Computational Thinking Levels of Non-Computing Students Through Peer Learning Strategies in Online Collaborative Learning Environment

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Abstract: This study aimed to evaluate the computational thinking skills of students majoring in Chemistry who participated in computational thinking activities before and after the intervention. Employing a quantitative research paradigm with a survey research design, the study involved 29 students from the Bachelor of Science in Education program who took Programming Language as an elective. A purposive sampling technique was used to select the participants. The Computational Thinking Scale was utilized to measure the students' computational thinking skills. Results indicated that while students demonstrated high computational thinking skills comparable to those with computing backgrounds, the implementation of peer learning strategies did not yield significant effects on skill development. Additionally, the study explored peer learning patterns during computational thinking activities, revealing that students exhibited cognitive knowledge, planning, assessment, and monitoring characteristics. A positive and robust relationship was found between the stages of computational thinking skills and the four observed peer learning patterns. Students' perceptions of their computational thinking skills showed high problem-solving abilities but lower scores in critical and cooperative thinking. This study provides valuable insights for researchers and educators in designing computational thinking activities and offers an overview of the computational thinking tendencies among prospective teachers in Malaysia.

Keywords: Computational Thinking, Peer Learning, Online collaborative Learning Environment, Non-Computing Students

1. Introduction

Computational thinking is one of the prominent problem-solving frameworks in 2023. The term "computational thinking" was popularized by Jeannette Wing in her 2006 article in Communications of the ACM (Wing, 2006). Wing defines computational thinking as a "method of problem solving, system design, and understanding human behavior using the fundamentals of computer science" (Wing, 2006). However, Barr et al. (2011) argue that Wing's definition of computational thinking is insufficient for driving policymakers and helping educators build a comprehensive framework for teaching computational thinking. In response, the National Science Foundation (NSF), the International Society for Technology in Education (ISTE), and the Computer Science Teachers Association (CSTA) proposed a more detailed definition. They define computational thinking as "a method of problem-solving that includes techniques such as problem definition, abstraction, logical thinking, algorithmic competence, generalization, and the transfer of solutions to address various other problems" (CSTA, 2011).

Wing (2006) notes that numerous studies demonstrate the integration of computational thinking into classroom teaching (Gresse von Wangenheim et al., 2019; Kirçali & ÖZdener, 2022; Shahin et al., 2021). Several countries, including the United States, Sweden, Finland, Italy, and the Netherlands, have incorporated elements of computational thinking into their national curricula. However, computational thinking is not typically the primary focus of learning; instead, it is often taught indirectly through subjects like programming, computer science, and other related disciplines (del Olmo-Muñoz et al., 2020; Mannila et al., 2014; Merino-Armero et al., 2022).

In the enthusiasm for incorporating computational thinking into teaching, Yeh et al. (2011) highlighted the challenge of teaching computational thinking to non-computing major students. This challenge arises because non-computing majors often lack the problem-solving frameworks that are more common among students majoring in computing. The gap in thought processes between non-computing students and those in computing-related courses should be addressed, in line with the vision of Papert (1988) and Wing (2006), who advocated for computational thinking to be learned by students across various disciplines.

Regarding teaching and learning strategies, Jiang (2021) observed that current methods for teaching computational thinking do not sufficiently promote student interaction and collaborative learning. This observation is supported by research from Agbo et al. (2019), which indicates that peer learning is not the primary strategy employed for teaching computational thinking in higher education institutions. Consequently, there is a growing need to explore peer learning as an effective approach for teaching computational thinking to students in higher education.

Although many studies show that teaching computational thinking skills has been implemented across various courses, research on assessing the level of computational thinking skill remains limited (Lyon & J. Magana, 2020). This gap highlights a challenge for researchers who develop modules, strategies, and frameworks for teaching, as the effectiveness of these modules is often not tested. Additionally, the lack of a comprehensive understanding of computational thinking complicates efforts to compare computational thinking skill across different contexts (Eloy et al., 2021).

