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Improving the Computational Thinking Abilities of Junior High School Students Through Problem-Based Learning

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ABSTRACT

This study aims to improve the Computational Thinking (CT) abilities of seventh-grade students at SMPN 37 Surabaya, based on initial findings indicating that most students in this class exhibit low CT abilities. Efforts to improve CT abilities were made through implementing the Problem-Based Learning (PBL) model, which is effective in facilitating problem-solving skills. The research method used was Classroom Action Research (CAR) with a spiral approach by Stephen Kemmis and Robin McTaggart, conducted over multiple cycles to monitor the gradual development of students' CT abilities. Data were collected through post-tests at the end of each cycle to evaluate improvements in students' CT abilities. Data analysis was conducted using a CT assessment rubric, categorizing students based on CT skills and foundations. The data analysis results indicated an increase in CT scores across each research cycle. In Cycle I, there was an increase of 0.2 in CT scores, with a completion rate of 60% and an average CT score of 15.13. In Cycle II, the CT score improvement reached 0.38, with a completion rate of 93% and an average CT score of 21.53. These findings demonstrate that the implementation of the PBL model significantly improves students' CT abilities. The progression from low to medium and high skill categories by the end of Cycle II highlights the effectiveness of PBL in developing students' CT abilities, making this model relevant for improving critical and systematic thinking skills among students.

Kata Kunci:
Computational Thinking (CT);

ABSTRAK

Penelitian ini bertujuan meningkatkan kemampuan *Computational Thinking* (CT) siswa kelas VII di SMPN 37 Surabaya, berdasarkan pada temuan awal yang menunjukkan bahwa mayoritas siswa di kelas tersebut memiliki kemampuan CT yang rendah. Upaya peningkatan kemampuan CT ini dilakukan melalui penerapan model *Problem-Based Learning*

Penelitian Tindakan Kelas (PTK);
Problem-Based Learning (PBL).

(PBL), yang dikenal efektif dalam memfasilitasi keterampilan pemecahan masalah. Metode penelitian yang digunakan adalah Penelitian Tindakan Kelas (PTK) dengan pendekatan spiral dari Stephen Kemmis dan Robin McTaggart, yang diterapkan dalam beberapa siklus untuk memantau perkembangan kemampuan CT siswa secara bertahap. Pengumpulan data dilakukan melalui *post-test* pada akhir setiap siklus untuk mengevaluasi peningkatan kemampuan CT peserta didik. Analisis data dilakukan menggunakan rubrik penilaian CT yang telah dirancang, dengan mengelompokkan siswa berdasarkan kategori kemampuan CT dan fondasi CT. Hasil analisis data menunjukkan adanya peningkatan skor CT pada setiap siklus penelitian. Pada siklus I, terjadi peningkatan skor CT sebesar 0,2 dengan persentase ketuntasan mencapai 60% dan rata-rata skor CT sebesar 15,13. Pada siklus II, peningkatan skor CT mencapai 0,38 dengan persentase ketuntasan sebesar 93% dan rata-rata skor CT mencapai 21,53. Temuan penelitian ini menunjukkan bahwa penerapan model PBL secara signifikan dapat meningkatkan kemampuan CT peserta didik. Peningkatan dari kategori kemampuan rendah menjadi sedang hingga tinggi pada akhir siklus II menunjukkan efektivitas PBL dalam mengasah keterampilan CT peserta didik, menjadikan model ini relevan untuk diterapkan dalam meningkatkan keterampilan berpikir kritis dan sistematis di kalangan peserta didik.

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INTRODUCTION

The Programme for International Student Assessment (PISA) conducts a triennial evaluation to measure the competencies of 15-year-old students in reading, mathematics, science, innovative fields, and well-being across countries that are part of the Organisation for Economic Co-operation and Development (OECD). Its goal is to analyze global educational trends by assessing the academic performance of these students in reading, mathematics, and science[1].

In the 2018 PISA assessment, Indonesia ranked 62nd out of 70 countries with a reading score of 371, significantly below the average of 487, a mathematics score of 379 compared to the average of 489, and a science score of 396 compared

[1] Therese N. Hopfenbeck et al., "Lessons Learned from PISA: A Systematic Review of Peer-Reviewed Articles on the Programme for International Student Assessment," *Scandinavian Journal of Educational Research* 62, no. 3 (May 4, 2018): 333–53, https://doi.org/10.1080/00313831.2016.1258726.

to the average of 489. These findings suggest that Indonesian students performed below the average levels of countries participating in the PISA assessment conducted by the Organisation for Economic Co-operation and Development (OECD) in reading, mathematics, and science. According to a report from the OECD, published on https://gpseducation.oecd.org/, Indonesia's ranking improved in 2022 relative to 2018. Nevertheless, despite this improvement in rank, the average scores of Indonesian students in reading, mathematics, and science decreased. Specifically, Indonesia scored 359 in literacy, below the global average of 469; 366 in mathematics, compared to the worldwide average of 358; and 383 in science, while the global average is 384. This decline also observed in several other countries, is largely attributed to the educational challenges posed by the COVID-19 pandemic, which left many education systems worldwide inadequately prepared.

The PISA scores of Indonesian students in reading, mathematics, and science remain below the global average, highlighting the need for educational improvement. Integrating Computational Thinking (CT) skills into the curriculum presents a potential solution. CT skills improve students' analytical and problem-solving capabilities and foster a deeper understanding of complex concepts, which can lead to improved proficiency in the core PISA areas. Additionally, by developing strong CT skills, students worldwide, including those in Indonesia, are better equipped to boost academic performance, face the challenges of the digital era, compete globally, and contribute to scientific and technological advancements[2].

Computational Thinking (CT) reflects a versatile problem-solving method that can be widely applied[3] and spans across various scientific fields[4]. This skill is recognized as crucial not only for computer scientists but also for individuals from diverse disciplines, highlighting the importance of mastering CT from an early age[5]. CT involves the cognitive processes needed to formulate problems and

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[2] Elif Polat et al., "A Comprehensive Assessment of Secondary School Students' Computational Thinking Skills," *British Journal of Educational Technology* 52, no. 5 (September 20, 2021): 1965–80, https://doi.org/10.1111/bjet.13092.

