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Privict Social Sciences Journal

Volume 6
Issue 1 January, 2026

Article 25

12-01-2026

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To cite this article: Fuadillah, E. (2026). The application of computational thinking and experiential learning concepts to improve algorithm skills among Junior High School Students of Salman Al Farisi Bandung. *Priviet Social Sciences Journal, 6*(1), 259-269.

https://doi.org/10.55942/pssj.v6i1.1100

To link to this article: https://doi.org/10.55942/pssj.v6i1.1100

Private Social Sciences Journal
E-ISSN 2798-866X
P-ISSN 2798-6314
https://doi.org/10.55942/pssj.v6i1.1100

Volume 6
Issue 1
January Edition 2026

The application of computational thinking and experiential learning concepts to improve algorithm skills among Junior High School Students of Salman Al Farisi Bandung

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Received 18 November 2025
Revised 07 January 2026
Accepted 12 January 2026

ABSTRACT

Computational thinking (CT) is a 21st-century skill that is currently receiving widespread attention in many developed countries, where it has been incorporated into primary and secondary school curricula. Developing this skill requires a learning model that provides students with direct experience; one such model is experiential learning. This model emphasises that real-life experiences are the primary source of knowledge formation and computational thinking skills. This study aims to apply the concept of computational thinking to programming algorithms for junior high school students. This was achieved by comparing the learning outcomes of experimental classes that implemented an experiential learning model with computational thinking with those of a control class that used conventional methods. The results of the analysis showed that the average student learning outcome value in the experimental class was 87.826, compared to 81.36363 in the control class. Based on the t-test, the calculated t-value of 1.33676 is smaller than the t-table value of 1.68107, so H_0 is accepted and H_1 is rejected. Therefore, there is no significant difference in learning outcomes between the two groups. However, applying computational thinking through experiential learning models shows a positive upward trend in student learning outcomes and provides a more meaningful learning experience for understanding programming algorithm concepts.

Keywords: computation thinking; experiential learning; programming algorithms

1. INTRODUCTION

Computational thinking first appeared in a book entitled "Mindstorm", written by Seymour Papert in 1980 (Boucinha et al., 2019). The book explains that the use of computers, especially in education, is essentially divided into two major aspects. First, computers are used to develop skills that are useful for life, and second, computers are used to change the paradigm of thinking about how humans view science. The paper connects computational thinking with digital pedagogy in modern education. There is considerable thought that computational Thinking is a fundamental skill for enhancing students' abilities and character, especially at the K-12 level (elementary to high school) (Shih, 2019). In 2012, national curricula in many developed countries, such as the UK, began introducing a more hands-on computing approach to students. Computer Science (CS) was one of the subjects taught to students at the time to bridge the gap between technology and education. Developed countries have implemented computational skills. thinking as part of the national curriculum for all K-12 students.

Computational Thinking describes how humans think by following the way computers work, namely by placing each task block sequentially, often known as an algorithm. Computers also group each task into smaller sub-tasks that are then executed in turn. The computer's ability to process each task consistently demonstrates that it works in a highly efficient manner. Computational thinking is an approach that connects how computers work with how humans think. Simply put, computational thinking is a problem-solving ability by applying computer science concepts (Boom et al., 2018). Computational thinking is also known as humans formulating problems by watching computers work (Doleck et al., 2017). Understanding computational Thinking is not about writing programs directly, but about how humans think effectively in solving every problem.

Recognising the importance of computational thinking in K-12 student learning, this research focuses on applying computational thinking to improve junior high school students' understanding of algorithmic concepts. According to research conducted by (Boucinha et al., 2019), the delivery of Computational Thinking requires a cycle or sequence that can enhance students' experience of solving each problem. Problem-solving ability is closely related to students' achievement index. Previous research suggests that problem-solving skills can be trained using an experiential model. learning (Nayazik, 2017). Experiential model Learning provides a picture of problem-solving abilities by emphasizing understanding personal experiences as the object of student learning. Students' past experiences can be a valuable source of information, such as past problems and experiences, thus serving as a direct object in training students to solve problems (Adminpintarharati, 2020).

