



Enhancing Computational Thinking and Learning Engagement through STEM-based Water Turbine Project

Diana Maulidia*

Department of Science Education, Universitas Pendidikan Indonesia, West Java, Indonesia

Nanang Winarno

Department of Science Education, Universitas Pendidikan Indonesia, West Java, Indonesia

Lilik Hasanah

Department of Science Education, Universitas Pendidikan Indonesia, West Java, Indonesia

Mutiara Syifa

Department of Special Education, Illinois State University, United States

*Correspondence author: dianamaulidia@student.upi.edu

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Abstract:

In today's digital era, students face challenges in developing critical thinking and problem-solving skills essential for success in an increasingly complex world. Computational Thinking (CT) has emerged as a pivotal 21st-century skill for innovation and problem-solving. This study investigates the impact of STEM-based learning through a water turbine project on students' CT and Learning Engagement (LE) at the secondary school level. A quasi-experimental approach with a pretest-posttest control group design was employed. The participants were 76 of 445 8th-grade students from secondary schools in Bandung, Indonesia, divided equally into experimental and control groups, each comprising 38 students. Statistical analyses using the Mann-Whitney U test on n-gain scores revealed a significant improvement in CT for the experimental group compared to the control group ($U = 50.00$, sig. < 0.001 , and a large effect size ($r = 0.80$). Similarly, LE in the experimental group increased significantly compared to the control group ($U = 10.50$, sig. < 0.001 , and a large effect size ($r = 0.85$). These results highlight that STEM learning through the water turbine project effectively enhances students' CT and LE. This study demonstrates the potential of STEM-based approaches to foster essential 21st-century skills among secondary school students. However, further research is needed to explore its application across diverse contexts and skill areas.

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Introduction

The rapid proliferation of information and communication technologies demands a broad set of 21st-century competencies, including autonomous learning, practical application of knowledge, scientific reasoning, data interpretation, collaboration, and ethical use of technology (Weber & Greiff, 2023). Central to these competencies is Computational Thinking (CT), a cognitive skill set shaped by the integration of advanced technologies. CT has become essential for addressing complex issues across disciplines and in daily life (Çoban & Korkmaz, 2021; Kafai & Proctor, 2022; Lee et al., 2024). Initially introduced by Wing (2006), CT was defined as the process of formulating problems and devising solutions that can be executed computationally. In recent years, this foundational concept has been significantly expanded. Scholars have begun to frame CT not only as a set of technical problem-solving skills but also as a broader socio-technical literacy encompassing cognitive processes, interdisciplinary understanding, and the ethical use of digital tools (Lodi & Martini, 2021; Kafai & Proctor, 2022). These modern interpretations highlight CT not only as a technical skill but also as a foundational competence for navigating complex challenges across educational and real-world contexts.

According to Lee et al. (2024), computational thinking integrates creative, analytical, and algorithmic thinking with problem-solving skills, making it a key cognitive competence for addressing complex problems in STEM education. Integrating computational thinking into learning activities can enhance both academic quality and computational thinking skills (Arık & Topçu, 2022; Liu et al., 2023). In the digital economy era, embedding computational thinking skills within the educational system is vital for preparing a society capable of competing globally (Chongo et al., 2021). However, studies report that Indonesian students' computational thinking abilities remain relatively low, as reflected in national assessments and international benchmarks such as TIMSS and PISA, which show poor performance in critical thinking and problem-solving. These findings indicate a gap in current learning strategies that fail to develop students' CT skills adequately.

Understanding the factors influencing learning processes is essential for developing computational thinking (CT) skills. However, in real classroom settings, students often show low levels of engagement, particularly in science learning, characterized by minimal participation, lack of persistence, and a tendency to rely on rote memorization rather than inquiry or problem-solving (Denning & Tedre, 2021). This condition significantly undermines the effectiveness of instruction, especially in fostering higher-order thinking, such as CT. Two persistent challenges – the lack of active learning strategies and limited student engagement – have been widely reported as barriers to effective science education (Gao & Hew, 2022). Learning engagement itself involves behavioral, emotional, cognitive, and agentic dimensions that collectively contribute to optimal learning outcomes (Xu et al., 2023). When students are fully engaged, they tend to adopt deep learning strategies, maintain focused attention, and connect academic content to real-life situations, fostering conceptual understanding and critical thinking (Donham et al., 2022; Xu et al., 2023). In contrast, disengaged students are more likely to become passive recipients of information, which inhibits the development of CT competencies. Although many studies highlight the importance of engagement for achieving academic success,

efforts to link engagement directly to CT development, particularly in science classrooms, remain limited and underexplored (Peel et al., 2022; Liu et al., 2023; Martín-Núñez et al., 2023). This suggests that fostering CT should not be viewed solely as a cognitive exercise; instead, it must also address the emotional and behavioral dimensions of engagement that sustain students' willingness and persistence in tackling complex problems.

Computational thinking has become a cornerstone of 21st-century skills within STEM education. Modern studies emphasize its critical role not only in supporting STEM learning but also in fostering metacognitive awareness and higher-order thinking. For instance, Markandan et al. (2022) developed a Metacognitive Empowerment module that uses CT to enhance student engagement and understanding in Biology. Similarly, Lee et al. (2024) demonstrate that scaffolding CT within Jupyter Notebook environments significantly improves STEM students' higher-order thinking, practical skills, and engagement. These findings reaffirm CT's central role in preparing learners for complex, real-world problem solving. STEM approaches are recognized as effective methods for cultivating CT skills (Peel et al., 2021), encompassing core competencies such as algorithmic problem-solving, pattern recognition, data representation, and logical reasoning (Yin et al., 2022; Lee et al., 2024). Integrating CT within STEM education enables students to apply knowledge in practical contexts, fostering higher-order thinking, creativity, and problem-solving. Hands-on STEM projects offer real-world applications for these skills, enhancing engagement and effectiveness compared to traditional methods.

