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Center-Based Learning Through the Traditional Game *Mpa'a Ncimi Lombo Tembe* to Enhance Young Children's Computational Thinking Skills

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Abstract

Computational thinking in early childhood needs to be developed through concrete experiences, play, and contexts that are close to children's lives. This study aimed to analyze the implementation of *Center-Based Learning* based on the traditional game *Mpa'a Ncimi Lombo Tembe* to improve *computational thinking* among children aged 4–6 years and examine changes in *decomposition, pattern recognition, abstraction,* and *algorithmic thinking*. The study employed a mixed-methods approach with a *sequential explanatory* design. The quantitative phase used a *quasi-experimental pretest-post test control group design* involving 20 children, consisting of 10 children in the experimental group and 10 in the control group. Data was collected through performance tasks and observations of 16 *computational thinking* behaviors, while qualitative data came from observations, teacher interviews, and documentation. Quantitative data were analyzed using descriptive statistics, gain-score comparison, and analysis of covariance, while qualitative data were analyzed thematically and integrated with the quantitative findings. The results showed that the experimental group's mean score increased from 36.70 to 54.30, whereas the control group increased from 31.70 to 42.80. The difference in improvement between groups was statistically significant, $t(18) = 5.845$, $p < 0.001$, with a very large effect size, Cohen's $d = 2.61$. All four components and all 16 observed behaviors improved, with the largest increase occurring in *abstraction*. Learning implementation reached 95.00%. These findings indicate that this traditional game can support culturally situated unplugged learning for developing *computational thinking* through concrete, active, and meaningful experiences.

Keywords: Center-Based Learning; Computational Thinking; Traditional Games; Early Childhood; *Mpa'a Ncimi Lombo Tembe.*

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INTRODUCTION

Computational thinking is an important skill to develop in early childhood because it supports children's abilities to understand problems, recognize patterns, select relevant information, organize solution steps, and evaluate and revise solutions (Tulqulub et al., 2026). Rather than being limited to computer use or programming, computational thinking can be developed through concrete, play-based experiences. In early childhood, it includes four key components: decomposition, pattern recognition, abstraction, and algorithmic thinking, which can be observed through sequencing, problem-solving, testing, and debugging activities (Cecchetti & Granone, 2026). In this study, computational thinking refers to the ability of children aged 4–6 years to break down tasks, recognize patterns, select relevant information, and organize and revise sequences of actions (Anggryani et al., 2025; Tulqulub et al., 2026). These abilities are represented by four indicators and 16 observable behaviors (Kucab et al., 2025; Purwasih et al., 2024; Hardiyanti et al., 2025).

Because young children learn primarily through play, exploration, movement, concrete experiences, and social interaction, play-based and unplugged approaches are particularly appropriate for developing computational thinking. Unplugged activities can introduce computational concepts without digital devices through objects, games, movement, patterns, stories, and problem-solving activities (Rahmawati & Agustin, 2024; Chen et al., 2026). Previous studies have shown that board games, storytelling, tangible media, and embodied learning can support children's computational thinking through problem-solving, sequencing, decision-making, pattern recognition, and strategy testing (Bratitsis et al., 2023; Busuttil & Vassallo, 2026; Estrella et al., 2026; Pellas, 2025; Kwon et al., 2025; Yang, 2024). Research comparing plugged and unplugged approaches also confirms the relevance of unplugged activities for young children because they provide concrete and accessible learning experiences (Garcia-Marques et al., 2026; Zeng & Yang, 2026).

This issue is particularly relevant in the Bima region, where children's systematic thinking and problem-solving abilities remain challenging, especially in developing strategies, recognizing patterns, and completing tasks independently. Therefore, learning approaches should combine computational thinking with active, concrete, and culturally meaningful experiences.

Although research on early childhood computational thinking has grown considerably, most studies use specially designed games, robots, tangible tools, or unplugged activities (Bratitsis et al., 2023; Garcia-Marques et al., 2026; Pellas, 2025). Research using local traditional games as unplugged computational thinking environments within Center-Based Learning remains limited (Chen et al., 2026; Rahmawati & Agustin, 2024). Traditional games offer authentic learning contexts involving rules, movement, interaction, decision-making, and cultural meaning. They therefore have the potential to integrate cognitive development, play, social interaction, and local culture.

Based on this gap, this study aims to examine the implementation of Center-Based Learning based on the traditional game Mpa'a Ncimi Lombo Tembe to enhance computational thinking among children aged 4–6 years. The study focuses on the development of decomposition, pattern recognition, abstraction, and algorithmic thinking, as well as the learning processes that support these abilities. The study is expected to contribute to play-based, unplugged, embodied, and culturally situated approaches to computational thinking in early childhood education.

