



Analysis And Comparison of Computational Thinking Skills of Elementary School Students in Science Learning on Ecosystem and Food Chain Materials in Public and Private Schools

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Article Info	Abstract
Keywords: <i>computational thinking; science learning; ecosystems; food chain; primary schools; public and private schools</i> Received: 12/06/2026 Revised: 19/08/2026 Accepted: 04/09/2026	Background: Computational thinking (CT) has become an essential competency in twenty-first-century education and is increasingly integrated into elementary science learning. Ecosystem and food chain topics provide opportunities for students to analyze relationships, identify patterns, and apply systematic reasoning. However, comparative studies examining computational thinking among public and private elementary school students within science learning contexts remain limited. Methods: This study employed a quantitative comparative design involving 29 fifth-grade students from one public elementary school and one private elementary school in Purwakarta, Indonesia. Data were collected using Data were collected using an eight-item open-ended test selected from an initial pool of 16 items through expert validation and empirical testing designed to assess four dimensions of computational thinking: decomposition, pattern recognition, abstraction, and algorithmic thinking. Descriptive statistics and the Mann–Whitney U test were used to analyze the data. Results: The findings revealed that private school students achieved higher computational thinking scores than public school students. Among the four dimensions, abstraction showed the highest level of achievement, whereas algorithmic thinking demonstrated the lowest performance. Statistical analysis indicated a significant difference in computational thinking skills between the two groups ($p = 0.008$), suggesting that differences in learning experiences may be associated with differences in computational thinking development. Conclusion: The study highlights the potential of ecosystem and food chain learning as a meaningful context for fostering computational thinking in elementary science education. The findings also emphasize the importance of providing structured learning experiences, including problem-solving and coding-related activities, to support the development of computational thinking skills among elementary school students.

INTRODUCTION

Rapid technological advancement has transformed many aspects of modern society, including education. As digital technologies become increasingly integrated into everyday life, schools are expected not only to deliver subject knowledge but also to equip students with competencies required for the twenty-first century. These competencies include critical thinking, creativity, collaboration, communication, and problem-solving skills that enable learners to adapt to complex and dynamic environments (Li et al., 2020; Voogt et al., 2015). In increasingly technology-driven learning environments, these competencies are complemented by digital literacy and computational thinking, which help students understand and respond to complex problems systematically (Kong & Abelson, 2019). Therefore, educational practices should provide learning experiences that integrate digital literacy and computational thinking while fostering higher-order thinking and systematic problem-solving.

Among the various competencies emphasized in contemporary education, computational thinking (CT) has gained substantial attention from researchers and practitioners. Wing (2006) defines computational thinking as a systematic methodology for unpacking complex problems and structuring resolutions that are interpretable by both individuals and technological systems. While initially rooted in informatics, this approach has evolved into a versatile cognitive framework utilized across various academic fields, notably scientific and mathematical studies (Grover & Pea, 2013). Previous studies indicate that computational thinking contributes to the development of logical reasoning, analytical thinking, and structured approaches to problem-solving (Sengupta et al., 2018; Shute et al., 2017). Therefore, CT is increasingly recognized as a foundational competency that supports students' ability to deal with complex situations and make informed decisions.

The computational thinking framework is commonly described through four interconnected components: decomposition, pattern recognition, abstraction, and algorithmic thinking (Brennan & Resnick, 2012). The core of this cognitive framework relies on four pillars: breaking down intricate issues into digestible segments (decomposition), discerning trends or commonalities within data (pattern recognition), isolating pivotal information while filtering out peripheral noise (abstraction), and designing a step-by-step logical pathway to arrive at a solution (algorithmic thinking) (Korkmaz et al., 2017; Shute et al., 2017). Together, these components provide a useful framework for examining how students approach and resolve challenges in different learning contexts.