Additionally, this integration can bridge the educational technology access gap by providing inclusive learning opportunities through broader STEM contexts beyond formal computer science (Gundersen & Lampropoulos, 2025; Sari et al., 2025). However, despite these promising potentials, the implementation of STEM-based CT instruction often remains limited in practice, particularly in resource-constrained school settings. Many teachers struggle to translate theoretical STEM-CT frameworks into concrete classroom activities, and students often engage in projects that emphasize products rather than processes, reducing opportunities to develop authentic CT skills. Furthermore, there is a lack of contextual integration, especially in science topics such as energy, where learning is frequently abstract and disconnected from real-life challenges (Denning & Tedre, 2021). Bridging CT and engagement through STEM, therefore, requires designing projects that are both contextually meaningful and accessible, ensuring that students see personal and societal relevance in what they create.

Energy is a pivotal concept in the physics curriculum, especially at the secondary education level, where bridging theoretical knowledge and practical applications is essential. Energy is not only fundamental for understanding natural and technological systems but also essential for addressing contemporary sustainability challenges and transitioning toward clean energy futures (Guerra-Mota et al., 2024; Ramachandran et al., 2024). In Indonesia, the physics curriculum emphasizes renewable energy sources (Fadhilah et al., 2023). Renewable energy education plays a crucial role in raising students' awareness and understanding of sustainability by embedding energy topics within authentic, real-world contexts that encourage active exploration and environmental stewardship (Pambudi et al., 2024).

However, students' understanding of energy is often limited by teaching methods that focus overly on idealized systems and basic calculations, hindering their grasp of complex concepts (Fadhilah et al., 2023). These limitations underscore the need for integrative approaches, such as STEM-based learning, to provide more relevant and impactful learning experiences.

The integration of STEM education has become a crucial approach for fostering computational thinking (CT) and enhancing student engagement in the classroom. Numerous studies have shown that STEM learning, particularly when combined with project-based learning (PjBL), effectively cultivates CT skills, critical thinking, collaboration, and creativity (Yulianti et al., 2022; Tariq et al., 2025). However, despite its potential, STEM-based instruction often places heavy emphasis on digital tools – such as block-based programming or Arduino platforms – that may not be readily available in many school contexts (Yin et al., 2022; Gundersen & Lampropoulos, 2025; Vasconcelos et al., 2025). This creates a practical gap; students in resource-limited schools may not benefit equally from STEM-CT training due to limited access to digital technologies.

Moreover, although project-based STEM learning has been associated with increased academic performance, the explicit link between STEM approaches and student learning engagement, especially in science topics such as energy, remains underexplored (Pujawan & Suryawan, 2021). Most prior studies also emphasize cognitive outcomes, such as problem-solving and content mastery, while giving less attention to the emotional and behavioral dimensions of engagement that are crucial for sustaining CT development (Peel et al., 2022; Liu et al., 2023). In the context of physics education, energy is a fundamental yet often abstract topic. When taught in a disconnected or overly theoretical way, students struggle to apply what they learn to real-life contexts (Fadhilah et al., 2023).

Given these challenges, it is essential to design a STEM learning model that is not only accessible and technology-independent but also explicitly integrates engagement and contextual relevance. This study introduces a novel approach using a water turbine project as a medium to implement STEM-PjBL principles without relying on advanced technological tools. By designing, building, and testing a functional turbine, students engage in active, hands-on learning that stimulates CT dimensions such as problem decomposition, critical thinking, data analysis, and iterative testing (Lin et al., 2021; Manikutty et al., 2022). In addition, the project is anchored in real-world energy challenges, such as renewable energy solutions, providing social relevance and increasing emotional and behavioral engagement.

Therefore, this research is motivated by the need to bridge two critical gaps: (1) the limited accessibility of technology-driven STEM-CT instruction, and (2) the underrepresentation of learning engagement in STEM education, especially within energy-related content. By proposing a low-barrier, human-centered, and contextually grounded model of STEM learning, this study offers an inclusive strategy that simultaneously enhances CT skills and fosters deeper learning engagement. Based on the background outlined above, the objectives of this research are: (1) is there a significant difference in computational thinking between the control group and the experimental group applied with STEM learning? (2) is there a significant difference in learning engagement between the control group and the experimental group

applied to STEM learning? (3) is there a significant difference in the improvement of computational thinking between male and female students in the control and experimental groups? (4) is there a significant difference in the improvement of learning engagement between male and female students in the control and experimental groups?

Research Method

This study aims to investigate the impact of an integrated STEM learning model on students' computational thinking skills and learning engagement using a quasi-experimental method. The quasi-experimental method is a research design that does not involve random assignment, the process of randomly placing participants into experimental or control groups (Fraenkel et al., 2022). The research design is a pretest-posttest control-group design with a nonequivalent control group. In this design, the control and experimental groups are selected without random assignment. Both groups undergo a pretest (O_1) to measure their initial abilities and a posttest (O_2) to measure the outcomes after the intervention. The intervention (X) is given only to the experimental group, while the control group receives no treatment. This design aims to evaluate the intervention's effectiveness by comparing posttest scores between the two groups. This research design is based on the theory proposed by Creswell and Creswell (2017), as presented in Table 1.

Table 1. Experiment Design

Class	Pretest (O_1)	X	Posttest (O_2)
Experiment	O_1	X	O_2
Control	O_1	X	O_2

This study was conducted in a secondary school in Bandung, Indonesia. The population in this study consisted of 445 8th-grade students aged 13-14 years old. The sampling technique used was convenience sampling. Convenience sampling was chosen because it is often challenging to select samples randomly or to use systematic non-random sampling (Fraenkel et al., 2022). In such situations, convenience sampling offers a practical solution given the limitations of time and resources. Class 8A was selected as the experimental group, and Class 8B as the control group. Each class consisted of 38 students. The experimental group comprised 20 female and 18 male students, while the control group comprised 21 female and 17 male students, as shown in Table 2.

Table 2. Participant Design

Gender	Experiment Class		Control Class	
	Number of Students	Percentage	Number of Students	Percentage
Female	20	53%	21	55%
Male	18	47%	17	45%
Total	38	100%	38	100%

The instruments used in this study are the Computational Thinking Level Scale (CTLS) and a Learning Engagement questionnaire, both of which were validated through expert judgment by two physics lecturers to ensure content-related validity –i.e., how well the instruments logically measure the intended variables. The

validation process concluded that these instruments are relevant, valid, and suitable for use in this research.