Based on the description above, this research examines in more depth the application of the computational concept. Thinking for Middle School Students Using the Experiential Model Learning in Programming Algorithm Material (Case Study of VIII Grade Students at Salman Al Farisi Middle School, Bandung). The researcher is also interested in evaluating the comparative results between conventional learning and learning that applies computational concepts. So, the results of this research can be a solution to train students' abilities in solving algorithmic problems.

2. RELATED RESEARCH

Computational thinking is a new form of literacy in the 21st century. It is closely related to computational theory, which is the study of algorithms and how they can be implemented in a computer program (Alfina, 2017). However, computational thinking is not only about solving problems; it is also about how problems are solved (Nuraisa et al., 2019). It breaks down each problem into several effective and efficient parts or stages (Nuraisa, Saleh and Raharjo, 2021). Thinking has played an important role in education in many developed countries and has been implemented in the curriculum (Sung, 2019), education with the STEM model (Tang et al., 2020) , as a learning medium (Grover, 2017), a learning environment (Muñoz-Repiso & Caballero-González, 2019), of course, in other learning activities. This shows that CT can be part of the learning process to support critical thinking and problem solving (Zhang and Nouri, 2019). Computational thinking is divided into four parts in Figure 1.

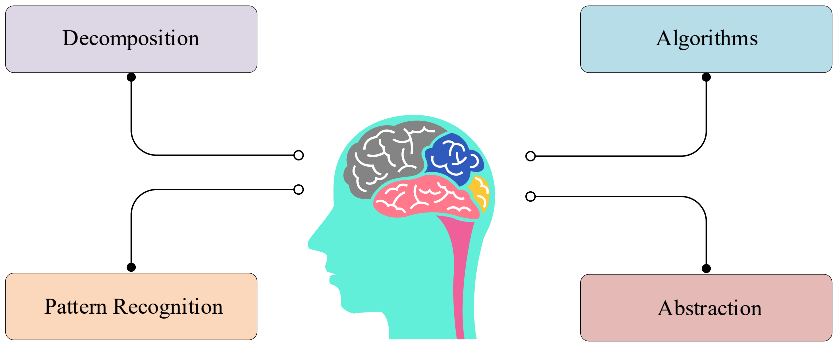

Figure 1. Computational Thinking

First, decomposition involves breaking down complex problems into smaller, more manageable ones. Second, pattern recognition involves looking at each problem separately and seeing if similar problems have been solved before, making problem-solving more efficient. Third, abstraction involves paying attention only to important details and ignoring unimportant information. Fourth, algorithms design simple steps or rules to solve each problem (Shih, 2019).

Experiential Learning Theory (ELT), developed by David Kolb in 1980, describes a holistic learning model in the learning process (Adminpintarharati, 2020). Experiential learning theory is a basic framework for exploratory learning activities that prioritize direct experience (Shih, 2019). There are many views on learning from experience. However, the experiential learning model Learning is based on the philosophy that "the most important factor that influences learning is what students already know. Make sure what you teach students is in line with what they already know " (Boucinha et al., 2019). There are four series in the experiential delivery process learning proposed by David Kolb is as follows in Figure 2.

