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The effect of an adaptive scaffolding-based learning website on students' computational thinking skills

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ABSTRACT

Computational Thinking (CT) learning in Informatics may be challenging when students begin with different levels of competence, while uniform task difficulty and support do not adequately address these differences. An adaptive scaffolding-based learning website offers a possible solution by adjusting learning levels and providing progressive assistance according to students' initial competence. This study examined the effect of the website on the CT skills of Grade X students. A quantitative quasi-experimental study with a nonequivalent control group pretest-posttest design involved 72 students, comprising 36 students in the experimental group and 36 in the control group. The experimental group used the adaptive scaffolding-based website, whereas the control group received conventional instruction through teacher explanations, classroom discussions, practice questions, and assignments without the adaptive website or tiered hints. Data were analyzed using N-Gain, normality and homogeneity tests, an independent-samples t-test, and Cohen's d. The experimental group obtained a higher mean N-Gain than the control group (0.58 vs. 0.36), with a statistically significant difference ($p < .001$) and a large effect (Cohen's $d = 2.43$). Decomposition showed the greatest improvement among the CT indicators (N-Gain = 0.699). The adaptive website significantly improved students' CT skills through competency-based progressive scaffolding support. Future studies should involve broader samples, longer interventions, and additional learning outcomes.

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INTRODUCTION

As digital technology continues to expand, Informatics education is increasingly expected to develop more than students' conceptual understanding, including their systematic reasoning, problem-solving abilities, and computational literacy (Kafai & Proctor, 2022; Palop et al., 2025). Within this broader educational context, Computational Thinking (CT) is particularly important because it enables learners to formulate problems and construct solutions using computational processes that are applicable across learning contexts (Wing, 2006; Ocampo et al., 2024). These processes encompass algorithmic thinking, decomposition, abstraction, and pattern recognition, through which learners can break problems into smaller components, identify recurring patterns, distinguish relevant information, and organize solution steps in a logical sequence (Anggraini et al., 2025; Ekayana et al., 2025; Pirzado et al., 2025).

The growing need for CT development is closely related to the demands of digital and Informatics learning, in which students are expected to address data-, algorithm-, and technology-related problems both independently and collaboratively (Connolly et al., 2021; Kafai & Proctor, 2022). Evidence from previous studies suggests that students can achieve better CT and learning outcomes when interactive learning media are used instead of conventional instruction (Ekayana et al., 2025). In a quasi-experimental study involving 112 students, the authors reported a significant difference between groups ($t = 6.474$, $p < .001$). The experimental group increased from 41.64 to 79.71 and achieved an N-Gain of 0.65, whereas the control group recorded an N-Gain of 0.46.

AI-based interactive digital games have also been associated with CT development, particularly through learning activities that engage students in analysis, abstraction, and the construction of problem-solving strategies (Anggraini et al., 2025). Anggraini et al., (2025) reported a significant positive relationship between AI-based interactive digital game development and CT ($r = 0.407$, $p = .001$), with the model accounting for 30% of the variance in students' CT ($R^2 = 0.300$). A similar potential has been observed in web-based learning for supporting CT development. In the study by Selano et al., (2024), students' CT scores increased from 73.6 to 97.3 after using a web-based e-module integrated with Project-Based Learning, producing a high N-Gain of 0.898. Taken together, these findings suggest that technology-based learning can effectively support CT when learning activities are designed around interaction, contextual learning, and problem solving (Selano et al., 2024; Salwa et al., 2024).

Despite these positive findings, strengthening CT in classroom learning remains challenging. Because students begin learning with different levels of prior ability, the difficulty of a task may not always correspond to their readiness, while feedback may also lack a sufficiently gradual progression (El-Sabagh, 2021; Ocampo et al., 2024). These differences can leave some students struggling with problem solving, whereas others may need more demanding tasks to further develop their thinking skills (Sayed et al., 2023; Maryono et al., 2025). Adaptive learning environments can respond to differences in learner characteristics and performance, but the specific form and degree of that adaptation depend on the learning context. In existing applications, learner characteristics have been used to guide content presentation, exercise navigation, and feedback in adaptive e-learning, whereas CT-oriented scaffolding has been applied to assist students during problem solving (Sayed et al., 2023; Shin et al., 2025). What remains less certain is whether students' initial CT competence, differentiated task difficulty, and progressive scaffolding can be brought together within the same learning process. This issue is particularly relevant to Informatics learning, where topics such as algorithms, programming, and digital problem solving require support that responds systematically and adaptively to students' performance (Oksila et al., 2025; Shin et al., 2025).