Computational Thinking Level Scale (CTLS)

The Computational Thinking Scale (CTS) developed by (Korkmaz et al., 2017) was adapted for this study. The instrument consists of 29 items distributed across five dimensions: creativity, algorithmic thinking, cooperativity, critical thinking, and problem solving. Each item is rated on a five-point Likert scale (1 = never, 5 = always), with six items negatively worded and reverse-coded before analysis. The original validation study, conducted with university students, reported satisfactory psychometric properties with Cronbach's alpha values ranging from 0.727 to 0.869 across dimensions and 0.822 for the entire scale. For this study, the instrument was translated into Indonesian and underwent content validation to ensure suitability for the target sample of secondary school students. Total scores were normalized to a 20–100 range and categorized into three levels: low (20–51), medium (52–67), and high (68–100). The detailed structure of the CTS instrument is presented in Table 3.

Table 3. Dimensions of CTLS Instrument

Dimensions	Number of questions)
Creativity	8
Algorithmic thinking	6
Cooperativity	4
Critical thinking	5
Problem solving	6

Learning Engagement (LE)

The Learning Engagement Questionnaire used in this study was adapted from (Reeve & Tseng, 2011). It consisted of 22 items designed to measure students' learning engagement on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). The instrument encompasses four dimensions — agentic, behavioral, emotional, and cognitive engagement — that together provide a comprehensive representation of students' involvement in the learning process. Agentic engagement reflects students' constructive contributions to the instructional flow they experience, while behavioral engagement addresses on-task attention and effort. Emotional engagement captures students' interest, enjoyment, and curiosity, and cognitive engagement emphasizes the use of elaboration and metacognitive strategies. Reliability evidence from the original validation study showed satisfactory internal consistency for all four dimensions ($\alpha = 0.78\text{--}0.94$). In this study, the total scores were transformed to a 0–100 scale using normalization methods, with categories of low (4–33), medium (34–66), and high (67–100). The detailed distribution of items across each dimension is presented in Table 4.

Table 4. Dimensions of Learning Engagement Instrument

Dimensions	Number of questions)
Agentic engagement	5
Behavioral engagement	5
Emotional engagement	4
Cognitive engagement	8

To ensure the accuracy and validity of the research results, a series of statistical procedures was conducted. First, data normality was assessed using the Shapiro-Wilk test (García-Martínez et al., 2023). If the data were not normally distributed, non-parametric statistical tests were considered. Next, the homogeneity of variance between the control and experimental groups was tested using Levene's test, which assesses whether variances are equal across groups. This step is critical to ensure fair comparisons between groups and prevent bias caused by unequal variances. Since the data did not meet the normality assumption, non-parametric tests were employed as alternatives. The Mann-Whitney U test was used to compare differences between the control and experimental groups for CT and LE, and to analyze gender-based differences within each group. This test was chosen because it does not require assumptions of normality or homogeneity of variance. Additionally, the Wilcoxon Signed-Rank Test was used to analyze pretest-posttest differences within each group. This test is appropriate for paired data (e.g., students' pretest and posttest scores) and measures changes in the observed variable after the intervention. As a measure of effect size, the r -value was calculated for the Mann-Whitney U test and the Wilcoxon test, providing information on the magnitude of differences between groups or over time. This effect size is valuable for assessing the practical significance of the observed differences. Finally, normalized gain scores were calculated to evaluate improvements in computational thinking and learning engagement following the intervention, offering a clearer picture of the effectiveness of STEM-based instruction.

The study began with a preparation phase, which included identifying the research topic, designing an experiment with control and experimental groups, and developing STEM-based learning tools, such as a water turbine project. The learning tools and assessment instruments were first piloted to ensure their validity and reliability. During the implementation phase, the first session involved a pretest in both classes to measure students' CT skills and LE prior to the intervention. Pretest data were collected for subsequent analysis. From the second to the fifth session, STEM-based learning was implemented in the experimental class, where students designed, constructed, and tested water turbines.

In contrast, the control class followed conventional teaching methods, including lectures, class discussions, and Q&A sessions, without experimental or project-based activities. However, the control class also conducted presentations, with students assigned to create digital presentation materials. In the sixth session, a posttest was conducted in both classes to assess improvements in computational thinking skills and learning engagement following the intervention, as shown in Table 5.

Table 5. Experiment Class Activities

Meeting	Activity	Science Concept	Developed STEM
Meeting 1st	Understanding the problem and pretest	<ul style="list-style-type: none"> - Energy resources - Renewable energy - Problem-solving in energy alternatives 	Science Students understand energy transformation, hydrodynamics,
Meeting 2nd	Planning and designing a water turbine	<ul style="list-style-type: none"> - Basic hydrodynamics 	

Meeting	Activity	Science Concept	Developed STEM
		- Mechanical energy to electrical energy conversion	and renewable energy sources.
Meeting 3 rd	Building and testing water turbine	- Hydrodynamics - Energy conversion	Technology Students apply tools and technology to design, build, and test water turbines.
Meeting 4 th	Evaluating and improving turbine design	- Problem-solving - Optimization in energy systems	Engineering Students develop and optimize water turbine prototypes to solve real-world energy challenges.
Meeting 5 th	Finalizing and presenting the water turbine project	- Communication in science - Evaluating sustainability	Mathematics Students collect, analyze, and interpret data from turbine performance and efficiency tests.
Meeting 6 th	Posttest and reflection	Assessing understanding and impact of STEM-based learning	

Posttest data were collected for further analysis. Data analysis included normality testing with the Shapiro-Wilk test and homogeneity testing with Levene's test. Since the data did not meet the assumptions of normality and homogeneity, the Mann-Whitney U test was employed to compare scores between the control and experimental groups. The Wilcoxon signed-rank test was used to analyze within-group differences between pretest and posttest scores. Additionally, the effect size (r) was calculated to determine the magnitude of the treatment effect. Finally, the study findings were compiled into a report detailing the key results, their interpretation, and the implications for STEM-based learning in classrooms. To provide a clear overview of the sequential process in this study, the research procedures are summarized in a flowchart shown in Figure 1. This figure highlights the key phases of the quasi-experimental design, including preparation, implementation, and data analysis.

