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The Influence of the Coding and Artificial Intelligence Program on Fifth Graders' Computational Thinking Skills

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Abstract

The massive use of technology, which has become a dominant and transformational force, requires students to develop computational thinking (CT) skills from elementary school. However, observations in class VC Keboansikep 2 Public Elementary School showed that students' CT skills were low, despite students' familiarity with technology. This study aims to examine the influence of the Coding and Artificial Intelligence (CAI) program on 27 students' CT skills in class VC Keboansikep 2 Public Elementary School. The research used a quantitative approach with a pre-experimental one-group pretest-posttest design. Data were collected through a 20-item multiple-choice test based on CT indicators. Data were analyzed using descriptive and inferential statistics. Descriptive results showed an average pretest of 64.26 and posttest of 82.22, with an increase of 17.96 points. The paired sample t-test obtained Sig. (2-tailed) < 0.001, showing a significant influence. The N-Gain average of 0.5693, showing moderate effectiveness. The results show that the CAI program has had a significant influence and quite an effective impact on improving the CT skills. Theoretically, the CAI program aligns with Vygotsky's social constructivism theory, and practically encourages schools and policymakers to strengthen the CAI program in preparing a generation capable of creating technology-based solutions through CT.

Keywords: artificial intelligence; coding; computational thinking; elementary school

INTRODUCTION

With the massive use of technology in the 21st century, the roles of digitalization and artificial intelligence (AI) have become dominant forces transforming various aspects of human life, including education (Daulay et al., 2025; Normansyah et al., 2025; Surur et al., 2024). Data from the Ministry of Communication and Information in collaboration with UNICEF shows that 98% of children and adolescents in Indonesia are familiar with the internet, and 79.5% of them actively use it (Kominfo, 2023). Meanwhile, the latest survey by the Indonesian Internet Service Providers Association records that the national internet penetration rate has reached 80.66% or approximately 229.4 million users (APJII, 2025). Other studies also report that 75% of children aged 7–12 in Indonesia use digital devices for at least two hours per day (Hasan et al., 2023). Elementary school students today are a generation born in the digital technology era, accustomed to the internet and AI, and already proficient in using gadgets (Fitri et al., 2025; Adzkia & Refdinal, 2024). This phenomenon indicates that Indonesian students are growing up in a highly intensive digital environment. Ideally, students should not just be passive users of technology, but also possess thinking skills appropriate for the demands of the digital age, namely computational thinking skills.

Computational thinking (CT) is a fundamental skill that must be possessed in the 21st century as a basis for understanding and using technology (Rahmadhani et al., 2024; Abidin et al., 2023). CT is the process of thinking using computational steps to solve complex problems systematically, resulting in effective and efficient solutions (Nurwita et al., 2025; Ghifari et al., 2024; Şen, 2023). The main essence of CT is to think like a computer scientist when facing problems (Helsa et al., 2023). According to Wing (2017), CT encompasses four main indicators: decomposition, pattern recognition, abstraction, and algorithms. Decomposition emphasizes breaking down a large problem into smaller parts. Pattern recognition helps identify similarities in data or problems. Abstraction emphasizes filtering important information and ignoring unimportant details. Algorithms focus on arranging logical and systematic steps (Irawan et al., 2025). Therefore, it can be concluded that CT is a thinking process that uses the basic ideas of computer science, including decomposition, pattern recognition, abstraction, and algorithms, in formulating problems, creating solutions, and developing solutions effectively and efficiently.

However, high exposure to technology does not necessarily translate into adequate CT skills (Fitri et al., 2025; Elmawati et al., 2024; Acevedo-Borrega et al., 2022). The data shows the opposite reality. The results of the 2023 Bebras Challenge, which assessed the CT skills of international students, showed that 87% of Indonesian students scored below the minimum threshold of 50. This condition aligns with the 2022 Program for International Student Assessment (PISA) report, which ranked Indonesia at 63rd out of 81 countries with an average score of 366, far below the OECD average of 472 (OECD, 2022). Initial observation results in class VC at Keboansikep 2 Public Elementary School also showed a similar condition; the majority of students were not yet able to decompose problems, analyze patterns, perform abstractions, and develop algorithms when faced with technology-based problems. Ironically, the interview results show that the majority of students are already familiar with using AI technologies such as ChatGPT, image generators, and even deepfake content. Various studies confirm that without strong CT skills, students will only become passive users of technology, even at risk of decreasing higher-order thinking skills (Normansyah et al., 2025; Murtiningsih et al., 2024; Muvid et al., 2025; Otoluwa et al., 2025).