A range of instructional approaches has been explored to strengthen CT, including mobile learning, web-based e-modules, game-based learning, adaptive e-learning, and instructional scaffolding (Connolly et al., 2021; Selano et al., 2024; Tikva & Tambouris, 2023). The relevance of website-based media lies in their ability to combine flexible access with organized learning materials, interactive activities, and automatic recording of students' learning activities (Oksila et al., 2025; Salwa et al., 2024). By responding to students' characteristics or performance, adaptive e-learning can modify the content, level of difficulty, and learning activities presented by the system (El-Sabagh, 2021; Sayed et al., 2023). For complex learning tasks, scaffolding provides progressive assistance that can help manage cognitive load while supporting students' learning independence (Doo et al., 2020; Peng et al., 2022). Yet, relatively little research has brought these functions together in one CT-oriented learning environment where students' initial competence is identified first and then used to determine both task difficulty and scaffolding support.

To address this gap, the present study employed a learning website that incorporates adaptive scaffolding. Within the website, students are assigned to adaptive learning levels and receive progressive assistance while working on CT case studies. Operationally, the adaptive scaffolding mechanism determines students' learning levels from their pretest scores and delivers tiered hints as they work through the case studies. The pretest serves as the initial cognitive map of students' CT competence; the resulting information is then used to assign the appropriate learning level and determine the scaffolding support provided afterward. The approach was selected because, in a digital learning environment, adaptive scaffolding can personalize support, vary the assistance provided according to students' needs, and strengthen problem-solving effectiveness (Munshi et al., 2022; Triana-Vera & López-Vargas, 2025). Evidence also suggests that scaffolding can contribute to CT development, particularly in programming tasks, problem-solving activities, and game- or simulation-based learning (Shin et al., 2025; Tikva & Tambouris, 2023).

Although interactive media, adaptive e-learning, and scaffolding have been examined in previous studies, limited evidence is available on their integration through a learning website that uses pretest-based initial cognitive mapping, CT case studies, and tiered hints, particularly for Grade X senior high school Informatics learning. Earlier studies have largely examined mobile learning, digital games, e-modules, or general adaptive e-learning. Although these approaches have produced positive findings, their emphasis has generally been placed on overall learning outcomes, personalization, or scaffolding rather than on linking students' initial CT competence to differentiated CT tasks and tiered support. For example, interactive mobile learning achieved an N-Gain of 0.65 for CT (Ekayana et al., 2025), while a web-based PjBL e-module achieved an N-Gain of 0.898 (Selano et al., 2024). Benefits have also been reported for adaptive personalized learning and CT-related scaffolding, particularly in learning effectiveness and problem-solving performance (Sayed et al., 2023; Shin et al., 2025). However, empirical testing of a website that combines adaptive levels, CT case studies, and tiered hints through a quasi-experimental design remains limited (Anggraini et al., 2025; Maryono et al., 2025). Accordingly, empirical evidence is needed to determine whether an adaptive scaffolding-based learning website can effectively improve students' CT skills.

Building on this background, the study examines whether the use of an adaptive scaffolding-based learning website affects the Computational Thinking skills of Grade X students in Informatics. The learning sequence implemented through the website begins with a pretest, followed by adaptive level determination, material presentation, level-based case studies, tiered hints, and a posttest, and concludes with a summary of learning outcomes. Four indicators were used to assess CT skills in this study: decomposition, pattern recognition, abstraction, and algorithmic thinking. At the theoretical level, the study extends empirical evidence concerning how initial cognitive mapping can be integrated with adaptive scaffolding in CT learning. From a practical perspective, the study offers a web-based learning design in which students' initial competence is linked to differentiated CT case studies, tiered hints, exercises, and feedback.

METHOD

A quantitative quasi-experimental approach was adopted in the present study, using a nonequivalent control group pretest-posttest design. Because the participants were drawn from existing classes, individual randomization could not be conducted; therefore, the nonequivalent group design was selected. The research design is presented in Table 1.