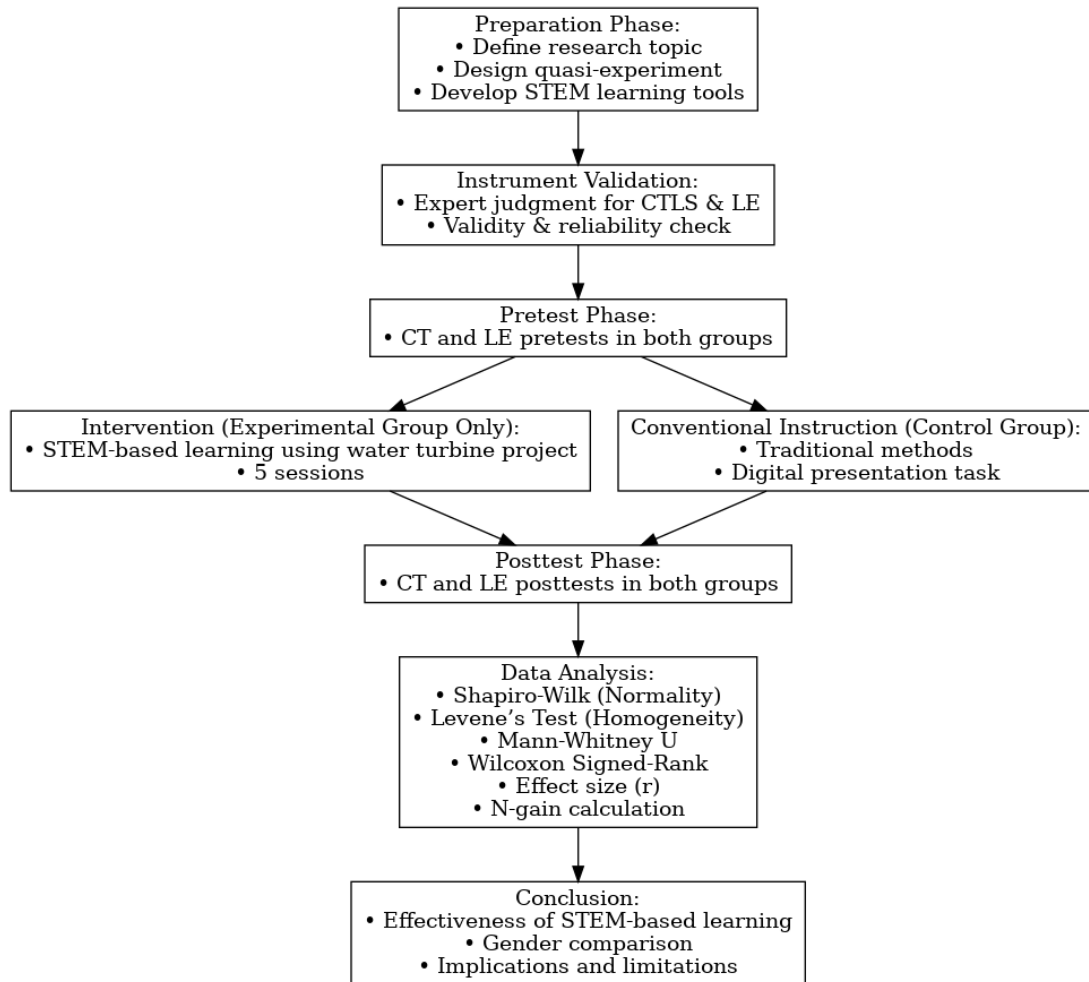


Figure 1. Flowchart of Research Method

Results and Discussion

Descriptive Statistics for CT

In the CT Control class, the average student score increased from 63 in the pre-test to 68 in the post-test. The pre-test score distribution had a skewness of -0,547, which became more left-skewed in the post-test, with a value of -0,675. This negative skewness reflects a distribution tail extending toward lower scores, indicating that most scores were above the mean. Skewness measures the asymmetry of a data distribution; a negative value indicates that the data tend to concentrate above the mean, whereas a positive value suggests the opposite. The kurtosis values for the pre-test (-1,43) and post-test (-1,94) indicated a relatively flat distribution (platykurtic), suggesting a more even spread of data than in a normal distribution. Kurtosis measures the degree of peakedness in a distribution. Negative kurtosis indicates a flatter distribution with shorter tails, whereas positive kurtosis indicates a more peaked (leptokurtic) distribution with longer tails and a higher concentration of data around the mean. In the CT Experiment class, the average student score increased significantly, from 65 on the pre-test to 77 on the post-test. The post-test scores had a skewness value of 0.513, indicating a right-skewed distribution with the tail extending toward higher scores, meaning most scores were below the mean. The kurtosis value for the post-test (1,34) indicated a relatively peaked distribution (leptokurtic), reflecting a higher concentration of data around the mean, as shown in Table 6

Table 6. Descriptive Statistics for CT

Class		Mean	SD	Skewness			Kurtosis		
				Statistic	SE	Z	Statistic	SE	Z
CT Control	Pre	63	3,78	-0,547	0,383	-1,43	0,297	0,75	0,40
	Post	68	4,26	-0,675		-1,94	1,230		1,64
CT Experiment	Pre	65	3,44	-0,496		-1,30	-0,347		-0,46
	Post	77	5,41	0,513		1,34	0,499		0,67

Descriptive Statistics for LE

In the LE Control class, the average student score increased from 67 in the pre-test to 70 in the post-test. The skewness value for the pre-test was -0,315, becoming slightly more left-skewed in the post-test at -0,467. This negative skewness in both tests suggests that most scores cluster above the mean. The kurtosis values for the pre-test (-0,758) and post-test (-0,825) indicated a flat distribution (platykurtic), indicating that the data were more evenly spread than in a normal distribution. In the LE Experiment class, the average student score increased from 70 in the pre-test to 82 in the post-test. The skewness value for the post-test was 0.389, indicating a mild right skew, with most scores falling below the mean. The post-test kurtosis value (1,230) indicated a relatively peaked distribution (leptokurtic), indicating a higher concentration of scores around the mean, as shown in Table 7.