[3] Shuchi Grover and Roy Pea, "Computational Thinking in K–12," *Educational Researcher* 42, no. 1 (January 1, 2013): 38–43, https://doi.org/10.3102/0013189X12463051.

[4] Shuchi Grover and Roy Pea, "Computational Thinking: A Competency Whose Time Has Come," in *Computer Science Education* (Bloomsbury Academic, 2018), https://doi.org/10.5040/9781350057142.ch-003; Jeannette M. Wing, "Computational Thinking and Thinking about Computing," *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 366, no. 1881 (October 28, 2008): 3717–25, https://doi.org/10.1098/rsta.2008.0118.

[5] Andreas Giannakoulas and Stelios Xinogalos, "Studying the Effects of Educational Games on Cultivating Computational Thinking Skills to Primary School Students: A Systematic Literature Review," *Journal of Computers in Education*, November 21, 2023, https://doi.org/10.1007/s40692-023-00300-z; Danial Hooshyar et al., "From Gaming to Computational Thinking: An Adaptive Educational Computer Game-Based Learning Approach," *Journal of Educational Computing Research* 59, no. 3 (June 23, 2021): 383–409, https://doi.org/10.1177/0735633120965919.

develop strategies to identify the most effective, efficient, and executable solutions, which can be carried out by information processing agents, either human-based or computer-based (hardware, software, or a combination of both). According to Chen et al.[6] and Kite & Park[7], Computational Thinking (CT) involves problem-solving and reasoning processes using computer science concepts and skills to achieve deeper understanding. Kwon et al.[8] define CT as a cognitive process in which individuals apply analytical and algorithmic methods to formulate, analyze, and solve problems. Additionally, Wing[9] emphasizes that CT encompasses the ability to solve problems using specific algorithms, enabling their reuse by both humans and computers to address similar issues.

Based on the explanation above, we can understand that CT skills are essential for every student to possess and develop. By improving CT skills, students can improve cognitive and intellectual abilities and become accustomed to solving real-world problems[10]. CT is a fundamental skill that is crucial for every individual to master to be better prepared for the challenges of the 21st century[11], as CT involves a systematic approach to problem-solving, whether simple or complex. This skill includes structured problem-solving methods, the ability to break down complex problems into simpler and more understandable parts, abstract thinking to identify patterns and relationships, and the development of automated solutions supported by technology[12].

CT skills are based on several foundational concepts. These foundations include decomposition, pattern recognition, abstraction, and algorithm design[13].

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[6] Peng Chen et al., "Fostering Computational Thinking through Unplugged Activities: A Systematic Literature Review and Meta-Analysis," *International Journal of STEM Education* 10, no. 1 (July 4, 2023): 47, https://doi.org/10.1186/s40594-023-00434-7.

[7] Vance Kite and Soonhye Park, "What's Computational Thinking?: Secondary Science Teachers' Conceptualizations of Computational Thinking (CT) and Perceived Barriers to CT Integration," *Journal of Science Teacher Education* 34, no. 4 (May 19, 2023): 391–414, https://doi.org/10.1080/1046560X.2022.2110068.

[8] Kyungbin Kwon et al., "Computational Thinking Practices: Lessons Learned from a Problem-Based Curriculum in Primary Education," *Journal of Research on Technology in Education* 55, no. 4 (July 3, 2023): 590–607, https://doi.org/10.1080/15391523.2021.2014372.

[9] Jeannette M. Wing, "Computational Thinking's Influence on Research and Education for All," *Italian Journal of Educational Technology* 25, no. 2 (2017): 7–14, https://doi.org/https://doi.org/10.17471/2499-4324/922.

[10] Edelberto Franco Silva et al., "A Literature Review of Computational Thinking in Early Ages," *International Journal of Early Years Education* 31, no. 3 (July 3, 2023): 753–72, https://doi.org/10.1080/09669760.2022.2107491.

[11] Grover and Pea, "Computational Thinking in K–12."

[12] Ting Chia Hsu et al., "How to Learn and How to Teach Computational Thinking: Suggestions Based on a Review of the Literature," *Computers & Education* 126 (November 2018): 296–310, https://doi.org/10.1016/j.compedu.2018.07.004.

[13] Soumela Atmatzidou and Stavros Demetriadis, "Advancing Students' Computational Thinking Skills through Educational Robotics: A Study on Age and Gender Relevant Differences," *Robotics and Autonomous Systems* 75 (January 2016): 661–70, https://doi.org/10.1016/j.robot.2015.10.008; Giannakoulas and Xinogalos, "Studying the Effects of Educational Games on Cultivating Computational Thinking Skills to Primary School Students: A Systematic Literature Review";

Ye et al.[14] provided further clarification on each foundational aspect of CT. Decomposition involves breaking complex problems into smaller, more manageable parts. Pattern recognition entails identifying recurring patterns within a problem to facilitate solutions based on prior patterns. Abstraction refers to distinguishing relevant information from irrelevant data. Lastly, algorithm design involves creating a step-by-step process to solve a particular problem.

As the digital world continues to rapidly evolve, digital literacy is becoming increasingly important. Mastering digital literacy from an early age equips individuals with the skills to navigate future opportunities and challenges. In Indonesia, several educational institutions have begun incorporating Computational Thinking (CT) to foster digital literacy. The government, through the annexes of Ministerial Regulations (Permendikbud) No. 35, 36, and 37 of 2018, introduced informatics as an elective subject at the middle and high school levels, starting from the 2019/2020 academic year. In the annex of Permendikbud No. 37, Computational Thinking (CT) is explicitly mentioned as one of the core competencies in the informatics curriculum. However, CT can be integrated into almost all subjects, including mathematics.