Table 1. Quasi-Experimental Design

No.	Group	Pretest	Intervention	Posttest
1	Control	O1	X1	O2
2	Experimental	O3	X2	O4

The sample comprised 72 students from two classes, each consisting of 36 students; one class served as the experimental group and the other as the control group. The use of cluster sampling reflected the selection of intact classes that were already established at the school. Instruction in the experimental class was delivered through the adaptive scaffolding-based learning website, whereas the control class followed conventional instruction. For the control class, conventional instruction involved teacher explanations, classroom discussions, practice questions, and assignments, with no adaptive website or tiered hints.

Students engaged with the material through problem-solving activities and case studies in which they were required to identify problems, recognize patterns, determine relevant information, and organize solution steps logically. The intervention was implemented across three meetings, each lasting 2 × 45 minutes. Students in the experimental class used the adaptive scaffolding-based learning website, whereas the control class received conventional instruction covering the same material and learning objectives.

CT development through the website followed a structured sequence beginning with a pretest and adaptive level determination, followed by material presentation, case-study completion, hint provision, and a posttest, and ending with a summary of learning outcomes. Students' pretest scores served as the basis for determining their adaptive learning levels. A pretest score below 50 placed a student in the basic level, scores from 50–75 corresponded to the intermediate level, and scores above 75 indicated the advanced level. Three levels of hints were incorporated into each case study, allowing support to become progressively available when students encountered difficulties in problem solving. Students' initial abilities determined the level of learning difficulty through the adaptive mechanism, while scaffolding supplied progressive assistance throughout problem solving (Kafai & Proctor, 2022; Shute et al., 2017). The criteria used to determine the adaptive levels are presented in Table 2.

Table 2. Adaptive Level Criteria

No.	Adaptive Level	Pretest Score	Bloom Taxonomy	Cognitive Category
1	Basic	< 50	C2–C3	LOTS–MOTS
2	Intermediate	50–75	C4	Initial HOTS
3	Advanced	> 75	C5	HOTS

The research instrument was structured around four CT indicators: decomposition, abstraction, pattern recognition, and algorithmic thinking. Together, these indicators represent systematic processes used in problem solving (Brennan & Resnick, 2012; Wing, 2006). The definition of each Computational Thinking indicator is presented in Table 3.

Table 3. Computational Thinking Indicators

No.	Indicator	Explanation
1	Decomposition	The ability to divide complex problems into simpler components
2	Pattern Recognition	The ability to recognize patterns, regularities, or similarities within a problem
3	Abstraction	The ability to identify relevant information while excluding irrelevant details
4	Algorithmic Thinking	The ability to organize problem-solving steps in a logical and systematic sequence

The study employed three forms of learning instruments: a pretest, a posttest, and case studies. Each pretest and posttest contained 20 multiple-choice items with five response options, with the items developed according to the four CT indicators. Twelve case studies were distributed across the three adaptive levels, with hints available to support students as they progressed through each case. The website also recorded students' learning levels, completion time, hint usage, learning progress, and final scores. Students and teachers used these records mainly to monitor learning activities; the log data were not included in the inferential statistical analysis. Effectiveness was determined from students' pretest and posttest CT scores, followed by N-Gain analysis, normality and homogeneity testing, an independent-samples t-test, and Cohen's d calculation. The details of the research instruments are presented in Table 4.

Table 4. Research Instruments

No.	CT Element	Pretest	Posttest	Case Study	Hint
1	Decomposition	5 items	5 items	3 cases	9 hints
2	Pattern Recognition	5 items	5 items	3 cases	9 hints
3	Abstraction	5 items	5 items	3 cases	9 hints
4	Algorithmic Thinking	5 items	5 items	3 cases	9 hints
Total		**20 items**	**20 items**	**12 cases**	**36 hints**

The website media, learning materials, and Computational Thinking Skills test instrument were subjected to expert validation. For the materials and CT instrument, feasibility percentages and Aiken's V were used to evaluate feasibility and content validity, whereas media validation relied on feasibility percentages because only one validator was involved. The pretest and posttest were also trialed with 36 Grade X students to examine item validity, reliability, difficulty, and discrimination. Pearson Product-

Moment correlation was applied to assess item validity, while Cronbach's Alpha was used to evaluate reliability.

The trial indicated that all 20 pretest items and 20 posttest items met the validity criteria, with the obtained r-value exceeding the r-table value of 0.329. The resulting Cronbach's Alpha of 0.842 indicated that the instrument had high reliability. Analysis of item difficulty and discrimination likewise indicated that the items were suitable for use; several items required minor revisions, but these changes did not alter the main question indicators.