METHOD

This study used a mixed-methods sequential explanatory design, beginning with a quantitative quasi-experimental phase followed by a qualitative phase. The study involved children aged 4–6 years from two early childhood education institutions. The experimental group received Center-Based Learning based on the traditional game *Mpa'a Ncimi Lombo Tembe* for eight sessions, while the control group received routine learning activities.

Children's computational thinking was assessed through four components: decomposition, pattern recognition, abstraction, and algorithmic thinking. Data were collected through performance tasks, observations, interviews, and documentation. Quantitative data were analyzed using descriptive statistics, assumption tests, ANCOVA or appropriate nonparametric tests, and effect size analysis. Qualitative data were analyzed thematically and integrated with the quantitative findings to explain children's learning experiences, strategies, interactions, scaffolding, and error correction.

The study followed an input–process–output framework, in which Center-Based Learning and the traditional game served as the input, play and scaffolding constituted the process, and the development of computational thinking represented the output.

RESULT AND DISCUSSION

The results are systematically presented based on children's *computational thinking* abilities before and after the intervention, comparisons of improvements between the experimental and control groups, analyses of each *computational thinking* component, and the implementation of *Center-Based Learning*. The presentation of the results focuses on empirical findings and statistical analyses without providing theoretical interpretations, which are presented in the discussion section.

Description of Children's *Computational Thinking* Abilities Before and After the Intervention

This study involved 20 children aged 4–6 years who were divided into an experimental group and a control group. The experimental group consisted of 10 children who participated in learning activities at TK Mutmainah, Kala Village, Donggo District, while the control group consisted of 10 children from TKN Pembina, Tonda Village, Madapangga District. *Computational thinking* abilities were measured through 16 observable behaviors representing four components: *decomposition, pattern recognition, abstraction,* and *algorithmic thinking*. Each behavior was assessed using a 1–4 scale, resulting in a total *computational thinking* score ranging from 16 to 64.

The descriptive analysis showed an increase in *computational thinking* scores in both groups after the learning activities. In the experimental group, the mean score increased from 36.70 at *pretest* to 54.30 at *posttest*. In the control group, the mean score increased from 31.70 at *pretest* to 42.80 at *posttest*.

Table 1. Descriptive Statistics of Children's *Computational Thinking* Abilities

Group	N	Pretest Mean	SD	Posttest Mean	SD	Gain
Experimental	10	36.70	3.23	54.30	2.87	17.60
Control	10	31.70	1.95	42.80	3.33	11.10

Based on Table 1, the experimental group showed a mean increase of 17.60 points, whereas the control group showed an increase of 11.10 points. Thus, the difference in mean improvement between the two groups was 6.50 points. When expressed as a percentage of the maximum possible score, the mean score of the experimental group increased from 57.34% at *pretest* to 84.84% at *posttest*. In the control group, the mean score increased from 49.53% to 66.88%. Based on the calculation of the *normalized gain*, the experimental group obtained a value of 0.65, whereas the control group obtained a value of 0.34.

Comparison of Improvements in *Computational Thinking* Between Groups

The subsequent analysis examined *gain scores* to determine differences in changes in *computational thinking* abilities between the experimental and control groups. The experimental group obtained a mean *gain* of 17.60, while the control group obtained a mean *gain* of 11.10. An *independent-samples t-test* conducted on the *gain scores* yielded $t(18) = 5.845$ with $p < 0.001$. This result indicates a statistically significant difference in the improvement of *computational thinking* abilities between the experimental and control groups.

Table 2. Results of the Gain Score Difference Test

Group	Mean Gain	*t*	df	*p*	Cohen's *d*
Experimental	17.60	5.845	18	< 0.001	2.61
Control	11.10	—	—	—	—

The effect size analysis yielded a Cohen's *d* value of 2.61, indicating a very large effect size. Thus, the difference in improvement between the experimental and control groups was not only statistically significant but also substantial in terms of effect magnitude.

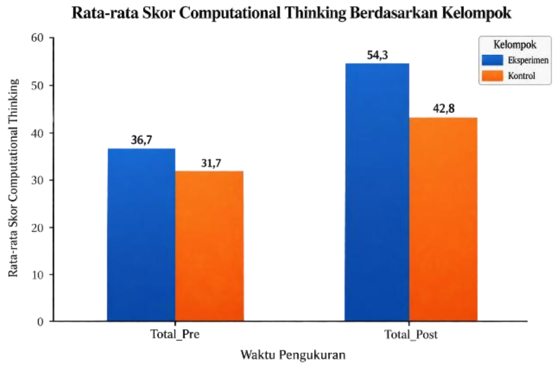

Figure 1. Comparison of Mean *Pretest* and *Posttest* Scores

Figure 1 illustrates the changes in the mean *computational thinking* scores from *pretest* to *posttest* in the experimental and control groups. Both groups demonstrated increases in scores, with a greater increase observed in the experimental group.