Table 7. Descriptive Statistics for LE

Class		Mean	SD	Skewness			Kurtosis		
				Statistic	SE	Z	Statistic	SE	Z
LE Control	Pre	67	3,17	-0,422	0,383	-1,10	0,031	0,75	0,04
	Post	70	3,28	-0,690		-1,80	1,325		1,77
LE Experiment	Pre	70	2,92	-0,477		-1,25	-0,579		-0,77
	Post	82	4,48	0,045		0,12	-0,603		-0,80

Normality and Homogeneity Tests

The Shapiro-Wilk normality test results indicate that some groups did not meet the normality assumption. For the CT group, the p-values were 0,339 for the pre-control group, 0,161 for the post-control group, 0,164 for the pre-experimental group, and 0,220 for the post-experimental group, suggesting that the data were normally distributed. However, in the LE group, the p-value for the post-control group was 0,020, which is below the threshold of 0,05, indicating that the data were not normally distributed. Therefore, the dataset does not satisfy the normality assumption, as shown in Table 8.

Table 8. Normality Test Result

Class		Shapiro-Wilk	
		Statistic	P value
CT Control	Pre	0,968	0,339
	Post	0,958	0,161
CT Experiment	Pre	0,958	0,164
	Post	0,962	0,220
LE Control	Pre	0,970	0,380
	Post	0,930	0,020
LE Experiment	Pre	0,950	0,091
	Post	0,969	0,365

The homogeneity test using Levene's Statistic indicates that the data did not meet the assumption of homogeneity. Based on the mean, Levene's value was 2.570 with a p-value of 0.014. For the median and the median with adjusted degrees of freedom, Levene's values were 2.217 with p-values of 0.033 and 0.034, respectively. Additionally, based on the trimmed mean, Levene's test yielded a value of 2.448 and a p-value of 0.019. Since all p-values are below the 0.05 threshold, the variances across groups are not homogeneous, as shown in Table 9.

Table 9. Homogeneity Test Result

	Levene Statistic	df	df2	Sig.
Based on Mean	2,570	7	296	0,014
Based on Median	2,217	7	296	0,033
Based on Median and with adjusted df	2,217	7	241	0,034
Based on Trimmed Mean	2,448	7	296	0,019

Comparison of Computational Thinking and Learning Engagement Between Control and Experimental Groups

The results of the Mann-Whitney U Test indicate significant differences between the control and experimental groups in CT and LE. In the pretest results, the experimental group showed higher mean ranks compared to the control group, with $Z = -3,40$ for CT and $Z = -4,06$ for LE. The effect sizes were $r = -0.39$ for the CT results and $r = -0.47$ for the LE results, as shown in Table 10.

Table 10. Mann-Whitney U Test for Pretest Result

Group	Mean Rank	U	Z	P value	Effect Size
CT Control	29,93	396,50	-3,40	<0,001	-0,39
CT Experiment	47,07				
LE Control	28,28	333,50	-4,06	<0,001	0,47
LE Experiment	48,72				

In the posttest results, significant differences remained evident between the two groups. For the CT variable, the experimental group demonstrated higher mean ranks than the control group ($Z = -5.983$, $r = -0.69$), indicating a large effect size. Meanwhile, for the LE variable, the analysis revealed a huge effect size ($Z = -7.451$, $r = -0.85$), with the experimental group showing substantially higher mean ranks than the control group (see Table 11).

Table 11. Mann-Whitney U Test for Posttest Result

Group	Mean Rank	U	Z	P value	Effect Size
CT Control	23,39	148	-5,983	<0,001	-0,69
CT Experiment	52,61				
LE Control	19,66	6	-7,451	<0,001	0,85
LE Experiment	57,34				

Thus, the results of this study indicate that students' computational thinking skills and learning engagement improved in the experimental group following the

treatment. However, since significant differences were also observed in the pretest results, further analysis is needed to determine the extent to which these improvements are directly attributable to the treatment.

Differences in Computational Thinking Between the Control and Experimental Group

The present study investigated the differences in CT between experimental and control groups. Previous research has highlighted the effectiveness of STEM-based learning in fostering Computational Thinking skills (Lin et al., 2021; Li & Oon, 2024; Tariq et al., 2025; Vasconcelos et al., 2025). The pretest results indicated that the experimental group had a significantly higher mean rank in CT than the control group ($Z = -3.40$; $r = -0.39$), suggesting better initial abilities in this domain. This difference might stem from factors such as prior learning experiences or a stronger motivation toward STEM-based learning (Martín-Núñez et al., 2023). Following the STEM-based learning intervention, the posttest results revealed that the experimental group maintained a significantly higher CT performance compared to the control group ($Z = -5.983$; $r = -0.69$), with a large effect size. This finding reinforces the idea that STEM-based learning effectively enhances CT skills. Activities in STEM-based learning, such as problem analysis, logical reasoning, and problem-solving, are key to the development of CT (Lin et al., 2021; Tadena & Salic-Hairulla, 2021). This significant difference indicates that while the experimental group exhibited stronger initial abilities, the STEM-based learning approach contributed substantially to further improvements in their CT skills (Lin et al., 2021; Rahayu, 2022). Overall, these findings align with previous studies, confirming that STEM-based learning not only supports cognitive skill development but also actively enhances students' engagement in analytical thinking and problem-solving processes. This underscores the value of integrating STEM approaches into education to promote essential 21st-century skills.