The development of computational thinking is frequently associated with coding and programming activities. Papert (1980) argued that programming environments allow learners to construct knowledge actively while strengthening logical and abstract reasoning skills. Likewise, visual programming platforms such as Scratch provide opportunities for students to explore ideas creatively while practicing structured problem-solving processes (Resnick et al., 2009). Numerous studies have reported positive relationships between coding experiences and the growth of computational thinking competencies, particularly in areas related to logical reasoning and algorithmic processes (Kalelioglu et al., 2016). At the elementary school level, integration of educational technologies, hands-on science activities, and robotics-based learning can further enrich students' learning experiences and support the development of confidence in problem-solving situations (Nuraeni et al., 2026). These findings suggest that meaningful engagement with coding-related activities can contribute to students' long-term cognitive development.

Introducing computational thinking during primary education is considered particularly important because this stage provides an early opportunity to develop fundamental reasoning and problem-solving abilities (Grover & Pea, 2013; Ocampo et al., 2024; Román-González, 2015). Students begin forming habits of logical inquiry and structured thinking that influence later

learning experiences (Román-González, 2015). Existing research indicates that the growth of computational thinking is shaped by multiple factors, including instructional strategies, learning environments, and opportunities to engage in meaningful problem-solving activities (Ocampo et al., 2024). Supportive school environments and learning cultures also play an important role in nurturing students' readiness to engage in higher-order thinking processes (Fajrussalam et al., 2025). Furthermore, experiences involving coding and inquiry-based learning have been shown to strengthen students' abilities to reason systematically and develop procedural solutions to problems (Grover & Pea, 2013). Recent studies within STEM education similarly demonstrate that authentic, real-world investigations can promote computational thinking by encouraging students to analyze situations and generate evidence-based solutions (Cantlon et al., 2024).

Science learning provides a particularly suitable context for fostering computational thinking because both domains emphasize investigation, analysis, modeling, and systematic reasoning. Scientific inquiry often requires learners to identify relationships among variables, interpret patterns, and explain complex phenomena through logical reasoning. For this reason, integrating computational thinking into science instruction has been reported to support students' understanding of scientific concepts and improve their ability to approach problems in a structured manner (Tang et al., 2020). Previous studies have also highlighted the positive influence of computational thinking integration on students' analytical abilities, conceptual understanding, and problem-solving performance within science education (Tikva & Tambouris, 2021). These findings indicate that science classrooms offer valuable opportunities for both developing and assessing computational thinking skills.

Dynamic topics in primary science education, such as food webs and ecological balance, offer fertile ground for embedding computational thinking practices. Because these subjects depict networks of living things engaging with their surroundings, understanding them requires children to trace natural trends, synthesize multi-layered dynamics, and model how systemic adjustments unfold over time (Hmelo-Silver et al., 2007; Ogegbo & Ramnarain, 2022). The complexity of these concepts makes them suitable contexts for evaluating how students employ decomposition, abstraction, pattern recognition, and algorithmic thinking when solving scientific problems. Consequently, ecosystem and food chain materials can serve as meaningful contexts for investigating computational thinking among elementary school learners.

Although interest in computational thinking research has expanded considerably, a large proportion of existing studies focus on programming instruction or involve participants from secondary and higher education settings (Tang et al., 2020). Research examining computational thinking among elementary school students, particularly within science learning contexts, remains comparatively limited (Ocampo et al., 2024). Furthermore, studies comparing computational thinking performance between public and private elementary school students are still scarce, especially when linked to ecosystem and food chain learning. This gap indicates the need for further investigation to better understand how computational thinking develops in different educational settings at the primary level.

In the Indonesian elementary education context, comparing public and private schools is important because these schools may differ in learning resources, technology integration, and opportunities for innovation-oriented learning. However, differences in computational thinking between school types should not be interpreted as being caused solely by school status, because factors such as school accreditation, facilities and infrastructure, curriculum implementation, and instructional practices may also influence students' learning experiences. Therefore, the present study focuses on comparing students' computational thinking performance across the two school contexts without attributing the observed differences to a single institutional factor. Such differences can influence students' opportunities to engage in problem-solving and computational

thinking activities (Organisation for Economic Co-operation and Development, 2019). Previous studies have also shown that learning environments, instructional experiences, and opportunities for exploration contribute to the development of computational thinking skills (Gong et al., 2020; Iwata et al., 2020). Moreover, the Merdeka Curriculum emphasizes digital literacy, problem-solving, and computational thinking as important competencies for elementary students (Kementerian Pendidikan, Kebudayaan, Riset, dan Teknologi, 2022). However, schools may vary in their capacity to implement these competencies effectively. Therefore, investigating computational thinking across public and private elementary schools is necessary to provide empirical evidence regarding how different educational contexts may support the development of computational thinking in science learning.