The objectives of this research are as follows:

- To measure the change in computational thinking level among non-computing major students before and after participating in computational thinking activities within an online collaborative learning environment.
- To analyze peer learning patterns exhibited by non-computing major students during online collaborative learning sessions.
- To examine the relationship between students' computational thinking tendencies and their identified peer learning patterns in an online collaborative learning environment.
- To assess students' perceptions of their computational thinking skills after participating in an online collaborative learning environment

2. Methodology

The study employed a quantitative research design utilizing a survey research approach. Survey research provides an overview of patterns, behaviors, and viewpoints by analyzing a sample from a larger population, as described by Creswell and Creswell (2018). This approach allows researchers to collect data on various constructs or opinions in numerical form. The raw data collected in this study will be analyzed using statistical methods to produce descriptive findings, such as frequency, mean, mode, and median, as well as to examine relationships between variables. Additionally, the validity and reliability of the data can be assessed independently using statistical techniques

2.1 Samples

When planning the sampling method, the researcher considered two non-probability sampling techniques: convenience sampling and purposive sampling. Convenience sampling involves selecting a sample based on its accessibility and ease of reach for the researcher. On the other hand, purposive sampling involves selecting a sample based on specific criteria or characteristics that align with the research objectives. In purposive sampling, the researcher deliberately chooses participants who possess particular attributes relevant to the study (Etikan et. al., 2015).

For this study, purposive sampling was chosen to ensure that the sample aligned closely with the research objectives. Specifically, the researcher aimed to select participants who were Bachelor of Science with Education students, not majoring in computing, and enrolled in a Programming Language course. This choice was made to meet the first objective of the study, which focuses on understanding computational thinking among non-computing students. A total of 29 students majoring in chemistry education were selected using purposive sampling. This method was appropriate because it allowed the researcher to target a specific group that fits the criteria necessary for addressing the study's goals, ensuring that the participants would provide relevant and insightful data.

2.2 Instruments

This study employs instruments developed by other researchers. Before data collection begins with an adapted instrument, the researcher must ensure that the instrument effectively measures the intended construct (Creswell, 2015). It is crucial to address any threats to the construct validity of the instrument before conducting the study, allowing the researcher to consider modifying the instrument or selecting an alternative if necessary. The original study that developed the Computational Thinking Scale, the Group Metacognition Scale, and the Computational Thinking Skills Scale reported validity through Confirmatory Factor Analysis and a combination of Kaiser-Meyer-Olkin and Bartlett tests. Since the instrument used in this study is contextually similar to the original study, the researcher adopted it directly. This approach has been utilized in previous research by Chongo, Osman and Nayan (2020), Wong (2002), and Lapawi and Husnin (2020).

2.2.1 Reliability of Research Instruments

After confirming that the instrument accurately measures the intended construct, the researcher should also ensure its reliability. The reliability of an instrument refers to the consistency of results it produces; a reliable instrument should yield the same results if the study is repeated by other researchers (Creswell, 2015). Reliability testing is particularly important for instruments that assess multiple constructs simultaneously, such as the Computational Thinking Scale (which measures 5 constructs), the Group Metacognition Scale (4 constructs), and the Computational Thinking Skills Scale (4 constructs). This is because items within the construct may inadvertently measure other constructs (Ruel, Wagner, Gillespie, 2015). Reliability can be assessed using the Cronbach Alpha Reliability Coefficient.

In addition to utilizing the instrument developed by K.-Y. Tang et al. (2020), the researcher employed a checklist to evaluate the skill levels demonstrated in student forum writings. The rationale for using the checklist is to regularly assess students' skill levels. Employing multiple methods to measure cognitive skills is a well-established strategy in assessing students' computational thinking (X. Tang et al., 2020).

2.2.2 Pilot Study

A pilot study was conducted to check instruments' reliability, following the confirmation of the research methodology, design, and instruments. The pilot study involved 29 students enrolled in the Bachelor of Science in Education Studies with a specialization in Physics. This group of students are not the same samples used for real study. To ensure the reliability of the instruments, we employed statistical methods to measure reliability using Cronbach's Alpha coefficient.

The pilot study was carried out in a controlled setting to simulate the conditions of the main research. Participants were given a preliminary version of the research instruments, including surveys and assessments, which they completed over a specified period. Data collected from the pilot study were analyzed to identify any issues with the instruments, such as ambiguous questions or procedural inconsistencies. Based on the feedback and analysis, necessary revisions were made to improve the clarity and effectiveness of the research tools before proceeding with the full-scale study

2.3 Research procedure

An online form collection platform was used to gather data for this research. Two types of instruments were employed: (i) pre-tests and post-tests, and (ii) surveys. Pre-tests were administered to collect information on student demographics and to assess the initial level of computational thinking skills before implementing computational thinking activities. The post-test included the same questions as the pre-test, with additional sections to evaluate peer learning patterns and student perceptions of computational thinking. All instructions, questions, and answers in the forms were provided in English, the language of the original instruments.

