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The Implementation of Project Based Learning to Enhance Computational Thinking Ability for Primary School Students

Li Ying[1], Jiraporn Chano[1*]

[1]*Mahasarakham University, Maha Sarakham, Thailand*

E-mail: jiraporn.j@msu.ac.th
*Corresponding author

Article Info	Abstract
Received: 20 July 2025 Reviewed: 1 August 2025 - 10 December 2025 Accepted: 21 December 2025 Published: 31 December 2025	Purpose This study examines the efficacy of Project-Based Learning (PBL) in enhancing Computational Thinking Ability (CTA) among fifth-grade students in Guilin, Guangxi, China, addressing a critical gap in primary education by integrating PBL with computational pedagogy. Grounded in Pappert's (1980) constructionist theory and Vygotsky's (1978) sociocultural theory, the research aims to compare CTA development through PBL versus traditional methods, offering insights into innovative teaching strategies aligned with the Curriculum Standards for Information Technology in Compulsory Education (2022) and global digital literacy demands (OECD, 2019). Methodology A quasi-experimental design was employed, involving 60 fifth-grade students from a primary school in Guilin, divided into an experimental group (n=30) using PBL and a control group (n=30) using traditional teaching. The 7-week intervention, conducted from May to July 2025 with 14 class hours, utilized pre- and post-tests, observational checklists, and teacher interviews to assess CTA across decomposition, abstraction, pattern recognition, and algorithmic thinking. Data were analyzed using paired- and independent-samples t-tests. Results/Findings (1) The experimental group's total CTA mean score increased significantly from 63.43 (SD = 2.81) to 90.74 (SD = 2.43), with effect sizes (Cohen's d) ranging from 3.36 to 10.32 , indicating substantial within-group improvement; (2) Compared to the control group's post-test mean of 63.79 (SD = 2.85), the experimental group outperformed with a mean difference of 26.95 ($t (58) = 39.45$, $p < 0.001$, $d = 10.01$) , confirming PBL's superiority; (3) Among CTA dimensions, pattern recognition showed the largest gain (mean difference = 7.52, $d = 8.91$), while algorithmic thinking had a smaller effect ($d = 2.95$), suggesting variability due to limited coding experience. Qualitative feedback supported PBL's collaborative benefits, though time and resource challenges were noted. Implication The substantial improvement in CTA among the experimental group provides robust empirical evidence for integrating PBL into the primary school curriculum, particularly for Information Technology. Educators are encouraged to shift from traditional, lecture-based methods to student-centred, project-based approaches to foster deeper computational thinking skills.

Keywords: Project-based learning; Computational thinking ability; Traditional teaching; Decomposition; Abstraction; Pattern recognition; Algorithmic thinking

1. Introduction

1.1. Computational thinking in educational contexts

Computational thinking (CT) has emerged as a critical skill in the 21st-century educational landscape, encompassing problem-solving processes such as decomposition, abstraction, pattern recognition, and algorithmic thinking (Wing, 2006). As defined by Wing (2006), CT involves formulating problems and their solutions in ways that computers and humans can understand, making it a foundational competency across disciplines. The OECD Future of Education and Skills 2030 framework underscores the necessity of digital literacy to prepare students for a technology-driven world (OECD, 2019). Similarly, China's Curriculum Standards for Information Technology in Compulsory Education (2022) emphasize integrating CT into primary education to foster innovative thinking. The Fourth Industrial Revolution, characterized by rapid technological advancements, further amplifies the demand for CT skills to equip students for future workforce challenges (Schwab, 2016). This global shift necessitates pedagogical approaches that move beyond traditional methods to cultivate CT effectively in young learners.

1.2. Challenges in primary CT education

Despite its importance, primary education systems often struggle with effective teaching strategies for CT, an area that remains underexplored.Traditional instructional methods, which prioritize lecture-based knowledge transmission, have been found inadequate, with only 12% of curricula effectively fostering CT skills (Grover & Pea, 2013). Such approaches typically emphasize rote learning, limiting opportunities for students to engage in problem-solving or collaborative tasks that develop CT. Project-Based Learning (PBL), rooted in Papert's (1980) constructionist theory, offers a promising alternative by engaging students in authentic, hands-on projects that mirror real-world challenges. PBL encourages active participation and critical thinking, aligning with the developmental needs of primary students in the concrete operational stage (Piaget & Inhelder, 1969). However, the integration of PBL to enhance CT in primary schools remains underexplored, particularly in structured educational settings.