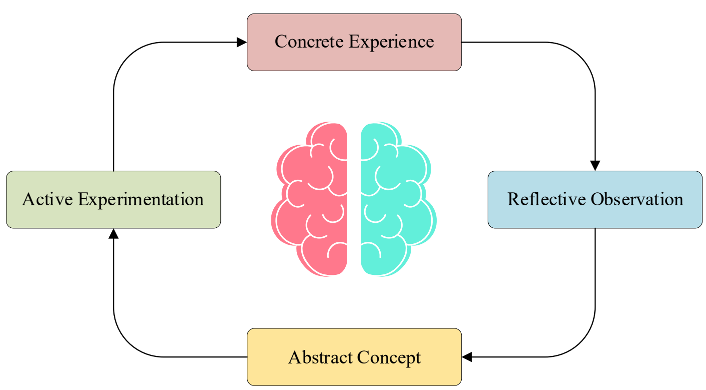

Figure 2. Experiential Learning According to David Kolb

First, concrete Experience is a learning process through direct involvement in real-life experiences. Students gain knowledge by actively interacting with specific situations and demonstrating sensitivity to the context and conditions they encounter. Second, reflective Observation is the process by which students conduct in-depth observations of their experiences before making decisions. Reflection involves examining events from various perspectives. Third, abstract Conceptualization is a process that focuses on the formation of concepts and theoretical understanding based on reflection. Learners use logical reasoning to connect experiences with new principles or ideas. Fourth, active Experimentation is a process in which students test learned concepts through direct application in real-world situations. This process involves real-life actions, interactions with others, and the courage to take risks as part of the learning process.

Conventional learning, often referred to as classical learning, is a teacher-centred learning model. Classical learning is often referred to as 'lecture learning' because lectures are a common form of communication between teachers and students during the learning process (Lestari and Sofyan, 2014). In this learning model, a teacher teaches a group of students using a syllabus, with meetings held according to a predetermined schedule. Conventional learning has many limitations. However, this learning model is the most widely used.

According to Sumarto in (Lestari & Sofyan, 2014), conventional learning methods have several advantages: (1) Simple methods that are easy to understand and easy to do; (2) Broader delivery of material because students tend to already understand the methods applied. This means that a lot of lesson material can be summarised or the main points explained in a short time; (3) The material delivered can be selected in detail, which is considered more important; (4) The teacher can control the class situation, because the learning process is fully known by the teacher. (5) Class organisation can be arranged to be simpler.

Most people think that an algorithm is a programming language used to create a program. This is not wrong, as algorithms are closely related to calculations and logic. Programming algorithms are closely related to programming languages, computer science, mathematics and numeracy. In general, an algorithm is a set of logical, systematic steps for solving a problem or achieving a specific goal. In everyday life, we often use algorithms without realising it because they are closely related to the steps involved in problem solving. Algorithms have a structure that can be used to solve a problem. (Maulana, 2017).

3. METHOD

Methodology refers to the overall series of activities undertaken in research. This research involves several steps to achieve the desired results, from defining the problem formulation to the final stage, drawing conclusions. This is shown in Figure 3.

