

The Effectiveness of the Koding LIFE Platform in Enhancing Elementary Students' Computational Thinking

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Abstract

The rapid advancement of Education 4.0 and Society 5.0 has placed computational thinking at the forefront of 21st-century competencies, yet its effective development in elementary school contexts remains constrained by limited interactive instructional media, teachers' restricted technological backgrounds, and the perceived abstraction of coding and artificial intelligence concepts. This study aimed to examine the effectiveness of the Koding LIFE digital learning platform in improving elementary students' computational thinking skills in coding and artificial intelligence learning. A quasi-experimental pretest–posttest control group design was employed, involving 120 students drawn from five elementary schools in Boyolali Regency, Indonesia, assigned to an experimental group ($n = 60$) and a control group ($n = 60$) through cluster random sampling. Computational thinking was measured across four components using a validated instrument (Aiken's $V \geq 0.84$; Cronbach's $\alpha = 0.87$). The results demonstrated that students in the experimental group achieved significantly higher posttest scores than those in the control group ($t(118) = 5.235$, $p < 0.001$, Cohen's $d = 0.956$), with a mean gain of 18.62 points compared to 6.48 points in the control group. These findings indicate that the Koding LIFE platform, through its interactive, visualization-based, and problem-solving-oriented features, effectively fosters computational thinking development in elementary learners. This study contributes empirical evidence supporting the integration of coding and AI learning platforms in elementary education and offers a replicable pedagogical model for schools with limited technological resources.

Keywords: computational thinking, Koding LIFE, learning platform, coding education, elementary school

Introduction

In the era of the fourth industrial revolution, where digital transformation reshapes every sector, education systems are increasingly being reimagined as “Education 4.0” and “Education 5.0,” integrating artificial intelligence, data, robotics, and smart learning environments to prepare learners for a hyperconnected, human-centered Society 5.0 (Adel, 2024; González-Pérez & Ramírez-Montoya, 2022). In response to these developments, schools and universities are expected not only to digitize content and procedures but also to redesign curricula, pedagogy, and assessment so that learners can thrive amid disruptive technologies and evolving work practices (Alenezi, 2023). Within this transformation, coding is increasingly framed as a new form of literacy, comparable in importance to reading and writing, because it supports

computational thinking, problem solving, and the ability to understand and shape digital systems rather than merely consume them (Dağ et al., 2023; Budiarto et al., 2026). Research in preschool and primary education further demonstrates that age-appropriate coding, robotics, and unplugged activities can effectively foster young learners' computational thinking, collaboration, and communication, thereby supporting the development of broader digital and twenty-first century skills from the earliest years of schooling (Carayannis & Morawska-Jancelewicz, 2022; Huang & Wang, 2025). Consequently, digital competence is no longer optional but a foundational requirement, with elementary teachers expected to master technology, data, and human literacies while cultivating these capacities in students so that future citizens and workers can participate fully and responsibly in Industry 4.0 and Society 5.0.

Despite these global advancements and expectations, translating such visions into effective classroom practices remains a significant challenge, particularly in elementary schools in developing country contexts. Field observations conducted in several elementary schools in Boyolali Regency reveal a number of practical barriers in implementing coding and artificial intelligence (AI) learning. Many teachers assigned to teach these subjects lack formal backgrounds in information technology, which constrains both their instructional confidence and their ability to employ effective pedagogical strategies. In addition, the limited availability of appropriate instructional media for coding education results in learning activities that remain predominantly teacher-centered rather than interactive and exploratory. Students also experience difficulties in understanding AI concepts, which are often perceived as abstract and cognitively demanding for elementary-level learners. Consequently, classroom practices tend to prioritize conceptual delivery over hands-on learning experiences that are essential for fostering students' computational thinking skills. These conditions highlight a persistent gap between the aspirations of digital-era education and the realities of classroom implementation, underscoring the need for pedagogical approaches and learning tools that can support meaningful coding and AI education in elementary school contexts.

