furthermore, Pearson correlation analysis was used to examine the relationship between CTS results and Bebras Challenge scores, assessing the correlation between these two assessment tools. Overall, this mixed-methods approach offered a comprehensive understanding of the program's impact on students' learning experience and capability development.

5. Findings

5.1. Improvements in CT skills by The Course

The paired-samples t-test results showed significant improvements in all five CT dimensions: Creativity, Collaboration, Critical Thinking, Problem-solving Thinking, and Algorithmic Thinking. Additionally, the Bebras Challenge Score increased from an average of 3.84 to 4.08. While this improvement was not statistically significant ($p = 0.217$), it still shows improvement in students' performance. These findings indicate that the course was effective in enhancing students' CT skills across all measured dimensions (as shown in Table 1).

Table 1. Results of paired-samples t-test across computational dimensions

Dimension	Mean (pre)	Mean (post)	Mean Difference	Std. Deviation	t	df	p-value
Creativity	2.91	4.53	-1.62	.41	-15.12	14	<.001
Algorithmic Thinking	3.63	4.18	-.55	.72	-2.9	14	0.011
Collaboration	3.81	4.61	-.80	.65	-4.7	14	<.001
Critical Thinking	3.45	4.45	-1.00	.59	-6.48	14	<.001
Problem-solving Thinking	2.58	4.81	-2.22	.34	-24.97	14	<.001
Bebras Challenge Score	3.84	4.08	-.24	.72	-1.2	14	.217

5.2. Lack of Correlation Between CT Dimensions Survey Results and Bebras Challenge Scores

The Pearson correlation analysis of the pre-test data shows no significant relationship between the dimensions of Computational Thinking (CT) as measured by Korkmaz's scale and the Bebras Challenge scores. Specifically, the correlations between the Bebras Challenge score and the CT dimensions—Creativity (0.327), Collaboration (-0.051), Critical Thinking (-0.397), Problem-solving Thinking (-0.091), and Algorithmic Thinking (-0.464)—are either weak or negligible, with none reaching statistical significance. This lack of significant correlation suggests that Korkmaz's scale may not effectively capture or prioritize key CT abilities such as pattern recognition, decomposition, and algorithm design, which are central to the Bebras Challenge.

5.3. Participant Experiences with AI-integrated STEAM Curriculum

Thematic analysis of interview data revealed recurring themes centered on Engagement and Interest, Challenges and Problem-Solving, Perceived Benefits, and Suggestions for Improvement. Participants expressed enthusiasm for ML projects, particularly those fostering creativity and autonomy, with their favorites like the owl chatbot and co-designed chatbot. One participant noted, "I felt like the chatbot was quite versatile after we finished programming it."

Programming was a highlight, described as a way to make machines "smarter and more capable," while also enhancing logical thinking and English skills. Challenges included technical issues like "nested structures", language barriers, and unreliable internet connections. Students often solved these independently, using logical step-by-step analysis. Suggestions for improvement included introducing more advanced programming languages, providing better English support, and interdisciplinary integration. Overall, the project was seen as transformative, improving problem-solving and programming skills, and inspiring excitement for AI's real-world applications. As one participant summarized, "AI is not far from us—it's already embedded in our daily lives, and learning this can change how we see the world."

6. Conclusion and Discussion

This study demonstrated the effectiveness of the AI-ML course in enhancing students' CT skills, as evidenced by the CTS survey and the Bebras Challenge test. Yet, the lack of correlation between these two assessment tools highlights the complementary nature of these assessment tools, suggesting that their combined use provides a more holistic and comprehensive evaluation of students' computational thinking skills. Furthermore, students reported increased engagement, skill development, and awareness of AI's real-world applications through ML projects despite encountering challenges like technical difficulties, language barriers, and infrastructure issues. Addressing these challenges through refined project designs, language support, and technical solutions could optimize the learning experience. Overall, the course successfully fostered students' CT skills and AI literacy, preparing them to adapt to and excel in an AI-driven world.

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