25 (3), 2024, 1214-1223
Jurnal Pendidikan MIPA
e-ISSN: 2685-5488 | p-ISSN: 1411-2531
http://jurnal.fkip.unila.ac.id/index.php/jpmipa/

Problem-Based vs Design-Based Learning: Which Better Develops Computational Thinking in Middle School Science Students?

Rizka Elan Fadilah*, Supeno, Rusdianto, Ulin Nuha, Soraya Firdausi, Ferry Budi Prasetya, Nuril Ayyamil Izza, & Siti Khasfiyatin
Departement of Science Education, University of Jember, Indonesia

Abstract: Computational thinking has become a crucial skill for students because it gives them the tools to solve complicated issues using organized methods. Implementing Problem-based learning and Design-based learning in science learning has significantly enhanced students' skills. This research aims to ascertain which of the two models is better for facilitating computational thinking skills among middle school students in science learning. The study used a sample of 69 middle school students selected through random sampling. This research employs a quasi-experimental, multi-group, post-test-only design. The instrument utilized in this research is a computational thinking skills test comprising five questions. The data were analyzed using one-way ANOVA to test the hypotheses. Tukey test results indicate that the mean difference score between the PBL and DBL groups is 1.2609, with a significance value greater than 0.05. The study confirms that Problem-based learning is more effective than Design-based learning in facilitating students' computational thinking skills. However, the difference between the two is not particularly noteworthy. PBL and DBL represent viable pedagogical approaches that can enhance middle school students' computational thinking skills in science learning.

Keywords: problem-based learning, design-based learning, computational thinking skill.

▪ INTRODUCTION

Computational thinking is an essential skill in the 21st century. This is because the world requires technology. Almost all decisions are data-driven. This makes thinking algorithmically, deciphering problems, and developing systematic solutions even more critical (Bhatnagar et al., 2022). Therefore, computational thinking has become a necessary skill for students because it gives them the tools to solve complicated issues using organized methods. Computational thinking (CT) constitutes a fundamental aspect of contemporary science education, encompassing problem-solving, modeling, simulation, and systems thinking practices. It underscores a comprehensive approach to learning, integrating diverse pedagogical strategies within the context of pre-service science teacher education (Yun, et al. 2024). Computational thinking is a problem-solving approach encompassing abstraction, decomposition, and algorithm design. It goes beyond the confines of traditional education and cultivates abilities that may be applied in other fields, such as mathematics and data science (Kang, 2024; Mendrofa, 2024; Nuzzaci, 2024).

Computational thinking skills are also essential in science learning. Furthermore, integrating computational thinking into science learning can significantly enhance student engagement and skills, such as the efficacy of a process-oriented and unplugged method for integrating critical thinking skills (Kite & Park, 2023). Integrating computational thinking into science learning also fosters creativity and innovation, encouraging learners to approach scientific inquiries from multiple perspectives and apply abstract reasoning to solve real-world problems (Annamalai, 2022). The integration of computational

Rizka Elan Fadilah
*Email: rizkaelan.fkip@unej.ac.id
DOI: http://dx.doi.org/10.23960/jpmipa/v25i3.pp1214-1223
Received: 24 November 2024
Accepted: 13 December 2024
Published: 15 December 2024

thinking (CT) into science education has been shown to enhance learning outcomes. The implementation of CT in science education enables students to navigate the levels of biological organization and explore complex concepts such as evolution. Furthermore, CT encourages engagement with emergent properties, facilitating a deeper understanding of complex systems across multiple disciplines (Christensen & Lombardi, 2024).

However, teachers implement some learning models when students learn science at school. For some reason, some teachers still use traditional learning models. The traditional learning model, primarily characterized by face-to-face instruction, has been a foundational approach in education (Starosta, 2023). The traditional learning model places significant emphasis on rational cognition and objective knowledge acquisition, with less attention paid to the role of life experience and spiritual development in individuals. This approach can result in a lack of communication and dialogue between teachers and students, leading to an isolated learning environment (Zang, 2011). Traditional learning models often struggle to develop computational thinking skills because they emphasize rote memorization and standardization testing and fail to cultivate problem-solving and critical thinking skills (Nuzzaci, 2024).