Computational thinking has emerged as a foundational 21st-century competence, often placed alongside reading, writing, and arithmetic as a basic literacy needed to navigate a digital society, because it provides systematic ways to decompose problems, recognize patterns, abstract key structures, and design algorithms that apply across academic subjects and real-world contexts (Lodi & Martini, 2021; Wu et al., 2024; Yang et al., 2025). Studies show that stronger computational thinking supports higher-order problem-solving, from elementary fraction learning to engineering and computer science tasks, and underpins creativity, collaboration, and critical thinking that are central to modern employability and citizenship (Amri et al., 2022). At the same time, digital learning platforms are transforming how coding and computational thinking are taught, by enabling interactive simulations, automated feedback, adaptive tasks, and remote access to powerful computing resources (Alshammary & Alhalafawy, 2023; Cirneanu & Moldoveanu, 2024; Rincón et al., 2025). Meta-analytic evidence indicates that well-designed digital platforms produce small but positive gains in learning outcomes compared with traditional classrooms, and targeted interventions such as debugging supports or mind-mapping in graphical programming can significantly strengthen specific computational thinking sub-skills and self-efficacy (Yang et al., 2025). These platforms also make scalable, personalized coding education feasible for diverse learners and contexts, positioning them as key infrastructure for embedding computational thinking as a universal 21st-century skill rather than a niche capability reserved for future programmers.

Despite the increasing recognition of computational thinking and the growing use of digital platforms in coding education, existing studies largely focus on general digital learning environments or secondary and higher education contexts, leaving limited empirical evidence

on how structured digital platforms can effectively support computational thinking development in elementary coding and artificial intelligence learning (Alshammary & Alhalafawy, 2023; Wu et al., 2024). Moreover, while previous research has demonstrated the potential of coding activities, robotics, and programming tools to enhance computational thinking, few studies have examined how platform-based learning environments can address practical classroom constraints such as limited teacher technological backgrounds, abstract AI concepts, and the lack of interactive instructional media in elementary schools (Dağ et al., 2023; Monteiro et al., 2021). This gap has both academic and practical consequences. Academically, it limits the development of context-specific frameworks for computational thinking in early education. Practically, it leaves teachers without empirically validated pedagogical models to effectively implement coding and artificial intelligence learning in resource-constrained elementary classrooms. Addressing this gap, the present study introduces the Koding LIFE digital learning platform, designed to provide an interactive environment that integrates coding and artificial intelligence learning activities aimed at fostering elementary students' computational thinking skills. The novelty of this study lies in its integration of platform-based coding instruction with computational thinking development within the context of elementary AI education, combined with empirical evaluation through a quasi-experimental design.

Therefore, this study aims to examine the effectiveness of the Koding LIFE platform in improving elementary students' computational thinking in coding and artificial intelligence learning. The findings are expected to contribute to the growing body of research on technology-enhanced coding education and to provide practical insights for implementing computational thinking-oriented learning platforms in elementary school contexts.

Method

This study employed a quasi-experimental research design to examine the effectiveness of the Koding LIFE learning platform in enhancing elementary students' computational thinking skills (Sukmadinata, 2012). Specifically, the research adopted a pretest–posttest control group design, which allows comparison between students who experience the intervention and those who follow conventional instruction. In this design, both the experimental and control groups were first administered a pretest to measure their initial computational thinking abilities (Sugiyono, 2022). Subsequently, the experimental group received the instructional treatment through the Koding LIFE platform, while the control group continued learning through conventional classroom instruction. After the learning intervention was completed, both groups were given a posttest to assess changes in their computational thinking performance. The comparison between pretest and posttest scores across the two groups was used to determine the effectiveness of the Koding LIFE platform in improving students' computational thinking skills.

Table 1. Research Design Scheme

Group	Pretest	Treatment	Posttest
Experimental	O1	X	O2
Control	O1	–	O2

Description:

O1 : Pretest computational thinking

X : Learning using the LIFE Coding platform

O2 : Posttest computational thinking

This study was conducted in several elementary schools in Boyolali Regency, Indonesia, where coding and artificial intelligence have begun to be introduced as part of digital literacy initiatives. The population consisted of 120 elementary schools that had implemented coding and artificial intelligence learning activities. Using a cluster random sampling technique, five schools were selected as the research sample. Three schools which SDN 1 Sranten, SDN 2 Karangnongko, and SDN 1 Gunungsari were assigned to the experimental group, where students learned through the Koding LIFE digital learning platform, while two schools (SDN 3 Mojo and SDN Munggur) formed the control group, where students received conventional instruction. This grouping enabled a comparison of learning outcomes between students who used the Koding LIFE platform and those who experienced traditional classroom instruction.

