

Identification of Computational Thinking Patterns in Students' Mathematical Problem Solving: Empirical Evidence from Algebra Learning Activities

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Submitted: 17 November 2025; Revised: 25 February 2026; Accepted: 10 March 2026

ABSTRACT

Computational thinking (CT) is increasingly recognized as a core competency in STEM education, yet little empirical evidence exists on how CT patterns naturally emerge in algebraic reasoning outside programming contexts. This study investigates how secondary students demonstrate CT components during algebra problem-solving. A mixed-methods design was applied with 120 students completing algebra tasks. Data were collected through assessments, interviews, and classroom observations. The elements of CT, namely pattern recognition, decomposition, abstraction, and algorithmic reasoning, are systematically coded and analyzed using qualitative and quantitative approaches. Findings revealed that pattern recognition (80%) and decomposition (70%) were widely observed across achievement levels. In contrast, abstraction (45%) and algorithmic reasoning (35%) appeared more frequently among high-achieving students. Statistical analysis confirmed significant differences in CT sophistication across achievement groups, highlighting progression from basic recognition to advanced reasoning. The novelty of this study lies in its empirical demonstration of CT within algebraic problem-solving, independent of programming environments. Unlike prior research emphasizing coding, it shows how CT components naturally emerge in mathematics tasks. By analyzing achievement-level differences, it provides fresh evidence of developmental trajectories in CT. These results position algebra as a strategic entry point for CT development, bridging mathematical reasoning and computational approaches. They suggest that intentional pedagogical design can foster advanced CT skills in conventional classrooms, offering practical guidance for curriculum innovation in mathematics education.

Keywords: *Computational Thinking, Mathematical Problem Solving, Algebra Learning, Cognitive Patterns, STEM Education*

Identifikasi Pola Berpikir Komputasional dalam Pemecahan Masalah Matematika Siswa: Bukti Empiris dari Kegiatan Pembelajaran Aljabar

ABSTRAK

Pikiran komputasional (CT) semakin diakui sebagai kompetensi inti dalam pendidikan STEM, namun sedikit bukti empiris yang tersedia tentang bagaimana pola CT secara alami muncul dalam penalaran aljabar di luar konteks pemrograman. Studi ini menyelidiki bagaimana siswa sekolah menengah menunjukkan komponen CT selama pemecahan masalah aljabar. Desain campuran metode diterapkan dengan 120 siswa yang menyelesaikan tugas aljabar. Data dikumpulkan melalui penilaian, wawancara, dan pengamatan di kelas. Elemen-elemen CT, yaitu pengenalan pola, dekomposisi, abstraksi, dan penalaran algoritmik, secara sistematis dikodekan dan dianalisis menggunakan pendekatan kualitatif dan kuantitatif. Hasil penelitian menunjukkan bahwa pengenalan pola (80%) dan dekomposisi (70%) sering diamati di semua tingkat prestasi. Di sisi lain, abstraksi (45%) dan penalaran algoritmik (35%) lebih sering ditemukan di kalangan siswa berprestasi tinggi. Analisis statistik mengonfirmasi perbedaan signifikan dalam tingkat kematangan CT di antara kelompok prestasi, menyoroti perkembangan dari pengenalan dasar hingga penalaran tingkat lanjut. Keunikan studi ini terletak pada pembuktian empirisnya mengenai CT dalam pemecahan masalah aljabar, tanpa bergantung pada lingkungan pemrograman. Berbeda dengan penelitian sebelumnya yang menekankan pada pemrograman, studi ini menunjukkan bagaimana komponen CT secara alami muncul dalam tugas-tugas matematika. Dengan menganalisis perbedaan tingkat pencapaian, penelitian ini memberikan bukti baru mengenai jalur perkembangan dalam CT. Hasil ini menempatkan aljabar sebagai titik masuk strategis untuk pengembangan CT, menjembatani penalaran matematis dan pendekatan komputasional. Temuan ini menyarankan bahwa desain pedagogis yang terencana dapat mengembangkan keterampilan CT tingkat lanjut di kelas konvensional, memberikan panduan praktis untuk inovasi kurikulum dalam pendidikan matematika.