Innovative learning models play an essential role in developing student's computational thinking skills through increased experimentation, repetition, and collaboration. Innovative learning models allow students to effectively apply concepts, practices, and perspectives in various contexts (Dening & Tedre, 2019). Some examples of innovative learning models are Problem-Based Learning (PBL) and Design-Based Learning (DBL). Implementing PBL and DBL in science learning has significantly enhanced students' skills and learning outcomes (Ainun & Maryati, 2024; Ladachart et al., 2023). PBL and DBL are recognized as learning models that can develop computational thinking skills (Loyens et al., 2023; Puente et al., 2011).

Problem-based learning (PBL) is a valuable approach to science learning because it effectively improves students' ability to write scientific reports, encourages active learning, and develops critical thinking and problem-solving skills (Ramdani et al., 2023). Problem-based learning (PBL) is distinguished by a student-centered approach, collaborative challenges, the role of teachers as facilitators, and formative assessment processes. It prioritizes holistic learning, critical and creative thinking, and the cultivation of autonomy and self-regulation in educational settings (Vasconcelos et al, 2023).

Design-based learning (DBL) is characterized by open-ended, hands-on, authentic, and multidisciplinary design tasks. Teachers facilitate the acquisition of knowledge and provide guidance to students as they progress from novice to expert engineers. Assessment employs a combination of formative and summative methods, with an emphasis on peer collaboration and teamwork (Puente, et al. 2013). DBL has been shown to improve students' understanding of scientific concepts. Based on research conducted by Ladachart et al. (2023), eighth-grade students who engaged in different DBL approaches showed significant improvements in content learning, especially in the science-through-design method. Both models underscore the importance of active student participation and complex problem-solving, promoting critical analytical and collaborative skills (Loyens et al., 2023; Puente et al., 2011).

However, research is still needed on which learning model can best cultivate students' computational thinking. Previous research has yet to identify which model between PBL and DBL is the best in facilitating the computational thinking skills of middle school students in science learning. Previous research focused more on implementing PBL and DBL individually but did not make direct comparisons in the context of computational thinking skills in science learning. The main objective of this research is to find out which model is better between the two models in facilitating the computational thinking skills of middle school students in science learning. This research is essential to provide empirical guidance for educators and policymakers regarding models more effective in developing computational thinking skills in middle school students.

▪ METHOD

Participants

The population in this study were all grade VIII students at SMPN 2 Ajung Jember. The sample employed in this study comprised 69 students from grade VIII at SMPN 2 Ajung Jember. The sampling technique utilized in this study was clustered random sampling. Samples were chosen from pre-existing groups or classes. Classes are selected, and then the students in those classes are used for the study (Dreyhaupt et al., 2017). One was a control class, one was an experiment class using a problem-based learning model, and another was an experiment class using design-based learning models. The selection of classes was based on a representation of varying academic abilities so that the study results could better represent the population. this stratification criterion allows for wider variations in scholastic ability.

Research Design and Procedures

This type of study was quantitative research with a quasi-experiment multi-group post-test-only design. Quasi-experimental design refers to research methods that evaluate interventions without random assignment. These studies are essential when randomized controlled trials are not feasible, but they require careful assessment of internal validity and risk of bias due to their unique design features (Barker, et al., 2024). In the context of this study, the use of random assignment was not feasible due to limitations in access or constraints that necessitated the division of pre-existing groups. The use of a quasi-experimental design allows researchers to overcome this limitation by employing pre-formed groups as research samples.

This study employs a post-test-only design to mitigate the potential for students to "learn" from the pre-test and thereby provide more optimal responses in the post-test. By evaluating students only after the intervention, this design reduces the risk of such learning occurring. The study's primary focus is on students' computational thinking skills after the models have been implemented (Yang, 2023; Boom, 2022).

Table 1. Quasi-experiment multi-group post-test-only design

Group	Treatment	Post-test
Experiment $_1$	X_1	O_1
Experiment $_2$	X_2	O_2
Control	-	O_3

The research procedure commences with the identification of the study's population and sample. Subsequently, the implementation of learning through the use of PBL and DBL in each of the experiments' 1st and 2nd classes is undertaken. The control class employs the standard learning approach that is commonly utilized by teachers. Following the implementation of PBL and DBL in each class, a computational thinking skills test was administered to students. The collected data were then subjected to statistical analysis to gain insight into the influence of the variables under investigation.