The primary instrument used in this study was a computational thinking test administered in two stages which were pretest and posttest, to evaluate students' initial abilities and learning gains following the instructional intervention. The test items were developed based on four widely recognized components of computational thinking: decomposition, pattern recognition, abstraction, and algorithmic thinking, each operationalized through structured problem-solving tasks requiring students to analyze problems, identify patterns, simplify complex situations, and formulate step-by-step solutions. The instrument was designed to be appropriate for elementary school students while capturing essential aspects of computational reasoning, and its results served as the primary data for examining the effectiveness of the Koding LIFE platform. As shown in table 2.

Table 2. Computational Thinking Test Instrument Grid

No	Aspect of Computational Thinking	Indicator	Description of Ability Measured
1	Decomposition	Identifying parts of a problem	Students are able to break down a complex problem into smaller and manageable parts
		Organizing problem components	Students are able to classify information or elements involved in a problem
2	Pattern Recognition	Identifying similarities	Students are able to recognize similarities or recurring structures in problems
		Identifying patterns	Students are able to detect patterns that can help simplify problem solving
3	Abstraction	Selecting essential information	Students are able to distinguish important information from irrelevant details
		Simplifying problems	Students are able to represent problems in simplified forms or models
4	Algorithmic Thinking	Designing solution steps	Students are able to formulate logical and sequential steps to solve problems
		Evaluating solution procedures	Students are able to check and improve solution procedures logically

Adaptation from Altıok & Üçgül (2025) Mee et al. (2025), Valls Pou et al. (2022)

The validity of the computational thinking test items was analyzed using Aiken's V coefficient based on expert judgments regarding the relevance of each item to the computational thinking

indicators (Kaplan, 2023). The reliability of the instrument was examined using Cronbach's Alpha to determine the internal consistency of the test items (Tucker et al., 2023). The results of the validity and reliability analyses are presented in Tables 3 and 4.

Table 3. Results of Instrument Content Validity (Aiken's V)

No	Aspect	Indicator	Item Code	Aiken's V	Category
1	Decomposition	Identifying parts of a problem	CT1	0.86	Valid
2	Decomposition	Organizing problem components	CT2	0.88	Valid
3	Pattern Recognition	Identifying similarities	CT3	0.84	Valid
4	Pattern Recognition	Identifying patterns	CT4	0.87	Valid
5	Abstraction	Selecting essential information	CT5	0.89	Valid
6	Abstraction	Simplifying problems	CT6	0.85	Valid
7	Algorithmic Thinking	Designing solution steps	CT7	0.90	Valid
8	Algorithmic Thinking	Evaluating solution procedures	CT8	0.88	Valid

Interpretation:

$V \geq 0.80$ = High validity

Table 4. Results of Instrument Reliability Test

Instrument	Number of Items	Cronbach's Alpha	Reliability Category
Computational Thinking Test	8	0.87	High Reliability

The data were analyzed using several statistical procedures to examine the effectiveness of the Koding LIFE platform in improving students' computational thinking skills. First, a normality test was conducted using the Kolmogorov–Smirnov test to determine whether the pretest and posttest data were normally distributed. Second, a homogeneity test was performed using the Fisher test to examine the equality of variances between the experimental and control groups. After confirming that the data met the assumptions of normality and homogeneity, hypothesis testing was carried out using an independent sample t-test to determine whether there was a statistically significant difference in computational thinking performance between students in the experimental group who learned using the Koding LIFE platform and those in the control group who received conventional instruction (Mishra et al., 2019).

Research Hypotheses:

H0: The computational thinking ability of students in the experimental group is not better than that of students in the control group.

H1: The computational thinking ability of students in the experimental group is better than that of students in the control group.

Results

Normality and Homogeneity Test

Prior to hypothesis testing, two prerequisite assumptions were examined: normality of data distribution and homogeneity of variances. The normality of pretest and posttest scores in both the experimental and control groups was evaluated using the Kolmogorov–Smirnov (K–S) test, while the homogeneity of variances between the two groups was assessed using the Levene test.

Table 5. Results of Normality Test

No	Group	Data	N	KS Stat	p-value	Sig. Level	Decision
1	Experimental	Pretest	60	0.048	0.998	> 0.05	Normal
2	Experimental	Posttest	60	0.043	1.000	> 0.05	Normal
3	Control	Pretest	60	0.098	0.580	> 0.05	Normal
4	Control	Posttest	60	0.070	0.908	> 0.05	Normal

As presented in Table 5, the Kolmogorov–Smirnov test results show that all datasets—pretest and posttest scores for both the experimental group (KS = 0.048, $p = 0.998$; KS = 0.043, $p = 1.000$) and the control group (KS = 0.098, $p = 0.580$; KS = 0.070, $p = 0.908$)—produced p -values greater than 0.05.