The gap between high technology exposure and low CT skills is a serious problem in elementary school education in the digital age. Education is at a crucial point in equipping students to face increasingly complex life problems by adapting to students' individual conditions (Larasati & Astuti, 2025; Bali et al., 2025; Noviyanti et al., 2023). Learning that can improve CT skills is needed as a key foundation so that students are not only proficient in using technology, but also able to use it intelligently (Majid et al., 2025). Coding education, which is now increasingly popular around the world, is the most promising and proven effective approach for improving CT (Irawan et al., 2025; Budiyanto et al., 2021). Several countries, such as Turkey, the United Kingdom, Finland, Australia, France, and Greece, have mandated coding skills in elementary schools (Handayani et al., 2025). The implementation of coding and AI curricula in schools can strengthen students' understanding and perception of technology while also improving students' CT skills (Purbohadi & Santoso, 2025; Irawan et al., 2025). Therefore, the Ministry of Education, Culture, Research, and Technology (MoECRT) has established the Coding and Artificial Intelligence (CAI) program as part of the learning outcomes for Phase C (Grades

V–VI of Elementary School/Islamic Elementary Schools) through the latest curriculum policy (Badan Standar, Kurikulum, dan Asesmen Pendidikan, 2025).

Several previous studies have shown that integrating technology and programming influences the improvement of CT skills. Research by Aminah et al. (2023) proved that using Scratch can significantly improve the CT skills of 8th-grade students. In line with this, research by Budiyanto et al. (2021) showed that the KARIN programming toy encourages early childhood children to develop CT. Furthermore, research by Irawan et al. (2025) found that using Python demonstrably improved the CT skills of prospective mathematics teachers. Meanwhile, research by Yunianto et al. (2024) found that integrating AI ChatGPT helped graduate students understand programming concepts more deeply. Finally, a bibliometric review by Handayani et al. (2025) found that there is still limited research on CT at the elementary school level. Although diverse, most of these studies still focus on the use of a single medium and are conducted at the early, middle, and high school levels. To date, there has been no research that specifically examines the influence of coding and artificial intelligence programs on elementary school students' CT skills. This condition certainly indicates a significant research gap that needs to be filled.

To address this gap, this study aims to examine the influence of the Coding and Artificial Intelligence (CAI) program on the CT skills of VC grade students at Keboansikep 2 Public Elementary School. Compared to previous research, this study has the novelty of integrating plugged & unplugged coding learning and AI exploration to enhance the CT skills of 5th-grade elementary school students. The main foundation of this study is Vygotsky's Social Constructivism theory (1978), which emphasizes that effective learning occurs through social interaction and scaffolding. Theoretically, this study is expected to contribute to the study of learning that integrates coding and AI to improve the CT skills of elementary school students. Practically, this study can serve as a reference for educators in equipping students to become intelligent technology users with adequate CT skills.

METHOD

This research method uses quantitative research. Quantitative research is research used to answer research questions by using numerical data, then using statistical methods for data processing (Sugiyono, 2023). The quantitative research method was chosen because this study aims to examine the influence of the CAI program on the CT skills of VC grade students at Keboansikep 2 Public Elementary School. This type of research uses a pre-experimental design. This type of research was chosen because the researcher did not yet have full control over external variables that could potentially influence the results of the dependent variable. This is because the research was only conducted in one class as the experimental class, without a control class, and the sample selection process was not conducted randomly (Sugiyono, 2023).

The research design used in this study is a one-group pretest-posttest design. This design was chosen to determine the difference in the effect of a treatment on the same group of subjects before and after the treatment (Sugiyono, 2023). This research was conducted in three stages: first, students were given a pretest to determine students' initial skills. Next, the treatment will be given, which involves implementing the CAI program. After the treatment is completed, the students will be given a posttest to measure the impact of CT skills by comparing the scores between the pretest and posttest. Table 1 shows the research design used in this study:

Table 1. One-Group Pretest-Posttest Design

Pretest	*Treatment*	*Posttest*
O_1	X	O_2

Source: Sugiyono (2023)

Notes:
O_1 = Pretest score (before treatment)
X = Treatment
O_2 = Posttest score (after treatment)