Changes in students' Computational Thinking Skills were quantified using N-Gain. N-Gain was obtained using the following calculation formula.

$$N - Gain = \frac{Posttest - Pretest}{Maksimum\ Skor - Pretest}$$

N-Gain scores were interpreted using three categories: low for $g < 0.30$, moderate for $0.30 \leq g < 0.70$, and high for $g \geq 0.70$. Prior to hypothesis testing, normality was checked with the Shapiro-Wilk test and variance homogeneity with Levene's test using the N-Gain data. As both assumptions were satisfied, the hypothesis was evaluated using an independent-samples t-test, with the interpretation based on the "Equal variances assumed" row. Treatment magnitude was subsequently estimated using Cohen's d. For interpretation, Cohen's d values of 0.20, 0.50, and 0.80 or above represented small, medium, and large effects, respectively.

RESULTS AND DISCUSSION

Results

Two classes participated in the study, comprising an experimental class and a control class. Instruction in the experimental class was delivered through the adaptive scaffolding-based website, whereas the control class followed conventional instruction. Before implementation, the instruments and learning devices underwent expert validation to establish their feasibility.

Three aspects were subjected to validation: media, learning materials, and the Computational Thinking Skills test instrument. The validation results were analyzed using feasibility percentages. Specifically for the validation of the material and test instrument, the analysis was also supported by Aiken's V index because it involved more than one validator. A summary of the validation results is presented in Table 5.

Table 5. Expert Validation Results

No.	Validation Aspect	Feasibility Percentage	Aiken's V	Category
1	Media expert	89.29%	-	Very Feasible
2	Material expert	98.61%	0.981	Very Feasible and Very Valid
3	Computational Thinking Skills instrument	97.60%	0.967	Very Feasible and Very Valid

Table 5 shows feasibility percentages of 89.29% for the media, 98.61% for the materials, and 97.60% for the Computational Thinking Skills instrument. Media expert validation was conducted by one validator; therefore, the analysis focused on the feasibility percentage and did not use Aiken's V. The corresponding Aiken's V values were 0.981 for the materials and 0.967 for the Computational Thinking Skills test instrument, both falling within the very valid category. Accordingly, the website, learning materials, and test instrument met the feasibility and validity requirements for use in the study.

The pretest and posttest instruments were also trialed with 36 Grade X students before their use in the main study. All 20 pretest items and 20 posttest items met the validity criteria. The instrument produced a Cronbach's Alpha of 0.842, indicating high reliability. Analysis of item difficulty and discrimination further showed that the items were suitable for use, although several items required minor revisions that did not alter the main question indicators.

After the learning devices were declared feasible, the learning process was implemented in the experimental and control classes. Both classes were given a pretest before the treatment and a posttest after the treatment. Table 6 summarizes the pretest, posttest, difference, and N-Gain results for the two groups.

Table 6. Descriptive Summary of Computational Thinking Skills Results

No.	Class	N	Mean Pre	Mean Post	Mean Difference	Mean N-Gain	Category
1	Control	36	55.28	71.39	16.11	0.36	Moderate
2	Experimental	36	55.14	81.11	25.97	0.58	Moderate

The pretest results indicated comparable starting levels between the two groups, with mean scores of 55.28 for the control class and 55.14 for the experimental class (Table 6). After the intervention, the mean posttest score increased to 71.39 in the control group and 81.11 in the experimental group. These changes corresponded to mean gains of 16.11 and 25.97 points, respectively. A similar difference was observed in N-Gain, with mean values of 0.36 for the control group and 0.58 for the experimental group. Although both groups remained in the moderate category, the experimental group showed the greater improvement in CT Skills.

The improvement in Computational Thinking Skills was further examined at the indicator level by comparing pretest, posttest, gain, and N-Gain scores for decomposition, pattern recognition, abstraction, and algorithmic thinking. The results are summarized in Table 7.

Table 7. Computational Thinking Skills by Indicator

CT Indicator	Control Pretest	Control Posttest	Gain	Control N-Gain	Experiment Pretest	Experiment Posttest	Gain	Experiment N-Gain
Decomposition	52.78	69.44	16.67	0.353	53.89	86.11	32.22	0.699
Pattern Recognition	53.89	69.44	15.56	0.337	52.22	79.44	27.22	0.570
Abstraction	51.67	72.78	21.11	0.437	58.89	83.89	25.00	0.608
Algorithmic Thinking	62.78	73.89	11.11	0.299	55.56	75.00	19.44	0.438

Across all four CT indicators, the experimental group recorded greater improvement than the control group (Table 7). For the experimental group, decomposition produced the highest N-Gain at 0.699 after increasing from 53.89 to 86.11, followed by abstraction at 0.608, pattern recognition at 0.570, and algorithmic thinking at 0.438. The corresponding N-Gain values in the control group were 0.353, 0.337, 0.437, and 0.299, respectively. Taken together, these results show that the experimental group improved more across each CT indicator when learning with the adaptive scaffolding-based website.

