Jurnal Didaktika Pendidikan Dasar
Direktorat Guru Pendidikan Dasar, Kemendikdasmen R.I.

Journal Homepage:
https://ojsdikdas.kemendikdasmen.go.id/index.php/didaktika

Vol. 10, No. 2, July 2026	**Copyright © 2026, is licensed under a CC-BY-SA**
Pages: 519-542	**Publisher: Direktorat Guru Dikdas, Kemendikdasmen R.I.**
DOI: https://doi.org/10.67686/didaktika.v10i2.2313	**E-ISSN: 2621-6094**

Exploration of Students' Computational Thinking on Geometric Transformations Through AI-Assisted Geogebra

Arie Wibowo
Unit Pelaksana Teknis Daerah Sekolah Menengah Pertama Negeri 5 Batu Ampar, Kalimantan Selatan, Indonesia
Correspondence Email: enengarie@gmail.com

Article Info

Received: March 24, 2026
Accepted: July 22, 2026
Published: July 30, 2026

Keywords

Computational Thinking;
Geometric Transformation;
GeoGebra;
Artificial Intelligence.

Abstract

Computational thinking (CT) is a key competence in 21st-century mathematics learning, particularly in geometry, which involves spatial reasoning and problem solving. This study aims to explore how students' CT develop when solving geometric transformation problems through artificial intelligence (AI)-assisted GeoGebra learning. The study employed an Educational Design Research (EDR) approach involving 18 junior high school ninth-grade students. The learning design followed a hypothetical learning trajectory with three increasingly complex challenges: translation with fixed orientation, translation with varied positions, and a combination of translation and rotation. Data were collected from student artifacts, including worksheets, AI prompts, GeoGebra commands and screenshots, teacher observations, and exit tickets, and analyzed qualitatively using deductive coding based on four CT components. The results show that students demonstrated strong abilities in decomposition and pattern recognition, while abstraction and algorithmic thinking remained the main challenges, especially in complex transformations. GeoGebra and AI primarily functioned as tools for reflection and debugging, rather than as direct solution providers. This study highlights the importance of scaffolded, challenge-based learning to support CT development in geometry. However, the findings are limited to a single learning session with a small sample size.

P-ISSN: 2580-006X
E-ISSN: 2746-0525

Kata Kunci

Berpikir Komputasional;
Transformasi Geometri;
GeoGebra;
Kecerdasan Artifisial.

Abstrak

Berpikir komputasional (BK) merupakan kompetensi utama dalam pembelajaran matematika abad ke-21, khususnya geometri, yang melibatkan penalaran spasial dan pemecahan masalah. Penelitian ini bertujuan untuk mengeksplorasi bagaimana perkembangan BK siswa ketika menyelesaikan masalah transformasi geometri melalui pembelajaran GeoGebra berbantuan kecerdasan artifisial (KA). Penelitian ini menggunakan pendekatan Educational Design Research (EDR) yang melibatkan 18 siswa kelas sembilan sekolah menengah pertama. Desain pembelajaran mengikuti lintasan pembelajaran hipotetis dengan tiga tantangan yang semakin kompleks: translasi dengan orientasi tetap, translasi dengan posisi bervariasi, dan kombinasi translasi dan rotasi. Data dikumpulkan dari artefak siswa, termasuk lembar kerja, prompt KA, perintah dan tangkapan layar GeoGebra, observasi guru, dan lembar refleksi akhir, dan dianalisis secara kualitatif menggunakan pengkodean deduktif berdasarkan empat komponen BK. Hasil penelitian menunjukkan bahwa siswa menunjukkan kemampuan yang kuat dalam dekomposisi dan pengenalan pola, sementara abstraksi dan pemikiran algoritmik tetap menjadi tantangan utama, terutama dalam transformasi kompleks. GeoGebra dan KA pada dasarnya berfungsi sebagai alat untuk refleksi dan debugging, bukan sebagai penyedia solusi langsung. Studi ini menyoroti pentingnya pembelajaran berbasis tantangan dan dukungan bertahap guru untuk mendukung pengembangan BK dalam geometri. Namun, temuan ini terbatas pada satu sesi pembelajaran dengan ukuran sampel yang kecil.

A. Introduction

The development of information and communication technology has significantly influenced mathematics education. In the 21st century, learning is no longer focused on routine procedures but on developing higher order thinking skills such as reasoning, problem-solving, and analytical thinking. In this context, mathematics learning is expected to provide meaningful experiences that enable students to apply concepts in solving real-world problems (Leinwand *et al.*, 2014).

One of the key competencies relevant to this shift is computational thinking (CT). Introduced by Wing (2006), CT refers to a problem-solving approach that involves decomposition, pattern recognition, abstraction, and algorithm design (Bocconi, *et al.*, 2016; Istiqlal et al., 2026) These processes are inherently aligned with mathematical practices, which require students to model problems, identify structures, and construct logical solution steps (Denning, 2017; Weintrop *et al.*, 2016). Thus, integrating CT into mathematics learning is considered essential to strengthen students' conceptual understanding and cognitive skills.

In geometry learning, particularly at the junior high school level as part of basic education, CT plays a crucial role due to the demands of spatial reasoning, representation, and logical thinking. One topic that strongly reflects CT processes is geometric transformations. Students are required to identify transformation types, determine parameters, and construct sequences of transformations, all of which involve core CT components.

However, in practice, students often encounter challenges when solving transformation problems. Based on classroom observations in grade IX, students typically identify transformation types instinctively but lack the ability to devise systematic solution procedures, especially when utilizing dynamic mathematics software. Frequently, students distinguish whether a transformation is a translation or a rotation, yet they cannot specify exact parameters or sequence the required steps to achieve the desired result. Additionally, students struggle to integrate visual representations with symbolic and algebraic expressions, as well as to formulate independent solution strategies. These observations align with previous studies indicating that students have difficulty pinning down transformation parameters, internalizing transformation concepts, and synchronizing representations in geometry learning (Elizar et al., 2022; Susilawati et al., 2026; Özerem, 2012)

This situation reveals a disconnect between students' conceptual understanding and their capacity to systematically construct algorithmic solutions, particularly in abstraction and algorithmic reasoning. Students frequently resort to trial-and-error approaches rather than logical deduction, focusing on final answers instead of grasping underlying processes. Consequently, their approach to mathematical problems remains procedural rather than analytical, impeding the development of robust computational thinking skills.