Disparities in institutional structures between state-run and independent institutions frequently shape pedagogical delivery and student cognitive growth. Extant literature indicates that non-government institutions often enjoy wider autonomy to pilot novel educational methodologies, whereas state schools generally adhere to more rigid regulatory and bureaucratic standards (Shavit et al., 2007). Variations in school resources, classroom environments, teacher-student interactions, and educational support systems can also affect students' academic development (Organisation for Economic Co-operation and Development, 2019). Several studies have reported that these contextual factors contribute to differences in cognitive outcomes, including problem-solving and critical thinking abilities (Hanushek & Woessmann, 2011). Research specifically related to computational thinking has similarly emphasized the importance of learning environments, instructional experiences, and opportunities for exploration in shaping students' CT development (Gong et al., 2020; Gonzalez-Pizarro et al., 2024; Iwata et al., 2020).

In Indonesia, differences in the implementation of technology-supported learning and innovation-oriented programs may create varied learning experiences for elementary school students. As schools adopt the Merdeka Curriculum, opportunities to develop digital literacy, problem-solving, and computational thinking may not be equally available across educational settings (Kementerian Pendidikan, Kebudayaan, Riset, dan Teknologi, 2022). These differences raise important questions regarding how computational thinking develops in different school contexts and whether students from public and private elementary schools demonstrate different levels of computational thinking in science learning. Therefore, this study aims to analyze and compare the computational thinking skills of public and private elementary school students in science learning on ecosystem and food chain materials.

METHODS

Using a quantitative comparative approach, this investigation examines differences in computational thinking (CT) proficiencies among learners in state and independent primary institutions. As outlined by Creswell & Creswell (2018), this framework is appropriate for identifying differences between groups on the variables being studied. This study was conducted from April to May 2026 in two elementary schools located in Purwakarta Regency, West Java, Indonesia. The participants were 29 fifth-grade students: 14 from a public elementary school and 15 from a private elementary school. The researchers used purposive sampling because the selected schools had implemented science instruction on ecosystem and food chain materials and provided students with introductory coding-related activities. The selected schools were comparable in grade level and geographical context, and the selection process identified no special learning programs specifically targeting computational thinking. These criteria were intended to support the comparability of the two groups and minimize the influence of external variables.

The research instrument is designed as an open-ended test to evaluate computational thinking through essay prompts. Essay questions were chosen because they are better suited to measuring students' computational thinking skills in depth, particularly logical reasoning, problem-solving, and other cognitive processes (Hikmawan et al., 2019). The foundational framework of this tool integrates four main aspects of computational thinking, namely decomposition, pattern recognition, abstraction, and algorithmic thinking (Brennan & Resnick, 2012; Shute et al., 2017), as well as incorporating the concept of computational thinking put forward by Wing (2006). The instrument also adapts the Computational Thinking Test for Elementary School Students (CTT-ES) created by Tsai et al. (2022), modified to suit the context of ecosystem and food chain materials in elementary school science learning. The initial instrument consisted of 16 contextual essay questions designed to measure students' ability to solve problems arising from real-world situations. Before being used in the main study, the instrument underwent validation by three experts (expert judgment): science subject-matter experts, computational thinking experts, and linguists. Validation by subject matter experts aims to ensure the suitability of questions with the concept of ecosystems and food chains; validation by computational thinking experts aims to ensure the representation of CT indicators in each question item, while validation by linguists aims to ensure clarity, readability, and language suitability that matches the demographic and developmental progress of young learners.