1.3. Significance and objectives of the study

This study addresses the gap in primary CT education by investigating the efficacy of PBL in enhancing computational thinking ability (CTA) among fifth-grade students. Grounded in Vygotsky's (1978) sociocultural theory, which posits that learning occurs optimally within the zone of proximal development through scaffolded activities, the research explores how PBL can facilitate CT skill acquisition. Recent studies suggest that systematic CT training is critical for primary education, yet effective pedagogical models are scarce (Kong et al., 2023). The study aims to: (1) compare students' CTA before and after PBL intervention, (2) compare CTA outcomes between PBL and traditional teaching methods, and (3) explore qualitative feedback on PBL implementation. By providing empirical evidence, this research seeks to inform curriculum design and teacher training, aligning with global and national educational standards.

1.4. Hypotheses and scope of the study

The study hypothesizes that: (1) students' post-test CTA scores will be higher than pre-test scores following PBL intervention, and (2) students taught through PBL will exhibit higher CTA scores than those taught via traditional methods. Conducted in a primary school in Guilin, Guangxi, China, the research targets fifth-grade students and spans seven weeks from May to July 2025, with a total of 14 class hours. A quasi-experimental design is employed, involving 60 students divided equally into an experimental group (PBL) and a control group (traditional teaching). The study focuses on assessing CTA across decomposition, abstraction, pattern recognition, and algorithmic thinking, using pre- and post-tests and observational data. Findings are expected to contribute to the development of innovative teaching strategies for primary CT education.

2. Literature review

2.1. Theoretical foundations of project-based learning

Project-Based Learning (PBL) is grounded in constructionist theory, which emphasizes learning through active creation of tangible artifacts (Papert, 1980). This approach posits that students construct knowledge by engaging in meaningful, hands-on activities that connect to real-world contexts. Savery (2015) defines PBL as a student-centered pedagogy that promotes deep understanding through extended project work. The PBL framework typically follows a five-stage model: goal setting, knowledge activation, collaborative construction, skill development, and self-assessment. During goal setting, teachers design projects aligned with curriculum objectives, ensuring complexity suitable for sustained inquiry. Knowledge activation engages students' prior understanding, while collaborative construction fosters teamwork and problem-solving. Skill development targets critical thinking and practical abilities, and self-assessment encourages reflection on learning outcomes. By facilitating active exploration and iterative problem-solving, PBL cultivates essential skills for addressing complex challenges, making it a robust framework for educational innovation (Savery, 2015).

2.2. Framework of computational thinking

Computational Thinking (CT) encompasses a set of problem-solving skills derived from computer science principles, applicable across disciplines (Wing, 2006). Wing (2006) identifies four core dimensions: decomposition, abstraction, pattern recognition, and algorithmic thinking. Decomposition involves breaking complex problems into manageable parts, while abstraction focuses on essential features, filtering out irrelevant details. Pattern recognition identifies similarities across problems to apply known solutions, and algorithmic thinking develops step-by-step procedures for problem resolution. Brennan and Resnick (2012) extend this framework, emphasizing the role of computational artifacts, such as coding projects, in reinforcing CT skills. Neurocognitive research further supports CT's educational value, demonstrating that systematic CT training enhances prefrontal cortex development, improving executive functions critical for complex problem-solving (Aref et al., 2020). These dimensions collectively enable students to approach challenges systematically, making CT a foundational competency for the digital age.

2.3. Applications of PBL in CT education

PBL has shown significant promise in fostering CT within Science, Technology, Engineering, and Mathematics (STEM) education. Kokotsaki et al. (2016) conducted a comprehensive review, finding that PBL enhances collaboration, creativity, and problem-solving skills by engaging students in authentic tasks. In CT education, PBL facilitates hands-on activities that align with CT dimensions, such as designing algorithms or analyzing patterns in group projects. Tools like Scratch, a block-based programming platform, have been integrated into PBL to support CT development by allowing students to create interactive games and animations (Valls Pou et al., 2022). Such tools enable students to experiment with computational concepts in a visual, accessible format, promoting engagement and skill acquisition. Studies indicate that PBL's emphasis on iterative design and peer collaboration creates a synergistic effect, enhancing CT outcomes in primary education settings (Kokotsaki et al., 2016; Valls Pou et al., 2022).

2.4. Research gaps and study positioning

Despite the growing emphasis on CT in primary education, significant gaps remain in its implementation, particularly in structured pedagogical approaches. Kong et al. (2023) highlight that current curricula often fragment CT components, failing to embed them in authentic, cross-curricular contexts. The lack of systematic PBL designs tailored for primary students limits the development of CT skills, as most studies focus on secondary or higher education (Kong et al., 2023). This study addresses these gaps by employing a quasi-experimental design to investigate PBL's efficacy in enhancing CT among fifth-grade students. By integrating PBL with tools like Scratch and aligning with national curriculum standards, the research seeks to provide empirical evidence on effective CT teaching strategies. This approach positions the study to contribute to both educational practice and policy, offering a replicable model for primary CT education.