To address these challenges, technology-based learning environments have been widely utilized in mathematics education. Dynamic mathematics software such as GeoGebra allows students to visualize and manipulate geometric objects interactively. GeoGebra integrates geometric, algebraic, and graphical representations within a dynamic environment, enabling students to explore relationships between different representations (Hohenwarter, et al., 2008; Sinclair & Yerushalmy, 2016).

P-ISSN: 2580-006X
E-ISSN: 2746-0525

Through such explorations, students can develop a more comprehensive understanding of mathematical concepts.

More importantly, GeoGebra can serve as a tool to support the development of computational thinking. By engaging in activities such as constructing objects, testing transformations, and refining results, students are encouraged to decompose problems, identify patterns, and develop solution procedures. However, the effectiveness of GeoGebra depends not only on students' technical ability to operate the software but also on their ability to think computationally. Without sufficient CT skills, students may use GeoGebra merely as a demonstration tool rather than as a medium for exploration, reasoning, and problem-solving.

In recent years, the emergence of generative artificial intelligence (AI) has introduced new possibilities in mathematics learning. AI can support students in generating explanations, exploring solution strategies, and articulating ideas that might otherwise remain implicit. By externalizing students' thinking, AI can enhance metacognitive awareness and support reflective learning processes.

However, the educational use of AI requires careful pedagogical design. Without appropriate guidance, students may rely on AI-generated outputs without critical evaluation, leading to reduced cognitive engagement. Therefore, AI should be positioned not as a solution provider but as a reflective partner that supports iterative thinking and reasoning. In this context, students' ability to construct meaningful prompts becomes essential, as it reflects key aspects of computational thinking, particularly abstraction and algorithmic thinking (Chen *et al*., 2025; Gerlich, 2025; Ediyanto, 2023; Ninghardjanti *et al.,* 2025).

The integration of GeoGebra and AI offers a complementary learning environment that combines visualization and reflection. GeoGebra enables students to explore and manipulate mathematical representations dynamically, while AI supports reasoning, explanation, and iterative refinement of ideas. This integration allows students to move between visual representations and structured problem-solving processes, thereby supporting the development of computational thinking in geometric transformation contexts (Narohita, 2023; Hohenwarter *et al.,* 2008; Yunianto *et al*., 2024; Ziatdinov & Valles, 2022).

Despite this potential, research examining the integration of GeoGebra and AI remains limited. Existing studies tend to focus on either dynamic mathematics software or AI separately, with little attention to how their combination supports computational thinking within specific mathematical domains. Moreover, empirical evidence on how students develop key CT components—such as decomposition, abstraction, and algorithmic thinking—in AI-assisted geometric transformation learning at the junior high school level is still scarce. This gap highlights the need for studies that investigate how computational thinking emerges in authentic classroom settings involving integrated technological environments.

There is still a lack of empirical studies investigating how key CT components—such as decomposition, abstraction, and algorithmic thinking—develop in technology-integrated learning environments. This gap highlights the need for research that explores how CT emerges in authentic classroom settings involving both GeoGebra and AI.

Based on this perspective, there is a need for learning designs that meaningfully integrate computational thinking, dynamic geometry technology, and artificial intelligence. Learning geometric transformations using GeoGebra assisted by AI provides a relevant context to examine how students' CT develops in authentic learning situations. This learning is designed through a structured, challenge-based learning trajectory that progressively increases in complexity, allowing students to build their understanding step by step while engaging in computational thinking processes.

Therefore, this study aims to explore how junior high school students' computational thinking develops in solving geometric transformation problems through GeoGebra learning assisted by artificial intelligence. This study contributes to the literature by providing an in-depth analysis of students' CT processes as well as design insights for scaffolded, challenge-based, and technology-supported geometry learning. The research question addressed is: What is the computational thinking process of junior high school students in solving geometric transformation problems through AI-assisted GeoGebra learning?

B. Method

1. Research Design

This research uses an Educational Design Research (EDR) approach. According to Plomp and Nieveen (2013), EDR is a research approach that aims to develop and test educational solutions systematically in real contexts, while producing theoretical knowledge that is relevant to practice. McKenney and Reeves (2018) emphasized that

P-ISSN: 2580-006X
E-ISSN: 2746-0525

EDR emphasizes the relationship between learning design, implementation in the classroom, and reflection on the results of that implementation.

The EDR approach was chosen because this research not only aims to determine learning outcomes, but also to understand students' thinking processes and the effectiveness of learning design in fostering CT. With EDR, researchers can explore how learning design works, the obstacles that arise, and improvements that can be made.

In this study, the Educational Design Research (EDR) approach is used to address two objectives: (1) to develop a GeoGebra- and AI-assisted geometric transformation learning design, and (2) to explore how students' computational thinking (CT)—defined as a problem-solving process involving decomposition, pattern recognition, abstraction, and algorithmic thinking—emerges during the implementation and reflection phases.

In this study, the Educational Design Research (EDR) approach was implemented as an initial design trial within the implementation and reflection phase. The learning design was tested in a single classroom session as a preliminary step to examine how the design functions in practice and to identify students' responses and emerging computational thinking processes. At this stage, the focus was not on long-term effectiveness but on evaluating the feasibility of the design and generating insights for subsequent refinement.

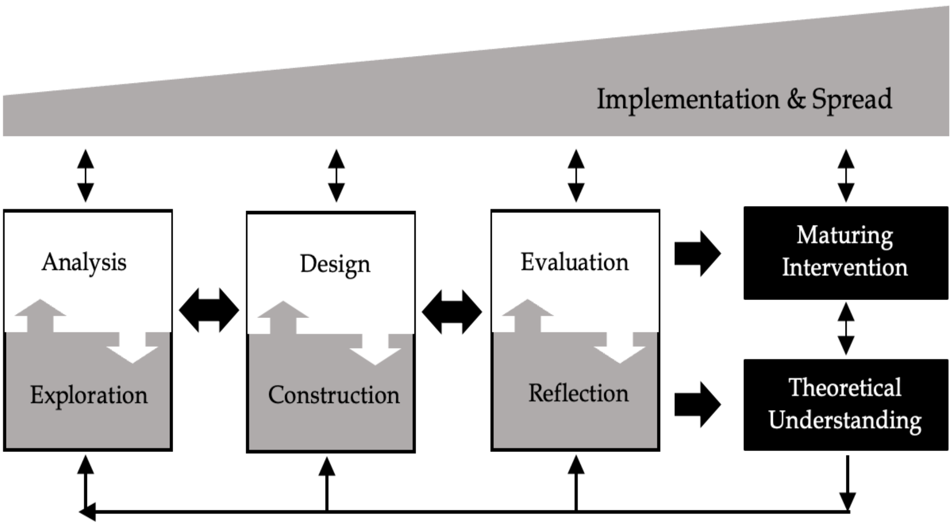

Figure 1. Framework for the Educational Design Research Approach in Research

2. Stages of Educational Design Research

This research was carried out through three main stages, namely the analysis and exploration stage, the design and construction stage, and the implementation and reflection stage.