The data collection process began with a pre-test to determine students' initial levels of computational thinking skills. This was followed by computational thinking activities with peers within the e-learning system. **Computational Thinking Activity 1** involved students writing a plan to develop video games in an online forum, with the writing process structured around the five phases of computational thinking. Students were given 8 days to complete their plans.

The study then proceeded with **Computational Thinking Activity 2**, where students were required to write comments on their peers' plans. Each student had to provide at least three comments on different peers' plans. This activity was also scheduled to follow the phases of computational thinking over 8 days.

The study concluded with a post-test to measure computational thinking skills after completing the two activities. Additionally, peer learning patterns were identified, and students' perceptions of their computational thinking skills were assessed through a survey. The surveys were created using Google Forms and distributed through the e-learning platform. Approval was obtained from the course coordinator to access the Programming Language learning portal within the e-learning system, allowing researchers to monitor peer learning activities. In summary, the entire research was conducted virtually through the e-learning platform.

To evaluate students' forum writing, both the researcher and an independent evaluator assess the presence of key computational thinking processes, including abstraction, decomposition, algorithmic thinking, evaluation, and generalization, in the students' discussions. Forum writings are scored as "0", "0.5", or "1" based on the depth of the discussion. A score of "0" is assigned if no aspects of computational thinking are present or if the student did not provide any response. A score of "0.5" is given if the student includes some response or demonstrates a partial aspect of computational thinking. A score of "1" is awarded for responses that fully comply with the assignment instructions and effectively demonstrate all required aspects of computational thinking.

2.4 Computational thinking activity

Students will be required to produce a computer game using Scratch. The produced computer game must comply with the criteria below:

1. Have at least one obstacle.
2. Have system scoring.
3. Have a punishment system.
4. Have a reward system.
5. Have instructions, game mechanics, and an objective to win.

To assist the students in completing the assignment, they will learn computational thinking through peer learning. They must write their thought process on each step in computational thinking (starting from decomposition, abstraction, thought algorithm, evaluation, and generalization). The researcher defines this process as a "writing plan."

For aspects of peer learning, their classmates must comment and give ideas for improvements to forum writing. They were required to comment with at least 3 friends. The researcher defines this process as "writing response. " Peer learning activity occurs in 3 different meetings. At the first meeting, they were given 24 hours to write a plan on the steps of decomposition and abstraction. After 24 hours, they are required to write responses to writing friends. Their second meeting will implement the same activity for steps, thoughts, algorithms, and evaluation. The final meeting only focused on generalization.

3. Results

In this section, we present the findings from our study. The results are organized to address each of the key objectives of the study.

3.1 Computational Thinking Skill

A pre-test has already been carried out to measure the level of skill of computational thinking students before the students undergoing computational thinking activities. Level skill computational thinking students were measured again in the post-test (Table 1).

Table 1. Level of Skill of Computational Thinking

	Before	After	Change
Mean	80.47	85.26	4.79
Mode	80.00	80.00	0.00
Median	82.11	84.21	2.11
Standard Deviation	14.77	10.28	18.62

Level skill computational thinking student presented Likert scale of "very, not agree," "no agree, "neutral," "agree," and "strongly agree” to numbers 1 to 5. The Likert Scale data obtained does not reflect actual level skill computational thinking. Therefore, Korkmaz and Bai (2019) suggest using Formula 1 to transform the Likert scale to standard scores with a minimum value of 20 and a maximum of 100 (Fig. 1).

$$x_{\text{standard score}} = \frac{x_{\text{Likert Scale}}}{\text{Bilangan Item}} \times 20$$

Fig. 1 Formula 1 for converting Likert scale scores to standard scores

Based on pre-and post-tests, 5 students do not have a change in skill of computational thinking, 15 students show improvement, and 9 students show a decreased skill. Korkmaz and Bai (2019) also provide an interpretation for the standard score, as in Table 2.