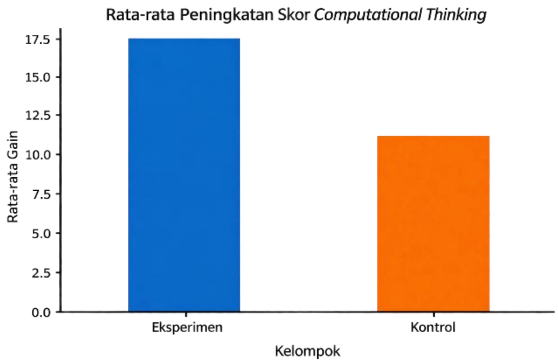

Figure 2. Comparison of Mean Gain Scores

Figure 2 shows that the mean *gain score* of the experimental group (17.60) was higher than that of the control group (11.10).

Analysis of Covariance of *Computational Thinking* Abilities

To control for potential differences in initial abilities between the experimental and control groups, an analysis of covariance (ANCOVA) was conducted, with *pretest* scores as the covariate and *posttest* scores as the dependent variable. The results indicated that the overall model was statistically significant, $F(2, 17) = 60.50$, $p < 0.001$, with $R^2 = 0.877$. This result indicates that the analytical model accounted for 87.7% of the variance in *posttest* scores based on the variables included in the model.

Table 3. Results of the Analysis of Covariance

Variable	*B*	SE	*t*	*p*
Pretest	0.743	0.217	3.422	0.003
Group	7.783	1.546	5.035	< 0.001

The *pretest* score showed a significant relationship with the *posttest* score ($B = 0.743$, SE = 0.217, $t = 3.422$, $p = 0.003$). After statistically controlling for *pretest* scores, the group variable remained significantly associated with *posttest* scores ($B = 7.783$, SE = 1.546, $t = 5.035$, $p < 0.001$). These findings indicate that the difference in *posttest* scores between the experimental and control groups remained evident after initial differences in ability were statistically controlled.

Changes in the Components of *Computational Thinking*

The next analysis examined the four components of *computational thinking*: *decomposition, pattern recognition, abstraction,* and *algorithmic thinking*. The results indicated increases in all four components in the experimental group.

Table 4. Changes in Scores Across the Four Components of *Computational Thinking*

Component	Experimental Pre	Experimental Post	Gain	Control Pre	Control Post	Gain
Decomposition	9.60	13.70	4.10	7.90	10.70	2.80
Pattern recognition	9.10	13.20	4.10	8.50	10.80	2.30
Abstraction	9.20	14.50	5.30	7.80	10.90	3.10
Algorithmic thinking	8.80	12.90	4.10	7.50	10.40	2.90

In the experimental group, the *decomposition* score increased from 9.60 to 13.70, representing an increase of 4.10 points. The *pattern recognition* score increased from 9.10 to 13.20, also representing an increase of 4.10 points. The *abstraction* score increased from 9.20 to 14.50, representing the largest increase of 5.30 points. Meanwhile, *algorithmic thinking* increased from 8.80 to 12.90, representing an increase of 4.10 points. In the control group, *decomposition* increased by 2.80 points, from 7.90 to 10.70. *Pattern recognition* increased by 2.30 points, from 8.50 to 10.80. *Abstraction* increased by 3.10 points, from 7.80 to 10.90. Meanwhile, *algorithmic thinking* increased by 2.90 points, from 7.50 to 10.40.

Descriptively, improvements across all four components were greater in the experimental group than in the control group. The largest improvement in the experimental group occurred in *abstraction*, with an increase of 5.30 points.

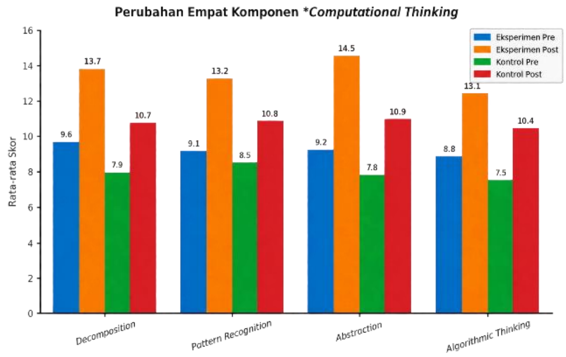

Figure 3. Changes in the Four Components of *Computational Thinking*

Figure 3 illustrates changes in the four *computational thinking* components in the experimental and control groups. All components showed increases in scores following the learning activities.

Analysis of the 16 *Computational Thinking* Behaviors

Behavior-level analysis was conducted on 16 indicators representing the four components of *computational thinking*: *decomposition, pattern recognition, abstraction,* and *algorithmic thinking*. The analysis compared the mean *pretest* and *posttest* scores of the experimental group. The measurement results indicated that all indicators showed increased scores following the implementation of the learning intervention.