This research was carried out through three main stages: analysis and exploration, design and construction, and implementation and reflection. In this study, the implementation was limited to an initial design trial within the implementation and reflection stage, positioning the research as an early-phase evaluation of the learning design.

The analysis and exploration stage were carried out by analyzing the curriculum, student characteristics, and general difficulties experienced by students in geometric transformation material. This analysis is based on teaching experience and initial classroom observations. The results of the analysis show that students tend to experience difficulties in aspects of abstraction and preparation of completion steps.

The design and construction stages were carried out by designing learning based on the contextual problem of moving the teacher's desk. Learning is designed using GeoGebra and AI with reference to the Hypothetical Learning Trajectory (HLT). HLT contains learning objectives, student activities, predictions of student responses, and anticipated teacher actions. Learning activities are structured in three gradual challenges with increasing levels of complexity.

The implementation and reflection stages are carried out by implementing the learning design in class IX. During implementation, data were collected to assess students' responses and their CT progress. Reflection is carried out to evaluate the strengths and limitations of the learning design.

3. Research Subjects and Settings

The research subjects consisted of 18 ninth-grade students from a single class, representing the entire population of students in that class. The relatively small class size reflects the actual classroom context in the school, and all students were involved in the learning activities and data collection. The students were organized into five small groups, each consisting of three to four members. The learning was conducted in a single session with a duration of 2 × 40 minutes. The learning activities utilized Chromebooks, GeoGebra Classroom, and text-based artificial intelligence tools.

 P-ISSN: 2580-006X
E-ISSN: 2746-0525

The contextual problems used as learning stimuli in the three challenges are shown in Figure 2.

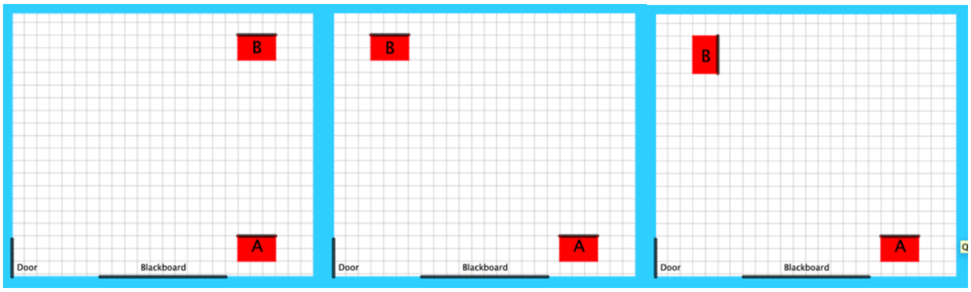

Figure 2. Contextual Problem of Geometric Transformation Used as A Learning Stimulus in Research Design

There are three challenges presented in learning. Challenge 1 is focused on developing decomposition and pattern recognition via translation with fixed orientation. Challenge 2 is designed to strengthen the abstraction by determining translation vectors with more complex position variations. Challenge 3 targets algorithm construction and debugging through a combination of translation and rotation that demands sequential planning of steps. These three challenges are designed to surface and observe the gradual development of each CT component in a real learning context.

4. Data Collection and Analysis Techniques

Data was collected through student worksheets, GeoGebra Classroom screenshots, AI prompts and GeoGebra commands, exit ticket results, and teacher observation notes. Data analysis was carried out qualitatively using thematic analysis with reference to four CT components: decomposition, pattern recognition, abstraction, and algorithm development (Bocconi, et al., 2016). The collected data were analyzed by linking each student artifact to the relevant CT component through a coding scheme. The coding results are then used to develop a description of students' CT development for each learning challenge. The analysis was conducted through several stages, including initial reading of the data, coding based on CT components, grouping of similar patterns, and interpretation of findings across different data sources. This stepwise process allows the identification of consistent patterns in students' computational thinking development.

5. Coding Scheme and Data Validity

Data analysis was conducted using deductive coding based on predefined operational indicators of computational thinking (CT), enabling a focused examination of how each component emerged during the learning process. Each student artifact was assigned a structured code representing data type, CT component, and group identity, including AI prompts (PR), GeoGebra commands (GG), screenshots (SS), worksheets (SW), and exit tickets (ET). For example, PR-CT-A-02 refers to an AI prompt produced by group 2 reflecting abstraction (CT-A), allowing systematic linkage between artifacts and CT components.

Table 1. CT Coding Scheme

Code	CT's Components	Indicators
CT-D	Decomposition	Identify the position & type of transformation
CT-P	Pattern Recognition	Determine orientation & comparability
CT-A	Abstraction	States the vector/center of rotation
CT-Alg	Algorithm	Arranging a sequence of commands

The coding process was conducted by the researcher as the primary coder, who has a background in mathematics education and experience in classroom teaching and qualitative data analysis. To enhance credibility, approximately 30% of the data were independently reviewed by a second coder with expertise in mathematics education. The subset was purposively selected to represent all data types and learning challenges, ensuring coverage of varied contexts and CT components. The remaining data were continuously re-examined by the primary coder through an iterative process to maintain consistency in coding decisions.

Discrepancies between coders were resolved through discussion. For example, an AI prompt initially coded as abstraction (CT-A) due to directional language was reconsidered as decomposition (CT-D) because it lacked explicit transformation parameters. Through this process, both coders refined the criteria, agreeing that abstraction requires explicit mathematical representation such as vectors or coordinates. The proportion of 30% was considered sufficient, as it included representative samples across all data types and learning contexts, aligning with qualitative research practices that emphasize iterative review and coverage of data variation rather than full double-coding.

P-ISSN: 2580-006X
E-ISSN: 2746-0525

Data validity was established through triangulation of sources and techniques by systematically comparing evidence across AI prompts, GeoGebra commands and screenshots, worksheets, observation notes, and exit ticket responses. The same CT components were identified across these data and cross-checked for consistency. For instance, abstraction (CT-A) identified in AI prompts was verified through the accuracy of transformation parameters in GeoGebra commands and corresponding worksheet representations, while algorithmic thinking (CT-Alg) was validated through command sequencing and iterative revisions after errors.

A CT component was considered to emerge consistently when it was supported by converging evidence across at least three types of student artifacts and aligned with the observable indicators defined in Table 2. Consistency was further established when similar patterns were found across multiple student groups within the same learning challenge.