3. Methods

3.1. Population and sample

The population for this study consisted of fifth-grade students enrolled in a primary school in Guilin, Guangxi, China. Specifically, it included students from 10 classes in the fifth grade, providing a diverse pool of participants engaged in information technology courses aligned with the Curriculum Standards for Information Technology in Compulsory Education (2022). This population was selected due to its representation of typical urban primary school demographics, where computational thinking (CTA) integration is increasingly emphasized to meet national digital literacy goals.

From this population, a sample of 60 students was selected using cluster random sampling to ensure representation across varying academic performance levels. The sample was evenly divided into an experimental group (n=30) receiving project-based learning (PBL) and a control group (n=30) following traditional teaching methods. This stratification maintained baseline equivalence between groups, facilitating reliable comparisons of CTA outcomes.

3.2. Design

This study employed a quasi-experimental design with one experimental group and one control group, incorporating pre-test and post-test measures to assess the impact of the intervention. This approach allowed for the examination of within-group changes and between-group differences while accommodating the practical constraints of a school setting, such as intact class assignments.

The independent variable was project-based learning (PBL), implemented in the experimental group through structured, student-centered activities. The dependent variable was computational thinking ability (CTA), evaluated across four dimensions: decomposition, abstraction, pattern recognition, and algorithmic thinking. The research process unfolded in sequential stages: a pre-test administered to both groups to establish baseline CTA levels; a 7-week intervention period from May to July 2025, totaling 14 class hours in information technology courses; a post-test to measure post-intervention CTA; and a follow-up questionnaire to capture teacher perspectives on PBL implementation. This timeline ensured sufficient exposure to the treatment while aligning with the academic calendar.

3.3. Research method

The research process followed a systematic sequence to develop and validate the project-based learning (PBL) activities aligned with computational thinking ability (CTA). It began with a literature search using keywords such as "project-based learning + computational thinking ability" to compile relevant textbooks, articles on PBL theory, educational psychology, and primary school CTA integration. These materials were analyzed to identify challenges in CTA development and to inform the design of PBL activities tailored to the four CTA dimensions: decomposition, abstraction, pattern recognition, and algorithmic thinking. Needs assessment followed, focusing on the integration of PBL in primary information technology courses to enhance student engagement and skill acquisition.

To ensure methodological rigor, interviews were conducted with experts in curriculum and instruction and with student representatives. These interviews validated the PBL activities' design and implementation, comparing them to traditional methods and assessing their alignment with curriculum objectives. Feedback from these sessions refined the activities, confirming their scientific appropriateness and relevance to primary students' cognitive levels.

3.4. Tools

Three primary research tools were developed to facilitate data collection on computational thinking ability (CTA) within the project-based learning (PBL) framework. First, lesson plans were designed for the 7-week intervention, consisting of 14 class hours tailored to primary information technology courses. These plans structured PBL activities to align with CTA dimensions, guiding students through project initiation, design, execution, and reflection phases. Second, the CTA assessment test served as the core measurement instrument, evaluating performance in decomposition, abstraction, pattern recognition, and algorithmic thinking. The test format included task-based items, with scoring detailed in Table 3 (Scoring Criteria for Computational Thinking Assessment Tests), where decomposition comprised 10 tasks worth 2.5 points each, abstraction 10 tasks at 2.5 points, pattern recognition 8 tasks at 3.125 points, and algorithmic thinking 8 tasks at 3.125 points, yielding a total of 100 points.

Table 1: Scoring criteria for computational thinking assessment tests summarizes the scoring structure

	Dimension	Tasks	Points per Task	Example Task
1	Decomposition	10	2. 5	Divide a folktale into 10 key events
2	Abstraction	10	2. 5	Summarize a science text into 50 words
3	Modeling	8	3. 125	Design a flowchart for a recycling system
4	Algorithm Design	8	3. 125	Create a coding sequence for a game in Scratch

Additional tools included observational checklists to record student engagement during sessions, questionnaires combining Likert-scale items for quantitative attitudes and open-ended questions for qualitative insights, and structured interview protocols for teacher reflections. Content validity for these tools was established through expert reviews, with average ratings of 4-5 on a 5-point scale across criteria such as clarity, relevance, and practicality.

3.5. Data collection

Data collection occurred across the three stages of the quasi-experimental design to capture both quantitative and qualitative indicators of computational thinking ability (CTA). In the pre-test phase, all 60 participants completed the CTA assessment to establish baseline scores across the four dimensions. During the 7-week intervention, observational checklists were used by teachers to document student participation and engagement in sessions, noting instances of collaborative problem-solving and dimension-specific activities. Post-intervention, the post-test was administered to measure CTA changes, while questionnaires and semi-structured interviews with teachers gathered feedback on PBL implementation and perceived effects on student skills.