Kata Kunci: *Pemikiran Komputasional, Pemecahan Masalah Matematika, Pembelajaran Aljabar, Pola Kognitif, Pendidikan STEM*

How to cite: Firdaus, A.Q., Suryanti, S., Hadi, F.N. (2026). Identification of Computational Thinking Patterns in Students' Mathematical Problem Solving: Empirical Evidence from Algebra Learning Activities. *Jurnal Riset Pendidikan dan Inovasi Pembelajaran Matematika (JRPIPM)*, 10(1), 22-32. <https://doi.org/10.26740/jrpijm.v10n1.p22-32>

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1. Introduction

The integration of computational thinking (CT) into mathematics education has gained significant attention as one of the essential skills of the 21st century. CT involves systematic and precise steps to solve problems, applicable across fields, and can improve procedural knowledge (Nuzzaci, 2024). Recent literature has highlighted the potential of CT in strengthening students' mathematical reasoning and promoting cross-disciplinary problem-solving skills in the context of STEM learning.

A review by Chan et al. (2022) identified five main types of CT tools used in mathematics integration, showing that geometry and measurement are the most frequently assessed mathematical topics, while algorithm design, abstraction, and debugging are the most frequently evaluated CT competencies. Ye et al. (2023) found that CT-based mathematics learning involves an interactive process between mathematical and computational reasoning, which is often supported by programming activities and student-centred pedagogical

approaches. Their systematic review revealed that effective integration occurs when mathematics is applied to build CT artefacts and generate new mathematical knowledge.

Several studies have provided further evidence of the relationship between CT and mathematical learning. [Aminah et al. \(2022\)](#) demonstrated that prospective mathematics teachers who successfully solved linear Diophantine equations used CT components such as reflective abstraction, algorithmic thinking, decomposition, and evaluation. Similarly, [Wu and Yang \(2022\)](#) identified a reciprocal relationship between CT and mathematical thinking, noting that classroom tasks rarely incorporated creative or critical-thinking dimensions that are essential for authentic integration of the two domains.

Recent research has extended the scope of CT-mathematics integration across K-12 education, revealing diverse methodological approaches. For instance, [Utami et al. \(2023\)](#) explored secondary students' functional thinking in algebra and found that learners used two main pattern-generation approaches: a recursive approach, which focused on arithmetic computation from term to term, and a correspondence approach, which linked variables and created symbolic representations. Across contexts, [Sarmasági et al. \(2025\)](#) examined the relationship between algebraic and computational thinking in six countries, reporting that integrated learning pathways and unplugged activities effectively enhanced proficiency in both domains, although they required extended practice time.

Despite this growing body of work, empirical understanding of how CT actually manifests in students' mathematical problem-solving processes remains limited. Systematic reviews consistently reveal gaps between theoretical frameworks and classroom-based evidence. For example, [Ye et al. \(2023\)](#) highlight that much CT-infused mathematics research fails to explicitly articulate how CT supports mathematical reasoning, while [Chan et al. \(2022\)](#) note that most research emphasizes technology-intensive CT approaches that often focus on programming tools rather than the cognitive processes that occur during traditional problem-solving. Similarly, [Dahshan and Galanti \(2024\)](#) emphasized the scarcity of CT research in early-grade mathematics (K-2), where teachers often struggle to connect mathematical knowledge with emerging CT concepts such as decomposition and abstraction.

Collectively, these reviews indicate that while CT-mathematics integration has theoretical support, systematic classroom evidence remains scarce. Consequently, there is an urgent need to identify and analyze how CT patterns naturally occur during students' mathematical reasoning, particularly within algebra, a foundational domain in mathematics education associated with abstraction, generalization, and symbolic reasoning. For instance, [Azizah et al \(2025\)](#) stated that students with linguistic-verbal intelligence excelled in meeting the four indicators of computational thinking, although they needed reinforcement in algorithms, while students with logical-mathematical and visual-spatial intelligence achieved three and two indicators, respectively.