Table 5. Scores of the 16 *Computational Thinking* Behaviors in the Experimental Group

No.	Component	Observed Behavior	Pretest	Posttest	Gain
1	*Decomposition*	Identifying task components	2.50	3.50	1.00
2	*Decomposition*	Determining the initial step	2.50	3.60	1.10
3	*Decomposition*	Completing tasks sequentially	2.10	3.10	1.00
4	*Decomposition*	Identifying difficult parts/seeking assistance	2.50	3.50	1.00
5	*Pattern recognition*	Recognizing similarities in color/shape/position	2.40	3.40	1.00
6	*Pattern recognition*	Continuing a pattern	2.20	3.40	1.20
7	*Pattern recognition*	Grouping objects based on patterns	2.20	3.10	0.90
8	*Pattern recognition*	Applying previously recognized patterns	2.30	3.30	1.00
9	*Abstraction*	Selecting appropriate tools	2.20	3.60	1.40
10	*Abstraction*	Ignoring irrelevant objects	2.30	3.40	1.10
11	*Abstraction*	Determining the main rule	2.20	3.70	1.50
12	*Abstraction*	Explaining the essence of the activity	2.50	3.80	1.30
13	*Algorithmic thinking*	Sequencing steps	2.30	3.30	1.00
14	*Algorithmic thinking*	Executing steps sequentially	2.10	3.00	0.90
15	*Algorithmic thinking*	Checking for errors	2.20	3.40	1.20
16	*Algorithmic thinking*	Correcting the sequence	2.20	3.20	1.00
Mean			**2.29**	**3.39**	**1.10**

Source: Research data, processed by the authors.

Based on Table 5, the mean score across the 16 *computational thinking* behaviors increased from 2.29 at *pretest* to 3.39 at *posttest*, representing a mean increase of 1.10 points. Improvements were observed across all indicators.

For *decomposition*, *posttest* scores ranged from 3.10 to 3.60. The highest score was observed for the behavior of determining the initial step, with a score of 3.60, which also showed the largest increase within this component, namely 1.10 points. The other three indicators each increased by 1.00 point.

For *pattern recognition*, *posttest* scores ranged from 3.10 to 3.40. The behavior of continuing a pattern showed the largest increase, from 2.20 to 3.40, or 1.20 points. Meanwhile, grouping objects based on patterns increased by 0.90 points, from 2.20 to 3.10.

The *abstraction* component showed the most pronounced improvement. The behavior of determining the main rule increased from 2.20 to 3.70, with a *gain* of 1.50 points, representing the largest increase among all 16 indicators. The behavior of selecting appropriate tools increased by 1.40 points, while explaining the essence of the activity increased by 1.30 points. The highest overall *posttest* score was also observed for explaining the essence of the activity, at 3.80.

For *algorithmic thinking*, *posttest* scores ranged from 3.00 to 3.40. The behavior of checking for errors increased by 1.20 points, from 2.20 to 3.40. Meanwhile, sequencing steps and correcting the sequence each increased by 1.00 point. Executing steps sequentially increased from 2.10 to 3.00, representing a *gain* of 0.90 points.

Overall, the analysis showed that all 16 behaviors improved in the experimental group. The highest *posttest* score was observed for explaining the essence of the activity (3.80), followed by determining the main rule (3.70), and determining the initial step and selecting appropriate tools (3.60 each). Based on the *gain* values, the greatest improvement occurred in determining the main rule (1.50), while the smallest improvements were observed in grouping objects based on patterns and executing steps sequentially, each with an increase of 0.90 points.

Implementation of *Center-Based Learning*

The implementation of *Center-Based Learning* was observed during the learning process to obtain data regarding the extent to which the implementation was consistent with the predetermined learning plan. Observations were conducted over three days of learning activities.

Table 6. Implementation of *Center-Based Learning*

Date	Mean Score	Percentage
August 10, 2026	3.80	95.00%
August 11, 2026	3.75	93.75%
August 12, 2026	3.85	96.25%
Mean	**3.80**	**95.00%**

Based on Table 6, the mean implementation scores for *Center-Based Learning* reached 3.80 out of a maximum score of 4, corresponding to an implementation rate of 95.00%. The highest implementation rate was recorded on August 12, 2026, at 96.25%, while the lowest was recorded on August 11, 2026, at 93.75%. The difference in implementation rates across the three observation days was 2.50 percentage points. Overall, the findings indicate that *computational thinking* abilities increased in both groups following the learning activities. The experimental group's mean score increased from 36.70 at *pretest* to 54.30 at *posttest*, whereas the control group's mean score increased from 31.70 to 42.80. The experimental group obtained a mean *gain score* of 17.60, compared with 11.10 in the control group.