Table 6. Results of Homogeneity Test (Levene Test)

No	Data	df1	df2	F Stat	p-value	Sig. Level	Decision
1	Pretest	1	118	0.725	0.396	> 0.05	Homogeneous
2	Posttest	1	118	1.232	0.269	> 0.05	Homogeneous

As shown in Table 6, the Levene test results for pretest scores ($F = 0.725$, $p = 0.396$) and posttest scores ($F = 1.232$, $p = 0.269$) yielded p -values greater than 0.05.

In summary, the results of both the normality and homogeneity tests confirm that the data meet the fundamental assumptions required for parametric statistical analysis. Accordingly, the use of the independent sample t -test for subsequent hypothesis testing is statistically justified.

Before evaluating the effectiveness of the Koding LIFE platform, a balance test was conducted to verify that the experimental and control groups had comparable initial computational thinking abilities prior to the instructional intervention. This test is essential to ensure that any observed differences in posttest performance can be attributed to the treatment rather than pre-existing differences between groups. Descriptive statistics for the pretest scores of both groups are presented in Table 7 below.

Table 7. Descriptive Statistics of Pretest Scores

Group	N	Mean	SD	Min	Max
Experimental	60	54.22	9.26	35.80	74.70
Control	60	55.80	10.31	38.00	80.00

As shown in Table 7, the mean pretest score of the experimental group was 54.22 (SD = 9.26), while the control group obtained a mean score of 55.80 (SD = 10.31). The results of the independent sample t -test on pretest scores are presented in Table 8.

Table 8. Balance Test Results — Independent Sample t -Test on Pretest Scores

Comparison	N ₁	N ₂	t-value	p-value	Sig. Level	Decision
Exp. Pretest vs Ctrl. Pretest	60	60	-0.887	0.377	> 0.05	H ₀ Not Rejected

As presented in Table 8, the independent sample t -test on pretest scores yielded $t = -0.887$ with $p = 0.377$. Therefore, H₀ was not rejected, confirming that the two groups were statistically equivalent in their initial computational thinking abilities before the instructional treatment was administered. These findings demonstrate that the experimental and control groups were in a

balanced condition at the outset of the study. Any subsequent differences in posttest performance between the two groups can therefore be attributed to the effect of the instructional intervention namely, the use of the Koding LIFE digital learning platform, rather than to pre-existing differences in students' computational thinking abilities.

Pretest and Posttest Results of Student's Computational Thinking and Hypothesis Testing

Figure 1 presents the descriptive statistics of pretest and posttest scores for both groups, including mean gain scores as an indicator of learning improvement.