This study was conducted at Keboansikep 2 Public Elementary School, located at Balai Desa Perum Permata Street, Keboansikep Village, Gedangan District, Sidoarjo Regency, East Java. The study was conducted over a period of 7 weeks, from September 1st to October 18th, 2025. The population of this study is all 5th-grade students in the odd semester of the 2025/2026 academic year at Keboansikep 2 Public Elementary School. The sample of this study is the VC class students, consisting of 27 students (including 16 male and 11 female). The sampling technique used is purposive sampling, which is a technique for determining samples based on specific considerations (Sugiyono, 2023). The selection of this class was based on initial observation results showing that the CT skills of VC grade students were the lowest compared to other classes and they had the highest exposure to technology. The research object of this study is the influence of the CAI program on the CT skills of students in class VC at Keboansikep 2 Public Elementary School. This study involves two variables as follows:

a. Independent variable (X) : Coding and Artificial Intelligence (CAI) Program.
b. Dependent variable (Y) : Students' computational thinking skills.

Research Hypothesis:

a. H_0: There is no significant influence of the Coding and Artificial Intelligence program on the computational thinking skills of VC grade students at Keboansikep 2 Public Elementary School.
b. H_1: There is a significant influence of the Coding and Artificial Intelligence program on the computational thinking skills of VC grade students at Keboansikep 2 Public Elementary School.

Data collection techniques are methods for gathering data to determine whether the collected data is relevant and reliable for answering the research problem formulation (Sugiyono, 2023). The data collection technique used is the administration of test instruments. A test is a measuring tool to determine the level of influence of treatment on students' skills (Arikunto, 2021). The test consists of 20 multiple-choice objective questions, each with 4 answer options with one correct answer. The questions are designed according to CT indicators, namely decomposition, pattern recognition, abstraction, and algorithms.

The test instrument has undergone content validity testing involving experts (validators), namely lecturers and teachers, to assess the alignment between the test items with the CT indicators, as well as the cognitive level of the students. Based on the validation results, all items were considered appropriate with minor revisions in terms of clarity of language, suitability with students' characteristics, and alignment with the intended indicators of CT. Next, an empirical validity test was conducted using Pearson Product Moment correlation. The results showed that

20 items in the pretest and posttest with a significance value (Sig.) < 0.05 were declared valid because $r_{count} > r_{table\ (0.381)}$. The valid items indicate that each question consistently measures the same construct as the total score, reflecting students' CT skills. After that, a reliability test was conducted using Cronbach's Alpha formula and obtained a value of 0.940, which is classified into the highly reliable category. This indicates that the instrument is very consistent and stable in measuring students' CT skills.

The data analysis techniques used in this study include descriptive data analysis and inferential data analysis. Descriptive statistical analysis was used to describe the characteristics of the sample, including the number of samples (n), the minimum value (min), the maximum value (max), the mean (m), and the standard deviation of the pretest and posttest scores. Meanwhile, inferential statistical analysis is used to determine the influence of the treatment given. Inferential statistical analysis is performed by comparing the results of pretest and posttest scores using statistical tests. The tests used are prerequisite tests such as normality and hypothesis tests such as the paired sample t-test and the normalized N-gain test. Table 2 shows the CT skill indicators used in this study:

Table 2. CT Skill Indicators

CT Skill Indicators	Description	Question Items
Decomposition	Students can understand problems by breaking down large problems into smaller, simpler, and easier-to-understand forms.	1-5
Pattern Recognition	Students can recognize patterns or identify similarities to build problem-solving solutions.	6-10
Abstraction	Students can filter important information and disregard unimportant information to solve a problem.	11-15
Algorithm	Students can systematically arrange problem-solving steps and create effective and efficient solutions.	16-20

Source: Elmawati et al. (2024)

RESULTS AND DISCUSSION

Results

Based on the data obtained through the data collection techniques that have been carried out, the results of the study regarding the influence of the CAI program on students' CT skills are divided into two parts: descriptive analysis and inferential analysis. Both sections are presented in detail in the following discussion:

Descriptive Statistical Analysis

Descriptive statistical analysis was obtained from the pretest and posttest scores of 27 students in class VC at Keboansikep 2 elementary school. The pretest and posttest data of the students were obtained through multiple-choice tests with 20 questions, each containing 4 answer choices with one correct answer. The scores used in the test are 1 and 0. Table 3 shows the results of the descriptive statistical tests in this study:

Table 4. Descriptive Statistics Test Results

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
Pretest Score	27	30	95	64.26	19.201
Posttest Score	27	50	100	82.22	14.566
Valid N (listwise)	27				