Table 2. Interpretation level skill computational thinking (Korkmaz and Bai, 2019)

Standard Score	Interpretation
20 – 51	Low
52 – 67	Intermediate
68 – 100	High

Based on the interpretation in Table 2, 25 students have a high level of skill, 3 students sit at intermediate, and 1 low-level student in pre-test. The post-test showed an increased skill to computational thinking, with 28 high-level students and 1 intermediate student. Next, Table 3 shows changes in detailed follow-measured constructs in an instrument: abstraction, decomposition, thought algorithm, evaluation, and generalization.

Table 3. Changes Level Computational Thinking Student According to Construct

	Abstraction	Decomposition	Algorithmic Thinking	Evaluation	Generalization
Mean	6.21	5.75	4.66	4.31	3.28
Mode	15.00	0.00	0.00	0.00	0.00
Median	5.00	0.00	0.00	0.00	0.00
Standard Deviation	18.83	20.22	19.08	20.69	19.83

The Wilcoxon Signed Rank Test was conducted to test the data since it was not normally distributed (Table 4). The level of skill of computational students before and after learning computational thinking in a collaborative learning mode environment was determined. Wilcoxon Signed Rank test shows that Z = -1.615, p = 0.106 (Table 5). A higher p-value of 0.05 indicates no significant difference against level skill computational thinking before and after computational thinking activity. Skill of computational thinking in test post (M = 80.47, SD = 14.77) is higher than test pre (M = 85.26, SD = 10.28) with a mean difference of 4.79.

Table 4. Findings Wilcoxon Signed Rank test

Ranks				
		N	Mean Rank	Sum of Ranks
Pre-test – post-test	Negative Ranks	9	10.39	93.50
	Positive Ranks	15	13.77	206.50
	Ties	5		
	Total	29		

Table 5. Findings statistics Wilcoxon Signed Rank test

Test Statistics	
	Pre-test – post-test
Z	-1.615
Asymp. Sig. (2-tailed)	.106

The student's responses were evaluated using a checklist to get a complete picture of skill computational thinking involving forum discussion. The researcher and an independent evaluator evaluated if there is a process of abstraction, decomposition, thinking algorithm, evaluation, and generalization in student discussions. The students discussion will be given "0", "0.5", and "1" based on depth description. If there are no aspects of computational thinking writing discussion, the said respondents do not do any writing in the forum, writing that given score "0". If available, a few aspects of partial computation comply with instructions assignments, writing the score "0.5". Finally, the proper response writing will have the full mark "1".

Table 6. Forum discussion score

	Abstraction	Decomposition	Algorithmic Thinking	Evaluation	Generalization	Total
Total	23.5	22.5	23.5	11.5	12.5	93.5
Mean	0.810	0.776	0.810	0.397	0.431	3.224
Mode	1.0	1.0	1.0	0.5	0.0	3.5
Median	1.0	1.0	1.0	0.5	0.5	3.5
Standard Deviation	0.281	0.343	0.364	0.280	0.395	1.131

Based on the evaluation made by the researcher and an independent evaluator, no students recorded the full mark of 5. 11 students scored 4 and 4.5, 12 students scored 3 and 3.5, and the remaining 5 students scored under 3. One of them did not send any response in the forum.

3.2 Peer Learning Patterns

Peer learning patterns were determined using an instrument by Biasutti and Frate (2018). Instruments evaluate pattern learning peer learning through four constructs: cognitive knowledge, planning, monitoring, and evaluation. Learning patterns friends same age student presented in shape number by match Likert scale "very not agree," "no agree, "neutral," "agree," and "strongly agree” to numbers 1 to 5. The maximum achievable points is 100 points. The frequency chart of peer learning pattern points noted by the student is presented in Fig. 2 and student's peer learning pattern as a whole is presented in Table 7.