To maintain data integrity, rigorous quality control measures were applied, including cross-checking entries against raw records for accuracy and completeness. All data were securely stored and anonymized, with discrepancies resolved through researcher verification, ensuring reliability for subsequent analysis.

3.6. Analysis

Quantitative data from pre- and post-tests were analyzed using descriptive statistics, including means and standard deviations (SD), to summarize CTA performance across dimensions. Inferential statistics involved paired-samples t-tests to assess within-group changes in the experimental group and independent-samples t-tests for between-group comparisons at post-test. All analyses were conducted using SPSS software, with significance set at $p < 0.001$ and effect sizes reported via Cohen's d to quantify practical significance. These methods provided robust evidence of PBL's impact on CTA development.

Qualitative data from interviews and open-ended questionnaire responses underwent thematic analysis to identify patterns in teacher reflections on PBL implementation. Themes included collaborative benefits and resource constraints. Table 1 (Roles and Responsibilities in Research Phases) outlines the division of tasks among researchers, teachers, and students, supporting the analytical framework. Additionally, Table 2 (Research Design and Outcomes: Experimental and Control Groups) summarizes the design stages and expected outputs, aiding interpretation of results.

Table 1: Roles and responsibilities in research phases

Role	Phase	Responsibilities
Researcher	Preparation	– Design CTA assessment tools for Decomposition, Abstraction, Modeling, and Algorithm Design (0-25 points each, based on Appendix 1). - Develop pre-test and post-test, ensuring alignment with curriculum standards. - Create observation checklists, questionnaires (Likert scale and open-ended questions), and interview protocols. - Train teachers on PBL implementation and data collection procedures.
Researcher	Implementation	– Monitor PBL and traditional teaching sessions to ensure fidelity. - Provide technical support for CTA tasks (e. g., modeling tools, algorithm design platforms). - Collect observation data on student engagement and teacher delivery.
Researcher	Evaluation	– Administer pre-test and post-test to both groups. - Analyze quantitative data (t-tests, ANOVA) to compare CTA scores (Appendix 2: Experimental group post-test means 90. 96, SD 0. 92; Control group 63. 79, SD 2. 85). – Analyze qualitative data from questionnaires and interviews to assess student attitudes and teacher feedback. - Report findings, highlighting PBL's significant improvement in CTA (80-85% Outstanding in post-test).
Teacher (Experimental Group)	Preparation	– Attend PBL training sessions. - Design PBL activities tailored to Decomposition (e. g., breaking down stories)), Abstraction (e. g., summarizing texts))), modeling (e. g., creating flowcharts)), and Algorithm Design (e. g., coding sequences).
Teacher (Experimental Group)	Implementation	– Facilitate PBL activities over 7 weeks, guiding students in collaborative projects. - Encourage student-driven problem-solving and reflection. - Record student participation and progress using observation checklists.
Teacher (Experimental Group)	Evaluation	– Assist in administering pre-test and post-test. - Provide qualitative feedback on student engagement and PBL effectiveness via interviews. – Ensure all students complete CTA tasks and questionnaires.
Teacher (Control Group)	Preparation	– Attend training on traditional teaching methods. - Prepare lesson plans focusing on Decomposition, Abstraction, Modeling, and Algorithm Design using conventional instruction (e. g., lectures, worksheets).
Teacher (Control Group)	Implementation	– Deliver traditional lessons over 7 weeks, focusing on direct instruction. - Monitor student participation and provide feedback. - Use observation checklists to record student performance.
Teacher (Control Group)	Evaluation	– Assist in administering pre-test and post-test. - Provide feedback on student performance and teaching experience via interviews. - Ensure all students complete CTA tasks and questionnaires.

Students (Experimental Group)	Preparation	– Participate in orientation to understand PBL and CTA tasks. – Form collaborative groups for project work.
Students (Experimental Group)	Implementation	– Engage in PBL activities, solving real-world problems using Decomposition (e. g., dividing tasks), Abstraction (e. g., identifying key variables), Modeling (e. g., creating process models), and Algorithm Design (e. g., designing step-by-step solutions). - Reflect on learning experiences through group discussions.
Students (Experimental Group)	Evaluation	– Complete pre-test and post-test (80-85% achieved Outstanding in post-test, mean 90. 96). - Respond to questionnaires assessing CTA confidence and attitudes. - Participate in interviews to share PBL experiences.
Students (Control Group)	Preparation	– Participate in orientation to understand traditional lessons and CTA tasks.
Students (Control Group)	Implementation	– Engage in traditional lessons, completing tasks in Decomposition, Abstraction, Modeling, and Algorithm Design via worksheets and direct instruction. - Participate in teacher-led discussions.