Source: Researcher's Processing Results Using IBM SPSS Statistics

Based on Table 4, which shows descriptive statistics test results, it can be seen that the average CT skills of the 27 students before the CAI program was implemented are still considered low. The average (mean) pretest score was 64.26, with the highest (maximum) score being 95, the lowest (minimum) score being 30, and a standard deviation of 19.201. After implementing the CAI program, there was a significant improvement in posttest results with an average score of 82.22, a maximum score of 100, a minimum score of 50, and a standard deviation of 14.566. The increase in the average score by 17.96 points shows that the CAI program has a positive impact on students' CT skills. Based on this data, it can be concluded that the CAI program can improve the CT skills of VC grade students at Keboansikep 2 Public Elementary School.

Figure 1. Box Plot of Pretest and Posttest Scores

Based on Figure 1, there is a clear change in distribution after the implementation of the CAI program. In the pretest, student scores ranged from 30-95, with Q1 at 50, the median at 65, and Q3 at 80. This shows that most students were in the moderate category, even with a significant spread in lower scores. In the posttest, the box plot shows an improvement in score distribution with a range of 50-100, Q1 at 70, the median at 85, and Q3 at 95. This quartile increase signifies a shift in value groups toward higher categories across the board. The IQR also decreased from 30 to 25, showing that the variation in student scores after the treatment became slightly more uniform. Additionally, the median increased by 20 points, showing that students not only experienced individual improvement but also collective improvement in CT skills after participating in the CAI program.

Table 5. Comparison of CT Skills by Indicator

CT Skill Indicators	Pretest (Mean)	Posttest (Mean)	Increase	Percentage
Decomposition	0.69	0.87	0.18	26.1%
Pattern Recognition	0.80	0.85	0.05	6.3%
Abstraction	0.50	0.74	0.24	49.2%
Algorithm	0.58	082	024	404%

Based on Table 5, all CT skills indicators increased after the implementation of the CAI program. For the decomposition indicator, the average score increased from 0.69 to 0.87, or by 26.1%. The pattern recognition indicator showed the smallest increase, from 0.80 to 0.85, or by 6.3%. The abstraction indicator showed the largest increase, from 0.50 to 0.74, or by 49.2%. Meanwhile, the algorithm indicator increased from 0.58 to 0.82, or by 40.4%. This shows that the CAI program is capable of improving all CT skills indicators for students.

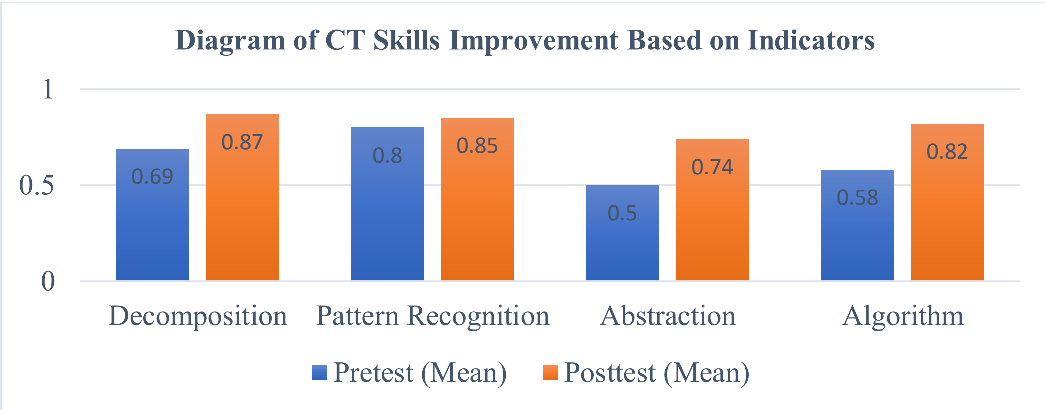

Figure 2. Diagram of CT Skills Improvement Based on Indicators

Based on Figure 2, the pattern of improvement in CT skills is more clearly visible through a visual comparison between pretest and posttest scores for each indicator. The most notable improvements were seen in higher-level indicators such as abstraction and algorithms. Meanwhile, basic indicators such as pattern recognition and decomposition showed smaller improvements. This visual shows that the CAI program is able to improve CT skills evenly.