Mathematics education emphasizes the problem-solving process rather than mere memorization of formulas. Mathematical competence can be understood both cognitively and pragmatically, depending on its defined purpose. This ability develops through the interaction between rational thought and logic[15]. Higher-order thinking skills are the result of a combination of computational and mathematical thinking processes[16]. The fundamental elements of computational thinking (decomposition, pattern recognition, abstraction, and algorithms) equip students with the tools to solve real-world problems. Consequently, science and mathematics education offer an ideal framework for incorporating computational

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Joohi Lee et al., "Classroom Play and Activities to Support Computational Thinking Development in Early Childhood," *Early Childhood Education Journal* 51, no. 3 (March 4, 2023): 457–68, https://doi.org/10.1007/s10643-022-01319-0; Jingsi Ma et al., "Game-Based Learning for Students' Computational Thinking: A Meta-Analysis," *Journal of Educational Computing Research* 61, no. 7 (December 14, 2023): 1430–63, https://doi.org/10.1177/07356331231178948; Filiz Mumcu et al., "Integrating Computational Thinking into Mathematics Education through an Unplugged Computer Science Activity," *Journal of Pedagogical Research*, June 10, 2023, https://doi.org/10.33902/JPR.202318528; Valerie J. Shute et al., "Demystifying Computational Thinking," *Educational Research Review* 22 (November 2017): 142–58, https://doi.org/10.1016/j.edurev.2017.09.003.

[14] Huiyan Ye et al., "Integration of Computational Thinking in K-12 Mathematics Education: A Systematic Review on CT-Based Mathematics Instruction and Student Learning," *International Journal of STEM Education* 10, no. 1 (January 18, 2023): 3, https://doi.org/10.1186/s40594-023-00396-w.

[15] Ronnie Karsenty, "Mathematical Ability," in *Encyclopedia of Mathematics Education* (Dordrecht: Springer Netherlands, 2014), 372–75, https://doi.org/10.1007/978-94-007-4978-8_94.

[16] Thiago S. Barcelos et al., "Mathematics Learning through Computational Thinking Activities: A Systematic Literature Review," *Journal of Universal Computer Science* 24, no. 7 (2018): 815–45, https://lib.jucs.org/article/23376.

thinking[17], which in turn strengthens the relevance of these subjects to both present and future professional practices[18].

To improve students' computational thinking (CT) skills in mathematical problem-solving, selecting an appropriate instructional model is crucial. Problem-Based Learning (PBL) is a promising approach in this regard. As noted by Wijnia et al.[19], PBL is a student-centered instructional strategy that immerses students in diverse problems, improving their conceptual understanding and mathematical problem-solving abilities. Yew and Goh[20] further assert that a key objective of PBL is to foster students' problem-solving skills. Similarly, Zumbach and Prescher [21] highlight that PBL sharpens critical thinking, encouraging students to construct knowledge and solve problems independently.

Moust et al.[22] and Shipton[23] identify five essential characteristics of the PBL model: real-world problems serve as learning triggers, small group cooperative learning, a student-centered approach, the teacher's role as a facilitator, and sufficient time for independent study. The PBL model follows a five-step learning process: introducing the problem, organizing student activities, guiding investigations, developing and presenting solutions, and evaluating the problem-solving process. These stages help students define the problem, decompose it into manageable components, and design algorithms for solutions, thereby promoting the development of computational thinking skills.

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[17] Irene Lee and Joyce Malyn-Smith, "Computational Thinking Integration Patterns Along the Framework Defining Computational Thinking from a Disciplinary Perspective," *Journal of Science Education and Technology* 29, no. 1 (February 22, 2020): 9–18, https://doi.org/10.1007/s10956-019-09802-x; Kevin P Waterman et al., "Integrating Computational Thinking into Elementary Science Curriculum: An Examination of Activities That Support Students' Computational Thinking in the Service of Disciplinary Learning," *Journal of Science Education and Technology* 29, no. 1 (February 22, 2020): 53–64, https://doi.org/10.1007/s10956-019-09801-y; David Weintrop et al., "Defining Computational Thinking for Mathematics and Science Classrooms," *Journal of Science Education and Technology* 25, no. 1 (February 8, 2016): 127–47, https://doi.org/10.1007/s10956-015-9581-5.

[18] Mumcu et al., "Integrating Computational Thinking into Mathematics Education through an Unplugged Computer Science Activity"; Weintrop et al., "Defining Computational Thinking for Mathematics and Science Classrooms."

[19] Lisette Wijnia et al., "The Effects of Problem-Based, Project-Based, and Case-Based Learning on Students' Motivation: A Meta-Analysis," *Educational Psychology Review* 36, no. 1 (March 28, 2024): 29, https://doi.org/10.1007/s10648-024-09864-3.

[20] Elaine H.J. Yew and Karen Goh, "Problem-Based Learning: An Overview of Its Process and Impact on Learning," *Health Professions Education* 2, no. 2 (December 2016): 75–79, https://doi.org/10.1016/j.hpe.2016.01.004.

[21] Joerg Zumbach and Claudia Prescher, "Problem-Based Learning and Case-Based Learning," in *International Handbook of Psychology Learning and Teaching* (Cham, Switzerland: Springer Cham, 2023), 1235–53, https://doi.org/10.1007/978-3-030-28745-0_58.

[22] Jos Moust et al., *Introduction to Problem-Based Learning*, 4th ed. (Houten: Routledge, 2021), https://doi.org/10.4324/9781003194187.

[23] Brett Shipton, "Problem-Based Learning," in *Signature Pedagogies in Police Education: Teaching Recruits to Think, Perform and Act with Integrity* (Bathurst, Australia: SpringerBriefs in Policing, 2023), 53–67, https://doi.org/10.1007/978-3-031-42387-1_5.

Problem-based learning (PBL) has been shown to effectively improve students' mathematical thinking abilities, particularly in critical, creative, and computational thinking (CT). Research conducted by Fadilla et al.[24], Kardoyo et al.[25], and Liu & Pásztor[26] indicate that this model significantly improves students' critical thinking abilities. demonstrates that this approach significantly improves students' critical thinking skills. Likewise, other studies indicate that PBL promotes the development of creative thinking[27]. Additionally, Moreno-Palma et al.[28] report that PBL improves computational thinking. Collectively, these studies confirm that PBL positively impacts various aspects of students' thinking skills, including critical, creative, and computational thinking.