Table 2: Research design and outcomes: experimental and control groups

Stage	Step	Description	Outcome/What is Obtained
Before the Experis Ent	Participant Selection	60 fifth-grade students selected using stratified sampling.	A balanced sample representing diverse academic abilities.
	Pre-Test	All students take a pre-test measuring computational thinking (CTA) skills.	Baseline data on students' initial CTA abilities.
	Group Division	Students are divided into two groups: Experimental (PBL) and Control (Traditional).	Two groups with equal baseline levels for comparison.
During the Experis Ent	PBL Teaching	Experimental group undergoes Project-Based Learning activities for 4 weeks.	Data on the effects of PBL teaching on CTA skills.
	Traditional Teaching	Control group follows traditional teaching methods for the same duration.	Data on the effects of traditional teaching on CTA skills.
	Intervention n Monitoring	Observations and checklists used to track student engagement and activity.	Qualitative data on classroom dynamics and engagement levels.
After the Experis Ent	Post-Test	Both groups take a post-test measuring computational thinking abilities.	Final data to compare CTA skill improvement across groups.
	Data Analysis	Quantitative (t-tests, regression) and qualitative (interviews, surveys) methods are applied.	Insights into the effectiveness opal compared to traditional teaching.
	Comparison n of Results	Pre- and post-test scores analyzed to evaluate learning improvements.	Evidence of the impact opal on CTA development.
	Conclusion s and Recommend dations	Results synthesized to draw conclusions and propose educational strategies.	Practical insights for integrating PBL into primary education.

4. Results

4.1. Development of PBL activities

The project-based learning (PBL) activities were developed over a 7-week period and integrated into the primary information technology curriculum, comprising 14 class hours. These activities were structured to progressively build computational thinking ability (CTA) through hands-on projects, such as decomposing real-world problems into subtasks, abstracting key concepts from scenarios, recognizing patterns in data sets, and designing algorithmic sequences for simple simulations. Each weekly session followed a scaffolded format: initiation with problem posing, collaborative exploration, iterative refinement, and reflective evaluation, ensuring alignment with the four CTA dimensions identified in the methodology.

Expert evaluation of the activities confirmed their high suitability for primary students. Three specialists in curriculum and instruction reviewed the lesson plans using a 5-point Likert scale across seven criteria, including clarity, relevance to CTA, alignment with PBL principles, developmental appropriateness, measurability, comprehensive coverage, and overall coherence. Ratings averaged 4.5 (SD=0.3), with strengths in practicality for classroom use and integration of CTA tasks. Feedback emphasized the activities' ability to foster student-centered learning without overwhelming cognitive demands, leading to minor revisions for enhanced task examples. This validation supports the activities' readiness for implementation in the experimental group, contributing to observed CTA gains.

4.2. CTA ability comparison

Pre- and post-test scores revealed substantial differences in computational thinking ability (CTA) between the experimental and control groups, highlighting the intervention's impact. For the experimental group (n=30), the total pre-test mean was 63.43 (SD=2.81) out of 100, indicating moderate baseline proficiency. Post-test scores rose markedly to 90.74 (SD=2.43), reflecting a 27.31-point gain. In contrast, the control group (n=30) showed minimal change, with pre-test mean of 62.43 (SD=2.79) and post-test mean of 63.79 (SD=2.85), a negligible 1.36-point increase. These shifts underscore PBL's role in accelerating CTA development.

Dimension-specific distributions further illustrate variability: decomposition improved from 16.06 (SD=0.71) to 22.46 (SD=0.90) in the experimental group; abstraction from 16.79 (SD=0.74) to 22.96 (SD=0.92); pattern recognition from 15.00 (SD=0.72) to 22.56 (SD=0.93); and algorithmic thinking from 15.58 (SD=0.64) to 22.76 (SD=2.86). The control group exhibited stability across dimensions, with post-test SDs remaining low.

4.3. Within-group comparison

4.3.1. Decomposition

Paired-samples t-tests for the experimental group demonstrated significant improvement in the decomposition dimension, essential for breaking down complex problems into manageable parts. Pre-test scores averaged 16.06 (SD=0.71), reflecting limited initial ability to segment tasks, such as dividing a folktale into key events. Post-test scores increased to 22.46 (SD=0.90), a mean difference of 6.40 points. The t-value was 35.12 (df=29, $p<0.001$), with a large effect size (Cohen's d=7.84), indicating PBL's effectiveness in enhancing this foundational CTA skill through project-based task division.

This gain aligns with the intervention's emphasis on collaborative decomposition activities, where students iteratively refined subtasks in group projects. The reduced variability post-test suggests greater consistency in skill application, supporting PBL's role in equitable skill development across participants. In comparison, the control group's decomposition scores remained stable, underscoring the method's specific benefits.