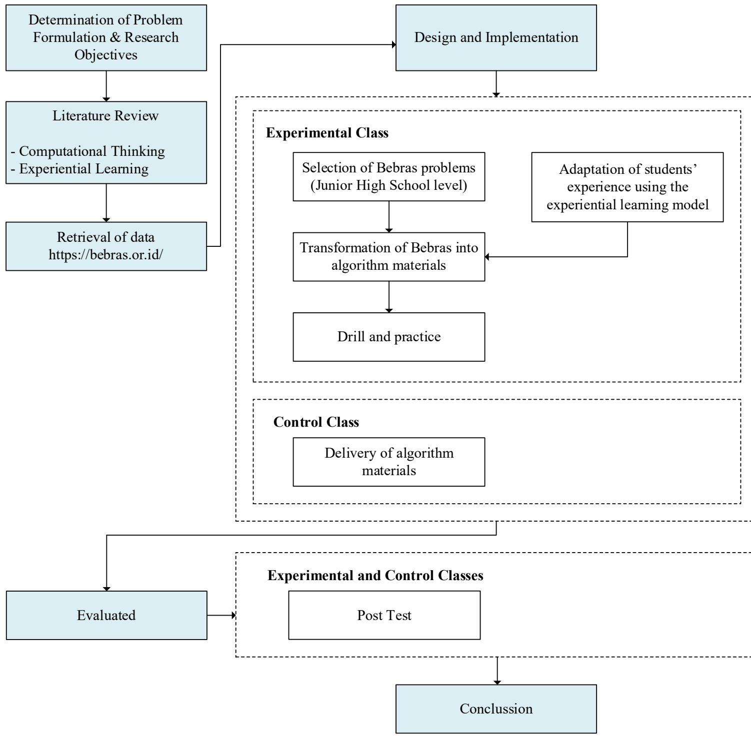

Figure 3. Research Methodology

As can be seen in Figure 3, design and implementation are the main stages in conducting research. The method used in this study is a quasi-experiment. A quasi-experiment is a research approach that aims to determine the effect of a treatment on another variable under controllable conditions. In this method, researchers use an existing group of subjects as a treatment group without using random sampling. At this stage, the experimental group was subjected to computational methods. This approach was implemented using the Bebras Questions Challenge, which was then transformed into algorithmic material for junior high school students. However, the material was considered too difficult for junior high school students to understand, so it was delivered using an experiential learning model, which prioritises direct experience (Shih, 2019). Next, students carry out repeated exercises using the drill method and practise. Meanwhile, the control class was given conventional algorithm material. The design used was an intact group comparison design consisting of two classes: one for the experimental class (learning with computational methods and experiential learning) and one for the control class (learning with the conventional method) (Mulyono & Agustin, 2020). A description of the research conducted can be found in Table 1.

Table 1. Insact Group Comparison

Class	Treatment	Post-test
Experiment	X	O_1
Control	-	O_2

Information
X : Given treatment
: Without treatment
O_1 : Measurement of the experimental group
O_2 : Control group measurement

This study involved 45 eighth-grade students from Salman Al Farisi Junior High School Bandung. There were 23 students in the experimental class and 22 in the control class. The students had previously received basic material on programming algorithm concepts. The population was selected at the school because teachers had difficulty providing students with an understanding of programming algorithm concepts. Therefore, it was necessary to implement computational thinking with an appropriate learning model.

4. RESULT AND DISCUSSION

The research implementation begins by providing algorithm material to students by applying computational concepts. thinking and experiential. After the treatment phase, a post-test was administered to both groups. The test results for eighth-grade students at Salman Al Farisi Middle School, Bandung, on algorithms and programming material can be described as follows.

Post results the programming algorithm material test conducted at the end of the meeting can generally be seen in Table 2

Table 2. Descriptive Post-Test Results

Parameter	Experiment Class	Control Class
N	23	22
Mean	87,82608	81,36363
Median	82,5	100
Modus	100	100
Max	100	100
Min	45	45
S. Deviasi	16,34053	15,31353

The results of the descriptive analysis in Table 2 regarding students' understanding of algorithms after the test show that the average score for the experimental class was higher than for the control class. This suggests that the Computational Learning approach, Thinking and Experiential Learning, positively influences student learning outcomes. The maximum and mode scores in both classes were both 100, suggesting that some students had achieved optimal mastery of the material. The minimum score of 45 indicates variation in students' abilities to understand algorithm concepts. The standard deviations of 16.34 and 15.31 for the experimental and control classes, respectively, indicate that the distribution of data scores in the two groups is relatively close. Overall, these descriptive results demonstrate that the experimental class achieved better learning outcomes than the control class following Computational Learning. Thinking and Experiential Learning.

Student learning outcomes of programming algorithm material in the experimental class after treatment with the computational concept thinking and experiential Learning using Bebras questions that have been transformed into algorithm material indicate that there is an increase in good algorithmic ability, as shown in Table 3.