As one of the public schools in Surabaya, SMPN 37 Surabaya has made Informatics, which includes Computational Thinking (CT) material, a compulsory subject for students in grades VII, VIII, and IX. However, despite receiving training in computational thinking, students' CT abilities, particularly in grade VII, remain relatively low. Observations conducted in Class VIIE reveal that 57% of the 30 students exhibit low CT skills. Specifically, 80% of students struggle to decompose complex problems into simpler components, 73% have difficulty distinguishing important information from irrelevant information in problem-solving, 57% cannot recognize patterns in problems to find solutions, and 50% are unable to design effective steps to solve given problems. These findings highlight the need for targeted interventions to improve students' CT skills, given the importance of this ability in addressing 21st-century challenges. Consequently, based on the above considerations, the researcher is interested in conducting Classroom Action Research (CAR) titled "Improving The Computational

[24] N Fadilla et al., "Effect of Problem-Based Learning on Critical Thinking Skills," *Journal of Physics: Conference Series* 1810, no. 1 (March 1, 2021): 012060, https://doi.org/10.1088/1742-6596/1810/1/012060.
[25] Kardoyo et al., "Problem-Based Learning Strategy: Its Impact on Students' Critical and Creative Thinking Skills," *European Journal of Educational Research* 9, no. 3 (July 15, 2020): 1141–50, https://doi.org/10.12973/eu-jer.9.3.1141.
[26] Yong Liu and Attila Pásztor, "Effects of Problem-Based Learning Instructional Intervention on Critical Thinking in Higher Education: A Meta-Analysis," *Thinking Skills and Creativity* 45 (September 2022): 101069, https://doi.org/10.1016/j.tsc.2022.101069.
[27] Shelagh A. Gallagher, "The Role of Problem-Based Learning in Developing Creative Expertise," *Asia Pacific Education Review* 16, no. 2 (June 28, 2015): 225–35, https://doi.org/10.1007/s12564-015-9367-8; Kardoyo et al., "Problem-Based Learning Strategy: Its Impact on Students' Critical and Creative Thinking Skills"; S. Suciati et al., "Problem-Based Learning Models: Their Effectiveness in Improving Creative Thinking Skills of Students with Different Academic Skills in Science Learning," *Jurnal Pendidikan IPA Indonesia* 12, no. 4 (January 12, 2024): 672–83, https://doi.org/10.15294/jpii.v12i4.44752; Kani Ulger, "The Effect of Problem-Based Learning on the Creative Thinking and Critical Thinking Disposition of Students in Visual Arts Education," *Interdisciplinary Journal of Problem-Based Learning* 12, no. 1 (March 6, 2018), https://doi.org/10.7771/1541-5015.1649.
[28] Natalia Moreno-Palma et al., "Effectiveness of Problem-Based Learning in the Unplugged Computational Thinking of University Students," *Education Sciences* 14, no. 7 (June 25, 2024): 693, https://doi.org/10.3390/educsci14070693.

Thinking Abilities of Junior High School Students Through Problem-Based Learning".

Methods

This Classroom Action Research (CAR) was conducted with 30 students from class VII-E at SMPN 37 Surabaya during the 2024/2025 academic year's odd semester. The research involved assigning students specific tasks to engage them in the learning process. The study utilized the spiral model introduced by Stephen Kemmis and Robin McTaggart, which consists of multiple cycles, each comprising four stages: 1) planning, 2) execution, 3) observation, and 4) reflection[29]. Both qualitative and quantitative research methods were employed in this study. According to Sugiyono[30], qualitative research generates descriptive data from verbal statements or behavioral observations, while quantitative research yields numerical data based on test results.

A group of students will participate as research subjects and will complete a diagnostic test featuring two-story problems that assess their computational thinking skills. Following their responses, the researcher will analyze the results by evaluating each answer provided. The scoring rubric employed is adapted and developed from the framework established by Weintrop et al.[31] The assessment rubric is detailed in **Table 1** below.

Table 1. Rubric for Assessing Computational Thinking Skills

CT Foundation	Reaction to the Question	Score
Decomposition	The student did not provide an answer.	0
	Unable to identify and decompose the problem into a simpler form, resulting in incorrect answers.	1
	Able to investigate and decompose a complex problem into a practical form correctly, but the answer is still incorrect.	2
	Able to investigate and decompose a complex problem into a practical form correctly, but it is still incomplete.	3
	Able to investigate and decompose a complex problem into a practical form completely and correctly.	4
Pattern Recognition	Does not answer or recognize patterns present in the problem.	0
	Can recognize some patterns in the problem, but there are errors during the problem-solving process.	1
	Can recognize some patterns in the problem and apply them correctly during the problem-solving process.	2
	Can recognize all patterns present in the problem, but there are errors during the problem-solving process.	3
	Can recognize all patterns present in the problem and apply them correctly during the problem-solving process.	4

[29] Norhiza Mohd Salleh and Mohd Syafiq Aiman, "Improving the Quality of Pupils' Response in Science Inquiry Teaching: A Participatory Action Research," *Procedia - Social and Behavioral Sciences* 191 (June 2015): 1310–16, https://doi.org/10.1016/j.sbspro.2015.04.482.

[30] Sugiyono, *Metode Penelitian Kuantitatif, Kualitatif, Dan R&D* (Bandung: Alfabeta, 2019).

[31] David Weintrop et al., "Assessment of Computational Thinking," in *Computational Thinking in Education* (New York: Routledge, 2021), 90–111, https://doi.org/10.4324/9781003102991-6.

CT Foundation	Reaction to the Question	Score
Abstraction	Failing to answer or unable to identify important information.	0
	Able to identify only a small amount of important information, with numerous irrelevant details concerning problem resolution.	1
	Capable of identifying some important information, but still includes many irrelevant aspects in addressing the problem.	2
	Able to identify most of the important information, though there are still a few irrelevant sections related to problem resolution.	3
	Capable of identifying and focusing on important information while disregarding irrelevant parts in addressing the problem.	4
Algorithm Design	Does not answer or is unable to formulate a set of problem-solving procedures	0
	Can formulate a structured set of problem-solving procedures but lacks logic, or can create an unstructured but logical set of problem-solving procedures, with answers still incorrect.	1
	Can create a structured set of problem-solving procedures but lacks logic, or can create an unstructured but logical set of problem-solving procedures, with correct answers.	2
	Can formulate structured and logical steps for problem-solving, but the answers are still incorrect.	3
	Can create clear and logical structured steps that are correct for problem-solving.	4

After scoring each student's answer sheet, the next step is to categorize the students into several groups. This study will categorize students based on two categories: the category of computational thinking (CT) ability and the category of each CT foundation. This research employs the categorization type developed by Azwar[32] as follows.