4.3.2. Abstraction

For abstraction, which involves identifying essential elements while ignoring irrelevant details, the experimental group showed robust progress. Pre-test means stood at 16.79 (SD=0.74), based on tasks like summarizing scientific texts to 50 words. Post-intervention, scores reached 22.96 (SD=0.92), yielding a mean difference of 6.17. Statistical analysis yielded a t-value of 32.45 (df=29, $p<0.001$) and Cohen's d=7.35, confirming substantial enhancement attributable to PBL's focus on distilling core variables in project summaries.

The intervention's reflective phases likely contributed to this outcome, as students practiced abstracting patterns from real-world scenarios. Post-test SD slightly increased, possibly due to diverse abstraction strategies emerging in advanced projects, yet overall uniformity improved. This dimension's gains highlight PBL's capacity to foster higher-order filtering skills, distinct from the control group's static performance.

4.3.3. Pattern recognition

Pattern recognition, critical for identifying recurring structures in data, exhibited the strongest gains in the experimental group. Pre-test scores averaged 15.00 (SD=0.72), from tasks like flowcharting recycling systems. Post-test results climbed to 22.56 (SD=0.93), with a mean difference of 7.56. The paired t-test produced a t-value of 39.87 (df=29, $p<0.001$) and the largest effect size (Cohen's d=8.94), evidencing PBL's potency in this area via iterative pattern detection in collaborative simulations.

Activities involving visual modeling tools during the intervention appeared instrumental, enabling students to recognize and adapt patterns dynamically. The modest SD rise post-test indicates varied proficiency levels stabilizing through peer feedback. Compared to other dimensions, this marked improvement suggests pattern recognition's responsiveness to PBL's exploratory nature, contrasting the control group's minimal shifts

4.3.4. Algorithmic thinking

Algorithmic thinking, encompassing step-by-step solution design, showed significant but comparatively moderated improvement. Experimental group pre-test means were 15.58 (SD=0.64), derived from Scratch-based coding sequences. Post-test scores advanced to 22.76 (SD=2.86), a mean difference of 7.18. Results from the paired t-test included a t-value of 16.25 (df=29, $p<0.001$) and Cohen's d=3.36, still indicating a large effect but with greater variability than other dimensions.

This pattern may stem from participants' limited prior coding exposure, as PBL projects introduced sequential logic gradually. The elevated post-test SD reflects diverse algorithmic approaches, yet the overall uplift affirms the method's value in building procedural reasoning. Unlike the control group's slight progress, these findings position algorithmic thinking as a key PBL beneficiary, albeit with potential for extended practice.

4.4. Between-group post-test comparison

Between-group comparisons of post-test scores affirmed PBL's superiority across total CTA and dimensions. The experimental group's total mean of 90.74 (SD=2.43) exceeded the control's 63.79 (SD=2.85) by 26.95 points, with an independent t-test yielding t(58)=39.45 (p<0.001) and Cohen's d=10.01, denoting a very large effect. Dimensionally, decomposition differed by 6.51 (d=7.92), abstraction by 6.61 (d=7.99), pattern recognition by 7.52 (d=8.91)—the widest gap—and algorithmic thinking by 6.31 (d=2.95).

These disparities, detailed in Table 3 (Paired-Samples t-Test Results for Experimental Group) for within-group effects and Table 6 (Independent-Samples t-Test Results for Post-Test Scores) for between-group contrasts, illustrate PBL's targeted enhancement. Pattern recognition's prominence suggests its alignment with PBL's pattern-exploration emphasis, while algorithmic thinking's smaller d may indicate baseline experience influences. Overall, 80-85% of experimental participants achieved outstanding levels post-test, versus minimal control advancements.

Table 3: Paired-samples t-test results for experimental group

Dimension	Pre-Test Mean (SD)	Post-Test Mean (SD)	Mean Difference	t-value	p-value	Cohen's d
Decomposition	16. 06 (0. 71)	22. 46 (0. 90)	6. 40	35. 12	<0. 001	7. 84
Abstraction	16. 79 (0. 74)	22. 96 (0. 92)	6. 17	32. 45	<0. 001	7. 35
Modeling	15. 00 (0. 72)	22. 56 (0. 93)	7. 56	39. 87	<0. 001	8. 94
Algorithmic Thinking	15. 58 (0. 64)	22. 76 (2. 86)	7. 18	16. 25	<0. 001	3. 36
Total CTA	63. 43 (2. 81)	90. 74 (2. 43)	27. 31	48. 76	<0. 001	10. 32

Between-group post-test comparisons confirmed PBL's superiority, with the experimental group's total CTA mean of 90.74 exceeding the control's 63.79 by 26.95. The independent t-test yielded t=39.45 (p<0.001), d=10.01. Dimensionally, pattern recognition showed the greatest disparity (mean difference=7.52, d=8.91), while algorithmic thinking had a smaller gap (d=2.95), possibly due to baseline experience differences. Between-group results are summarized in Table 4 (Independent-Samples t-Test Results for Post-Test Scores).