After completing the expert validation stage, the instrument was tested with 28 elementary school students who had characteristics similar to those of the research subjects. The trial was conducted to evaluate the instrument's empirical validity, reliability, discriminating power, and difficulty level. The initial instrument consisted of 16 questions. One item was excluded from the empirical validity analysis because all students answered it correctly, resulting in no variation in scores and preventing further validity analysis of the item. Thus, 15 items were analyzed for empirical validity, of which nine met the validity criteria. From these valid items, eight were subsequently selected for the main study by considering the representation of all four computational thinking aspects: decomposition, pattern recognition, abstraction, and algorithmic thinking. The blueprint of the instruments used in the main study is presented in Table 1.

Table 1. Blueprint of Computational Thinking Instruments

Aspects of CT	Operational Indicators	Question Number	Cognitive Level
Decomposition	Identify components in a system	1, 2	C4
Pattern Recognition	Finding a relationship or similarity	3, 4	C4
Abstraction	Summing up the core of the problem	5, 6	C4, C5
Algorithmic Thinking	Constructing a sequence of steps/solution logic	7, 8	C6, C4

Each aspect is represented by two items, ensuring a balanced proportion in measuring students' computational thinking skills. After the validity test and the selection of question items for the research, the instrument's reliability was assessed using the split-half technique to determine its consistency. The reliability coefficient of 0.78 was obtained from the 15 items analyzed during the pilot testing stage, before the final selection of eight items for the main study. The results of the instrument reliability test are presented in Table 2.

Table 2. Instrument Reliability Test Results

Aspects	Results
Number of respondents	28 students
Number of questions analyzed	15 questions
Reliability coefficient	0,78
Category	Reliable

Based on the reliability test results, the instrument had a reliability coefficient of 0.78, indicating it is reliable and suitable for use in the main study. Data collection was conducted by administering computational thinking tests to two groups of students: public and private elementary school students. The test was carried out under relatively the same controlled conditions to maintain consistency in the research procedure and minimize potential bias. In addition, brief informal interviews were conducted with the science teachers in both schools to obtain contextual information regarding coding-related learning activities. The interview data were used only to support the interpretation of the findings and were not analyzed as primary qualitative data.

The research data were analyzed using descriptive and inferential statistics. Descriptive statistics were used to characterize students' computational thinking abilities, including mean scores, standard deviations, minimum and maximum scores, both overall and for each aspect of computational thinking. Before the hypothesis test was conducted, the data were tested for normality using the Shapiro–Wilk test. The public school group did not meet the assumption of normality ($p < 0.05$), whereas the private school group met the assumption of normality ($p > 0.05$). Because one of the groups was not normally distributed, differences in computational thinking scores between the two groups were analyzed using the nonparametric Mann–Whitney U test at a significance level of 0.05. Instrument validity and reliability were assessed using the Anates version 4 application, while statistical analysis was conducted using IBM SPSS Statistics version 21.

RESULT AND DISCUSSION

Descriptive analysis was conducted to characterize elementary school students' computational thinking abilities in relation to ecosystem materials and food chains. The analysis showed that the computational thinking ability of private school students tended to be higher than that of public school students.

Table 3. Descriptive Statistics of Computational Thinking Ability

Type of School	N	Mean	Standard Deviation	Minimum	Maximum
Public Schools	14	23,21	3,886	19	32
Private Schools	15	26,67	3,519	21	32

Based on Table 3, private school students obtained an average computational thinking score of 26.67, while public school students obtained an average of 23.21. The findings indicate that private school students tend to have higher computational thinking ability than public school students. In addition, the maximum score in both groups was 32, while the minimum score for public school students was lower than that for private school students. The lower standard deviation in the private school group indicates less variation in computational thinking scores compared with the public school group.

To obtain a deeper picture of students' computational thinking abilities, an analysis was also carried out across all aspects of computational thinking, including decomposition, pattern

recognition, abstraction, and algorithmic thinking. The results of descriptive analysis are generally presented in Table 4.

Table 4. General Profile of Computational Thinking Ability by Aspect

Aspect of Computational Thinking	Mean	Standard Deviation
Decomposition	6,07	1,811
Pattern Recognition	6,17	2,172
Abstraction	6,62	1,347
Algorithmic Thinking	6,00	1,832

Based on Table 4, the abstraction aspect obtained the highest average score of 6.62. These results show that students are relatively able to simplify information and focus attention on important elements in ecosystem and food chain problems. In addition, the standard deviation score for the abstraction aspect is the lowest among the aspects, indicating that students' abilities in this aspect are relatively more even.