Table 2. Categorization of Division

Category	Interval
Low	$X \leq \bar{x} - std.$
Moderate	$\bar{x} - std. < X < \bar{x} + std.$
High	$X \geq \bar{x} + std.$

Notes:

$$\bar{x} = \frac{x_{max} + x_{min}}{2} \qquad \ldots 1)$$[33]

[32] Saifuddin Azwar, *Metode Penelitian Psikologi* (Yogyakarta: Pustaka Pelajar, 2017).
[33] Azwar.

$$\boldsymbol{std} = \frac{x_{max}-x_{min}}{4} \quad \ldots 2)^{34}$$

Based on equations 1) and 2), several categories are obtained as shown in **Table 3** and **Table 4**.

Table 3. Categorization of Computational Thinking Foundations

CT Foundation Categories	Interval
Low	$X \leq 2$
Moderate	$2 < X < 6$
High	$X \geq 6$

Table 4. Categorization of Students' Computational Thinking Abilities

CT Ability Categories	Interval
Low	$X \leq 12$
Moderate	$12 < X < 20$
High	$X \geq 20$

To measure students' proficiency in computational thinking, classical completeness analysis is used, which can be calculated using the following formula:

$$\boldsymbol{P} = \frac{\boldsymbol{Number\ of\ students\ who\ have\ completed}}{\boldsymbol{number\ of\ students}} \times \mathbf{100\%}$$

Furthermore, to assess the extent of students' computational thinking development, the scores obtained in each cycle will be evaluated using Hake's Gain index, as follows.

$$\boldsymbol{G} = \frac{\boldsymbol{final\ score - initial\ sore}}{\boldsymbol{maximum\ score - initial\ score}} \qquad \ldots 3)^{35}$$

The category for Gain follows the Hake criteria[36], as shown in **Table 5** below.

Table 5. Gain Categorization

Category of CT Improvement	Indeks Gain Interval
Low	$G \leq 0{,}3$
Moderate	$0{,}3 < G \leq 0{,}7$
High	$G > 0{,}7$

Consequently, students' computational thinking (CT) skills are deemed to have improved if there is an increase in scores on CT ability assessments across each cycle, alongside a higher percentage of students successfully employing CT skills. The evaluation of CT improvement following the implementation of the

[34] Azwar; Alfredo Ramirez and Charles Cox, "Improving on the Range Rule of Thumb," *Rose-Hulman Undergraduate Mathematics Journal* 13, no. 1 (2012): 1–15, https://scholar.rose-hulman.edu/rhumj/vol13/iss2/1.

[35] Setiya Utari et al., "Application of Learning Cycle 5e Model Aided Cmaptools-Based Media Prototype to Improve Student Cognitive Learning Outcomes," *Applied Physics Research* 5, no. 4 (July 11, 2013): 69–76, https://doi.org/10.5539/apr.v5n4p69.

[36] Utari et al.

Problem-Based Learning (PBL) model relies on test scores. Moreover, progress is assessed through the rise in CT test scores from one cycle to the next. This research will be considered complete when at least 80% of students in a given cycle achieve scores above 12, with a minimum rating of 'moderate' in CT ability.

RESULT AND DISCUSSION

Cycle I

In Cycle I, the instructional activities adhered to the module created by the researcher, emphasizing the addition and subtraction of algebraic expressions. This cycle comprised two sessions, each spanning 2×2 class periods, totaling 4×40 minutes. A problem-based learning model was utilized to improve students' computational thinking (CT) skills. Upon concluding the learning activities in Cycle I, the researcher conducted a post-test that incorporated CT skills into each question. Student performance was evaluated using a rubric detailed in **Table 1**, and the results of the CT skills assessment for Cycle I are illustrated in **Figure 1**.

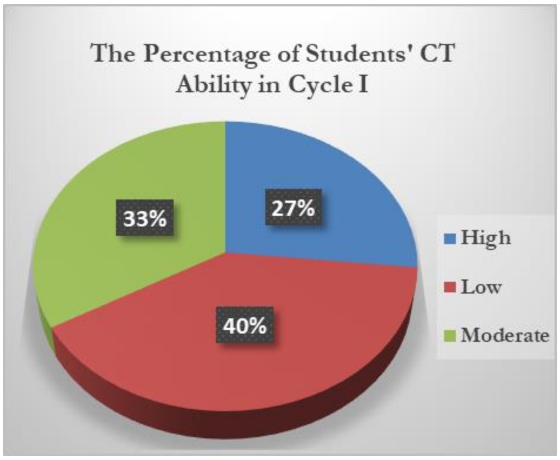

Figure 1. The Percentage of Students' CT Ability in Cycle I

According to the data presented in **Figure 1**, 40% of students fall into the low category for Computational Thinking (CT) skills, while 33% are classified as medium, and 27% as high, with an average CT score of 15.13. In Cycle I, there is a noted increase in the proportions of students in both the medium and high categories, as well as an improvement in the average CT score when compared to the pre-test average of 9.8. To evaluate the improvement in CT skills more comprehensively, a Gain analysis will be performed as outlined below.

$$G = \frac{\text{final score of Cycle I} - \text{initial test score}}{\text{maximum score} - \text{initial test score}}$$

$$G = \frac{15{,}13 - 9{,}8}{32 - 9{,}8} = 0{,}2$$

There was a 0.2 increase in CT ability. However, based on **Table 4**, this increase is still considered low. Although an improvement occurred, the results indicate that the learning activities implemented have not been fully effective in optimizing the development of students' CT skills. Further, a more detailed analysis of students' CT abilities will be conducted, covering the four main pillars of CT: decomposition, pattern recognition, abstraction, and algorithm. This analysis aims to gain a deeper understanding of which areas require improvement in the learning process.

a. Analysis of Students' Decomposition Ability

The following are the decomposition scores of students in Cycle I.