Instrument

The instrument used in this study was a computational thinking skills' test (post-test) consisting of five questions. Each question focuses on one aspect of computational thinking skills: decomposition, pattern recognition, abstraction, algorithm design, and evaluation (Khenner, 2024). A more detailed examination of the computational thinking skills test in question as illustrated in Table 2.

Table 2. Computational thinking skills' test

No	Aspect	Indicator	Number of Questions	Question Number
1	Decomposition	Learners can analyze complex problems and reduce them to a series of sub-problems, thereby facilitating more efficient resolution.	1	1
2	Pattern recognition	Learners can establish connections between the physical and conceptual aspects of a problem, thereby facilitating the development of an effective solution	1	2
3	Abstraction	Learners can ascertain the specifics of an abstract representation of a pattern, thus enabling its application to problem-solving.	1	3
4	Algorithm design	Learners can demonstrate the capacity to analyze the algorithm or series of steps, that must be completed to achieve a solution to a problem	1	4
5	Evaluation	Learners are able to apply analytical skills in order to guarantee the accuracy and efficacy of algorithms developed for problem-solving purposes	1	5
		Total Number of qestions	5	

Data Analysis

The data analysis technique employed in this study was conducted through the direct collection of data after the administration of the intervention or treatment. The data from the computational thinking skills test (post-test) were analyzed using the SPSS 25 program. A one-way ANOVA analysis was employed to test the hypotheses. One-way ANOVA (analysis of variance) is utilized to ascertain whether the means of three groups (control and experimental classes) are significantly disparate, thereby allowing for the identification of a single group whose mean is distinct from the others (Milanes-Banos, 2024). Moreover, a posthoc Tukey test was conducted to ascertain the models' impact on computational thinking skills. The Tukey test was selected as a posthoc test because it is an appropriate method for testing the significance of the mean difference between the control and experimental classes (Graham, 2023).

▪ RESULT AND DISSCUSSION

Statistic Analysis

Before further data analysis, descriptive statistical tests were conducted to describe and present data on computational thinking skills in the three groups. The results of this descriptive analysis are presented in Table 3.

Table 3. Descriptive analysis

	Group		
	Control	**PBL**	**DBL**
Mean	59.0000	70.1739	68.9130
95% convidence interval for mean lower bound	51.8980	63.1276	63.9176
95% convidence interval for mean upper bound	66.1020	77.2202	73.9085
5% Trimmed Mean	58.9324	70.9058	68.7802
Median	61.0000	73.0000	68.0000
Variance	269.727	265.514	133.447
Std. Deviation	1.64234E1	1.62946E1	1.15519E1
Minimum	29.00	32.00	50.00
Maximum	91.00	94.00	91.00
Range	62.00	62.00	41.00
Interquartile Range	24.00	20.00	20.00
Skewness	-.051	-.676	.175
Kurtosis	-.416	-.103	-.746

The descriptive analysis yielded the following results: the PBL group exhibited the highest average value (70.1739), indicating the most optimal performance, followed by the DBL and control groups. The confidence interval for the mean indicates that the PBL group exhibits a significantly higher mean than the control group. The discrepancy between the PBL and DBL groups is relatively minor and may not be statistically significant. With regard to data variability, the DBL group exhibits the lowest degree of variability. This suggests that the DBL group's data is more consistent when compared to the control and PBL groups. Conversely, the control and PBL groups display higher variability, resulting in a greater dispersion of data within the two groups.

Before conducting the hypothesis test, the normality and homogeneity tests were performed. This was done as a pre-landing test to facilitate the subsequent one-way ANOVA test. The one-way ANOVA test requires samples from normal and homogeneous distributed populations. Therefore, both assumptions must be met for the conclusions from the hypothetical testing to be accurate and reliable (Chatzi & Doody, 2023). The normality test results are presented in Table 4.