Differences in Learning Engagement Between the Control and Experimental Groups

The findings of this study reveal significant differences in LE between the experimental and control groups. The pretest results indicated that the experimental group had a higher mean rank on LE than the control group ($Z = -4.06$; $r = -0.47$), suggesting greater initial student engagement in the experimental group. This difference might be attributed to factors such as student motivation or prior exposure to interactive learning activities (Zheng et al., 2023). After the STEM-based intervention, the posttest results showed that the experimental group demonstrated significantly higher learning engagement than the control group ($Z = -7.451$; $r = -0.85$), with a large effect size. This indicates that STEM-based learning significantly enhances student engagement. By involving students in hands-on activities, problem-solving, and collaboration, STEM-based learning creates an interactive, immersive environment that enhances overall student engagement. These findings align with prior research, underscoring the critical role of interactive, collaborative STEM-based activities in enhancing students' engagement. By promoting active participation and deep engagement in the learning process, STEM learning supports the development of skills vital to long-term academic success.

Gender Differences in Computational Thinking and Learning Engagement

The Mann-Whitney U test was employed to examine potential gender-based differences in computational thinking and learning engagement gains, given the non-normal distribution of gain scores derived from pretest and posttest data. Analysis of the CT Control group revealed a Mann-Whitney U value of 153.50, a Z-score of -0.745, and a p-value of 0.456. In the CT Experiment group, the U value was 177.00, with a Z-score of -0.088 and a p-value of 0.930. For the LE Control group, the U value was 172.50 ($Z = -0.186$, $p = 0.852$), while the LE Experiment group yielded a U value of 178.00 ($Z = -0.059$, $p = 0.953$). Given that all p-values exceeded the 0.05 significance threshold, the results indicate no statistically significant gender differences in improvements in either computational thinking or learning engagement across all groups. Furthermore, the calculated effect size (r) for each group was small: -0.12 for CT Control, -0.01 for CT Experiment, -0.03 for LE Control, and -0.01 for LE Experiment, as shown in Table 12.

Table 12. Mann-Whitney U Test for Posttest Result

Group	Gender	N	Mean Rank	U	Z	P value	Effect Size
CT Control	Male	17	18,03	153,50	-0,745	0,456	0,12
	Female	21	20,69				
CT Experiment	Male	18	19,33	177,00	-0,088	0,930	0,01
	Female	20	19,65				
LE Control	Male	17	19,85	172,50	-0,186	0,852	0,03
	Female	21	19,21				
LE Experiment	Male	18	19,61	178,00	-0,059	0,953	0,01
	Female	20	19,40				

Research on computational thinking (CT) and learning engagement (LE) among secondary school students is a significant area, as it can provide deep insights into the cognitive and behavioral aspects of students' learning processes (Denning & Tedre, 2021; Lee et al., 2024). This study aims to explore the differences in students' pretest and posttest performance in CT and LE, with an emphasis on variations that may be influenced by gender.

In this study, students' pretest and posttest performance in CT and LE were examined. The analysis showed no significant differences between male and female students in the improvement of CT or LE. This finding suggests that gender may not be a significant factor in the development of computational thinking and learning engagement at the secondary school level (Harangus & Katai, 2020; Lei et al., 2020; Denning & Tedre, 2021). Moreover, the low effect sizes across all groups (e.g., -0.12 for CT Control and -0.01 for CT Experiment) indicate that the gender differences are practically weak.

These results align with more recent evidence showing minimal gender differences in computational thinking. For instance, Hsu et al. (2022) found no significant gender disparities in programming self-efficacy or attitudes toward educational robots in an interdisciplinary CT activity. Similarly, a systematic review summarizes that most studies conducted in primary and middle school settings do not report gender-based CT differences. Moreover, El-Hamamsy et al. (2025) introduced a gender-fair CT assessment instrument that maintains measurement impartiality across

genders. Recent pedagogical research underscores that gender-responsive CT activities can effectively minimize disparities in CT competence between male and female students. The present study adds to this body of knowledge by offering empirical evidence on how integrated STEM-based instruction can foster both computational thinking and learning engagement equitably among secondary school students, thereby enriching our understanding of inclusive and effective science education practices. While computational thinking is considered an important skill for academic success and future careers, this study suggests that gender does not significantly influence the development of these skills at the secondary school level. This finding aligns with the results of [Paucar-Curasma et al. \(2023\)](#), which, based on inferential analysis, indicate no significant differences between male and female students in any of the computational thinking skills. These findings also emphasize the importance of an inclusive learning approach to ensure that all students can develop equally in cognitive skills and learning engagement.

Impact of STEM Learning on Computational Thinking and Learning Engagement

Based on the n-Gain analysis, there is a significant difference in improvement between the control and experimental groups for CT and LE. For CT, the control group achieved an n-Gain of 0.13, which falls into the low category. In contrast, the experimental group achieved an n-Gain of 0.33, which falls into the moderate category. This indicates that the learning approach used in the experimental group was more effective at enhancing students' computational thinking skills than the one used in the control group. For LE, the control group obtained an n-Gain of 0.09 (low category), while the experimental group achieved an n-Gain of 0.39 (moderate category). A Mann-Whitney U test was conducted to compare the n-Gain scores for CT and LE between the control and experimental groups. For CT, the control group had a mean rank of 20.82, whereas the experimental group had a significantly higher mean rank of 56.18 ($U = 50.00$, $Z = -6.983$, $p < 0.001$). The effect size, $r = 0.80$, indicates a significant effect of the intervention on CT development. Similarly, for LE, the control group had a mean rank of 19.78, compared to 57.22 in the experimental group ($U = 10.50$, $Z = -7.392$, $p < 0.001$). The effect size for LE ($r = 0.85$) suggests a substantial positive impact of the intervention on learning engagement, as shown in Table 13.

Table 13. Mann-Whitney U Test for n-Gain Result

Group	n-Gain	Mean Rank	U	Z	Asymp. Sig. (2-tailed)	Effect Size
CT Control	0,13	20,82	50,00	-6,983	<0,001	0,80
CT Experiment	0,33	56,18				
LE Control	0,09	19,78	10,50	-7,392	<0,001	0,85
LE Experiment	0,39	57,22				

To provide a more objective evaluation of the changes within each group and ensure the validity of the observed improvements, the Wilcoxon Signed-Rank Test was conducted. The Wilcoxon Signed-Rank Test revealed significant differences between pre- and post-test scores across all groups. In the control group, computational thinking scores increased significantly from pre- to post-test ($Z = -5.344$, $p < 0.001$),

with a large effect size ($r = 0.867$). Similarly, the experimental group demonstrated a significant improvement in CT scores ($Z = -5.381$, $p < 0.001$), with a large effect size ($r = 0.873$). Analysis of learning engagement scores in the control group revealed a significant pre- to post-test difference ($Z = -5.443$, $p < 0.001$), with a large effect size ($r = 0.883$) confirming the substantive nature of this improvement. The experimental group also exhibited a significant increase in LE scores ($Z = -5.380$, $p < 0.001$), again demonstrating a large effect size ($r = 0.872$), as shown in Table 14.