The *independent-samples t-test* indicated a significant difference in *gain scores* between the two groups ($t(18) = 5.845$, $p < 0.001$), with a Cohen's d of 2.61. The ANCOVA results showed that the overall model was significant ($F(2,17) = 60.50$, $p < 0.001$, $R^2 = 0.877$). After controlling for *pretest* scores, the group variable remained significantly associated with *posttest* scores ($B = 7.783$, SE = 1.546, $t = 5.035$, $p < 0.001$). At the component level, all four *computational thinking* components in the experimental group increased. *Decomposition* and *pattern recognition* each increased by 4.10 points, *abstraction* increased by 5.30 points, and *algorithmic thinking* increased by 4.10 points. The implementation of *Center-Based Learning* across the three observation days reached a mean of 95.00%.

Overall, the findings indicate a difference in the improvement of *computational thinking* abilities between the experimental and control groups, with a greater mean improvement observed in the experimental group.

DISCUSSION

The findings indicate that the implementation of *Center-Based Learning* based on the traditional game *Mpa'a Ncimi Lombo Tembe* contributed positively to the development of *computational thinking* among children aged 4–6 years. This change was reflected in the increase in the experimental group's mean score from 36.70 at *pretest* to 54.30 at *posttest*, representing an increase of 17.60 points. Meanwhile, the control group increased from 31.70 to 42.80, or by 11.10 points. This difference in improvement was supported by the results of the *independent-samples t-test*, which yielded $t(18) = 5.845$, $p < 0.001$, with a Cohen's d of 2.61. The ANCOVA results further indicated that after controlling for *pretest* scores, group membership remained significantly associated with *posttest* scores ($B = 7.783$, SE = 1.546, $t = 5.035$, $p < 0.001$). Empirically, these findings indicate that the improvement in *computational thinking* in the experimental group was greater than that observed in the control group.

This difference can be understood in terms of the characteristics of the intervention provided to the experimental group. *Center-Based Learning* based on a traditional game does not position children as passive recipients of instruction but as active participants in play-based activities. Children are given opportunities to observe, choose, experiment, organize actions, encounter errors, and revise their strategies. Such a sequence of experiences creates conditions that allow computational thinking processes to develop through concrete activities. Thus, the improvement in *computational thinking* observed in this study cannot be separated from the quality of the learning experiences provided to the children during the game activities.

Conceptually, these findings are consistent with Wing (2006), who described *computational thinking* as a way of thinking for formulating problems and organizing solutions systematically. *Computational thinking* is not limited to computer use, programming, or digital technology; rather, it encompasses thinking processes that can be applied across various problem-solving contexts. In early childhood education, this concept needs to be translated into activities that are appropriate for children's developmental characteristics. Young children do not necessarily require algorithmic representations in the form of formal code or symbols. Instead, they can develop the foundations of *computational thinking* through activities that require them to break tasks into components, recognize patterns, select necessary information, organize steps, and correct errors.

This approach is reflected in the four *computational thinking* components used in this study: *decomposition, pattern recognition, abstraction,* and *algorithmic thinking*. These components were not taught as isolated concepts but were integrated into game-based activities. Such integration enabled children to experience computational thinking processes directly. When children divided an activity into several parts, they engaged in *decomposition*. When they recognized regularities in colors, shapes, positions, or movements, they engaged in *pattern recognition*. When they determined relevant tools or rules and disregarded unnecessary information, they used *abstraction*. Finally, when they organized sequences of actions, executed procedures, identified errors, and revised those sequences, they demonstrated *algorithmic thinking*. Thus, the game served as a medium connecting the concept of *computational thinking* with children's concrete experiences.

The improvement across the four components indicates that the learning intervention provided relatively comprehensive learning experiences. *Decomposition* increased by 4.10 points, *pattern recognition* increased by 4.10 points, *abstraction* increased by 5.30 points, and *algorithmic thinking* increased by 4.10 points. The greatest improvement occurred in *abstraction*. This finding indicates that the game activities provided strong opportunities for children to learn how to select relevant information, identify the main rules, and understand the essence of an activity. These abilities are important aspects of thinking because children are not merely exposed to available information but begin to determine which information is necessary for achieving a particular goal.

The improvement in *decomposition* indicates that children became increasingly able to understand a task as a sequence of activities that could be completed step by step. At the beginning, children tended to perceive the game as a unified activity. After repeated play experiences, they became increasingly able to identify task components, determine the initial action, complete tasks sequentially, and communicate which parts they considered difficult. This change was particularly evident in the behavior of determining the initial step, which increased from 2.50 to 3.60. This improvement suggests a developmental shift from spontaneous action toward more directed action.