Table 4. Normality test results

	Kolmogorov-Smirnov		Shapiro-Wilk	
Group	**Statistic**	**Significance (p-value)**	**Statistic**	**Significance (p-value)**
Control	0.077	0.200	0.982	0.933
PBL	0.141	0.200	0.949	0.279
DBL	0.132	0.200	0.960	0.461

The results of the normality tests, as indicated by both the Kolmogorov-Smirnov and the Shapiro-Wilk tests, yielded a p-value greater than 0.05, thereby confirming the assumption of normality. It can thus be concluded that the data exhibits a normal distribution. The subsequent test is the homogeneity test. The objective of the test is to ascertain that the data employed is derived from a homogeneous population. The results of the homogeneity test can be seen in Table 5.

Tabel 5. Homogeneity test result

		Levene Statistic	**df1**	**df2**	**Sig.**
CTS	Based on Mean	1.644	2	66	.201
	Based on Median	1.464	2	66	.239
	Based on Median and with adjusted df	1.464	2	60.473	.239
	Based on trimmed mean	1.595	2	66	.211[R1]

Considering the homogeneity test results, the significance value for all methods exceeds 0.05. This indicates that the variance in data between groups is homogeneous. Once both parametric test assumptions have been fulfilled, hypothesis testing can be conducted using the one-way ANOVA test.

Computational Thinking Skills

One-way ANOVA was utilized to determine the difference in computational thinking skills between the control and experimental groups employing the PBL and DBL models. If the significance value is more significant than 0.05, then the null hypothesis (H0) is accepted. Conversely, if the significance value is less than 0.05, the null hypothesis (H0) is rejected. One-way ANOVA test results are presented in Table 6.

Table 6. ANOV[R2]A

CTS

	Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
Between Groups	1722.812	2	861.406	3.865	.026
Within Groups	14711.130	66	222.896		
Total	16433.942	68			

The results of the one-way ANOVA test indicate that the significance value is less than 0.05 ($p < 0.05$), thereby rejecting the null hypothesis (H0). It can be concluded that there were significant differences in computational thinking skills between the three groups (control and experimental groups). The One-Way ANOVA test can only determine whether there is a difference or no difference in computational thinking skills between groups. To know which group has the greatest impact on computational thinking skills, a different pairway test must be done. So, the chosen test is the Pos-Hoc test. The Pos-Hoc test used is the Tukey Test. The Tukey test results are presented in Table 7.

Table 7. Tukey test result

CTS
Tukey HSD

(I) GROUP	(J) GROUP	Mean Difference (I-J)	Std. Eror	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Control [R3][W4]	PBL	-1.11739130435E1*	4.40252808478E0	.036	-2.1729866416E1	-6.1795967112E-1
	DBL	-9.91304347826E0	4.40252808478E0	.070	-2.0468996851E1	.6429098941
PBL	Control	1.11739130435E1*	4.40252808478E0	.036	.6179596711	2.1729866416E1
	DBL	1.26086956522E0	4.40252808478E0	.956	-9.2950838071E0	1.1816822938E1
DBL	control	9.91304347826E0	4.40252808478E0	.070	-6.4290989410E-1	2.0468996851E1
	PBL	-1.26086956522E0	4.40252808478E0	.956	-1.1816822938E1	9.2950838071E0

The results of the Tukey test indicate that there is a statistically significant difference between the control group and the PBL group, with a mean difference value of -1.1739 and a p-value less than 0.05. Therefore, it can be concluded that the PBL group is more effective in facilitating students' computational thinking skills than the control group.

The mean difference value between the control group and the DBL group is -9.9130, with a significance value greater than 0.05. Therefore, it can be stated that the DBL group is more effective in facilitating students' computational thinking skills compared to the control group, although the difference between the two is not particularly significant.

Moreover, the mean difference value between the PBL and DBL groups is 1.2609, with a significance value greater than 0.05. Therefore, it can be stated that the PBL group is more effective than the DBL group in facilitating students' computational thinking skills, although the difference between the two is not particularly noteworthy.

The mean difference derived from the Tukey Test results indicates that PBL models exhibit a higher mean difference compared to the other two groups. This is by several studies also state that PBL can improve students' computational thinking skills because it can improve the ability to innovate, collaboration, algorithmic cognition, and creativity (Widiningrum et al., 2024; Zhang et al., 2024; Chang et al., 2023). PBL can make students participate actively in solving complex problems, which promotes a deeper understanding of computational thinking concepts such as decomposition and algorithmic thinking (Rey et al., 2021). Collaborative learning environments in PBL encourage peer interaction, enhancing communication and collective problem-solving abilities (Kwon et al., 2021).