Table 6: Independent-samples t-test results for post-test scores

Dimension	Experimental Post-Test Mean (SD)	Control Post-Test Mean (SD)	Mean Difference	t-value	p-value	Cohen's d
Decomposition	22. 46 (0. 90)	15. 95 (0. 70)	6. 51	30. 23	<0. 001	7. 92
Abstraction	22. 96 (0. 92)	16. 35 (0. 71)	6. 61	31. 45	<0. 001	7. 99
Modeling	22. 56 (0. 93)	15. 04 (0. 73)	7. 52	34. 67	<0. 001	8. 91
Algorithmic Thinking	22. 76 (2. 86)	16. 45 (0. 72)	6. 31	11. 87	<0. 001	2. 95
Total CTA	90. 74 (2. 43)	63. 79 (2. 85)	26. 95	39. 45	<0. 001	10. 01

5. Discussion

The significant enhancements in computational thinking ability (CTA) observed in the experimental group align closely with Vygotsky's (1978) Zone of Proximal Development (ZPD) theory, which posits that structured guidance within collaborative contexts enables learners to surpass independent capabilities. In this study, PBL's phased activities—such as group-based decomposition tasks—provided scaffolded support that faded progressively, facilitating transitions from guided exploration to autonomous application. This is evidenced by the total CTA mean rising from 63.43 (SD=2.81) to 90.74 (SD=2.43), with large effect sizes across dimensions (e.g., d=8.94 for pattern recognition). The reduced post-test variability (SD=2.43) further suggests PBL fostered consistent skill mastery, contrasting the control group's stagnation at 63.79 (SD=2.85). Such outcomes underscore how PBL operationalizes ZPD in primary settings, promoting deeper cognitive engagement through real-world problem-solving.

Comparisons with prior research reinforce the findings' validity while highlighting contextual nuances. Huang et al. (2022) reported a 41% engagement increase and 32% spatial comprehension gain via scaffolded digital tools in dance education, paralleling this study's 27.31-point CTA uplift and emphasis on multimodal PBL tasks. Similarly, Zhao and Watanabe (2023) documented a 35% retention rate for cultural motifs under guided analysis, akin to the sustained dimension-specific improvements here, particularly in abstraction (d=7.35). However, unlike Zhao and Watanabe's multi-group design, this quasi-experimental setup yielded even larger effects (total d=10.01), attributable to PBL's extended project duration. These alignments affirm PBL's cross-disciplinary potential, though the current focus on primary CTA addresses a gap in fragmented K-12 applications noted by Grover and Pea (2013).

The educational implications of these results emphasize PBL's role in dimensionally elevating CTA, offering a scalable model for primary curricula. By targeting decomposition and pattern recognition—dimensions with the highest gains (mean differences of 6.40 and 7.56, respectively)—PBL equips students with foundational skills for interdisciplinary problem-solving, as per Wing (2006). In practice, this translates to enhanced digital literacy under China's 2022 standards, where traditional methods yielded negligible progress (mean difference=1.36). Teachers can adapt the 7-week framework to integrate CTA into subjects like science, fostering autonomy and collaboration without additional resources. Ultimately, widespread adoption could narrow achievement gaps, preparing students for AI-driven futures as outlined in the State Council of China's (2017) plan.

Despite robust outcomes, several limitations warrant consideration. The quasi-experimental design, while practical, relied on intact classes rather than random assignment, potentially introducing selection biases despite baseline equivalence (pre-test means: 63.43 vs. 62.43). The 7-week duration captured immediate effects but overlooked long-term retention, as short interventions may not sustain gains per Kong et al. (2023). Additionally, the single-institution sample from Guilin limits generalizability to diverse rural or international contexts, where resource access varies. Reliance on self-reported interviews for qualitative insights could introduce social desirability bias, though triangulation with observations mitigated this. Future refinements should incorporate longitudinal tracking and multi-site replication to bolster causal inferences.

Theoretically, this study extends PBL literature by empirically linking it to CTA in primary education, bridging Vygotsky's (1978) ZPD with Papert's (1980) constructionism through quantifiable metrics like Cohen's d values exceeding 7.00 in three dimensions. Practically, it provides educators with validated tools—such as the CTA test rubric—for curriculum integration, addressing implementation gaps in fragmented CTA training (Grover & Pea, 2013). By demonstrating PBL's superiority over traditional methods ($t=39.45$, $p<0.001$), the findings inform policy, such as enhancing teacher training under OECD (2019) frameworks. This contributes a replicable model for global digital education, promoting equitable skill development in resource-constrained settings.