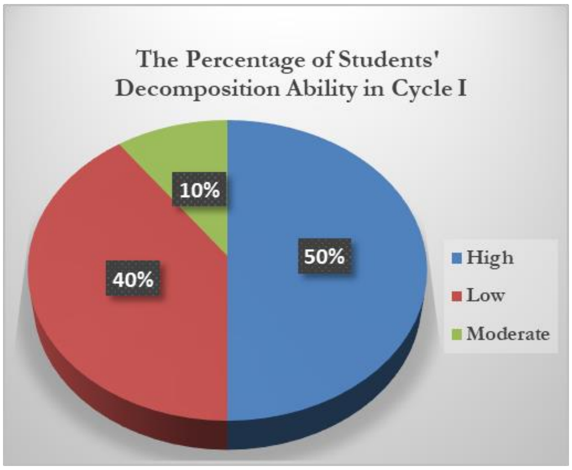

Figure 2. The Percentage of Students' Decomposition Ability in Cycle I

Based on the presented data, the majority of students (60%) have successfully broken down complex problems into simpler parts, demonstrating an adequate understanding of the decomposition process. However, 10% of them are still facing minor challenges, which may require additional support or explanation. On the other hand, 40% of the students are experiencing significant difficulties in the decomposition process, indicating that nearly half need special attention. This may suggest that the teaching strategies implemented have not been fully effective for this group, or that the material presented is too complex.

In addition, the average score of students in the decomposition foundation is 4.7, which falls into the medium category according to **Table 3**. These findings indicate that although most students have demonstrated mastery of decomposition skills, further efforts are needed to achieve a more optimal level of understanding.

b. Analysis of Students' Pattern Recognition Ability

The following are the pattern recognition scores of students in Cycle I.

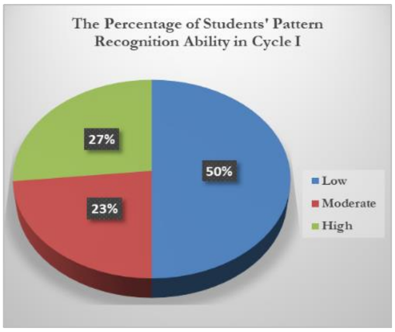

Figure 3. The Percentage of Students' Pattern Recognition Ability in Cycle I

Based on the data presented, only 27% of students successfully recognized patterns in problems effectively, indicating their strong pattern recognition skills in finding appropriate solutions. Additionally, 23% of students could identify patterns, but they still faced some challenges, suggesting the need for further improvement in understanding and applying patterns. However, the main challenge lies with 50% of students who struggle to identify and determine the correct patterns to solve given problems. This highlights that nearly half of the students require more intensive support to improve their pattern recognition skills.

The average score of students in pattern recognition foundations is 3.4, placing them in the moderate category according to **Table 3**. This score reflects that despite some progress, most students remain at a fairly basic skill level. This finding highlights the need for greater emphasis on practice and the development of pattern recognition skills to achieve deeper understanding and improve effectiveness in problem-solving among students.

c. Analysis of Students' Abstraction Ability

The following are the abstraction scores of students in Cycle I.

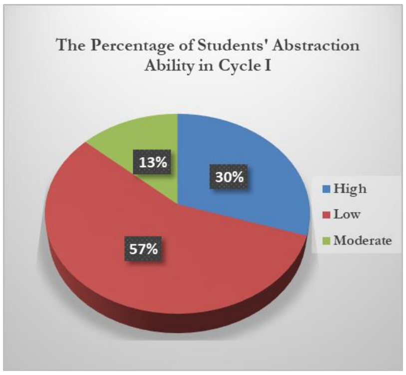

Figure 4. The Percentage of Students' Abstraction Ability in Cycle I

Based on the presented data, only 30% of students succeeded in distinguishing essential information from irrelevant information during problem-solving processes. This indicates a sufficient understanding of abstraction and the ability to identify highly important information. Additionally, 13% of students demonstrated abstract reasoning skills but encountered several challenges, highlighting the need for additional support or reinforcement. However, 57% of students still experience significant difficulties in differentiating relevant from irrelevant information. This underscores that more than half of the students require special attention to develop their abstraction skills further.

The average score of students in the abstraction foundation is 3.3, categorizing them as moderate according to **Table 3**. This score reflects that despite some progress, the majority of students still possess basic skill levels. This finding highlights the need for a more focused learning approach and more intensive strategies to improve students' abilities in abstraction processes, enabling them to more effectively identify and process relevant information for problem-solving.

d. Analysis of Students' Algorithm Design Ability

The following are the algorithm design scores of students in Cycle I.

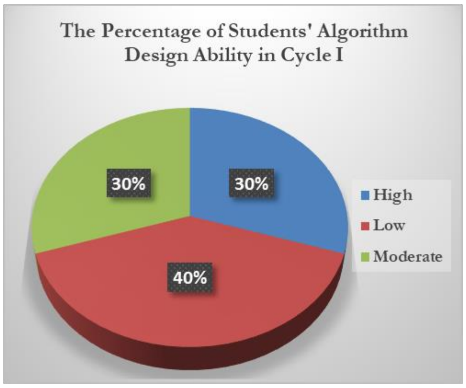

Figure 5. The Percentage of Students' Algorithm Design Ability in Cycle I

Based on the data presented, 30% of students have successfully formulated the correct algorithmic sequence in problem-solving, indicating adequate algorithmic skills capable of correct application. Additionally, another 30% of students can also devise appropriate algorithms, although they still encounter some challenges that may require adjustments or additional support to refine their skills. However, 40% of students still face significant difficulties in formulating the correct algorithmic steps to solve problems. These difficulties indicate that nearly half of the students require special attention and further guidance to improve their abilities in designing and implementing algorithms.

The average score of students on the algorithm foundation is 3.7, which falls into the medium category according to **Table 3**. This score indicates that although there has been progress in understanding algorithmic concepts, the students' level of mastery remains at a basic level. Therefore, these findings highlight the need for more intensive and diverse learning strategies to strengthen algorithmic skills. Such improvement efforts may include additional practice, the use of visual aids like flowcharts, and more intensive guidance to help students develop and apply more effective algorithmic steps in problem-solving.

Based on the findings from Cycle I, it was observed that 60% of the students had achieved mastery in computational thinking (CT) skills. However, this study cannot be considered successful, as the mastery percentage is still below 80%. Therefore, Cycle II is necessary to address and improve certain aspects. These aspects require further attention in Cycle II, based on a thorough analysis of each fundamental component of the students' CT skills.