In addition to addressing this empirical gap, this study provides a unique perspective by placing CT in algebraic reasoning tasks in a non-programming classroom environment. Unlike many previous studies that rely heavily on technology-based interventions, this study shows how CT patterns emerge naturally through traditional mathematical problem solving. By focusing on algebra in areas central to abstraction, generalisation, and symbolic reasoning, this study highlights the cognitive mechanisms that enable students to transition from basic pattern recognition to higher-level processes such as abstraction and algorithmic thinking. This approach not only enriches the theoretical discourse on CT but also provides practical insights for educators seeking to develop CT skills in conventional mathematics teaching.

The novelty of this study lies in its empirical demonstration of computational thinking within algebraic problem-solving, independent of programming contexts. Unlike prior research that emphasizes coding environments, this study reveals how CT components naturally emerge in

traditional mathematics tasks. Furthermore, by analyzing achievement-level differences, it provides fresh evidence on how students progress from basic pattern recognition to abstraction and algorithmic reasoning. This perspective positions algebra as a strategic entry point for CT development, offering a bridge between mathematical reasoning and computational approaches.

Therefore, this study aims to bridge that empirical gap by investigating the manifestation of computational thinking patterns in students' algebra problem solving. By analyzing how students decompose problems, recognize patterns, abstract relationships, and apply algorithmic reasoning, this research seeks to provide deeper insights into the cognitive mechanisms that underlie effective mathematical problem solving. Moreover, understanding these patterns may inform the design of instructional scaffolds that deliberately cultivate CT within mathematics classrooms. This section presents the findings of the study according to the three formulated research questions: 1) How do students demonstrate computational thinking (CT) patterns during algebra problem solving? 2) How do CT patterns differ across students of varying achievement levels? and 3) How can the identification of CT patterns inform instructional strategies to improve mathematical reasoning and problem-solving skills?

2. Research Methodology

2.1 Research Design

This study employed a mixed-methods research design to examine computational thinking (CT) patterns demonstrated by students during algebraic problem-solving. The qualitative component involved in-depth content analysis of students' written solutions and recorded processes, using an analytical framework based on established CT constructs: decomposition, pattern recognition, abstraction, and algorithmic thinking. This approach aimed to trace students' cognitive strategies and reasoning patterns that signaled engagement in CT.

CT indicators were identified through a structured coding process. Two trained raters independently analyzed each response using a predefined coding scheme, and frequencies of coded indicators were calculated to transform qualitative findings into quantitative data. Inter-rater reliability was established using Cohen's kappa ($\kappa > 0.80$), indicating strong agreement. Any discrepancies were resolved through discussion until consensus was achieved.

The quantitative component employed descriptive statistics (frequencies and percentages) and inferential analyses to examine differences and relationships. One-way ANOVA with Tukey's HSD post-hoc tests was conducted to compare CT patterns across achievement groups (low, medium, high). Additionally, Pearson correlation and linear regression analyses were used to explore associations between CT components and problem-solving performance. This mixed-methods design enabled both in-depth exploration and statistical validation of CT patterns in authentic classroom contexts.

2.2 Research Context and Participants

The research was conducted in a junior high school setting where algebra represents a key component of the mathematics curriculum. The study site was selected for three primary reasons:

1. Diverse student population: Students represent a wide range of mathematics achievement levels, providing a rich context for exploring how CT manifests across different ability groups.

2. Sustainable curriculum reform: The school implemented curriculum initiatives that emphasized 21st-century competencies such as computational thinking and problem-solving, which aligned with the goals of CT integration.
3. Balanced teaching environment: Teachers used a combination of conventional and innovative pedagogical strategies, allowing the study to observe authentic problem-solving behaviors without a heavy technological bias.

A total of 120 students from grades 8 and 9 participated in the study. Participants were purposively selected to ensure equitable representation across low-, medium-, and high-achieving groups, based on previous math performance.

2.3 Data Collection Procedures

Data were collected through three main sources: students' written solutions, semi-structured interviews, and classroom observations.

1. Written Tasks: Students solved carefully designed algebra problems aligned with curriculum standards and intentionally structured to elicit different CT components.
2. Interviews: Semi-structured interviews were conducted with a subset of 20 students to explore their reasoning processes and clarify cognitive strategies underlying their written responses.
3. Observations: Classroom observations were carried out during problem-solving sessions to capture behavioral evidence of CT, such as collaboration, decomposition, and iterative reasoning.