Table 14. Wilcoxon Signed-Rank Test for Pretest and Posttest Result

Group	N	Mean Rank	Sum of Ranks	Z	Asymp. Sig. (2-tailed)	Effect Size
CT Control	38	19,95	738,00	-5,344	<0,001	0,867
CT Experiment	38	19,50	741,00	-5,381	<0,001	0,873
LE Control	38	19,50	741,00	-5,443	<0,001	0,883
LE Experiment	38	19,50	741,00	-5,380	<0,001	0,872

The implementation of STEM-based learning through the water turbine project significantly enhanced students' computational thinking (CT) and learning engagement (LE). Each stage of the intervention was designed to cultivate specific CT skills and foster active participation. During the planning and design phase, students were required to integrate hydrodynamic principles and mechanical energy conversion, thereby promoting problem decomposition and the use of technological tools – key components of CT – as shown in Figure 2.

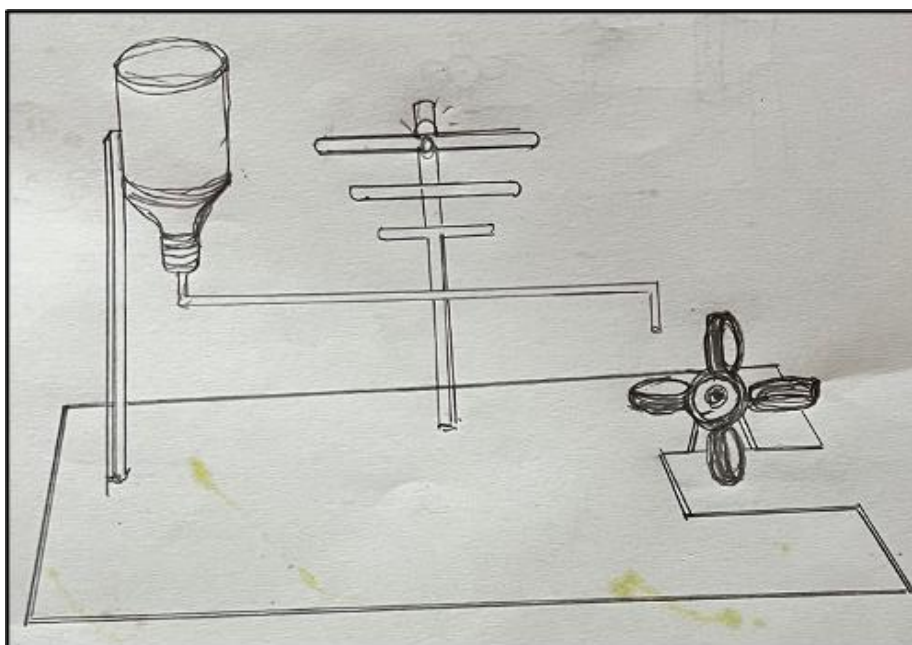


Figure 2. Students planning and designing a water turbine

In the building and testing phase, hands-on activities reinforced students' engineering skills and deepened their understanding of the relationship between theory and practice. This phase notably increased learning engagement, as students collaborated in real-world problem-solving scenarios, as shown in Figure 3.

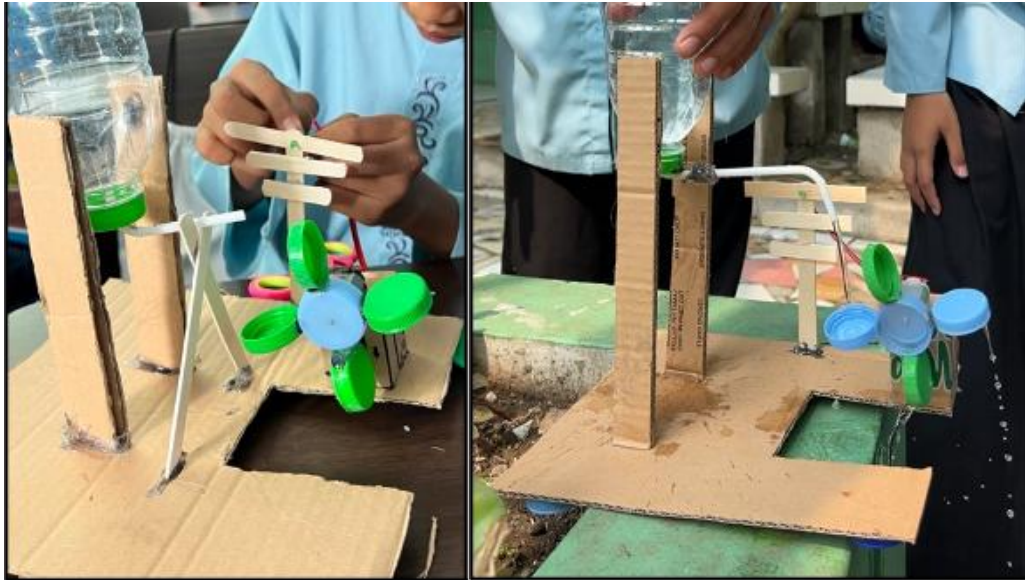


Figure 3. Students building and testing the water turbine

The most substantial impact on CT occurred during the evaluation and refinement stage, when students faced technical challenges, including a nonfunctional turbine light. This required them to analyze the root cause, eventually identifying faulty wiring and make iterative improvements, such as replacing cardboard with plywood for better stability. This process of troubleshooting and optimization directly contributed to the higher CT scores observed in the experimental group, as students actively engaged in data analysis, problem-solving, and iterative design thinking, as shown in Figure 3.