Inferential Statistical Analysis

Inferential statistical analysis is used to analyze sample data, and the results are applied to the population with the probability of error and truth expressed as a percentage (Sugiyono, 2023). This study was used to examine the influence of the CAI program on students' CT skills and to determine its effectiveness in improving students' CT skills. The tests to be used are the normality test, the paired sample t-test, and the N-gain test. The results of the prerequisite tests and hypothesis tests are presented as follows:

1. Prerequisite Tests

The prerequisite test in the form of the normality test was conducted to ensure that the data came from a normally distributed sample (Sugiyono, 2023). The normality tests for both pretest and posttest results in this study used the Shapiro-Wilk technique because the sample size was less than 50 people. The basis for decision-making is as follows: if the Sig. value is > 0.05, then the data is considered normally distributed. Conversely, if the Sig. value is < 0.05, then the data is considered not normally distributed. Table 6 shows the results of the normality test obtained from this study:

Table 6. Normality Test Results

Tests of Normality						
	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Pretest	.130	27	.200*	.954	27	.274
Posttest	.143	27	.165	.929	27	.066

*. This is a lower bound of the true significance.
a. Lilliefors Significance Correction

Source: Researcher's Processing Results Using IBM SPSS Statistics

Based on Table 6, which shows the normality test results, it is known that the Sig. value for the pretest is 0.274 and for the posttest is 0.066. Both of these significance values are greater than the established significance level ($\alpha = 0.05$), so it can be concluded that the pretest and posttest score data are normally distributed. Therefore, inferential data analysis can be continued using a parametric statistical test, namely the paired sample t-test. This aligns with Sugiyono's (2023) opinion, which states that parametric tests require normally distributed data. If this assumption is met, then parametric statistical analysis techniques can be used appropriately.

2. Hypothesis Testing

After ensuring the data is normally distributed, the next step is to perform hypothesis testing. Hypothesis testing is a temporary answer to the research problem that must be tested to prove whether the hypothesis can be accepted or rejected. In this study, hypothesis testing was conducted using the paired sample t-test and the N-gain test.

The paired sample t-test was used to test whether there was an effect between two paired data groups, in this study, specifically the influence of the CAI program on students' CT skills. This test is used because the data comes from the same group (students in one class) who are given a treatment and measured before and after the treatment. The decision-making basis for this test is as follows: if the Sig. (2-tailed) value is < 0.05, then H_0 is rejected and H_1 is accepted. Conversely, if the Sig. (2-tailed) value is > 0.05, then H_0 is accepted and H_1 is rejected. Table 7 shows the results of the paired sample t-test obtained from this study:

Table 7. Paired Sample t-Test Results

Paired Samples Test										
		Paired Differences							Significance	
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference		t	df	One-Sided p	Two-Sided p
					Lower	Upper				
Pair 1	Pretest - Posttest	-17.963	8.117	1.562	-21.174	-14.752	-11.499	26	<.001	<.001

Source: Researcher's Processing Results Using IBM SPSS Statistics

Based on Table 7, which shows the results of the paired sample t-test, it was found that the average difference (mean difference) between the pretest and posttest results was -17.963 with a standard deviation of 8.117 and a standard error mean of 1.562. The calculated t-value is -11.499 with 26 degrees of freedom (df) and a Sig. (2-tailed) value of < 0.001. Since the Sig. (2-tailed) value is smaller than the significance level ($\alpha = 0.05$) or Sig. (2-tailed) = 0.001 < $\alpha = 0.05$, H_0 is rejected and H_1 is accepted. Therefore, it can be concluded that there is a significant influence of the CAI program on the CT skills of VC grade students at Keboansikep 2 Public Elementary School.

The N-gain test is used to measure the effectiveness of the CAI program on improving students' CT skills within a group by comparing the difference between pretest and posttest scores to the maximum score. This test provides a quantitative description of the categories of student skills improvement. Table 8 shows the results of the N-gain test obtained from this study:

Table 8. N-gain Test Results

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
Ngain_Score	27	.00	1.00	.5693	.26636
Ngain_Persen	27	.00	100.00	56.9349	26.63572
Valid N (listwise)	27				

Source: Researcher's Processing Results Using IBM SPSS Statistics

Based on Table 8, which shows the results of the N-Gain test, the average N-Gain value for students' CT skills is 0.5693 or 56.93%. The minimum value is 0.00 and the maximum is 1.00, showing variations in improvement among students. Referring to Hake's (1998) interpretation of the criteria, an N-gain value between 0.3 and 0.7 is classified as the moderate category. Thus, it can be concluded that the CAI program is quite effective in improving the CT skills of students in class VC at Keboansikep 2 Public Elementary School.