Decomposition produced the largest gain among the four indicators in the experimental group: 32.22 points versus 16.67 points in the control group. This difference identifies decomposition as the indicator showing the strongest response to the adaptive scaffolding intervention. One possible explanation is that the learning activities and tiered hints guided students to approach complex problems by separating them into smaller, manageable components that corresponded to their initial learning levels.

The assumptions required for hypothesis testing were examined before the main statistical test was conducted, beginning with normality and homogeneity. Because each class contained 36 students, normality was assessed using the Shapiro-Wilk test. The normality test results are shown in Table 8.

Table 8. Normality Analysis Results for N-Gain Scores

No.	Class	Data	Shapiro-Wilk Sig.	Description
1	Control	N-Gain	0.268	Normal
2	Experimental	N-Gain	0.182	Normal

The Shapiro-Wilk results in Table 8 yielded significance values of 0.268 for the control class and 0.182 for the experimental class. Since both values were above 0.05, the N-Gain data in both groups met the normality assumption.

Variance homogeneity was then examined to determine whether the N-Gain distributions of the two classes had equivalent variances. The results of the homogeneity test are presented in Table 9.

Table 9. Homogeneity Analysis Results for N-Gain Scores

Data	Levene's Statistic	df1	df2	Sig.	Description
N-Gain	0.077	1	70	0.782	Homogeneous

As reported in Table 9, Levene's test produced a statistic of 0.077 with a significance value of 0.782. Since the significance value exceeded 0.05, the N-Gain variances were considered homogeneous across the two groups. Since the N-Gain data met the assumptions of normality and homogeneity, hypothesis testing was subsequently carried out using the independent-samples t-test, with reference to the "Equal variances assumed" row. The hypothesis test results are shown in Table 10.

Table 10. Independent Samples t-Test Results

Data	Statistical Test	t	df	Sig. (2-tailed)	Mean Difference	Description
N-Gain	Equal Variances Assumed	-10.214	70	0.000	-0.217083	Significant

The comparison of N-Gain scores showed a statistically significant difference between the control and experimental groups ($t(70) = -10.214$, $p < .001$; Table 10). The experimental group obtained the higher mean N-Gain, 0.58, compared with 0.36 in the control group, resulting in a 0.217-point difference in favor of the experimental group. These results indicate greater improvement for students learning under the adaptive scaffolding-based condition than for those receiving conventional instruction.

The magnitude of the intervention effect was quantified using Cohen's d, with the result presented in Table 11.

Table 11. Effect Size Results

Data	Control Mean	Experimental Mean	Pooled SD	Cohen's d	Category
N-Gain	0.36	0.58	0.09016	2.43	Large

The analysis produced a Cohen's d value of 2.43, which falls within the large-effect category because it exceeds 0.80. Thus, the adaptive scaffolding-based learning website was associated with a large effect on students' Computational Thinking Skills. Overall, the experimental group showed greater improvement than the control group, while the website was considered feasible and effective for supporting CT learning.

Discussion

The results provide evidence that the adaptive scaffolding-based learning website was feasible and effective for CT instruction. Expert validation classified the media, learning materials, and test instrument as very feasible, indicating that the learning components satisfied the required criteria before implementation. The experimental class also obtained a higher mean N-Gain (0.58) than the control class (0.36). The difference between the two groups was statistically significant ($t(70) = -10.214$, $p < .001$), and the Cohen's d value of 2.43 indicated a large effect. These results indicate that the improvement in CT Skills was greater among students who used the adaptive scaffolding-based website than among those who received conventional instruction.

The greater improvement may be associated with the combination of adaptive learning and progressive scaffolding used in the intervention. Students first received learning materials and case studies according to their initial levels, while tiered hints and feedback were provided during the problem-solving activities rather than giving the same support to all students. Through this sequence, the learning activities addressed the four CT indicators: decomposition involved breaking complex problems into smaller parts, pattern recognition was supported through exercises and case studies, abstraction focused on identifying relevant information, and algorithmic thinking involved arranging solution steps logically.