- Firstly, pattern recognition requires special attention, as 50% of students still struggle with identifying relevant patterns for problem-solving. To address this issue, it is crucial to implement a more in-depth learning approach, utilizing concrete examples and diverse exercises to reinforce students' understanding of this concept.
- For 57% of students who still face difficulties in distinguishing important information from irrelevant information, more intensive guidance is needed to assist those who are struggling.
- Third, improvements are also needed in the algorithmic foundation, as 40% of students still face difficulties in devising appropriate algorithmic steps.
- Finally, although 60% of students have shown progress in decomposition, 40% still struggle to break down problems into simpler components. Therefore, Cycle II must focus on a more structured approach to training students to decompose complex problems into subproblems, starting with simpler issues and progressing to more complex ones.

Cycle II

The learning process in Cycle II was generally not significantly different from Cycle I; however, it was focused as a follow-up to improve the CT test results of the students, which were previously assessed as not optimal. Cycle II consisted of two meetings with a total time allocation of 4×40 minutes. The material taught in the first meeting included two subtopics: rational numbers and ordering rational numbers, while the second meeting focused on operations with fractional numbers. The instructional model applied was problem-based learning. After completing the activities in Cycle II, the researcher administered a post-test that integrated CT skills into each question. Students were asked to answer these questions, and the researcher evaluated their responses using the scoring rubric provided in **Table 1**. The CT test results from Cycle I are shown in **Figure 6**, which demonstrates the development and effectiveness of the learning in Cycle II.

The data presented in Cycle II, illustrated in **Figure 6**, indicates a notable improvement in students' computational thinking (CT) skills compared to Cycle I. In Cycle II, only 7% of students were classified in the low CT ability category, 53% fell into the moderate category, and 40% were in the high category. The average CT score for Cycle II was 21.53, categorizing it within the high CT ability range. This represents a marked improvement over the Cycle I post-test average score of 15.13, highlighting the advancement in students' CT competencies.

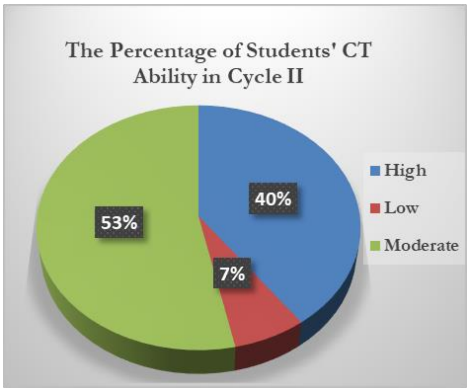

Figure 6. The Percentage of Students' CT Ability in Cycle II

In Cycle I, data revealed that 40% of students fell into the low computational thinking (CT) category, while 33% were in the medium category and 27% in the high category, resulting in an average score of 15.13. This cycle also demonstrated an improvement in CT skills compared to the pre-test, where the average score was only 9.8. A comparison between the two cycles indicates a notable reduction in the percentage of students categorized as low, decreasing from 40% in Cycle I to just 7% in Cycle II. Furthermore, there was a substantial increase in the percentages of students in the medium and high categories, with the high category rising from 27% to 40%. The average CT score improved significantly, increasing from 15.13 in Cycle I to 21.53 in Cycle II. To further assess the improvement in CT skills during Cycle II, a gain analysis will be conducted as follows.

$$G = \frac{\text{final score of Cycle II} - \text{final score of Cycle I}}{\text{maximum score} - \text{final score of Cycle I}}$$

$$G = \frac{21{,}53 - 15{,}13}{32 - 15{,}13} = 0{,}38$$

The CT ability increased by 0.38, which is a moderate category. The findings from this second cycle suggest that the improvement in the learning strategy has effectively improved students' CT abilities. Additionally, a thorough analysis will be undertaken concerning students' CT competencies, focusing on the four fundamental foundations of CT: decomposition, pattern recognition, abstraction, and algorithm, to achieve a more comprehensive understanding of the progression of each aspect of CT ability.

DISCUSSION

Analysis of Students' Decomposition Ability

Based on the data from the diagram in **Figure 7**, there is a significant improvement in students' decomposition abilities. In Cycle II, 97% of students successfully decomposed complex problems into simpler parts, showing a substantial increase compared to Cycle I, where only 60% of students could do so. The percentage of students experiencing minor difficulties also slightly increased, from 10% in Cycle I to 43% in Cycle II. Although this percentage has risen, it indicates that more students are beginning to grasp the concept of decomposition, though they still require further guidance to refine their skills.

The following are the decomposition scores of students in Cycle II

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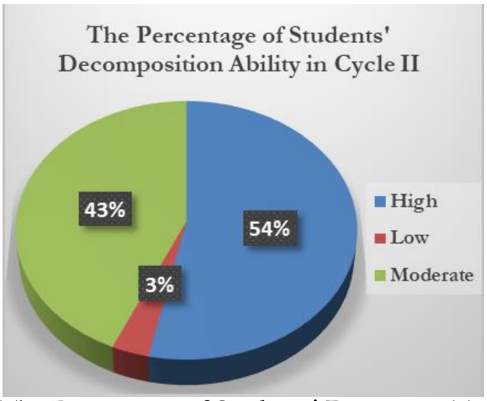

Figure 7. The Percentage of Students' Decomposition Ability in Cycle II

Conversely, the proportion of students encountering substantial challenges in the decomposition process significantly decreased from 40% in Cycle I to just 3% in Cycle II. This decline demonstrates that the improvements in the learning strategy effectively supported the majority of students who previously struggled with understanding the decomposition process. The average decomposition score in Cycle II reached 6.1, categorized as high according to **Table 3**, in contrast to the average score of 4.7 in Cycle I. Overall, Cycle II exhibits a notable improvement in students' decomposition skills compared to Cycle I. This progress indicates that the implemented approach, specifically problem-based learning, has effectively improved students' comprehension of breaking down complex problems, resulting in more favorable outcomes.

Analysis of Students' Pattern Recognition Ability

Based on the data from Cycle II, there was a significant improvement in students' pattern recognition abilities compared to Cycle I. In Cycle II, 30% of students successfully recognized patterns to solve problems effectively, showing an increase from 27% in Cycle I. Although this improvement is relatively small, it reflects progress in students' skills in finding appropriate solutions through pattern recognition. In Cycle II, 57% of students were able to recognize patterns despite facing some challenges, indicating a substantial improvement compared to Cycle I, where only 23% were in this category. These findings suggest that more students are beginning to develop pattern recognition skills, although they have not yet fully mastered this ability.