Discussion

Implementation of the CAI Program

The implementation of the CAI program in class VC of Keboansikep 2 Public Elementary School was carried out through seven meetings using the Problem-Based Learning (PBL) model, which was structured in stages. The first meeting began with a pretest to measure the students' initial CT skills. Starting from the second meeting, students were introduced to the basic concepts of CT for problem-solving. In the third meeting, students applied CT concepts as the foundation for coding through various plugged and unplugged activities. In the fourth meeting, students applied CT concepts as the basis for understanding AI logic and working principles. In the fifth meeting, students explored the utilization of AI. In the sixth meeting, students delved into AI literacy and ethics in the use of AI. In the seventh meeting, students took a posttest to measure changes in students' skills after the CAI program. The results of the program implementation showed a gradual increase in students' CT skills through each stage of the activities.

During the implementation process, the teacher provided scaffolding in a gradual and adaptive manner according to students' abilities, and this support was systematically reduced as students became more independent in learning. At the initial stage, the teacher played a dominant role by introducing technological concepts and guiding students through structured explanations and demonstrations. In the next stage, students engaged in collaborative learning through peer discussions to explore ideas, solve problems, and construct understanding together. Furthermore, students worked on student worksheets through a combination of guided, collaborative, and independent activities. This gradual reduction of scaffolding allows students to build understanding through hands-on experience and social interaction while solving technology-based problems, enabling them to gradually transition from guided learning to independent problem-solving and supporting the development of CT skills in a more structured and meaningful way.

The implementation of a CAI program integrated with the PBL model aligns with previous research findings that emphasize the importance of problem context in programming-based learning for enhancing students’ CT skills. Research conducted by Aksakal & Kucuk (2025) shows that the use of PBL in programming learning significantly improves students’ CT skills because students actively solve problems through meaningful, student-centered projects. The study also explains that problem-based programming activities encourage students to develop systematic thinking strategies, so that students not only understand concepts but are also able to apply them in real-world situations through systematic thinking. Furthermore, research by Omeh et al. (2025) and Wu et al. (2026) indicates that the use of PBL in interactive and adaptive programming instruction can enhance students’ programming skills and computational thinking abilities. These findings reinforce the notion that the implementation of CAI using the PBL model provides a contextual learning experience, fosters active student engagement, and strengthens systematic thinking skills.

On the other hand, improvements in students’ CT skills in the implementation of CAI program are also influenced by the gradual use of scaffolding. Research by Liu et al. (2026) shows that scaffolding in programming-based learning significantly improves students’ CT performance as well as the complexity of the solutions students’ produce. This study explains that scaffolding provided at the right time can reduce students’ cognitive load and help students develop thinking regulation gradually. Additionally, research by Jung et al. (2025) indicates that elementary school students require gradual support in understanding abstract programming concepts, such as algorithms and decomposition, making scaffolding a crucial strategy to bridge the gap between prior knowledge and new concepts. These findings are further supported by systematic review studies by Tariq et al. (2024) and Liu et al. (2024), which state that the integration of CT in learning will be optimal when supported by problem-based pedagogical strategies and structured scaffolding. Thus, the implementation of CAI that combines PBL and gradual scaffolding has proven capable of creating a constructive, adaptive, and effective learning environment for the continuous development of students’ CT skills.

Based on data analysis, it can be concluded that the implementation of the CAI program using the PBL model and the integration of gradual scaffolding in each session, starting from the introduction of CT concepts, coding practice, understanding the logic and principles of AI, AI utilization, and strengthening AI literacy and ethics, has proven to provide space for students to gradually improve students’ CT skills. This learning sequence encourages students to learn through direct experience in problem-solving and active interaction with technology, while the teacher acts as a facilitator by providing scaffolding. This approach makes learning more constructive, meaningful, and relevant for developing students' CT skills.