Table 3. Descriptive Learning Outcomes of The Experimental Class

Nilai	Frekuensi	Percentage (%)	Information
91,00 - 100	12	52%	Special
81,00 - 91,00	5	22%	Very Good
71,00 - 81,00	2	9%	Good
55,00 - 71,00	2	9%	Enough
40,00 - 55,00	2	9%	Not Enough
0 - 40,00	0	0%	Very Less

Based on the descriptive analysis in Table 3 regarding the distribution of learning outcomes in the experimental class, which consisted of 23 students, it can be seen that the majority of students demonstrated excellent achievement. Twelve students (52%) were in the 91–100 range, categorized as Excellent, indicating a very high level of mastery of algorithm concepts after implementing Computational Thinking and Experiential Learning. Furthermore, there are 5 students (22%) in the very good category with a score range of (81 - 91), and 2 students (9%) in the good category in the range of (71 – 81). Meanwhile, 2 students (9%) each are in the Sufficient (55 - 71) and Poor (40 - 55) categories. No students are included in the Very Poor (0 - 40) category, which indicates that all students have achieved the expected basic competency level. Overall, this distribution shows that the applied learning is able to encourage most students to achieve high learning outcomes, reflecting the effectiveness of the Computational Learning approach. Thinking and Experiential Learning to improve understanding of algorithms in experimental classes.

Meanwhile, the learning outcomes of students on programming algorithm material in the control class are shown in Table 4.

Table 4. Descriptive Learning Outcomes of The Control Class

Nilai	Frekuensi	Percentage (%)	Information
91,00 - 100	5	22%	Special
81,00 - 91,00	5	22%	Very Good
71,00 - 81,00	6	26%	Good
55,00 - 71,00	5	22%	Enough
40,00 - 55,00	1	4%	Not Enough
0 - 40,00	0	0%	Very Less

The results of the descriptive analysis in Table 4 are as follows: regarding the distribution of learning outcomes in the control class, which consists of 22 students, it is clear that the level of student achievement is quite diverse, with a tendency to be in the middle to upper category. A total of 5 students (22%) are in the score range of 91–100 with the Excellent category, and the same number, namely 5 students (22%) are in the Very Good category with a score range of (81 – 91). In addition, there are 6 students (26%) in the Good category (71 - 81), which is the group with the highest frequency, indicating that most students achieve good learning outcomes even without the application of the computational approach. thinking and experiential learning 5 students (22%) were in the Sufficient category (55 - 71) and 1 student (4%) was in the Poor category (40 - 55). No students were in the Very Poor category (0 - 40), so all students had reached the minimum level of mastery. Overall, these results indicate that although the control class was able to achieve good learning outcomes, the distribution was more even than the experimental class and did not show dominance in the very high category, so conventional learning was still less than optimal in encouraging the achievement of learning outcomes at the exceptional level.

The next test was a homogeneity test, which determined whether the student learning outcomes in the control and experimental classes were equivalent. This test is important for ensuring that class selection was based on similar conditions. The results of the homogeneity test are shown below.

Table 5. Homogenity Test

Class	N	Variance	F_{count}	F_{tabel}	Conclusion
Experiment	23	279,1502	1,13627	2,07331	Homogen
Control	22	245,6709			

Based on the results of the homogeneity test shown in Table 5, the calculated F_{count} was 1.13627 and the F_{table} was 2.07331, with a sample size of 23 students in the experimental group and 22 in the control group. The decision-making criteria for the homogeneity test are as follows: if the calculated F_{count} is less than the F_{table}, then the data is declared homogeneous; conversely, if the calculated F_{count} is greater than the F_{table}, then the data is declared inhomogeneous. As the calculated F_{count} (1.13627) is less than the F_{table} value (2.07331), it can be concluded that both data groups have the same variance, i.e. they are homogeneous. This means that the distribution of learning outcome data between the experimental and control classes is relatively similar. This fulfils one of the basic assumptions required for an independent t-test to be conducted in the next analysis stage. This homogeneity also shows that any differences in average learning outcomes are not caused by differences in data diversity, but rather by the influence of the learning treatment applied to each class. After conducting the homogeneity test, it was found that the experimental and control class data were homogeneous. However, as the number of samples differs ($n_1 \neq n_2$), the difference test (t-test) used is Pooled variance. Based on the calculation results obtained:

Table 6. T-test

Parameter	Experimental Class	Control Class
Mean	87,82608	81,36363
Variance	279,15019	245,67099
Digrees of Freedom (df)	43	
t_{count}	1,33676	
t_{table}	1,68107	

Based on Table 6, the t-test calculation shows that the calculated t_{counts} are smaller than the t_{table} values. Therefore, H_0 is accepted and H_a is rejected. It can therefore be concluded that there is no significant difference between the experimental and control classes. This study involved a series of tests comparing the results obtained in the experimental and control classes on algorithmic and programming material. The learning outcomes in question were how students applied computational concepts when thinking using the experiential model when learning about programming algorithms. The post-test obtained an average value (mean) of 87.82608 in the experimental class and 81.36363 in the control class, meaning the experimental class performed better than the control class.

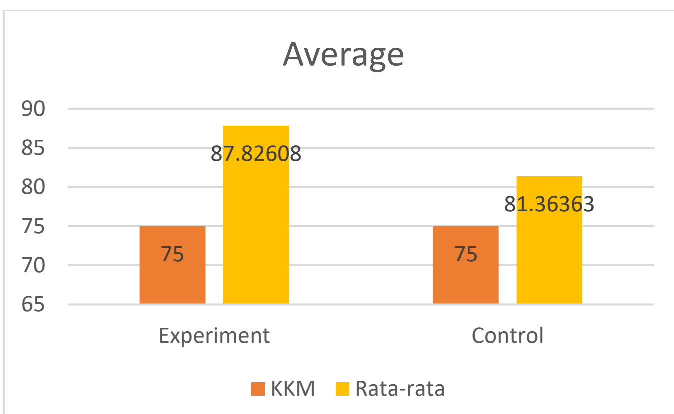

Figure 4. Average Earnings

As can be seen from Figure 4, which shows a comparison of the average learning outcomes between the experimental and control classes, both classes exceeded the KKM (minimum completeness criteria), which was set at 75. The average score for the experimental class was 87.83, while that for the control class was 81.36. This difference suggests that student learning outcomes in the experimental class were higher than in the control class. It suggests that applying the computational approach of thinking and experiential learning has a positive impact on students' understanding of algorithms.

Furthermore, the average difference of 6.46 points indicates a practically significant difference in achievement, although statistical tests indicate that this difference is not yet significant at the 5% confidence level. Overall, this graph reinforces the finding that computational thinking and experiential learning are able to increase learning outcomes above the minimum completion standard, while being superior compared to conventional learning methods used in the control class.

5. CONCLUSION

Based on the results of the research conducted, the computational approach of thinking about programming algorithms using Bebras questions has been applied. This challenge, adapted to the context of learning algorithms, has proven to be effective. The learning process is implemented using the experiential model. This was tested with grade VIII students at Salman Al Farisi Junior High School in Bandung, with 23 students in the experimental class and 22 in the control class. Analysis of the results showed a difference in average learning outcomes between the two groups: the experimental class obtained higher scores than the control class, with an average difference of 6.46 points. While this difference is not statistically significant, it does demonstrate a practical improvement in student learning outcomes following the implementation of Computational Learning. Thinking and experiential learning. Thus, the findings of this study can inform the development of algorithm learning strategies at junior high school level, particularly to improve understanding of basic programming concepts through a more contextualised, interactive approach.

Ethical Approval

Ethical approval was not required for this study.

Informed Consent Statement

Ethical approval was not required for this study.

Authors' Contributions

Not Applicable.

Disclosure Statement

No potential conflicts of interest were reported by the author.

Data Availability Statement

The data presented in this study can be downloaded from OECD Publications.

Funding

This research received no external funding.

Notes on Contributors

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