Table 2. Observable Indicators of Computational Thinking in Student Artifacts

CT Component	Observable Indicators	Evidence from Student Artifacts
Decomposition (CT-D)	Identifying initial and target positions; determining transformation type	Descriptions in worksheets and AI prompts specifying starting point, destination, and type of transformation
Pattern Recognition (CT-P)	Recognizing unchanged orientation and spatial relationships	Consistent identification of translation based on orientation in prompts and tasks
Abstraction (CT-A)	Representing transformation parameters (e.g., vector, center of rotation)	AI prompts and GeoGebra commands including explicit direction, magnitude, or coordinates
Algorithmic Thinking (CT-Alg)	Constructing ordered steps and revising procedures	Sequencing of GeoGebra commands and iterative correction after errors

6. Ethical Considerations

This study was conducted with formal permission from the school. All participants were informed about the purpose of the study, and their participation was voluntary. Considering that the participants were junior high school students as part of basic education, parental or guardian consent was obtained where required in accordance with school policy. To ensure confidentiality, all student data were anonymized, and no identifiable personal information was included in the analysis or reporting. The data were used solely for research purposes and handled in accordance with established ethical standards in educational research.

C. Results and Discussion

1. Results

a. CT Across Learning Challenges

Students' computational thinking (CT) development was analyzed across three learning challenges designed with increasing levels of complexity. The analysis focused on four CT components: decomposition, pattern recognition, abstraction, and algorithm development.

Challenge 1: Translation with Fixed Orientation

In Challenge 1, most students demonstrated strong abilities in decomposition and pattern recognition. They were able to identify initial and target positions and recognize that the orientation remained unchanged, indicating that translation was the appropriate transformation. All student groups successfully completed the task, suggesting adequate contextual understanding. However, this success was primarily supported by visual reasoning rather than well-developed abstraction or algorithmic thinking.

Students' abstraction abilities remained limited, as reflected in their AI prompts, which were generally vague and lacked explicit transformation parameters such as direction and magnitude. Consequently, students were not yet able to represent the problem in precise mathematical terms. As shown in Figure 3 (PR-CT-A-01), the initial AI prompt remains descriptive and does not include explicit transformation parameters such as direction and magnitude, indicating that students had not yet developed sufficient abstraction skills.

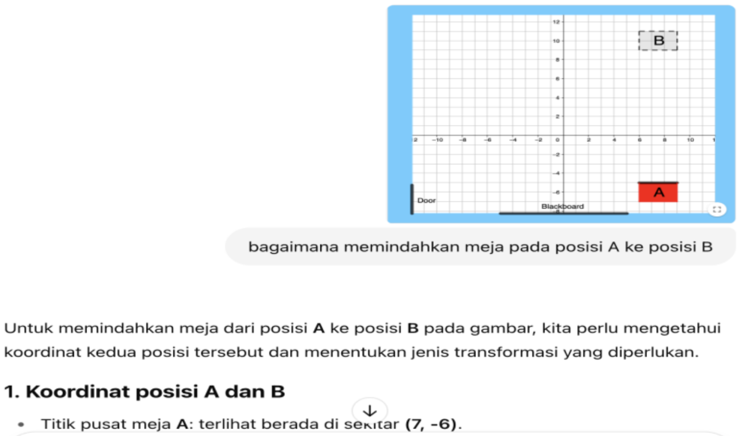

Figure 3. Initial AI prompt written by students in Challenge 1 which is still general in nature and does not contain specific transformation parameters (PR-CT-A-01).

P-ISSN: 2580-006X
E-ISSN: 2746-0525

After receiving teacher scaffolding, students began to refine their prompts and produce more structured questions when interacting with AI. As shown in Figure 4, students formulated more goal-oriented prompts by explicitly asking how to move the object from position A to position B using GeoGebra commands. Although the prompts still lack precise transformation parameters, they indicate an initial shift from descriptive to more procedural thinking, reflecting early development of abstraction.

This interaction also demonstrates an iterative thinking process, in which students evaluated and revised their prompts based on feedback and guidance. In this context, AI functioned not as a direct solution provider, but as a reflective partner that supported students in clarifying and refining their thinking.

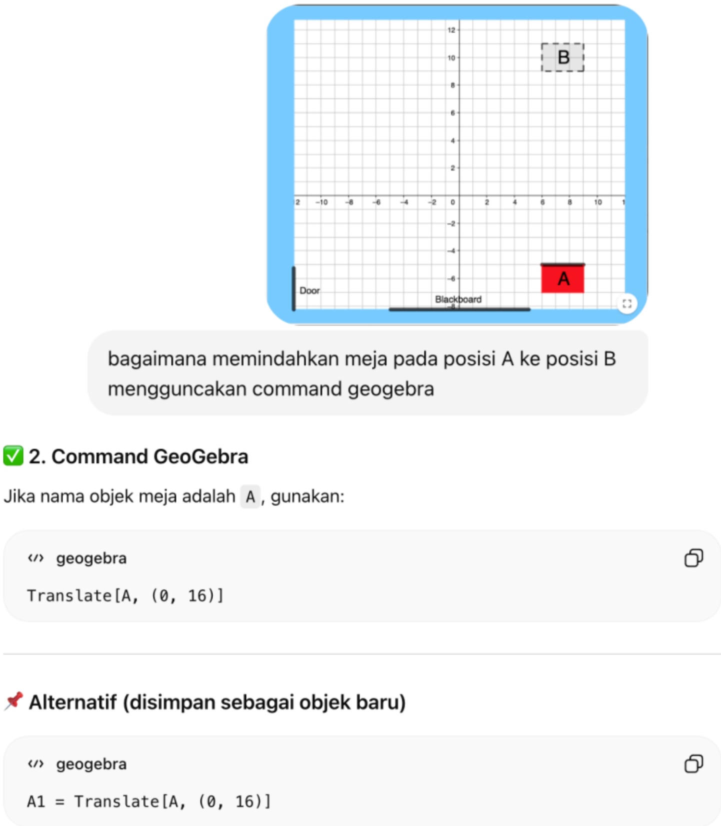

Figure 4. Refined AI prompt in Challenge 1 developed through teacher scaffolding, showing an initial shift toward more structured and goal-oriented problem representation (PR-CT-A-01).

Despite this initial improvement, students' abstraction remained limited, which continued to affect their ability to construct complete algorithms. This limitation in abstraction directly influenced students' algorithmic thinking. Several groups produced GeoGebra commands that only moved part of the object rather than the entire object, indicating incomplete procedural understanding. As shown in Figure 5, the artifact coded as GG-CT-Alg-02 demonstrates that students were not yet able to construct a complete and coherent sequence of transformation steps. This finding highlights a gap between students' conceptual understanding and their ability to implement that understanding algorithmically.