For example, some tasks ask students to determine the n th term of the sequence 3, 7, 11, Students showing pattern recognition identified the constant difference of 4. Decomposition was evident when they broke the problem into smaller steps before generalizing. Abstraction appeared when they expressed the relationship symbolically as $a_n = 4n - 1$. Algorithmic thinking was demonstrated when students articulated a step-by-step procedure to verify the formula. All student work was anonymized and coded using a standardized CT framework. Inter-rater reliability was established through collaborative coding sessions among trained researchers.

2.4 Data Analysis

Data analysis followed a sequential explanatory approach consistent with mixed-methods research.

1. Qualitative Analysis: Written responses and interview transcripts were coded for instances of decomposition, pattern recognition, abstraction, and algorithmic thinking. Codes were validated through Cohen's Kappa reliability testing to ensure consistency among raters.
2. Quantitative Analysis: Descriptive statistics (frequency counts and percentages) were computed for each CT component. In addition, inferential statistical tests (correlation and regression analyses) were conducted to examine relationships between CT patterns and students' problem-solving performance.
3. Cross-case Analysis: Comparative analyses were conducted to explore variations in CT application across achievement levels. These analyses illuminated differences in cognitive engagement and reasoning depth among students.

2.5 Validity and Reliability

To ensure the validity and trustworthiness of findings:

1. Construct validity was achieved by grounding all coding categories in established CT theoretical models ([Wing, 2006](#); [Ngadengon et al 2024](#)).
2. Triangulation was implemented across data types (written tasks, interviews, observations).
3. Inter-rater reliability was established through independent coding by multiple researchers (Cohen’s Kappa > 0.80).
4. Member checking was performed by conducting follow-up interviews with selected participants to confirm the accuracy of interpretations.

This rigorous validation process ensured that the identified CT patterns authentically represented students’ cognitive behaviors during algebra problem solving.

3. Research Result

3.1 Manifestation of Computational Thinking Patterns

Analysis of 120 student papers, interviews, and classroom observations revealed clear evidence of four components of Computational Thinking (CT), namely pattern recognition, decomposition, abstraction, and algorithmic thinking, occurring at varying frequencies.

Tabel 1. Frequency of CT Patterns Observed in Student Algebra Problem Solving

CT Component	Frequency (<i>n</i> = 120)	Percentage (%)	Qualitative Description
Pattern Recognition	96	80.0	Identification of recurring structures and relationships between variables. Students recognized that the sequence of terms followed a constant difference and predicted the next term accordingly.
Decomposition	84	70.0	Breaking complex algebra problems into smaller, manageable sub-tasks. Learners separated multi-step algebra tasks into smaller goals (e.g., simplifying expressions before substitution).
Abstraction	54	45.0	Generalizing algebraic rules and simplifying equations symbolically. Students generalized variable relationships, forming algebraic rules such as $y = 2x + 3$.
Algorithmic Thinking	42	35.0	Constructing logical, step-by-step procedures to solve problems. Students articulated ordered procedures, including looping and conditional reasoning within symbolic manipulation.

These findings indicate that pattern recognition was the most prevalent CT process. Many students identified arithmetic or geometric regularities and used these to predict subsequent values or simplify equations. Multiple studies provide robust evidence supporting this claim. [Henin et al., \(2019\)](#) further revealed that the human brain can track regularities within minutes, with neural systems rapidly encoding sequential patterns across different brain areas.

Decomposition was the second most common process. Students often restructured complex problems into sequential sub-tasks an approach that allowed more efficient processing and reduced cognitive load. While [Charitsis et al., \(2022\)](#) note it is “essential to software development” yet “the most challenging programming skill for learners to master.” Empirical

research supports decomposition's cognitive benefits. [Ma et al., \(2025\)](#) found that personalized decomposition support significantly improved learning gains, cognitive engagement, and critical thinking.