6. Conclusion

This study investigated the implementation of project-based learning (PBL) to enhance computational thinking ability (CTA) among primary school students, addressing key gaps in integrating innovative pedagogies with digital literacy demands. The primary purposes were threefold: (1) to compare CTA levels before and after PBL exposure, (2) to contrast post-intervention CTA between PBL and traditional teaching groups, and (3) to examine teacher perspectives on PBL's reflective application. Grounded in Papert's (1980) constructionism and Vygotsky's (1978) sociocultural theory, the research employed a quasi-experimental design with 60 fifth-grade students from a Guilin primary school, divided into an experimental group ($n=30$) receiving PBL and a control group ($n=30$) following conventional instruction. Over seven weeks from May to July 2025, encompassing 14 class hours, data were collected via pre- and post-tests assessing four CTA dimensions—decomposition, abstraction, pattern recognition, and algorithmic thinking—alongside observational checklists, questionnaires, and teacher interviews. Quantitative analysis utilized means, standard deviations, paired and independent t-tests, while qualitative insights derived from thematic coding.

Results demonstrated PBL's marked efficacy. The experimental group's total CTA score advanced from a pre-test mean of 63.43 (SD=2.81) to 90.74 (SD=2.43) post-test, a 27.31-point gain ($t=48.76$, $p<0.001$, $d=10.32$), with 80-85% achieving outstanding levels. Dimensionally, pattern recognition yielded the strongest improvement (mean difference=7.56, $d=8.94$), followed by decomposition ($d=7.84$) and abstraction ($d=7.35$), while algorithmic thinking showed a solid yet variable effect ($d=3.36$). Conversely, the control group exhibited negligible progress, with scores rising from 62.43 (SD=2.79) to 63.79 (SD=2.85) ($t=39.45$, $p<0.001$, $d=10.01$ for group difference). Thematic analysis of teacher reflections highlighted PBL's collaborative strengths in fostering engagement, though challenges like time constraints and limited coding exposure were noted, aligning with the intervention's focus on real-world projects. These findings confirm hypotheses 1 and 2, validating PBL's superiority in cultivating CTA for primary learners.

The study's framework offers a replicable model for educators seeking to embed PBL in primary curricula, particularly for CTA development under frameworks like China's 2022 Information Technology Standards. By delineating a structured 7-week sequence—from project initiation to reflection—the model ensures progressive skill-building, adaptable to diverse classroom contexts without requiring extensive resources. Tools such as the CTA rubric (Table 3) and phased lesson plans provide ready templates, while expert-validated protocols (average rating 4.75) enhance implementation fidelity. This approach not only bridges theoretical constructs like the Zone of Proximal Development with practical outcomes but also informs policy by quantifying PBL's impact (e.g., total $d=10.01$), supporting scalable teacher training initiatives as per OECD (2019) guidelines.

Broader contributions include advancing PBL-CTA integration literature, extending prior work like Kong et al. (2023) on collaboration by adding empirical effect sizes across dimensions. For practitioners, the model promotes equity in digital education, countering traditional methods' limitations in fragmented skill delivery (Grover & Pea, 2013). Future adaptations could extend to interdisciplinary applications, ensuring primary students gain enduring competencies for technological futures. Overall, this research equips stakeholders with evidence-based strategies to foster innovative thinking in an AI-era classroom.

7. Recommendation

Based on the empirical evidence of project-based learning (PBL)'s efficacy in elevating computational thinking ability (CTA)—evidenced by the experimental group's post-test mean of 90.74 (SD=2.43) surpassing the control's 63.79 (SD=2.85) with d=10.01—the following recommendations guide practical application and future inquiry. These build on the quasi-experimental findings, emphasizing scalable integration into primary curricula.

7.1. Teaching recommendation

Educators should prioritize PBL's structured phases to systematically build CTA dimensions, incorporating digital tools for enhanced interactivity and alignment with national standards.

- Implement the five-phase model with weekly activities, allocating 14 hours over 7 weeks to ensure progressive scaffolding without overload.
- Incorporate digital tools like Scratch for algorithmic thinking tasks, enhancing engagement as seen in the experimental group's d=3.36 gain.
- Provide targeted feedback during reflection phases to address variability, such as in algorithmic thinking, fostering sustained mastery aligned with 2022 curriculum standards.

7.2. Research recommendation

To extend the current quasi-experimental insights, subsequent studies should address identified limitations like short-term focus and single-site constraints, advancing methodological rigor.

- Conduct longitudinal designs tracking CTA retention beyond 7 weeks to assess durability of gains like pattern recognition (d=8.94).
- Employ multi-group randomized trials across institutions to mitigate single-site limitations and strengthen causal claims.
- Explore cross-cultural adaptations in diverse settings, such as rural China or international contexts, to evaluate generalizability under OECD (2019) frameworks

Declaration of conflicting interest

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