Meanwhile, the algorithmic thinking aspect obtained the lowest average score of 6.00. These results show that students still have difficulty in formulating problem-solving steps systematically and logically. In addition, the pattern recognition aspect has the highest standard deviation (2.172), indicating a fairly high variation in students' ability to recognize patterns and relationships among components within an ecological system. Further analysis was conducted to determine the profile of computational thinking ability by school type for each aspect. The results of the analysis are presented in Table 5.

Table 5. Profile of Computational Thinking Ability Based on Aspects and Type of School

Aspect of Computational Thinking	Mean Public Schools	Mean Private Schools
Decomposition	6,00	6,13
Pattern Recognition	5,36	6,93
Abstraction	6,50	6,73
Algorithmic Thinking	5,29	6,67

Based on Table 5, private school students showed higher average scores than public school students in all aspects of computational thinking. The largest differences were observed in pattern recognition and algorithmic thinking. In pattern recognition, private school students obtained an average score of 6.93, while public school students obtained an average of 5.36. These results show that private school students tend to be better at recognizing patterns of relationships among components in ecosystem materials and food chains.

In algorithmic thinking, private school students obtained an average score of 6.67, while public school students obtained an average of 5.29. These results show that private school students are more able to formulate problem-solving steps systematically and logically than public school students. Meanwhile, the smallest average differences were found in the aspects of decomposition and abstraction. In both aspects, students from both types of schools show relatively similar abilities in breaking down problems into simpler parts and simplifying information based on relevant elements.

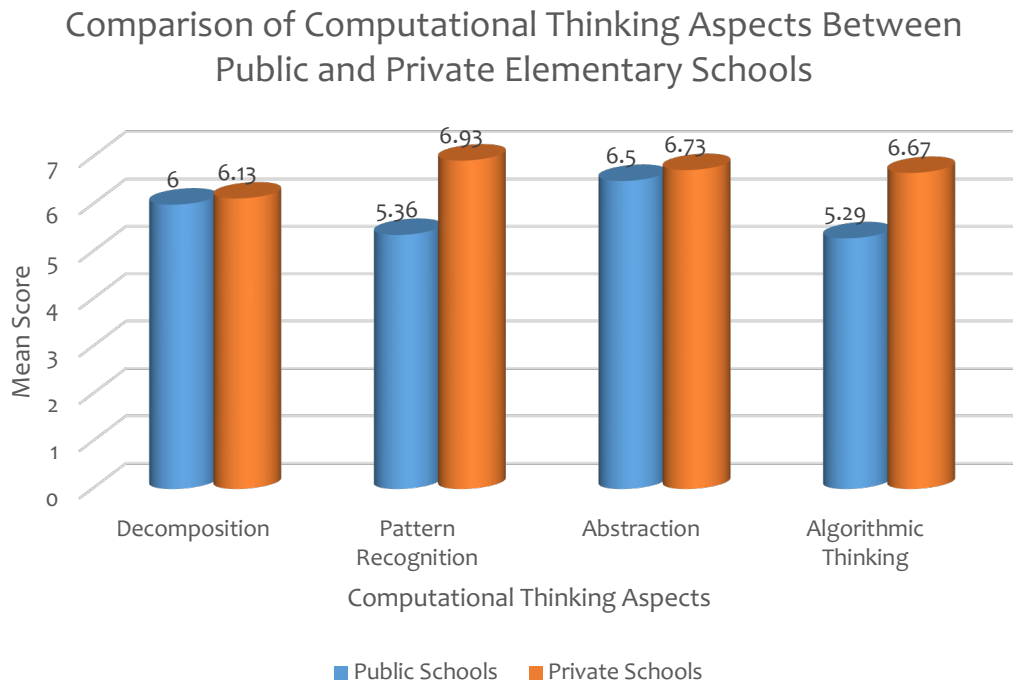


Figure 1. Comparison of Aspect-Based Computational Thinking Abilities in Public and Private School Students

Based on Figure 1, private school students achieve higher average scores than public school students across all aspects of computational thinking. The most prominent differences are evident in pattern recognition and algorithmic thinking. Meanwhile, in decomposition and abstraction, the two groups showed relatively small differences. This visualization makes it clear that the differences in computational thinking ability between groups do not occur equally in all aspects. Before testing for differences in computational thinking ability, the data were assessed for normality using the Shapiro–Wilk test. The results of the normality test are presented in Table 6.