The structure of the game provided strong support for the development of *decomposition* because each activity contained components and stages that could be observed directly. Children needed to know what to do first, which tools to use, what action should follow, and what condition needed to be achieved to complete the game. This structure implicitly taught children that a problem can be solved by breaking it into smaller and more manageable components. This finding is consistent with Pellas (2025), who reported that the use of *tangible* programming tools can support *problem decomposition* and other thinking abilities in young children. The present study extends this finding by providing *decomposition* experiences through a traditional game, allowing the process to occur within a play context that is more closely connected to children's social and cultural experiences.

The *pattern recognition* component also increased by 4.10 points. This improvement was evident in children's ability to recognize similarities in colors, shapes, or positions, continue patterns, group objects according to patterns, and apply previously recognized patterns to subsequent situations. Traditional games provide repeated experiences that enable children to observe regularities directly. Repeated movements, positions, rules, and the use of equipment provide opportunities for children to compare previous experiences with the situation they are currently encountering.

Pattern recognition is an important component of *computational thinking* because patterns allow children to use previous experiences to understand new problems. In this study, children did not receive pattern-recognition exercises separately from the game context. Instead, patterns emerged as part of the activities they needed to complete. This condition made pattern recognition more meaningful because children had a clear purpose when identifying a particular regularity. This finding supports Bratitsis et al. (2023), who demonstrated that games can be used to introduce *computational thinking* in early childhood through rules, sequencing, decision-making, and problem-solving.

The *abstraction* component showed the greatest improvement, namely 5.30 points. This improvement was reflected in children's ability to select appropriate tools, disregard irrelevant objects, identify the main rules, and explain the essence of the activity. In particular, the ability to determine the main rule increased by 1.50 points, from 2.20 to 3.70. This was the largest increase among the 16 observed behaviors. The finding indicates that the game environment provided children with opportunities to filter information and focus their attention on elements directly related to the objective of the activity.

At the early childhood level, *abstraction* does not need to be understood as the ability to produce formal representations. Rather, it can be observed through simple actions such as selecting necessary objects, disregarding unrelated objects, identifying rules that need to be followed, and explaining the essence of an activity. In this study, children encountered various objects, rules, and choices during play. These conditions required them to determine which information was necessary and disregard information that did not contribute to task completion. This process represents an early form of abstraction that is consistent with children's developmental characteristics.

This finding strengthens the results reported by Pellas (2025), who showed that concrete tool-based activities can support the development of abstract thinking abilities in young children. The present study extends this finding by demonstrating that concrete experiences for developing abstraction do not necessarily have to come from programming tools. Traditional games can also provide situations requiring children to select information, determine rules, and explain the essence of an activity. Thus, abstraction can be developed through simple play experiences when teachers design activities with clear cognitive objectives.

Algorithmic thinking increased by 4.10 points. This change indicates that children became increasingly capable of organizing steps, following sequences, checking for errors, and modifying their actions. In this study, algorithmic abilities were not developed through formal coding activities but through game procedures. Children needed to determine the first action, proceed to subsequent actions, and achieve the objective of the game through a particular sequence of actions.

These activities provided experiences with a structure similar to algorithmic processes. Children did not simply perform actions but needed to understand the relationship between one action and the next. When the sequence they followed resulted in an error, they had opportunities to review the steps they had taken and revise them. This process provided an initial experience of *testing* and *debugging*. Thus, errors in the game became part of the learning process rather than merely outcomes to be avoided.

This finding is important because it demonstrates that algorithmic abilities can be introduced to young children without using programming languages. Pellas (2025) demonstrated that concrete programming tools can support the development of algorithmic abilities in young children. Meanwhile, Fitriyah et al. (2026) showed that *unplugged coding* games can provide a context in which *computational thinking* behaviors emerge in early childhood. The present study extends these findings by demonstrating that traditional games can also function as an *unplugged* environment for developing algorithmic abilities when the structure of the game is systematically mapped onto *computational thinking* indicators.

The improvement across the 16 behaviors further strengthens these findings. The mean score across all behaviors increased from 2.29 at *pretest* to 3.39 at *posttest*, representing an increase of 1.10 points. All indicators improved, although the magnitude of improvement varied. The ability to determine the main rule showed the greatest improvement, namely 1.50 points. In contrast, the abilities to group objects based on patterns and execute steps sequentially showed the smallest improvements, each increasing by 0.90 points.

These differences indicate that the development of *computational thinking* in young children occurs progressively and is not uniform across behaviors. Behaviors related to information selection and rule identification appeared to respond more strongly to game-based experiences than behaviors requiring consistency in executing sequences. Children may understand rules relatively quickly because the rules are presented concretely within the game. In contrast, executing a sequence consistently requires coordination among comprehension, memory, attention, and action. Therefore, such behaviors may require more frequent practice and repeated opportunities.