The indicator-level results showed the largest improvement for decomposition. In the experimental group, decomposition reached an N-Gain of 0.699, compared with 0.353 in the control group, making it the indicator with the highest gain. This result may be related to the way the intervention guided students to separate complex problems into smaller and more manageable components. The initial cognitive mapping based on pretest performance may have helped align case difficulty with students' readiness, while the tiered hints offered more specific assistance when students encountered difficulties.

This sequence may have helped students form a clearer representation of a problem before proceeding to pattern recognition, abstraction, and algorithmic solution development. The findings therefore suggest that the adaptive scaffolding-based website may support not only overall CT improvement but also specific CT processes, with decomposition showing the greatest improvement in this study. This interpretation is consistent with computational thinking as a problem-solving process that involves problem formulation, information representation, abstraction, and the development of solution procedures (Brennan & Resnick, 2012; Shute et al., 2017; Wing, 2006). It also corresponds with findings reported by Contrino et al., (2024), Peng et al., (2022), and Shin et al., (2025), who found that adaptive scaffolding can assist students with complex tasks, improve learning performance, and reduce cognitive load.

The present findings are also in line with earlier research on technology-supported CT learning. Ekayana et al., (2025), for example, reported improvements in computational thinking and learning achievement through interactive mobile learning compared with conventional instruction. Related findings from Anggraini et al., (2025) and Buchori et al., (2025) showed that interactive digital technology can support CT-related indicators through learning activities that are active, contextualized, and structured. Yanto et al., (2023) found that Google Sites-based learning media were feasible for Informatics learning in vocational high schools. At the same time, research on adaptive e-learning and scaffolding has highlighted benefits related to personalization, student engagement, and problem-solving skills (Doo et al., 2020; El-Sabagh, 2021; Sayed et al., 2023; Triana-Vera & López-Vargas, 2025).

A major contribution of this study is the integration of adaptive level determination, CT-based case studies, tiered hints, exercises, and feedback within a single adaptive scaffolding-based learning website. Unlike approaches that mainly use mobile learning, e-modules, Google Sites, or adaptive e-learning for content delivery or general personalization, the website in this study uses students' initial abilities to guide the progression of CT learning and support. The findings should also be considered in light of the study limitations. The research involved only two classes, and effectiveness was evaluated mainly through pretest and posttest results. Future studies could extend this work by involving larger samples, using longer learning periods, and examining additional outcomes such as learning motivation, student engagement, long-term retention, and students' activity logs.

Overall, the findings suggest that the effectiveness of the adaptive scaffolding-based website is related to how personalized learning, progressive assistance, problem-based exercises, and feedback are integrated within one learning environment. This design enables support to respond to students' initial abilities while remaining available when difficulties occur in pattern recognition, decomposition, abstraction, and algorithmic thinking. In this respect, the study adds empirical evidence to technology-based CT learning and provides an Informatics learning design that is more adaptive, structured, and focused on CT development.

CONCLUSION

The findings indicate that the adaptive scaffolding-based learning website was feasible and effective for use in Informatics CT learning. Expert validation classified the website, learning materials, and test instrument as very feasible. The experimental class showed greater improvement than the control class, as reflected in the mean N-Gain scores of 0.58 and 0.36, respectively. Among the four CT indicators, decomposition showed the highest gain in the experimental group (N-Gain = 0.699), suggesting that the intervention may have provided stronger support when students were required to divide complex problems into smaller components.

Statistical analysis confirmed a significant difference in improvement between the two classes ($t(70) = -10.214$, $p < .001$). The effect size was large, with a Cohen's d of 2.43. These findings suggest that the integration of adaptive levels, CT case studies, tiered hints, exercises, and feedback can support the development of CT within the learning process. Scientifically, the study contributes to website-based Informatics learning by showing how adaptive mechanisms and scaffolding can be integrated into a single digital learning environment.

These findings should be interpreted in light of several limitations. The study involved a limited number of participants, used a relatively short treatment period, and relied on pretest-posttest measurement to assess the outcomes. Future studies could strengthen the evidence by involving larger and more diverse participant groups, extending the duration of the intervention, and applying the approach to a broader range of Informatics topics. Further research could also examine additional outcomes, including learning motivation, student engagement, learning independence, and retention of learning outcomes.

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