Based on the Tukey test results, it is also known that DBL can facilitate students' computational thinking skills, although it is not as good as PBL. DBL effectively enhances computational thinking skills by allowing students to engage in iterative design, problem-solving, and feedback, thus fostering a more profound understanding and application of these skills in practical contexts (Zhu et al., 2023). DBL also can increase abstract thinking, problem-solving, and logical thinking (Wang et al., 2022).

▪ CONCLUSION

Based on the discussion results, Problem-Based Learning (PBL) is a better model for facilitating the computational thinking skills of middle school students than Design-Based Learning (DBL) in science learning. The PBL group is more effective than the DBL group in facilitating students' computational thinking skills, although the difference between the two is not particularly noteworthy. Based on Tukey test the mean difference value between the PBL and DBL groups is 1.2609, with a significance value greater than 0.05. PBL is good for facilitating computational thinking skills because it can improve the ability to innovate, collaboration, algorithmic cognition, and creativity. DBL can facilitate students' computational thinking skills too by allowing students to engage in iterative design, problem-solving, and feedback, thus fostering a more profound understanding and application of these skills in practical contexts. PBL and DBL represent viable pedagogical approaches that can be employed to enhance middle school students' computational thinking skills in science learning. In future research, it would be beneficial to compare PBL with other learning models to ascertain their efficacy in improving computational thinking skills in science learning.

▪ REFERENCES

Annamalai, S., Che Omar, A., & Abdul Salam, S. N. (2022). Review of computational thinking models in various learning fields, International Journal of Education, Psychology and Counseling, 7 (48), 562-574.

Arencibia Rodríguez del Rey, Y., Cawanga Cambinda, I. N., Deco, C., Bender, C., Avello Martínez, R., & Villalba Condori, K. O. (2020). Developing computational thinking with a module of solved problems.

Barker, T. H., Habibi, N., Aromataris, E., Stone, J. C., Leonardi-Bee, J., Sears, K., ... & Munn, Z. (2024). The revised JBI critical appraisal tool for the assessment of risk of bias for quasi-experimental studies. JBI Evidence Synthesis, 22(3), 378-388.

Bhatnagar, P., Katiyar, D., & Goel, G. (2022). Data science helping in decision making. International Journal For Science Technology And Engineering. 10 (3): 1144-1147. https://doi.org/10.22214/ijraset.2022.40844

Boom, K. D., Bower, M., Siemon, J., & Arguel, A. (2022). Relationships between computational thinking and the quality of computer programs. Education and information technologies, 27(6), 8289-8310.

Chatzi, A., & Owen, D. (2023). The one-way ANOVA test explained. Nurse Researcher, 31 (3): 8-14. doi: 10.7748/nr.2023.e1885

Chang, C. Y., Du, Z., Kuo, H. C., & Chang, C. C. (2023). Investigating the impact of design thinking-based STEAM PBL on students’ creativity and computational thinking. IEEE Transactions on Education.

Dana, N., Christensen., Doug, Lombardi. (2024). Computational thinking through the lens of biological evolution learning: enhancing understanding through the levels of biological organization and computational complexity. Evolution: Education and Outreach, 17(1) doi: 10.1186/s12052-024-00202-3

Denning, P.J., Tedre, M. (2019). Computational thinking. The MIT Press, Cambridge, MA, USA.

Dreyhaupt, J., Mayer, B., Keis, O., Öchsner, W., & Muche, R. (2017). Cluster-randomized Studies in Educational Research: Principles and Methodological Aspects. GMS journal for medical education, 34(2), Doc26. https://doi.org/10.3205/zma001103

E., Khenner. (2024). 1. Computational thinking in the context of higher education: Analytical review. doi: 10.17853/1994-5639-2024-2-35-59

Gómez Puente, S. M., van Eijck, M., & Jochems, W. (2011). Towards characterising design-based learning in engineering education: a review of the literature. European Journal of Engineering Education, 36(2), 137-149.