Figure 4. Students evaluating and refining the water turbine design

Finally, the presentation stage allowed students to articulate their findings, analyze sustainability aspects, and communicate scientific ideas effectively. This not only strengthened their mathematical skills in data interpretation but also deepened their holistic understanding of sustainable energy solutions, further enhancing engagement, as shown in Figure 4.

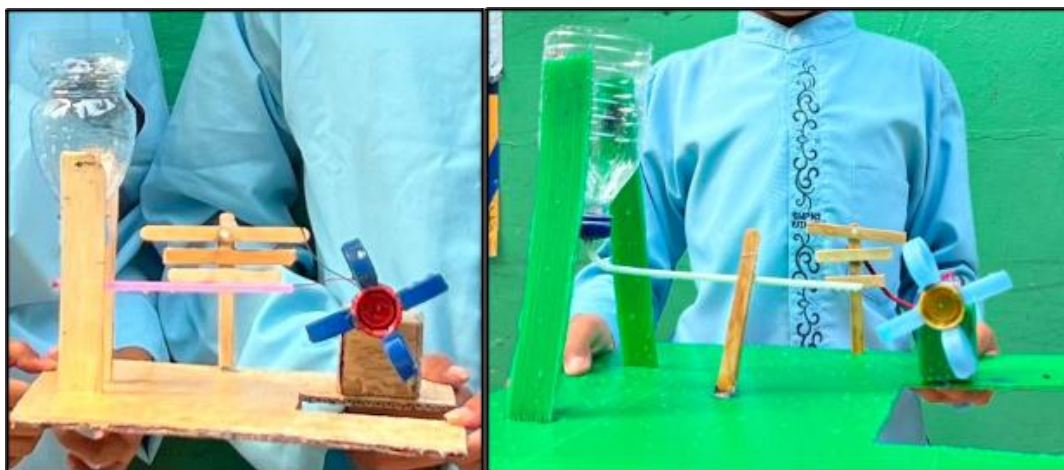


Figure 5. Students present their final water turbine

These activities align with the observed outcomes, in which the experimental group demonstrated greater improvement in CT (n-gain = 0.33) and LE (n-gain = 0.39) than the control group (CT n-gain = 0.13; LE n-gain = 0.09). The statistically significant differences ($p < 0.001$) and large effect sizes (0.80 for CT and 0.85 for LE) underscore the positive impact of the STEM approach. The iterative, hands-on nature of the project not only fostered computational thinking but also encouraged deeper learning engagement, supporting prior studies (Sun et al., 2021; Yin et al., 2022; Li & Oon, 2024) that highlight the benefits of STEM education on cognitive and affective domains. This aligns with findings from (Sun et al., 2021), which emphasize the role of affective engagement in sustained educational success, and with studies highlighting improvements in critical thinking and system thinking skills (Rahayu, 2022).

To further clarify how the STEM framework was embedded throughout the intervention, Table 15 summarizes the contributions of each STEM component to the learning process and the resulting student projects. This table emphasizes how each domain – Science, Technology, Engineering, and Mathematics – played a specific and interconnected role in fostering both computational thinking and learning engagement.

Table 15. Integration of STEM Components and Their Contributions to CT and LE Dimensions

STEM Element	Application in Learning	Contribution to CT	Contribution to LE
Science	Exploration of energy transformation, hydrodynamics, and renewable energy concepts	Supports critical thinking and problem-solving through inquiry and analysis of real-world phenomena	Increases cognitive and emotional engagement by connecting learning to authentic, socially relevant contexts
Technology	Use of tools and materials (syringes, bottles, LED, mini turbines)	Enhances creativity and algorithmic thinking via design solutions and troubleshooting	Boosts behavioral engagement through hands-on activity and tool manipulation
Engineering	Planning, designing, building, testing, and refining water turbine prototypes	Strengthens decomposition, iteration, and cooperation in solving complex technical problems	Encourages agentic and behavioral engagement by empowering students to refine and take ownership of their designs

STEM Element	Application in Learning	Contribution to CT	Contribution to LE
Mathematics	Measuring turbine output, comparing performance, and analyzing data	Reinforces logical reasoning and problem-solving through data interpretation and comparison	Promotes cognitive engagement via evidence-based decision-making and pattern recognition

Conclusion

This study demonstrates the positive impact of a STEM-based learning intervention on computational thinking and learning engagement in secondary school students. The experimental group, which received a five-session STEM intervention, showed significantly greater improvement than the control group. Specifically, the experimental group achieved an n-Gain mean of 0.33 for CT and 0.39 for LE, while the control group's n-Gain means were 0.13 and 0.09, respectively. These differences were statistically significant ($p < 0.001$) with large effect sizes, underscoring the substantial contribution of the STEM intervention. The control group did not receive the STEM intervention and served as a comparison group to assess the intervention's impact. No significant gender differences were observed in CT and LE improvements, suggesting equitable benefits across genders. Despite these promising results, several limitations must be acknowledged. The short intervention period restricts conclusions about the long-term sustainability of observed improvements. Future research should investigate the lasting effects of extended or repeated STEM interventions. The study's single educational context limits the generalizability of findings. Further research across diverse educational systems and cultural settings is needed. The pre-existing difference in initial abilities between the experimental and control groups, despite the randomization, may have influenced the results. Future studies should consider matching techniques or stratified random sampling to mitigate this.

Finally, the reliance on pre- and post-test measures may not fully capture the nuances of CT and LE. Incorporating diverse assessment methods, such as interviews or observations, could yield richer insights. Despite these limitations, the findings highlight the potential of STEM-based learning to enhance student outcomes. The marked differences between the experimental and control groups underscore the effectiveness of STEM interventions in promoting critical thinking, problem-solving, and active learning. Professional development for educators is crucial for effective STEM implementation. Policymakers and educational institutions should prioritize STEM integration to equip students for future success. Future research should address the identified limitations and explore the long-term impacts of STEM-based learning to ensure its sustained contribution to equitable and impactful education.

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