Table 6. Data Normality Test Results

Type of School	Statistics	Shapiro–Wilk	Sig.	Remarks
Public Schools	0,817		0,008	Not Normal
Private Schools	0,944		0,434	Normal

Based on the results of the normality test in Table 6, the data in the public school group have a significance value of 0.008 (< 0.05), indicating that the data are not normally distributed. Meanwhile, the data for the private school group have a significance value of 0.434 (> 0.05), indicating the data are normally distributed. Because one of the data groups did not meet the assumption of normality, the hypothesis test was carried out using the Mann–Whitney U nonparametric test.

Table 7. Mann–Whitney U Test Results

Aspects	Value
Mann–Whitney U	45,000
Z	-2,633
Asymp. Sig. (2-tailed)	0,008

The results of the Mann–Whitney U test in Table 7 show a significance value of 0.008. The value is less than 0.05, indicating a significant difference in computational thinking skills between

public and private elementary school students on ecosystem materials and food chains. These results indicate a significant difference in computational thinking scores between the two school groups in science learning, although the present study does not establish that school type itself caused the difference. In addition to statistical significance, effect size calculations were conducted to assess the magnitude of the difference between the two groups. Based on the Z-value of -2.633 and a total sample size of 29 students, the effect size (r) was 0.49 , indicating a medium-to-large effect and suggesting that the observed difference has practical relevance.

The findings indicate that elementary school students demonstrated a relatively good level of computational thinking in learning about ecosystems and food chains, although differences were observed across the four computational thinking aspects. Among these aspects, abstraction achieved the highest mean score. This result suggests that students were generally capable of identifying essential information and concentrating on the most relevant elements when solving science-related problems. Within ecosystem and food chain topics, learners appeared able to distinguish key relationships among ecological components, including interactions between producers, consumers, and decomposers. These findings suggest that contextual science materials may help students simplify complex information and focus on meaningful concepts. This interpretation is consistent with previous studies that describe abstraction as the process of filtering unnecessary information and emphasizing critical elements to support problem-solving and conceptual understanding (Cantlon et al., 2024; Curi et al., 2025). Furthermore, ecosystem concepts are closely connected to students' everyday experiences, which may help them construct simplified representations of ecological systems and understand relationships among their components more effectively (Weintrop et al., 2016).

In contrast, algorithmic thinking obtained the lowest average score, particularly among students from public schools. This finding indicates that students experienced greater difficulty when required to develop logical and sequential procedures for solving problems. Within science learning, algorithmic thinking involves the ability to explain processes systematically, identify causal relationships, and organize problem-solving steps in a coherent sequence. The relatively lower performance in this aspect may reflect limited exposure to instructional activities specifically designed to strengthen procedural reasoning and structured problem-solving skills. Previous research has similarly identified algorithmic thinking as one of the most demanding dimensions of computational thinking because it requires learners to combine logical reasoning with the construction of systematic procedures (Shute et al., 2017). Moreover, Grover & Pea (2013) emphasized that the development of algorithmic thinking depends heavily on sustained opportunities to engage in problem-solving and coding-related experiences. Consequently, insufficient exposure to such activities may hinder students' progress in this area.