Improvement in CT Skills

Based on the results of inferential statistics, the posttest average score increased by 17.96 points from the pretest average score. The increase in students' CT skills occurred because the CAI program was designed systematically and gradually. Furthermore, all CT skills indicators increased after the implementation of the CAI program. First, the decomposition indicator increased by 26.1% because students were trained to break down problems into smaller parts to find solutions. Second, the pattern recognition indicator showed the smallest increase of 6.3% because this skill was already relatively good from the start; students were already able to recognize and apply patterns to solve new problems. Third, the abstraction indicator showed the largest increase, at 49.2%, because students were trained to filter important information in the problem-solving process. Fourth, the algorithmic indicator increased by 40.4% because students were trained in using a systematic approach to arrange the steps for problem-solving. Therefore, it can be concluded that following the implementation of the CAI program, there was an improvement in all CT indicators, and a significant improvement in the advanced-level indicators namely abstraction and algorithms, while the improvements in the decomposition and pattern recognition indicators were relatively smaller because the baseline values were already high.

These findings are consistent with various previous studies indicating that programming and AI-based learning that actively engages students in understanding and solving problems using CT concepts has been shown to significantly improve the CT skills of elementary school students (Saragih et al., 2025; Ruangtip et al., 2025; Aminah et al., 2023; Cırıt & Aydemir, 2023; Ibrohim et al., 2023). Such learning encourages students to engage in higher-order thinking processes through contextual and challenging activities. Additionally, research by Rahmadhani et al. (2024) indicates that students' initial proficiency in the decomposition and pattern recognition indicators tends to be higher because these indicators are easier to understand. The abstraction and algorithm indicators require special support to foster higher-order thinking processes, as these processes place a burden on working memory and require gradual, challenging learning experiences. The CAI program is capable of providing open-ended tasks that allow students to develop advanced thinking skills. Thus, the CAI program not only maintains already strong foundational skills but also significantly enhances advanced skills (Guan et al., 2025).

Based on inferential statistics, the CAI program significantly influences students' CT skills because each learning stage provides appropriate scaffolding tailored to students' needs, enabling students to reach students' optimal potential in CT. Furthermore, the N-Gain score, which is in the moderate category, shows that the CAI program is quite effective in improving students' CT skills. This shows that although improvement occurred in most students, the level of effectiveness was not uniform. The variation in this improvement is influenced by differences in students' initial skills, the pretest ceiling effect on students with high initial scores, differences in learning styles and learning speed, and variations in each individual's learning motivation.

This result aligns with various previous studies that have shown that programming and AI-based learning are proven to have a significant influence on improving students' CT skills. Research by Irawan et al. (2025), Budiyanto et al. (2025), Weng et al. (2024), Yunianto et al. (2024), Sadik et al. (2024), and Jiang & Li (2021) shows that learning programming and AI learning can effectively improve all CT indicators simultaneously. Additionally, the N-Gain value categorized as moderate aligns with the results of various previous studies. Research by Coletta (2023) shows that N-Gain in education tends to be moderate because its distribution is normal and highly influenced by variations in students' initial skills and the pretest ceiling effect. Research by Christman et al. (2024) also found that N-Gain is influenced by instrument characteristics, so it is not always high even though the improvement is significant. Additionally, Bazán-Perkins & Santibáñez-Salgado (2025) and Curi et al. (2025) found that the variation in students' learning styles resulted in a moderate N-Gain.

Based on the data analysis results, it can be concluded that the CAI program significantly influences and quite effectively improves students' CT skills. The significant increase in pretest-posttest scores and the improvements in all CT indicators show that the phased and problem-based learning design has a real impact on the development of CT skills. The N-Gain value, which is in the moderate category, is influenced by variations in initial skills, the complexity of advanced CT indicators, the pretest ceiling effect, and differences in students' learning styles and speeds. Overall, the CAI program has proven to provide measurable and pedagogically relevant improvements in CT skills, and has great potential for continued optimization in elementary school learning.

The Results’ Connection to Vygotsky's Social Constructivism Theory

The research results showed a significant improvement in students’ CT skills through the implementation of a CAI program aligned with the theory of Social Constructivism proposed by Lev Vygotsky. According to Vygotsky (1978), the learning process occurs through social interaction that enables students to develop within the Zone of Proximal Development (ZPD), which is the gap between a student’s current abilities and the potential abilities they can achieve with assistance from more competent others. Vygotsky also explains the concept of scaffolding as a form of temporary support provided by teachers, peers, or learning aids (technology) until students are able to complete tasks independently. In this context, learning focuses not only on the final outcome but also on the process of interaction that helps students build understanding gradually.