Abstraction and algorithmic thinking were observed less frequently and required higher conceptual control. Students who demonstrated abstraction could symbolically represent patterns and ignore irrelevant details, while those showing algorithmic thinking planned logical solution pathways that could be systematically applied to similar tasks. These two higher-order CT elements appeared most often in responses from high-performing students, Confirming the findings of [Kulgemeyer et al., \(2021\)](#) that pre-existing reflection skills have a significant impact on the development of professional knowledge during practical experience, with reflection skills influencing the development of both content and pedagogical knowledge.

3.2 CT Patterns across Achievement Levels

Students were categorized into three performance groups (low, medium, and high) based on their previous mathematics achievement. A comparison of computational thinking (CT) manifestations across these groups is summarized in Table 2.

Table 2. CT Pattern Distribution by Achievement Level

CT Component	Low (%)	Medium (%)	High (%)
Pattern Recognition	65.0	80.0	95.0
Decomposition	52.0	70.0	85.0
Abstraction	18.0	30.0	62.0
Algorithmic Thinking	15.0	21.0	58.0

The comparison reveals a clear progression in CT sophistication across achievement levels. While all groups engaged in pattern recognition and decomposition, only high-achieving students frequently demonstrated abstraction and algorithmic thinking. The following is a report of inferential statistical results to support correlational conclusions.

Table 3. Inferential Statistical Results

CT Component	Correlation with Problem-Solving Success (r)	Significance (p -value)	Interpretation
Pattern Recognition	0.62	$p < 0.01$	Strong, statistically significant positive correlation. Students with higher pattern recognition skills tend to perform better in problem-solving.
Decomposition	0.54	$p < 0.01$	Moderate, statistically significant positive correlation. Breaking problems into smaller parts is linked to improved achievement.
Abstraction	0.45	$p < 0.05$	Moderate, statistically significant positive correlation. Ability to generalize concepts supports problem-solving success.
Algorithmic Thinking	0.41	$p < 0.05$	Moderate, statistically significant positive correlation. Structured step-by-step reasoning contributes to achievement.

Pearson correlation analyses were conducted to examine the relationship between computational thinking (CT) components and algebra problem-solving achievement. Results indicated significant positive correlations across all CT dimensions. Pattern recognition showed the strongest association with problem-solving success ($r = 0.62$, $p < 0.01$), followed by decomposition ($r = 0.54$, $p < 0.01$). Abstraction ($r = 0.45$, $p < 0.05$) and algorithmic thinking (r

= 0.41, $p < 0.05$) also demonstrated significant positive correlations. These findings confirm that higher levels of CT are associated with improved algebra problem-solving performance, thereby strengthening the correlational claims of the study.

These results are consistent with [O’Leary and Sloutsky \(2019\)](#), who argued that the monitoring and control components of metacognition can operate independently, with a sample size of 270 participants across three experiments. Qualitative data support these quantitative trends:

1. Low-achieving students relied mainly on procedural recall and trial-and-error, demonstrating partial recognition of number patterns but little generalization.
2. Medium-achieving students showed greater organization and selective decomposition but still struggled to articulate generalized rules.
3. High-achieving students demonstrated dynamic transitions between CT components, shifting from recognizing patterns to abstracting formulas and formulating algorithms for verification.

Qualitative interviews provided richer context: high-achieving students tended to verbalize their reasoning, describing algebraic manipulation as a sequence of conditional steps (“if x increases, then y doubles”). Analyzing iterations on Computational Thinking, focusing on the intersection between thinking processes and scalability, but not providing specific findings or evidence regarding the iterative processes of representation and automation ([Peracaula-Bosch, M., & González-Martínez, J., 2023](#)).

The evidence suggests an evolving, iterative understanding of CT, but a definitive confirmation of the exact mechanism of representation and automation would require more targeted research. These differences suggest that achievement level predicts both frequency and depth of CT manifestation, reinforcing that CT development depends on underlying conceptual understanding and metacognitive control.

3.3 Instructional Influence on CT Development

To examine instructional impact, two groups were compared: one taught using traditional instruction and another using CT-integrated scaffolding (over six weeks).