Gómez Puente, S. M., Van Eijck, M., & Jochems, W. (2013). A sampled literature review of design-based learning approaches: A search for key characteristics. International Journal of Technology and Design Education, 23, 717-732.

Kang, Y. (2024). Enhancing computational and data science thinking skills for k-12 education. proceeding of the 2nd international conference on social psychology and Humanity Studies.

Kite, V., & Park, S. (2024). Context matters: Secondary science teachers' integration of process-based, unplugged computational thinking into science curriculum. Journal of Research in Science Teaching, 61(1), 203-227.

Kwon, K., Ottenbreit-Leftwich, A. T., Brush, T. A., Jeon, M., & Yan, G. (2021). Integration of problem-based learning in elementary computer science education: effects on computational thinking and attitudes. Educational Technology Research and Development, 69, 2761-2787.

Ladachart, L., Radchanet, V., Phornprasert, W., & Phothong, W. (2024). Influence of different approaches to design-based learning on eighth grade students' science content learning and STEM identity. Pedagogies: An International Journal, 19(2), 300-325.

Loyens, S. M., Van Meerten, J. E., Schaap, L., & Wijnia, L. (2023). Situating higher-order, critical, and critical-analytic thinking in problem-and project-based learning environments: A systematic review. Educational Psychology Review, 35(2), 39.

Mendrofa, N. K. (2024). Computational thinking skills in 21st century mathematics learning. JIIP-Jurnal Ilmiah Ilmu Pendidikan, 7(1), 792-801.

Norma, A., Milanes-Baños. (2024). 2. Step-by-step one-way ANOVA analysis with the Jamovi program. doi: 10.29057/mjmr.v12i23.10664

Nur, A., & Maryati, M. (2024). 1. Problem based learning model in science learning on skills developed in elementary and junior high education units. Jurnal Penelitian Pendidikan IPA (JPPIPA), doi: 10.29303/jppipa.v10i6.6497

Nuzzaci, A. (2024). Incorporating computational thinking into education: from teacher training to student mastery. Journal of Education and Training: Macrothink Institute Inc. Vol 11 (2). Pp 70-77

Ramdani, Y., Syam, N. K., Karyana, Y., & Herawati, D. (2022). Problem-based learning in research method courses: development, application and evaluation. F1000Research, 11.

Vasconcelos, M. J., Caspurro, H., & Costa, N. (2023). Problem-based Learning: Composing in the classroom as a music learning challenge. Revista Electrónica de LEEME, (52).

Volodymyr, S. (2023). 1. Traditional, distance, blended learning in higher school in the context of comfort and effectiveness. Naukovij žurnal Hortic′koï nacìonal′noï akademìï, doi: 10.51706/2707-3076-2023-9-11

Wang, D., Luo, L., Luo, J., Lin, S., & Ren, G. (2022). Developing computational thinking: Design-based learning and interdisciplinary activity design. Applied Sciences, 12(21), 11033.

Weipeng, Y. (2023). 1. Promoting children's computational thinking: A quasi-experimental study of web-mediated parent education. Journal of Computer Assisted Learning, doi: 10.1111/jcal.12818

Widiningrum, W. N., Wahyuni, S., Hardyanto, W., & Sulhadi, S. (2024). Effect of PBL-Based scratch e-module in improving computational thinking and physics concepts. International Journal of Studies in Education and Science, 5(2), 124-139.

Yun, M., & Crippen, K. J. (2024). Computational Thinking Integration into Pre-Service Science Teacher Education: A Systematic Review. Journal of Science Teacher Education, 1-30.

Zachary, G. (2023). Supplemental Table 5. doi: 10.6084/m9.figshare.20263668

Zhang, Tian-bao. (2011). Basic characteristics of traditional classroom teaching and plight it is confronted. Theory and practice of education

Zhang, W., Guan, Y., & Hu, Z. (2024). The efficacy of project-based learning in enhancing computational thinking among students: A meta-analysis of 31 experiments and quasi-experiments. Education and Information Technologies, 1-33.

Zhu, G., Kow, J. F., Fan, X., Chit, L. S., & Ong, Y. S. Pedagogical design matters: integrating engineering design and knowledge building for undergraduates to practice and improve computational thinking skills.