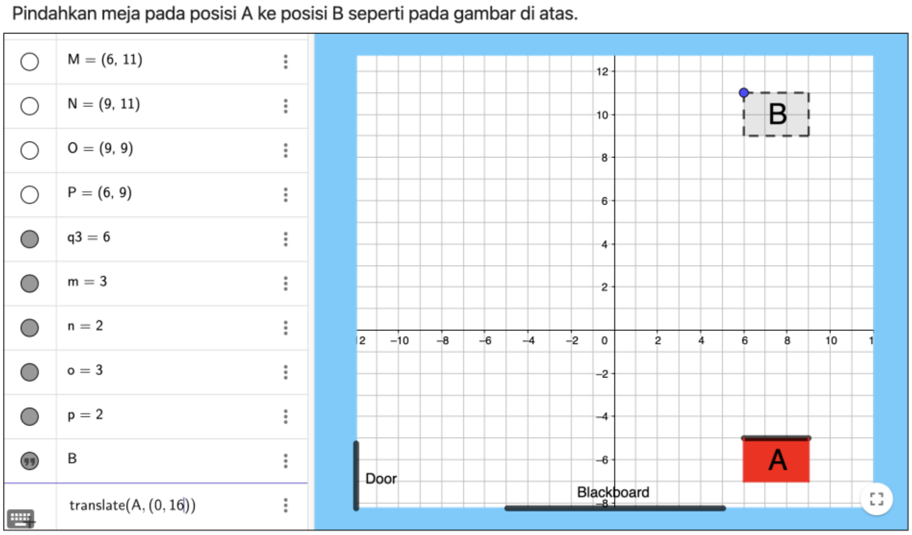

Figure 5. GeoGebra output showing an algorithm compilation error, where only points experience translation, not the entire table object (GG-CT-Alg-02).

Challenge 2: Translation with Positional Variations

In Challenge 2, students showed noticeable improvement in computational thinking, particularly in abstraction. Compared to the previous challenge, they produced more specific and structured AI prompts, including clearer references to object positions, directions, and spatial relationships, indicating a shift from descriptive reasoning toward more precise mathematical representation. As shown in Figure 6, these commands include explicit references to the direction and magnitude of displacement, indicating improved abstraction and the ability to translate contextual problems into mathematical forms.

P-ISSN: 2580-006X
E-ISSN: 2746-0525

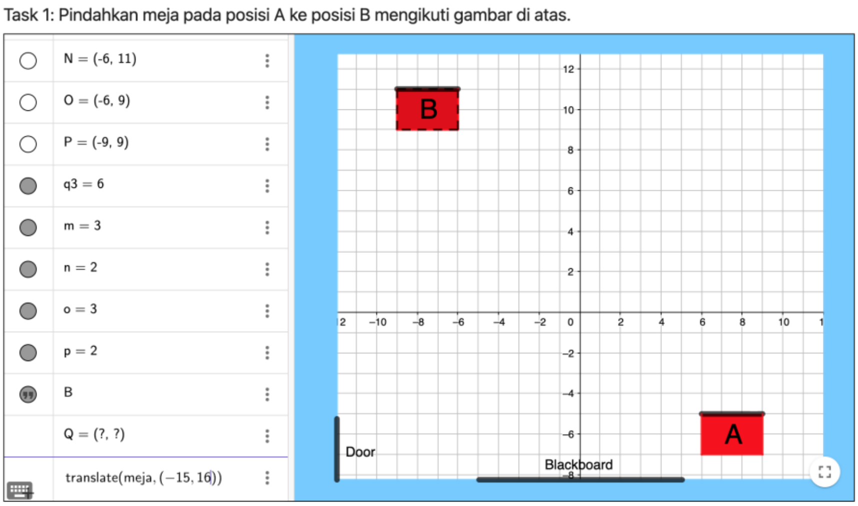

Figure 6. GeoGebra output showing the use of explicit transformation parameters in translation, indicating improvement in students' abstraction in Challenge 2.

All student groups were able to correctly complete the task, demonstrating successful application of the targeted computational thinking components in this context. However, this success should be interpreted cautiously, as it was achieved within a relatively simple and well-structured task that involved a single transformation. Therefore, it does not necessarily indicate stable or transferable mastery of computational thinking. This limitation becomes more evident in the next challenge, which requires coordinating multiple transformations.

Challenge 3: Combination of Translation and Rotation

In Challenge 3, students were required to solve more complex problems involving a combination of translation and rotation, requiring accurate abstraction and coherent sequencing of transformation steps. Consequently, their computational thinking was challenged at a higher level, particularly in abstraction and algorithmic thinking. Compared to the previous challenge, students experienced greater difficulty in determining the correct order and parameters of transformations, and many struggled to integrate them into a complete procedure, indicating that algorithmic thinking, especially in sequencing and coordinating multiple steps—remained a significant challenge. These difficulties led to iterative problem-solving, in which students tested their commands in GeoGebra, evaluated outcomes, and revised their approaches. As shown in Figure 7, several groups produced incorrect outputs due to errors in sequencing and parameter specification, suggesting that algorithmic thinking remained underdeveloped.

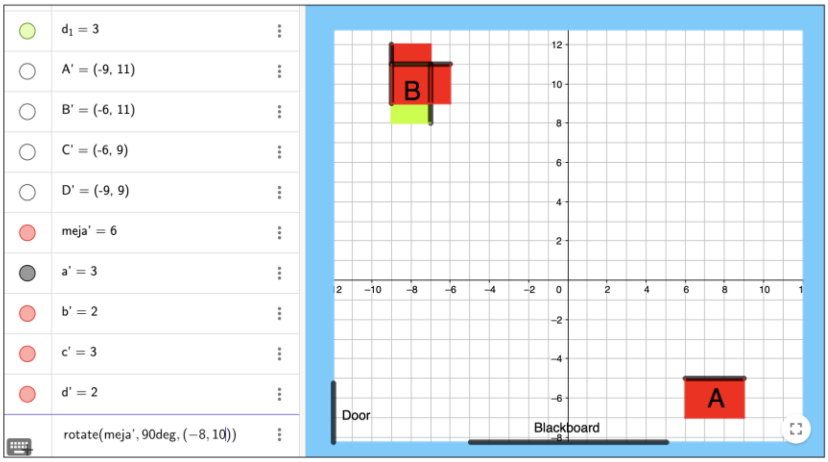

Figure 7. Debugging process in Challenge 3, where the translation is successful but the object orientation is not correct due to an error in determining the center of rotation.