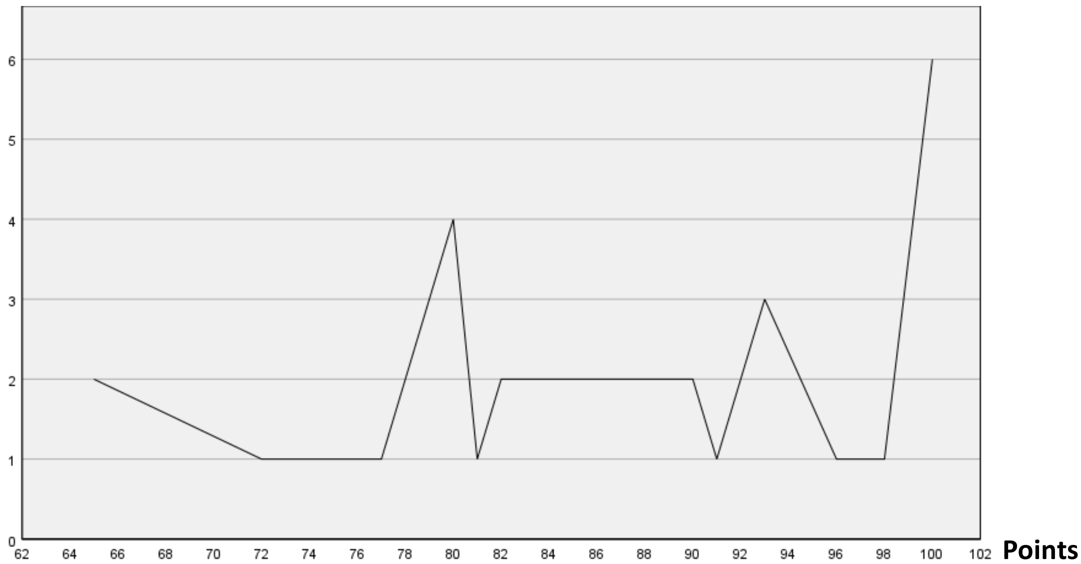

Fig. 2 Distribution of peer learning pattern points

Based on Table 7, the pattern mean value of peer learning patterns was recorded around 21.52 and 22.13. The mean value does not show significant variation between all four constructs. Out of 29 students who underwent activity learning thoughts computational, 6 showed full agreement (value Total = 100) against the statement in dimension knowledge cognition, planning, monitoring, and evaluation. 11 students recorded points between 80 and 90. Two students collected less than 70 points.

Table 7. Analysis of the pattern of peer learning

Dimensions	N	Minimum	Maximum	Total	Mean	Standard Deviation
Knowledge of Cognition	29	16.00	25.00	626.00	21.5862	2.90956
Planning	29	17.00	25.00	634.00	21.8621	2.44546
Monitoring	29	15.00	25.00	624.00	21.5172	3.01923
Evaluating	29	16.00	25.00	642.00	22.1379	2.58739

3.3 Relationships Between Levels Computational Thinking Skill and Peer Learning Patterns

In this section, the researcher tried to affirm whether the level of skill is relevant to peer learning patterns. Students' computational thinking skill in the post-test will be matched with dimensions from the Group Metacognition Scale. Spearman's correlation test has been conducted and presented in Table 8.

Table 8. Spearman correlation skill of computation thinking and peer learning

Pattern	Correlation with Computational Thinking Skill	
Knowledge of Cognition	Correlation Coefficient	.788**
	Sig. (2-tailed)	.000
	N	29
Planning	Correlation Coefficient	.865**
	Sig. (2-tailed)	.000
	N	29
Evaluation	Correlation Coefficient	.777**
	Sig. (2-tailed)	.000
	N	29
Monitoring	Correlation Coefficient	.780**
	Sig. (2-tailed)	.000
	N	29

Based on Table 8, level skill computational thinking has a strong correlation with knowledge of cognition (r = 0.788, N = 29), planning (r = 0.866, N = 29), evaluation (r = 0.764, N = 29), and monitoring (r = 0.785, N = 29). Computational thinking skill correlates significantly ($p < 0.05$) with peer learning patterns. Computational thinking skill correlates strongly with the "planning" dimension in GMS. On the other hand, computational thinking skill has the weakest correlation with evaluation.

3.4 Student Perception Towards Computational Thinking Skills

The final objective of this research is to ascertain the perception of students on skills in computational thinking. The study assesses students' perception of learned skills when learning computational thinking. There are 42 items, four construct skills thoughts computationally measured, i.e., problem-solving, cooperative learning critical thinking, creativity, and algorithmic thinking. Students' perceptions were presented in the form of numbers by matching the Likert scale "very not agree," "no agree, "neutral," "agree," and "strongly agree" to numbers 1 to 5. Based on the 42 items in the section measurement perception students, the maximum number of points one respondent can record is 210.