The following are the pattern recognition scores of students in Cycle II.

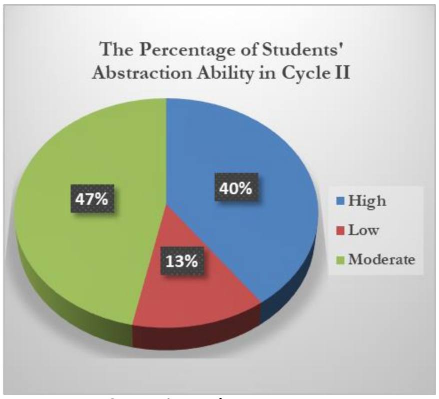

Figure 8. The Percentage of Students' Pattern Recognition Ability in Cycle II

Additionally, in Cycle II, 13% of students still struggled with identifying and determining patterns. This percentage represents a dramatic decrease compared to Cycle I, where nearly 50% of students could not differentiate between important and non-important information. This decrease indicates that the improvements in instruction have effectively assisted most students who previously faced difficulties. The average pattern recognition score also increased to 4.87, classified as moderate, compared to the average score of 3.4 in Cycle I. Overall, the comparison between the two cycles shows a significant improvement in students' pattern recognition abilities.

Analysis of Students' Abstraction Ability

The following are the abstraction scores of students in Cycle II.

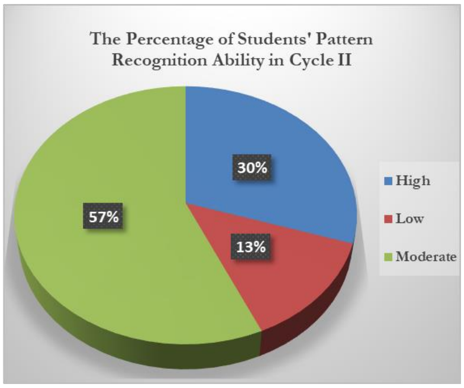

Figure 9. The Percentage of Students' Abstraction Ability in Cycle II

Based on the data from Cycle II above, there is a noticeable improvement in students' abstraction skills compared to Cycle I. In Cycle II, 40% of students were able to distinguish important information from irrelevant information, reflecting an increase from 30% in Cycle I. This finding indicates that more students are starting to develop a solid understanding of abstraction skills and can identify crucial information in problem-solving. Additionally, 47% of students in Cycle II were able to perform abstraction processes, although they still faced some challenges. This result represents a significant improvement compared to Cycle I, where only 13% were in this category. This development suggests that the teaching strategies have helped more students address some of their difficulties, though some still require further reinforcement. On the other hand, the percentage of students struggling to differentiate relevant from irrelevant information decreased drastically to just 13% in Cycle II, compared to 57% in Cycle I.

Moreover, the average score for students' abstraction skills significantly increased to 5.2, which falls into the moderate category, compared to the average score of 3.3 in Cycle I. The decrease in the number of students experiencing difficulties and the increase in the average score indicates that the improvements in teaching strategies have been effective in developing students' abstraction skills, aiding them in better understanding and managing information in problem-solving processes. Overall, the comparison between Cycle I and Cycle II demonstrates a clear improvement in students' abstraction abilities.

Analysis of Students' Algorithm Design Ability

The following are the algorithm design scores of students in Cycle II.

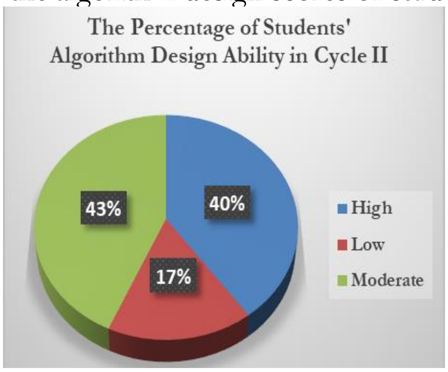

Figure 10. The Percentage of Students' Algorithm Design Ability in Cycle II

Based on the data presented for Cycle II, there is a significant improvement in students' ability to construct correct algorithmic flows. Specifically, 40% of students were able to create accurate algorithms to solve problems, marking an increase from the 30% achieved in Cycle I. This indicates an improved understanding of algorithmic concepts among the students. Additionally, 43% of students in Cycle II were still able to construct algorithms correctly despite encountering challenges, which is an improvement from the 30% observed in Cycle I. The challenges they faced suggest the need for adjustments or additional support to refine their skills. On the other hand, the percentage of students still struggling to distinguish relevant from irrelevant information decreased dramatically to 17% in Cycle II, compared to 40% in Cycle I. This reduction suggests the success of the learning strategy in helping the majority of students better understand and apply algorithmic steps.

Moreover, the average abstraction skill score of students significantly increased to 5.4, which falls into the moderate category, compared to the average score of 3.7 in Cycle I. Overall, this data indicates that the improvements made in Cycle II have successfully improved students' abilities to design and implement algorithms, although special attention is still needed for a small group facing significant difficulties.

The results from both cycles indicate that the problem-based learning model employed by the researcher significantly improved students' computational thinking (CT) skills, specifically in decomposition, pattern recognition, abstraction, and algorithm development. These outcomes are consistent with the research conducted by Moreno-Palma et al.[37], which suggests that problem-based learning effectively improves students' CT competencies. The study concluded after Cycle II, as the anticipated classical completeness was reached, with 97% of students demonstrating mastery. Therefore, Cycle III was not required.

CONCLUSION

This study demonstrates that the implementation of the problem-based learning model significantly improves students' computational thinking (CT) abilities. This improvement is evident in the average CT scores, which initially fell within the low category during the pre-test, subsequently increasing to the medium and high categories by the end of Cycle II. These findings indicate that the problem-based learning model is a valuable approach for educators to equip students with skills for tackling real-world problems, preparing them to face future challenges. This model effectively connects classroom learning with real-life contexts. Furthermore, it is recommended that future researchers consider the findings of this study when applying the problem-based learning model to other subjects, addressing the limitations identified in this research to improve the quality of subsequent research.

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