The interaction with AI in this stage highlights its role as a reflective partner. Students used AI to reconsider strategies, refine prompts, and explore alternative approaches. Rather than providing direct solutions, AI supported students in identifying inconsistencies and improving their reasoning through iterative reflection. Through this process, some groups were able to construct correct transformation sequences, indicating progress in algorithmic thinking, while others still struggled, particularly in coordinating multiple transformations. These findings suggest that although students' computational thinking had developed, higher-level coordination of abstraction and algorithmic thinking remained limited and required sustained support. Notably, only one group successfully completed the challenge by correctly combining translation and rotation. The final solution, shown in Figure 8 (GG-CT-Alg-04), demonstrates the integration of decomposition, abstraction, and algorithmic thinking in a coherent transformation sequence.

 P-ISSN: 2580-006X
E-ISSN: 2746-0525

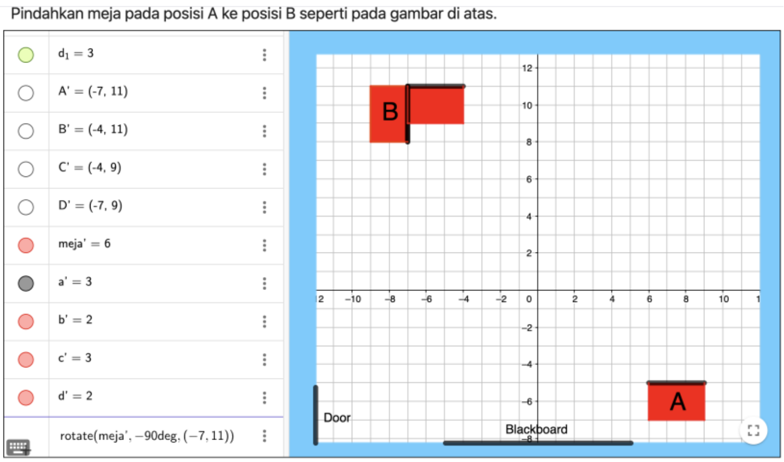

Figure 8. Final solution to Challenge 3 showing the combination of translation and rotation with appropriate object positions and orientations.

b. Summary of CT Development

A summary of students' computational thinking development across all challenges is presented in Table 3. The results show that decomposition and pattern recognition were consistently demonstrated across all challenges, while abstraction and algorithm development remained the most challenging components. Improvement in abstraction was observed in simpler contexts; however, these abilities were less stable in more complex tasks involving multiple transformations.

These findings also indicate that GeoGebra and AI function primarily as tools for reflection and debugging rather than as direct solution providers. Students who engaged in iterative testing and revision processes demonstrated stronger development in abstraction and algorithmic thinking.

Table 3. Summary of Student CT Achievements per Challenge

Challenge	CT-D	CT-P	CT-A	CT-Alg	Main Description
1	✓	✓	✕	✕	Wrong initial command, all groups were successful after scaffolding
2	✓	✓	✓	✓	The entire group completed without errors
3	✓	✓	◐	◐	Only one group succeeded after intensive scaffolding

Description:

✓ = fulfilled by the entire group

◐ = fulfilled by some groups

✕ = not yet fulfilled by most groups

c. Student Mistakes and Barriers

Further analysis of student artifacts revealed consistent patterns of errors, as summarized in Table 4. The most common errors included overly general prompts, incorrect object selection, and incorrect transformation sequences. These errors are closely associated with weaknesses in abstraction and algorithmic thinking.

Table 4. Types of Student Errors and Their Relationship to CT

Error Type	Example	CT's Components
The prompt is too general	"Move table from A to B"	Abstraction
Wrong Object	Translate (A, (0,16))	Algorithm Preparation
Wrong order	Rotation before translation	Algorithm Preparation

The findings suggest that students are still transitioning from intuitive visual reasoning to formal mathematical representation. Errors in transformation sequences indicate a limited understanding of the non-commutative nature of geometric transformations. Overall, these results confirm that the main challenge in technology-assisted transformation learning lies not in identifying transformation types, but in constructing precise and structured solutions.

d. Learning Outcomes

The analysis of learning outcomes shows that 12 out of 18 students (66.67%) achieved the intended learning objectives. These students demonstrated consistent performance in decomposition and pattern recognition, along with emerging abilities in abstraction and algorithm development.

The remaining 6 students (33.33%) experienced difficulties, particularly in determining rotation parameters and organizing transformation sequences. These findings are consistent with earlier results showing that abstraction and algorithmic thinking are the most challenging aspects of CT.

Overall, the results indicate that the learning design supports basic CT development but requires further refinement to strengthen higher-level CT components, especially in complex transformation tasks.

P-ISSN: 2580-006X
E-ISSN: 2746-0525

2. Discussion

a. Development of CT in Geometric Transformation Learning

The findings of this study indicate that students' computational thinking (CT) develops progressively but unevenly across its components. Decomposition and pattern recognition tend to emerge earlier, as they are supported by students' visual reasoning and intuitive understanding of spatial relationships. In contrast, abstraction and algorithmic thinking develop more slowly and remain the primary sources of difficulty.

This pattern is consistent with the perspective that CT involves multiple cognitive processes that develop progressively through structured learning experiences (Guzdial, 2016; Wing, 2006). Similarly, Weintrop et al. (2016) emphasize that abstraction and algorithmic thinking require higher levels of cognitive coordination compared to decomposition and pattern recognition.

The findings further suggest that while students can interpret transformation contexts visually, they encounter challenges when required to formalize this understanding into symbolic representations and structured procedures. This aligns with the theory of semiotic representation by Duval (2006), which highlights that the transformation of visual representations into symbolic forms is a critical and often difficult step in mathematical thinking.

It is important to note that these findings reflect students' initial responses within a short-term learning intervention. Therefore, the observed difficulties in abstraction and algorithmic thinking should be interpreted as emerging tendencies rather than stable characteristics of students' computational thinking development.

b. Role of GeoGebra in Supporting CT

GeoGebra serves as a dynamic learning environment that facilitates visualization and experimentation. Through GeoGebra, students can test and revise their solutions, receiving immediate feedback that supports debugging and iterative problem-solving processes. This supports the findings of (Hohenwarter et al., 2008) who argue that dynamic mathematics environments can enhance conceptual understanding by linking multiple representations.