Table 9. Descriptive statistics of students' perception

	Problem-Solving	Cooperative learning & critical thinking	Creativity	Algorithmic Thinking
N	29	29	29	29
Mean	4.28	3.77	4.1	4.17
Median	4.05	4	4	4
Mode	4.1	4.25	4.11	4
Standard Deviation	0.67	1.13	0.89	0.84

4. Discussion

The findings from the study address all four research questions, revealing insights into the changes in computational thinking levels, the nature of peer learning patterns, the relationship between computational thinking and peer learning, and students' perceptions of their computational thinking skills.

4.1 Discussion of Research Question 2

The 1st research question measured students' computational thinking tendencies before and after implementing peer learning strategies. Results indicated an increase in these tendencies, but the Wilcoxon Signed Rank test showed the change was not statistically significant. Tsai et al. (2020) have noted that most computational thinking assessments focus on learning outcomes rather than the thought process itself. To address this, they developed the Computational Thinking Scale, which was used in this study to evaluate computational thinking from a process perspective.

The Computational Thinking Scale assesses five dimensions: abstraction, decomposition, algorithmic thinking, evaluation, and generalization. The data revealed a general increase in computational thinking for 15 students, though 9 students showed a decrease, raising concerns.

Given the self-reported nature of the Computational Thinking Scale, the study also used a checklist method to independently assess students' abilities in abstraction, decomposition, algorithmic thinking, evaluation, and generalization through their forum discussions. This mixed-method approach, as suggested by K.-Y. Tang et al. (2020), provides a fuller picture of computational thinking tendencies (Lachney et al., 2019).

Comparison of the results from the Computational Thinking Scale and the checklist revealed discrepancies. The Scale showed strengths in abstraction, algorithmic thinking, and evaluation, with weaknesses in generalization. The checklist indicated strengths in abstraction and algorithmic thinking, but weaknesses in evaluation and generalization. Notably, some students did not submit forum results for evaluation and generalization, which affected the scores.

In summary, the study found that non-computing major students excel in abstraction, decomposition, and algorithmic thinking, indicating a tendency to focus on relevant information, break problems into smaller parts, and solve problems through sequential procedures (Tsai et al., 2020). The findings also highlight a gap in research using the Computational Thinking Scale, suggesting that this study contributes to filling that gap and opens discussions for further reinforcement.

4.2 Discussion of Research Question 2

The post-test measured students' peer learning patterns using the Group Metacognition Scale by Biasutti and Frate (2018), which assesses cognition knowledge, planning, monitoring, and evaluation. The results show minimal variation in the use of these patterns among students. Essentially, all students demonstrate similar levels of cognitive knowledge, planning, monitoring, and evaluation during peer learning.

Biasutti and Frate (2018) note that group-based metacognitive processes differ from individual ones. In peer learning, students show cognitive knowledge by sharing strategies for assignments and selecting relevant information for their peers. For planning, students define learning goals, manage time, and balance workloads. Monitoring involves exchanging information to solve problems, while evaluation means understanding task results and requirements.

This study provides insight into peer learning patterns among non-computing students. Biasutti and Frate (2018) suggested examining learning patterns across different majors, noting that education majors display stronger planning, monitoring, and evaluation skills compared to psychology majors. However, a direct comparison is challenging due to the lack of detailed respondent backgrounds in other studies using the Group Metacognition Scale (Yıldız & Seferoğlu, 2021).

4.3 Discussion of Research Question 3

This 3rd research question reveals a strong and significant correlation between computational thinking tendencies and peer learning patterns. It finds that cognitive aspects such as knowledge, planning, evaluation, and monitoring significantly impact students' computational thinking. However, the influence of specific peer learning patterns on computational thinking levels remains unclear and warrants further investigation.

Attempts to relate these findings to previous studies did not reveal direct correlations, as other research focuses on different aspects. Nonetheless, this study contributes valuable insights into peer learning. Previous studies explored various related topics, such as curriculum changes in collaborative learning with educational robots (Socratous & Ioannou, 2022), student autonomy in collaborative learning (Atman Uslu & Yildiz- Durak, 2022), and metacognitive support (Zheng et al., 2019).

4.4 Discussion of Research Question 4

The final research question addresses students' perceptions of computational thinking skills, specifically which skills are most adopted after learning computational thinking. This study uses the Computational Thinking Scale by Yagci (2019), which measures problem solving, critical and cooperative thinking, creativity, and algorithmic thinking.