The findings also demonstrate the importance of using behavioral indicators when assessing *computational thinking* in early childhood. Total scores can provide an overall picture of changes in ability, but behavioral-level analysis provides more specific information about which aspects have developed. In this study, analysis of the 16 behaviors enabled the researchers to identify that the greatest improvement occurred in determining the main rule, whereas relatively smaller improvements occurred in grouping objects based on patterns and executing steps sequentially. Such information can be used by teachers to determine more appropriate forms of *scaffolding* in subsequent learning activities.

The effectiveness of the intervention was also closely related to the characteristics of *Center-Based Learning*. The center-based environment provided opportunities for children to learn through activities that they actively engaged in. Children were given space to explore materials, interact with peers, try strategies, and solve problems. In this study, the learning stages—including play-environment preparation, pre-play guidance, core activities, during-play guidance, *recalling*, and closing activities—provided a sufficiently clear structure without eliminating opportunities for exploration.

The teacher's role was particularly important because center-based learning does not mean that teachers completely withdraw while children engage independently. Teachers continued to provide support through questions, prompts, reinforcement, and *scaffolding*. From a Vygotskian perspective, such assistance enables children to perform tasks within their *Zone of Proximal Development*. Gradual support allows children to move from dependence on assistance toward greater independence. In this study, *scaffolding* helped children understand rules, determine steps, select tools, and correct errors without taking over the problem-solving process.

This process helps explain why game-based activities can serve as an effective environment for developing *computational thinking*. When children encountered a problem, teachers did not immediately provide the solution. Instead, teachers directed children's attention through questions that encouraged them to think. When a child selected an incorrect sequence, for example, the teacher could ask the child to recall the previous step and consider which step should come next. Such interactions helped children develop problem-solving strategies through direct experience.

The traditional game context provided an additional dimension that is not always present in specially designed *computational thinking* media. Traditional games are part of children's cultural experiences and social lives. Children interact not only with objects and rules but also with peers, teachers, and their social environment. Therefore, *Mpa'a Ncimi Lombo Tembe* can be positioned as a form of *culturally situated learning* because the thinking processes occur within a cultural context that is familiar to children.

This approach is relevant to the sociocultural perspective, which views children's cognitive development as occurring through social interaction and the use of cultural tools. In this study, the traditional game functioned as a cultural artifact that simultaneously served as a learning resource. Children used their existing knowledge of the game as a foundation for developing more complex thinking abilities. Thus, the cultural context did not merely serve as the background of the learning activity but became an integral part of the cognitive development process.

The use of a traditional game also distinguishes this study from some previous *computational thinking* studies in early childhood that have used board games, robotics, *tangible* tools, or *unplugged* activities specifically designed for computational purposes. Garcia-Marques et al. (2026), for example, compared *plugged* and *unplugged* approaches to developing *computational thinking* in early childhood. Their findings indicate the important role of *unplugged* approaches in CT development. Fitriyah et al. (2026) likewise demonstrated that *unplugged* game activities can elicit CT behaviors among young children in the Indonesian context.

The present study extends this approach by integrating *unplugged learning* with local culture. *Mpa'a Ncimi Lombo Tembe* was not merely used to make learning more engaging but was pedagogically reconstructed based on the cognitive structures embedded in the game. Rules, sequences, patterns, tool selection, activity distribution, and opportunities for errors were mapped onto the four components of *computational thinking*. This process produced a learning experience that connected cultural experiences with cognitive development objectives.

From this perspective, traditional games can be understood as a *culturally situated unplugged computational thinking* environment. Such an environment has three main characteristics. First, the activities take place without dependence on digital devices. Second, the activities have a cultural context that is closely connected to children's experiences. Third, the structure of the game is intentionally directed toward eliciting *computational thinking* behaviors. These three characteristics position traditional games not merely as learning media but as sources of cognitive experiences that can be systematically developed.

The effectiveness of the approach was further supported by the high implementation rate of *Center-Based Learning*, which reached a mean of 95.00%. The high implementation rate indicates that the learning stages could be implemented in accordance with the planned design. Consistency in implementation is important because changes in children's abilities need to be associated with the learning experiences received by the experimental group. Thus, the high level of implementation provides a stronger basis for relating the improvement in *computational thinking* to the intervention provided.

The control group also demonstrated an improvement in *computational thinking*, namely 11.10 points. This finding indicates that routine learning activities can still provide experiences that support children's development. However, the improvement of 17.60 points in the experimental group indicates that learning activities specifically designed to elicit *decomposition, pattern recognition, abstraction,* and *algorithmic thinking* provided more intensive experiences. Therefore, the findings do not suggest that routine learning is ineffective; rather, they indicate the added value of deliberately designing play-based activities with explicit *computational thinking* development objectives.