However, the findings also indicate that GeoGebra does not automatically foster computational thinking. Without appropriate scaffolding, students tend to rely on trial-and-error strategies rather than engaging in reflective reasoning. This observation is consistent with recent studies showing that the effectiveness of digital technology in mathematics learning depends on its integration within well-designed tasks and appropriate teacher scaffolding (St Omer et al., 2025).

Thus, the effectiveness of GeoGebra depends not only on its technological affordances but also on how it is integrated into structured instructional activities that explicitly target CT development.

c. AI as a Reflective Partner in Learning

Artificial intelligence (AI) plays a significant role in supporting students' reasoning and reflection by providing alternative solution strategies. However, its effectiveness depends on the quality of students' interactions, particularly in constructing prompts.

When prompts are vague, AI outputs become less meaningful or even misleading. This finding aligns with recent studies by Holmes et al. (2019), who highlight that AI can support learning as a cognitive tool only when students actively engage in reflective processes. Furthermore, studies on generative AI in education suggest that excessive reliance on AI may lead to cognitive offloading, reducing students' critical thinking if not properly guided.

In this context, prompt construction can be viewed as part of abstraction and algorithmic thinking. Therefore, AI is most effective when positioned as a reflective partner that supports debugging, evaluation, and refinement of strategies rather than as a provider of direct answers.

d. Role of Scaffolding

The findings indicate that the development of computational thinking (CT), particularly in abstraction and algorithmic thinking, is strongly mediated by teacher scaffolding. In this study, scaffolding was enacted through guided questioning, timely feedback, and targeted prompts that directed students' attention to critical aspects of the task, such as identifying transformation parameters and organizing solution steps. This support enabled students to move from intuitive, visually driven reasoning toward more explicit and formal representations, particularly when translating contextual problems into GeoGebra commands.

More specifically, scaffolding facilitated abstraction by encouraging students to articulate key parameters (e.g., direction and magnitude of translation or center of rotation) within their AI prompts and supported algorithmic thinking by guiding

P-ISSN: 2580-006X
E-ISSN: 2746-0525

them to construct and refine sequences of commands. When students encounter errors in GeoGebra outputs, scaffolding also promotes reflective debugging, helping them evaluate inconsistencies and revise their procedures iteratively. This aligns with research emphasizing iterative reasoning and debugging as central to computational thinking development (Weintrop *et al.*, 2016).

These findings are consistent with the theory of the Zone of Proximal Development, which highlights the role of guided interaction in advancing cognitive development, as well as with (van de Pol *et al.*, 2010), who emphasize that effective scaffolding must be adaptive and contingent on learners' needs. In addition, studies in technology-enhanced mathematics learning suggest that meaningful learning emerges when digital tools are integrated with pedagogical support that promotes reflection and conceptual understanding (Holmes *et al*., 2019; Ziatdinov & Valles, 2022).

Taken together, the results suggest that the effectiveness of technology in supporting CT depends on its integration within structured instructional design and teacher scaffolding. While GeoGebra and AI provide affordances for visualization, experimentation, and reflection, it is the pedagogical orchestration that enables students to use these tools meaningfully to develop abstraction and algorithmic reasoning.

e. Pedagogical Implications

The findings of this study have several important implications for mathematics instruction. First, computational thinking should be explicitly integrated into instructional design rather than treated as an implicit outcome. As suggested by (Denning, 2017), CT must be cultivated through deliberate and structured learning activities.

Second, learning should be designed progressively, moving from simple to more complex tasks, in line with the concept of learning trajectories. This approach supports the gradual development of CT components, particularly abstraction and algorithmic thinking.

Third, the integration of GeoGebra and AI should emphasize exploration, reflection, and debugging rather than procedural execution. This aligns with constructivist learning principles, where students actively construct knowledge through interaction and reflection.

Finally, the development of prompt literacy should be considered an essential component of AI-assisted learning. Students need to be trained to formulate clear and meaningful prompts as part of their computational thinking development.

It is important to note that these implications are derived from a short-term learning intervention and should therefore be interpreted as preliminary. Further research with longer and more sustained implementations is needed to examine the long-term impact of these instructional approaches.

f. Limitations

This study has several limitations that should be considered when interpreting the findings. First, the implementation of the learning design was conducted in a single session as part of an initial design trial within the Educational Design Research (EDR) process. As a result, the findings may not fully capture the long-term development of students' computational thinking, particularly in abstraction and algorithmic thinking, which require sustained learning experiences.

Second, the findings are context-specific and based on a relatively small sample, which may limit their generalizability to broader educational settings. Therefore, future research is recommended to involve longer instructional interventions and larger, more diverse samples to examine the sustainability and transferability of CT development in technology-enhanced learning environments.

D. Conclusion

This study demonstrates that learning geometric transformations assisted by GeoGebra and artificial intelligence can support the development of computational thinking (CT) in junior high school students, particularly in strengthening decomposition and pattern recognition, while abstraction and algorithmic thinking remain the main challenges. The findings indicate that CT develops gradually through structured, challenge-based learning, where students perform well in simpler translation tasks but experience increasing difficulty when required to determine transformation parameters and construct algorithms in more complex tasks such as rotation and combined transformations. The results also show that GeoGebra and AI function primarily as tools for reflection and debugging rather than as providers of direct solutions, emphasizing that the quality of students' thinking processes depends on well-designed tasks and effective teacher scaffolding. Furthermore, AI integration in mathematics learning should be carefully designed to support, rather than replace, students' thinking, positioning AI as a cognitive partner that facilitates reflection and strategy refinement while maintaining the essential role of the teacher.

P-ISSN: 2580-006X
E-ISSN: 2746-0525

This study contributes both practically and theoretically by providing insights into the design of technology-enhanced mathematics learning through the integration of contextual tasks, dynamic geometry environments, and AI support to foster CT development. However, this study is limited by its implementation in a single learning session and a relatively small sample size, which may not fully capture the long-term development of students' computational thinking; therefore, further research with longer interventions and broader contexts is needed to examine the sustainability and generalizability of these findings.

Declaration of Competing Interest

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.

References

Bocconi, S., Chioccariello, A., Dettori, G., Ferrari, A., Engelhardt, K., Kampylis, P., & Punie, Y. (2016). Developing Computational Thinking in Compulsory Education. Implications for Policy and Practice. *EUR - Scientific and Technical Research Reports, 68*. https://doi.org/10.2791/792158.

Chen, Y., Wang, Y., Wüstenberg, T., Kizilcec, R. F., Fan, Y., Li, Y., Lu, B., Yuan, M., Zhang, J., Zhang, Z., Geldsetzer, P., Chen, S., & Bärnighausen, T. (2025). Effects of Generative Artificial Intelligence on Cognitive Effort and Task Performance: Study Protocol for a Randomized Controlled Experiment Among College Students. *Trials*, *26*(1). https://doi.org/10.1186/s13063-025-08950-3.