The four computational thinking aspects can be understood in relation to the characteristics of the ecosystem and food chain topic and the students' performance. Decomposition was assessed through students' ability to identify and separate the components of an ecosystem, such as producers, consumers, decomposers, and environmental factors. Pattern recognition was assessed through identifying relationships and recurring patterns among organisms within food chains. Abstraction involved identifying essential ecological relationships and distinguishing relevant information from less relevant details, while algorithmic thinking involved organizing ecological relationships and sequences, such as tracing the flow of energy through a food chain, in a logical and systematic manner. The mean scores indicate that abstraction was the strongest aspect (6.62), whereas algorithmic thinking was the lowest (6.00), suggesting that students performed relatively better when identifying essential information than when organizing solution procedures systematically.

A major finding of this study is the significant difference in computational thinking performance between public and private elementary school students. Students from private schools achieved higher overall computational thinking scores and outperformed public school students across all aspects of computational thinking. The largest differences were observed in

pattern recognition and algorithmic thinking, suggesting that private school students were generally more successful in identifying relationships among problem components and constructing structured solution procedures. Although both groups were introduced to coding-related activities, teacher interviews indicated that the two schools did not provide the same intensity of coding-related learning opportunities. However, this study did not systematically measure these differences through classroom observations or instructional documentation. Therefore, variations in coding-related learning experiences may explain for the observed differences, but this interpretation should be treated with caution. Previous studies have highlighted how educational environments and academic support systems influence students' cognitive development, including higher-order thinking and problem-solving abilities (Hanushek & Woessmann, 2011). Likewise, school policies and instructional practices can shape how much students are exposed to learning experiences that support the development of computational thinking (Shavit et al., 2007).

The findings may also be understood in relation to the role of unplugged coding activities. These activities introduce computational thinking concepts without requiring digital devices and instead engage students in instruction-based tasks, pattern identification, and step-by-step problem-solving exercises. Regular participation in such activities can help learners develop habits of logical reasoning and procedural thinking. In the private school context, teacher interviews suggested that unplugged coding activities were implemented more regularly, which may have provided students with more opportunities to organize instructions, analyze problems, and construct solutions systematically. Nevertheless, these differences were not systematically quantified in the present study. Previous studies have reported that coding-related learning experiences can support the development of logical, systematic, and structured thinking by encouraging students to formulate instructions and solve problems through sequential processes (Cantlon et al., 2024; Curi et al., 2025). Kalelioglu et al. (2016) further noted that programming activities are particularly effective for strengthening algorithmic thinking and problem-solving skills. Tikva & Tambouris (2021), reported similar conclusions, finding that programming and problem-solving activities positively contribute to the development of computational thinking competencies.

The most substantial differences between public and private school students were found in pattern recognition and algorithmic thinking. These aspects are closely associated with coding-related experiences because they require learners to identify recurring relationships, recognize structures within problems, and organize solution procedures systematically. Regular unplugged coding activities provide repeated opportunities to practice these cognitive processes. Consequently, the differences in reported coding-related learning experiences may be associated with the higher performance in pattern recognition and algorithmic thinking observed among private school students. However, this interpretation should be viewed cautiously because the present study did not systematically measure the intensity or quality of coding-related instruction.

More broadly, activities that require students to analyze problems, construct instructions, and complete tasks through sequential reasoning appear to support the development of logical and systematic thinking. Therefore, learning environments that intentionally incorporate such experiences may enhance computational thinking development. Nevertheless, previous studies indicate that coding experiences alone do not automatically improve every aspect of computational thinking. In their systematic review, Tang et al. (2020) concluded that multiple factors influence computational thinking outcomes, including instructional design, implementation duration, learner characteristics, and teaching strategies. Consequently, exposure to coding activities must be supported by well-structured and sustained learning experiences if meaningful improvements in computational thinking are expected. This perspective may help explain the variation in computational thinking performance observed among students in the present study.

The results also highlight the potential of ecosystem and food chain topics as contexts for developing computational thinking within science education. These topics require students to examine relationships among organisms, identify interaction patterns, analyze causal connections, and evaluate changes occurring within ecological systems. Such characteristics align closely with the principles of computational thinking, which emphasize analysis, modeling, and systematic problem-solving. According to Weintrop et al. (2016), science learning and computational thinking share similar cognitive processes, making science classrooms an appropriate setting for fostering computational thinking competencies. Therefore, integrating computational thinking into ecosystem and food chain instruction may provide meaningful opportunities for elementary school students to develop higher-order thinking skills while deepening their scientific understanding.