The ANCOVA results further support this interpretation. After initial ability was statistically controlled, the difference between the groups remained significant. This finding indicates that the difference in final outcomes was not solely attributable to differences in initial ability. However, this interpretation should be considered within the limitations of the research design. The relatively small sample size and the use of pre-existing groups limit the generalizability of the findings. Therefore, further studies involving larger samples, more diverse settings, and longer intervention periods are needed to examine the consistency of these findings.

The Cohen's d value of 2.61 indicates a very large effect size. In practical terms, this result suggests that *Center-Based Learning* based on a traditional game has strong potential to enhance *computational thinking*. Nevertheless, a very large effect size obtained from a small sample should be interpreted cautiously. The value indicates the magnitude of the difference within the study sample but should not be interpreted as evidence that the same effect magnitude will necessarily occur in a broader population.

Overall, the findings indicate that the development of *computational thinking* in early childhood can occur through the integration of play, concrete experiences, cultural contexts, *scaffolding*, and reflection. The *Mpa'a Ncimi Lombo Tembe* game provided the activity context and rules; *Center-Based Learning* provided an exploratory environment; teachers provided *scaffolding* according to children's needs; children were given opportunities to experiment and revise their strategies; and *recalling* provided space to reflect on their experiences. These interactions created a learning environment that enabled the four components of *computational thinking* to develop in an integrated manner.

The contribution of this study lies not only in providing evidence that traditional games can be used as learning media but also in explaining the pedagogical mechanism linking the structure of the game with the development of *computational thinking*. The study demonstrates that traditional games can be reconstructed into systematic learning environments when their characteristics are explicitly mapped onto the cognitive indicators to be developed. This approach expands the use of traditional games from recreational and cultural preservation functions toward a pedagogical function that supports children's cognitive development.

Thus, *Center-Based Learning* based on *Mpa'a Ncimi Lombo Tembe* can be viewed as an approach that integrates play-based learning, *unplugged learning*, culturally contextualized learning, and *computational thinking* development. Improvements across all components and 16 observable behaviors provide evidence that systematically designed play experiences can help children develop the abilities to decompose problems, recognize patterns, select relevant information, organize steps, and correct errors. These findings further emphasize that the development of 21st-century competencies in early childhood education does not require the removal of local cultural contexts. Rather, local culture can serve as an authentic source of learning experiences for developing children's thinking abilities in systematic, concrete, and meaningful ways.

CONCLUSION

Based on the research findings and discussion, it can be concluded that the implementation of *Center-Based Learning* based on the traditional game *Mpa'a Ncimi Lombo Tembe* contributes positively to the development of *Computational Thinking* among children aged 4–6 years. The implementation of learning through the Culture and Exploration Center, integrating active play, exploration, *scaffolding*, and *recalling*, provides learning experiences that enable children to develop their thinking skills in concrete and contextually meaningful ways. Empirically, the experimental group showed an increase in the mean *Computational Thinking* score from 36.70 to 54.30, whereas the control group increased from 31.70 to 42.80. This difference in improvement was statistically significant ($t(18) = 5.845$; $p < 0.001$), with a very large effect size (Cohen's $d = 2.61$). After controlling for initial ability through ANCOVA, the effect of group membership on the *posttest* scores remained statistically significant ($p < 0.001$). Improvements were also observed across all four *Computational Thinking* components, namely *decomposition, pattern recognition, abstraction*, and *algorithmic thinking*, with the greatest improvement occurring in *abstraction*. At the behavioral level, all 16 indicators demonstrated improvement, indicating that the changes were not limited to overall scores but were also reflected in children's observable behaviors when breaking tasks into smaller parts, recognizing patterns, selecting relevant information, sequencing actions, identifying errors, and improving strategies. These findings demonstrate that traditional games can be reconstructed as a contextual *unplugged computational thinking* environment when the structure of the game is systematically integrated with the learning objectives and indicators of children's cognitive development. Based on these findings, early childhood teachers are encouraged to develop *Computational Thinking* activities through concrete, active, and culturally relevant games while providing gradual *scaffolding* that allows children to try different approaches, make decisions, identify errors, and independently improve their strategies. Early childhood education institutions can incorporate traditional games into center-based learning innovations by mapping game rules, patterns, sequences, tools, and activities onto *Computational Thinking* developmental indicators. Curriculum developers and education administrators are also encouraged to consider a *culturally situated unplugged learning* approach as an alternative for developing children's thinking skills without relying on digital devices. For future researchers, the study can be extended by involving larger numbers of participants, more diverse research settings, and longer intervention periods to examine the consistency of the approach's effectiveness and strengthen the generalizability of the findings. Further research may also develop more comprehensive observational instruments to identify the development of individual *Computational Thinking* behaviors and investigate the sustainability and transfer of these skills across different learning contexts.

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