Results indicate that students perceive problem-solving as the most adopted skill, aligning with expectations since computational thinking is a problem-solving framework (Wing, 2006). Conversely, critical thinking and cooperative learning were the least adopted skills. Critical thinking involves understanding others' ideas actively, while cooperative learning refers to working in small groups toward a common goal (Johnson & Johnson, 1994). The findings suggest a need for further research to identify weaknesses in these areas.

In summary, while computational thinking training effectively enhances problem-solving, algorithmic thinking, and creativity, critical thinking and cooperative learning remain weaker. Future studies should separate these components for clearer insights.

5. Conclusion

Data from the study found that there was a small increase in the tendency of computational thinking after undergoing peer learning activities. However, statistical analysis shows that the increase in the tendency of the student's computational thinking is not significant. This study uses the Computational Thinking Scale instrument and a checklist to assess students' computational thinking tendencies and the data shows a discrepancy in the strength of computational thinking tendencies between the two assessment methods.

Apart from that, the researcher researched the learning patterns of students' peers by using the Group Metacognition Scale. The results of the study show that students do not exhibit any tendency towards a certain learning pattern because all students exhibit cognitive knowledge, planning, monitoring and evaluation in their learning activities at almost the same frequency.

This study has also identified some practices that can increase the effectiveness of peer learning in learning computational thinking skills such as investing time and effort to conduct peer learning, giving constructive and frequent feedback, conducting structured reflection and connecting learning with the application of world concepts real.

However, this study has several limitations. The duration of peer learning activities is seen to be short and the quality of feedback students receive from their peers is unsatisfactory. Future researchers should consider extending the duration of peer learning activities and focus on improving the quality of interaction and feedback between students.

In general, this study paves the way for other researchers to measure computational thinking tendencies from various academic backgrounds and further develop the understanding of how peer learning can help the development of computational thinking.

6. Suggestions

Based on the the most constraints factors that have been identified in this study, the researcher believes that a computational thinking assessment method that is more objective and not influenced by the respondent's perception needs to be developed. The researcher has considered the potential of the Bebras Challenge questions for assessing students' computational thinking tendencies as used in the study of Araujo et al. (2019), Lapawi and Husnin (2020) and Chongo et al. (2020). In order to adapt the Bebras Challenge to the assessment of computational thinking according to the framework of Selby and Woollard (2013)can be used, the questions of the Bebras Challenge should be modified so that each question can measure the computational thinking skills used in this study. In addition, questions that are not related to computational thinking such as questions such as the ethics of internet use can be eliminated. This suggestion is consistent with the study of Tsai et al. (2022) who developed the Computational Thinking Test for Elementary School Students (CTT-ES) and Marc et al. (2021) who developed the Algorithmic Thinking Test for Adults (ATTA).

The second recommendation is to conduct studies with larger sample sizes and diverse backgrounds. Studies conducted on a large and diverse sample size add to the confidence of other researchers in generalizing the results of studies conducted to the population (Creswell & Creswell, 2018). A comparison of students' backgrounds can also be carried out and then conclusions can be drawn on the probability that some learning strategies only work for students from certain backgrounds.

The third suggestion is from the point of view of research design. The researcher found that there is a lack of data collected quantitatively. By combining qualitative and quantitative methods, researchers hope that the data will become more meaningful and contribute more knowledge in this field. The researcher felt motivated to conduct a mixed method design especially to determine the learning patterns of students' peers. The results of this study on the learning patterns of students' peers show that students exhibit all four learning patterns measured in the Group Metacognition Scale instrument equally.

The fourth suggestion is to extend the period of peer learning in learning that exceeds 60 minutes. None of the studies listed in the peer learning study profile table measured the optimal duration of peer learning in improving students' computational thinking but this study took place over a long period such as one semester, and a minimum of 8 hours of interaction.

7. Co-Author Contribution

The authors affirmed that there is no conflict of interest in this article. Author1 carried out the fieldwork and aligned the whole article's write-up. Author2 wrote the research methodology and did the data entry. Author3 prepared the literature review. Author4 carried out the statistical analysis. Author5 carried out the interpretation of the results. Author6 wrote the conclussion. Author 7 prepared the abstract and wrote the suggestion section.

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