This result also aligns with various previous studies showing that the gradual implementation of programming and AI-based learning from Vygotsky's Social Constructivism theory is becoming a strong foundation for improving CT skills. Research by Hsu & Hsu (2025) and Nurwita et al. (2025) state that technology-based learning designed with constructivist principles is able to improve students' CT skills. These findings are supported by research by Weng et al. (2024), which shows that integrating programming and technology into learning creates learner-centered instructional designs and fosters active interaction among learners, technology, and the learning environment. The use of technology not only aids in understanding concepts but also facilitates the process of knowledge construction through hands-on experiences and problem-solving. Additionally, the study by Liu et al. (2026) demonstrates that scaffolding in programming education significantly enhances students’ CT skills, enabling them to develop more complex abilities in alignment with student’s learning needs.

These findings are also supported by a systematic review by Possaghi & Papavlasopoulou (2025), which shows that technology-based computational activities tend to be designed using constructivist approaches to develop CT skills more broadly. The study found that the use of tools such as programming software and the Internet of Things (IoT) encourages students to engage in real-world context-based activities, allowing students to develop computational skills through direct interaction with technology and students’ surrounding environment. Furthermore, research by Korte et al. (2025) and Santaengracia et al. (2026) indicates that learning based on programming, AI, and educational games supported by social interaction and shared reflection can enhance students' knowledge construction. Therefore, the implementation of CAI programs designed to be interactive, adaptive, and collaborative within the framework of Social Constructivism serves as a strong foundation for enhancing students' CT skills. Therefore, CAI programs reinforce Vygotsky's theory that social interaction and technological support are key elements in the development of students' CT skills.

Overall, the key results of this study show that implementation of the CAI program has a significant influence and quite an effective impact on improving students' CT skills. This improvement is not only statistically significant but also pedagogically relevant as it helps students adapt to the skills needs of the 21st century. Therefore, implementing the CAI program has great potential to support the transformation of elementary education toward the digital era, which emphasizes higher-order thinking skills and technological proficiency from an early age. The results of this study also reinforce the urgency of implementing the CAI curriculum in Phase C at elementary schools.

The results of this study have important implications both theoretically and practically for the world of elementary education. Theoretically, the study results show that the CAI program can be an effective strategy for improving students' CT skills and supporting Vygotsky's Social Constructivism theory. Practically, the results of this study also serve as a basis for schools and policymakers to strengthen the latest curriculum policies through the CAI program as a strategic step in preparing a generation that is not only technologically literate but also capable of understanding, analyzing, and creating computational technology-based solutions. The implementation of the CAI program also requires the role of teachers as facilitators who guide students to understand technological concepts, not just be passive users.

This study has several limitations. First, this study did not include a control group, so it was not possible to compare the results between the experimental and non-experimental groups. A study design with a control group would provide stronger comparisons and conclusions. Second, this study has not examined the influence of individual characteristics, such as gender differences or interest in technology, on students' CT skills. These factors have the potential to influence the results of improvements in CT skills. Therefore, future research is recommended to use an experimental design with a control group and to include longitudinal analysis to observe the long-term impact of the CAI program on students' CT skills.

CONCLUSION

Conclusion

Based on the results of the research and discussion, it can be concluded that the implementation of the CAI program has a significant influence and quite an effective impact on improving the CT skills of VC grade students at Keboansikep 2 Public Elementary School. The results of the descriptive statistical analysis show that the average posttest score increased by 17.96 points, showing a significant improvement in CT skills after the treatment was given. The results of the paired sample t-test showed a value (Sig. (2-tailed)) < 0.001, which means the CAI program significantly influences students' CT skills. The results of the N-Gain test showed an average value of 0.5693 (56.93%), which is in the moderate category, showing that the CAI program is quite effective in improving students' CT skills. The results of this study also show that the implementation of the CAI program aligns with Vygotsky's Social Constructivism theory and serves as a foundation for schools and policymakers to strengthen the latest curriculum policies through the CAI program as a strategic step in training students to use technology while developing CT skills, which are the main foundation for equipping this 21st-century generation.

Recommendations

Based on the results of the research, discussion, and conclusions, the researcher offers several recommendations as a follow-up to this study, namely: 1) Educators are advised to prepare themselves to implement the CAI program continuously in elementary schools, as it has been proven to improve students' CT skills; 2) Future researchers are advised to involve more than one class or school so that the research results can be generalized more widely, and to allow for a comparison of the CAI program's impact on students with different characteristics; 3) Future researchers are also advised to develop the CAI program with an interactive learning model and integrate innovative digital learning media to make it engaging.

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