The educational implications of this study suggest that computational thinking should be integrated more intentionally into science learning through activities that promote pattern analysis, problem-solving, and structured reasoning. Teachers may consider incorporating coding-related experiences, project-based learning, and inquiry-oriented activities that encourage students to apply computational thinking principles in authentic contexts. Such approaches can provide learners with repeated opportunities to practice decomposition, abstraction, pattern recognition, and algorithmic thinking. In addition, the findings emphasize the importance of creating supportive learning environments that nurture higher-order thinking skills from an early stage of education.

This study contributes to the growing body of research on computational thinking in elementary education, particularly within the context of science learning involving ecosystem and food chain materials. Furthermore, it extends existing literature by comparing computational thinking performance between public and private elementary school students, an area that remains relatively underexplored. As a result, the study provides empirical evidence that may support future efforts to design instructional strategies aimed at strengthening computational thinking in primary education. Several limitations should be acknowledged. First, the study involved a relatively small sample drawn from only two schools, which restricts the generalizability of the findings. Second, the research did not examine in detail the intensity and quality of students' coding experiences, factors that may influence computational thinking development. Third, other potentially relevant variables, such as socioeconomic background, gender, and instructional practices, were not included in the analysis. Future studies should use larger, more diverse samples and consider additional contextual factors better to understand computational thinking development among elementary school students.

CONCLUSION

This research examined the computational thinking abilities of primary school pupils in the context of ecosystem and food chain learning and compared the performance of individuals attending state versus independent institutions. The findings revealed notable differences in analytical problem-solving capabilities across both categories, with private educational institutions showing better results than their public counterparts. The greatest disparities were observed in pattern recognition and algorithmic thinking, whereas abstraction emerged as the strongest computational thinking component among students from both school types. The results suggest that variations in learning experiences and educational environments may contribute to differences in computational thinking development. More specifically, opportunities to engage in coding-related and problem-solving activities may be associated with differences in computational thinking development, particularly in students' abilities to identify patterns and construct systematic solution procedures. These findings highlight the importance of providing consistent and meaningful learning experiences that foster higher-order thinking skills from the elementary school level. Furthermore, the study demonstrates that ecosystem and food chain topics offer

valuable opportunities for integrating computational thinking into science education. The interconnected nature of ecological systems encourages students to analyze relationships, recognize patterns, and apply systematic reasoning, making these topics suitable contexts for developing computational thinking competencies. Based on these findings, elementary school teachers are encouraged to incorporate learning activities that promote structured problem-solving, pattern analysis, and logical reasoning within science instruction. Particular attention should be given to strengthening algorithmic thinking through activities such as sequencing tasks, process mapping, visual coding, and inquiry-based problem-solving. Future research should involve larger and more diverse samples and examine additional factors that may influence computational thinking development, including coding experience, instructional practices, and student background characteristics. This study contributes to the field of elementary science education by providing empirical evidence that computational thinking can be meaningfully integrated and assessed through ecosystem and food chain learning. The findings also contribute to the growing discussion on computational thinking in Indonesian primary education by highlighting the importance of learning contexts and instructional experiences in supporting the development of computational thinking skills. In addition, the study offers practical implications for teachers and schools in designing science learning activities that promote pattern recognition, logical reasoning, and algorithmic thinking from an early stage of education. Future research is recommended to employ a more systematic design by involving larger and more diverse samples from multiple schools and regions. Subsequent studies may also combine quantitative measures of computational thinking with classroom observations, teacher interviews, and analyses of instructional practices to examine how learning experiences and curriculum implementation contribute to the development of computational thinking skills. Longitudinal studies are further needed to investigate the development of computational thinking over time in elementary science education.

DECLARATION OF GENERATIVE AI

During the preparation of this manuscript, the author used ChatGPT to assist with brainstorming ideas and improving the formulation and organization of sentences, and Grammarly Pro to assist with grammar, spelling, and language checking. These tools were used only to support the writing and language-editing process. After using these tools, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

CONFLICTING INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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