Denning, P. (2017). Computational Thinking in Science. *American Scientist*, *105*(1), 67–77. https://doi.org/10.1511/2017.124.13.

Duval, R. (2006). A Cognitive Analysis of Problems of Comprehension in a Learning of Mathematics. *Educational Studies in Mathematics*, *61*(1), 103–131. https://doi.org/10.1007/s10649-006-0400-z.

Ediyanto, A. (2023). Integrasi Nilai-Nilai Pendidikan Karakter pada Mata Pelajaran Matematika dengan Modif COC KOBE. *Jurnal Nispatti*, *8*(1), 1-18. https://doi.org/10.26811/nispatti.v8i1.163.

Elizar, E., Trisna, T. A., & Ikhsan, M. (2022). Abilities and Difficulties of Ninth-Grade Students in Solving Geometry Transformation Problems. *Jurnal Pendidikan MIPA*, *23*(4), 1724–1737. https:// doi.org/10.23960/jpmipa/v23i4.pp1724-1737.

Gerlich, M. (2025). AI Tools in Society: Impacts on Cognitive Offloading and the Future of Critical Thinking. *Societies*, *15*(1), 6. https://doi.org/ 10.3390/soc15010006 .

Guzdial, M. (2016). *Learner-Centered Design of Computing Education: Research on Computing for Everyone*. Springer.

Hohenwarter, M., Hohenwarter, J., Kreis, Y., & Lavicza, Z. (2008, July 8). *Teaching and Calculus with free Dynamic Mathematics Software GeoGebra* [Paper Presentation]. The 11th International Congress on Mathematical Education (ICME 11), Monterrey, Mexico. https://www.researchgate.net/publication/228869636_Teaching_and_Learning_Calculus_with_Free_Dynamic_Mathematics_Software_GeoGebra.

Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial Intelligence in Education: Promise and Implications for Teaching and Learning* (1st ed.). Center for Curriculum Redesign.

Istiqlal, M., Retnawati, H., Widihastuti, W., & Sari, D. K. (2026). Assessing Students' Computational Thinking AbilityBased on Mathematical Reasoning. *Jurnal Ilmiah Peuradeun*, *14*(2), 773-796. https://doi.org/10.26811/peuradeun.v14i2.1602

Leinwand, S., Brahier, D. J., Huinker, D., Berry, R. Q., Dillon, F. L., Larson, M. R., Leiva, M. A., Martin, W. G., & Smith, M. S. (2014). *Principles to Actions: Ensuring Mathematical Success for All*. NCTM, National Council of Teachers of Mathematics.

McKenney, S., & Reeves, T. (2018). *Conducting Educational Design Research* (2nd ed.). Routledge.

Narohita, G. A. (2023). Pemanfaatan Aplikasi GeoGebra Mampu Meningkatkan Pemahaman Grafik Fungsi Kuadrat Siswa SMA Negeri 1 Singaraja. *Jurnal Nispatti*, *8*(1), 19-36. https://doi.org/10.26811/nispatti.v8i1.171.

Ninghardjanti, P., Umam, M. C., Subarno, A., Winarno, W., Langgi, N. R., & Widodo, J. (2025). Evaluating the Impact of AI on the Critical Thinking Skills Among the Higher Education Students by Combining the TAM Model and Critical Thinking Theory. *Frontiers in Education*, *10*, 1719625. https://doi.org/10.3389/feduc.2025.1719625.

Özerem, A. (2012). Misconceptions in Geometry and Suggested Solutions for Seventh Grade Students. *Procedia - Social and Behavioral Sciences*, *55*, 720–729. https://doi.org/10.1016/j.sbspro.2012.09.557.

Plomp, Tj., & Nieveen, N. (2013). *Educational Design Research. Part A: An introduction*. SLO.

Sinclair, N., & Yerushalmy, M. (2016). Digital Technology in Mathematics Teaching and Learning. In Á. Gutiérrez, G. C. Leder, & P. Boero (Eds.), *The Second Handbook of Research on the Psychology of Mathematics Education: The Journey Continues* (pp. 235–274). Sense Publishers. https://doi.org/10.1007/978-94-6300-561-6_7.

P-ISSN: 2580-006X
E-ISSN: 2746-0525

St Omer, S. M., Evers, K., Wang, C. Y., & Chen, S. (2025). Technology-Enhanced Mathematics Learning: Review of the Interactions Between Technological Attributes and Aspects of Mathematics Education from 2013 to 2022. *Humanities and Social Sciences Communications*, *12*(1), 1–13. https://doi.org/10.1057/s41599-025-05475-7.

Susilawati, S., Supriyatno, T. ., Yasin, A. F. ., Tasir, Z. ., Asmawati, R. I. ., Chakim, A. ., & Dalle, A. R. A. (2026). Integrating Computational Thinking and Spirituality in Developing Students' Critical Thinking: A Comparative Study of Indonesia and Malaysia. *Jurnal Ilmiah Peuradeun*, *14*(1), 413-438. https://doi.org/10.26811/peuradeun.v14i1.2439

Van de Pol, J., Volman, M., & Beishuizen, J. (2010). Scaffolding in Teacher–Student Interaction: A decade of research. *Educational Psychology Review*, *22*, 271–296. https://doi.org/10.1007/s10648-010-9127-6.

Weintrop, D., Beheshti, E., Horn, M., Orton, K., Jona, K., Trouille, L., & Wilensky, U. (2016). Defining Computational Thinking for Mathematics and Science Classrooms. *Journal of Science Education and Technology*, *25*(1), 127–147. https://doi.org/10.1007/s10956-015-9581-5.

Wing, J. (2006). Computational Thinking. *Communications of the ACM*, *49(3)*, 33–35. https://doi.org/10.1145/1118178.1118215 ,

Yunianto, W., Galic, S., & Lavicza, Z. (2024). Exploring Computational Thinking in Mathematics Education: Integrating ChatGPT with GeoGebra for Enhanced Learning Experiences. *International Journal of Education in Mathematics, Science and Technology*, *12*(6), 1451–1470. https://doi.org/10.46328/ijemst.4437 .

Ziatdinov, R., & Valles, J. R. (2022). Synthesis of Modelling, Visualization, and Programming in GeoGebra as an Effective Approach for Teaching and Learning STEM Topics. *Mathematics*, *10*(3), 398. https://doi.org/10.3390/math10030398.