Table 4. Effects of CT-Integrated Instruction on Student CT Performance

CT Component	Traditional Group (%)	CT-Integrated Group (%)	Improvement (%)
Pattern Recognition	74.0	86.0	+12.0
Decomposition	63.0	80.0	+17.0
Abstraction	32.0	67.0	+35.0
Algorithmic Thinking	24.0	52.0	+28.0

Students exposed to CT-integrated lessons exhibited notable gains in higher-order CT components, particularly abstraction (+35%) and algorithmic thinking (+28%). Classroom observations revealed that these students were more likely to verbalize rules, generate general formulas, and plan solution strategies collaboratively.

This pattern supports the findings of [Wu et al., \(2022\)](#) and [Ye et al., \(2023\)](#), which showed that embedding Computational Thinking discourse into mathematics encourages deep conceptual reasoning, instead of interactive and cyclical mathematical and computational reasoning processes. It also aligns with [Sarmasági et al. \(2025\)](#), showing that unplugged CT tasks can significantly enhance students’ understanding of algebraic structures when combined with explicit metacognitive prompts.

3.4 Discussion

The findings of this study expand on previous research on Computational Thinking (CT) in mathematics by providing classroom-based evidence of how CT patterns naturally emerge during algebraic problem solving. Although previous studies (e.g., [Chan et al., 2022](#); [Ye et al., 2023](#)) highlight the theoretical potential of integrating CT, they often lack empirical detail regarding the cognitive processes students use in traditional mathematical tasks. This research addresses this gap by demonstrating, through coded excerpts of student work and quantitative frequency results, that pattern recognition and decomposition are not only common but also fundamental to students' reasoning in non-programming contexts. For example, students frequently identified recurring structures in problem statements (pattern recognition) and broke complex tasks into manageable subcomponents (decomposition), with these strategies appearing in over half of the analyzed responses.

The unique contribution of this study lies in its identification of how higher-level CT skills, namely abstraction and algorithmic thinking, develop unevenly across different achievement levels and are significantly enhanced through structured instruction. Unlike previous reviews that emphasised technology-based approaches, [Kalogiannakis & Papadakis \(2020\)](#) describe computational thinking as the increasing interpolation of digital technology with human ideas, supported by programming and robotics. Our results show that CT can be developed through structured pedagogical design in conventional classrooms, without relying on programming tools. This positions CT as a diagnostic lens for understanding student cognition and a pedagogical target for curriculum innovation.

Furthermore, this study highlights the iterative nature of computational thinking (CT) development, where students transition from recognizing numerical patterns to abstracting symbolic rules and formulating algorithms for verification. This dynamic development highlights the importance of metacognitive support in developing deeper mathematical thinking. By positioning CT within algebra as central to abstraction and generalization, as research by [Knutson & Stagg \(2025\)](#) shows that teaching pattern recognition, decomposition, and algorithmic thinking fosters deeper understanding of algebra, this study provides empirical clarity in the ongoing debate about how CT and mathematical thinking are related. Overall, this discussion emphasises that CT is not an external skill imported from computer science, but rather an intrinsic cognitive process embedded in mathematical activities. This perspective advances the field by bridging theoretical frameworks with classroom realities, offering practical insights for educators seeking to meaningfully integrate CT into mathematics education.

Finally, by demonstrating CT's role in shaping algebraic reasoning, this study strengthens the argument that computational thinking should be explicitly integrated into mathematics curricula. Direct evidence specifically linking CT integration to broader STEM literacy outcomes is not explicitly quantified in the available sources. Doing so not only enhances students' problem-solving proficiency but also prepares them for broader STEM literacy in the digital age.

4. Conclusion

This study demonstrates that computational thinking (CT) is inherently embedded in students' mathematical problem solving, particularly in algebraic reasoning. The findings indicate that pattern recognition and decomposition constitute foundational CT processes across achievement levels, while abstraction and algorithmic thinking are more evident among high-achieving students or those receiving explicit CT-oriented instruction. The integration of

structured CT-based scaffolding significantly enhances students' conceptual understanding, strategic reasoning, and metacognitive awareness. These results highlight the pedagogical value of systematically embedding CT within mathematics instruction to promote transferable 21st-century competencies. Despite limitations related to the single-school context and task scope, this study provides empirical support for broader curricular integration of CT. Future research should examine longitudinal development across diverse mathematical domains and explore multi-site implementations to strengthen generalizability and instructional design frameworks.

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