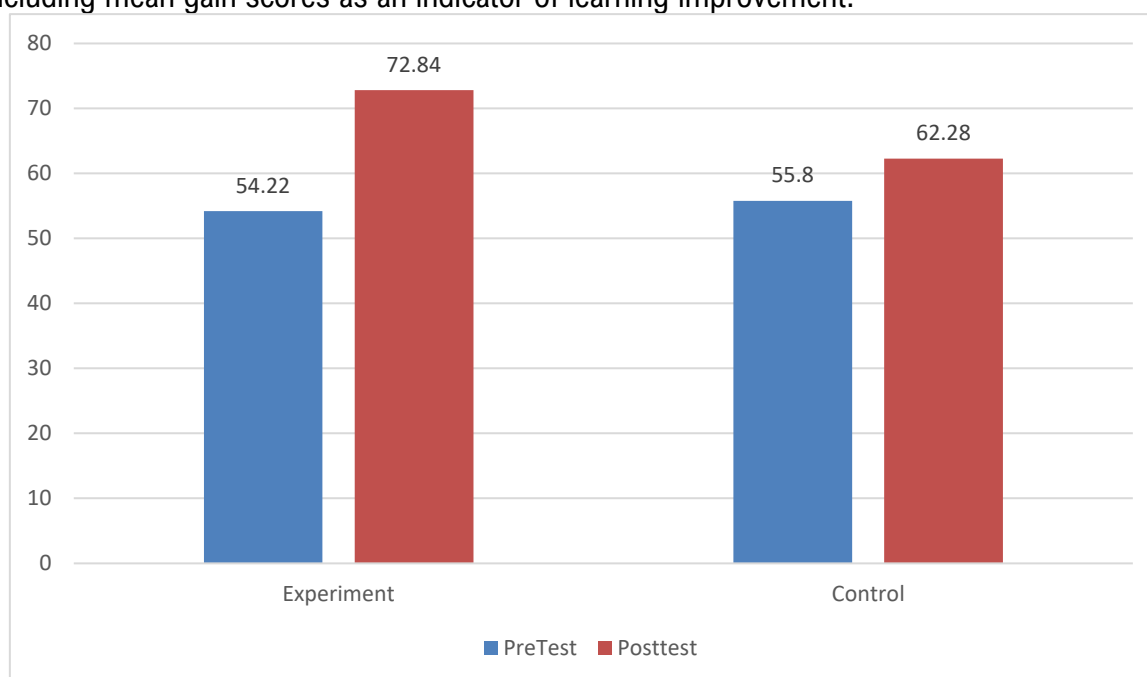


Figure 1. Descriptive Statistics of Pretest and Posttest Scores

Figure 1 presents the comparison of pretest and posttest mean scores between the experimental and control groups. The experimental group obtained a pretest mean score of 54.22 and a posttest mean score of 72.84. The control group obtained a pretest mean score of 55.80 and a posttest mean score of 62.28. The mean gain scores for the experimental and control groups were 18.62 and 6.48, respectively. As for, an independent sample t-test was conducted on the posttest scores, and the results are presented in Table 9.

Table 9. Independent Sample t-Test Results (Posttest Scores)

Mean Diff.	SE	t	df	p-value	Cohen's d	Effect Size	Decision
10.56	2.017	5.235	118	< 0.001	0.956	Large	H ₀ Rejected

The results of the independent sample t-test on posttest scores are presented in Table 10. The analysis yielded a mean difference of 10.56 (SE = 2.017), with $t(118) = 5.235$ and $p < 0.001$. The effect size was 0.956.

Discussion

The results showed that students in the experimental group obtained significantly higher computational thinking scores than those in the control group ($t(118) = 5.235$, $p < 0.001$, Cohen's $d = 0.956$), with an average gain of 18.62 points compared to 6.48 points — a difference

that reflects a large practical effect. The effectiveness of the Koding LIFE platform can be understood through its ability to provide structured and interactive coding activities, which directly train the four core components of computational thinking: decomposition, pattern recognition, abstraction, and algorithmic thinking. Computational thinking has been widely recognized as a 21st-century core literacy competency alongside reading, writing, and arithmetic (Lodi & Martini, 2021; Wu et al., 2024), and coding is one of the most effective vehicles for its development, requiring students to break down complex tasks, recognize patterns, design algorithms, and systematically correct errors (Dağ et al., 2023; Scherer et al., 2021). Evidence from preschool through high school reinforces this, showing that coding activities consistently improve computational thinking abilities along with related skills such as logical reasoning and abstraction (Critten et al., 2022).

On the other hand, the LIFE Koding platform places these activities in a digital environment that provides immediate feedback, encourages exploration of various solution paths, and supports independence and self-regulated learning (Blanc et al., 2025; Kurniawan et al., 2025), conditions that are highly relevant considering the limitations of interactive learning media and the limited technological background of teachers in elementary schools in Boyolali Regency. This finding is also in line with meta-analytic evidence showing that well-designed digital platforms produce meaningful improvements in learning outcomes compared to conventional learning (Budiarto et al., 2026; Roemintoyo et al., 2020), while also confirming the relevance of developing platform-based computational thinking in responding to the demands of Education 4.0 and Society 5.0 (González-Pérez & Ramírez-Montoya, 2022; Adel, 2024).

The effectiveness of the LIFE Koding platform is inseparable from several pedagogical features that distinguish it from conventional learning approaches. A well-designed digital platform has been shown to transform the coding learning experience from mere lectures to an experiential and exploratory process (Cirneanu & Moldoveanu, 2024). The platform's interactivity allows students to actively try, modify, and test their own code, so the learning process does not stop at conceptual understanding but continues to real-world applications that gradually build procedural understanding. Visualizing concepts in a digital environment helps elementary school students represent problems in a more concrete and understandable form (Monteiro et al., 2021; Dağ et al., 2023). The platform's immediate feedback allows students to quickly identify errors and iteratively refine their solutions, a key mechanism in strengthening self-efficacy and self-regulated learning (Alshammary & Alhalafawy, 2023). This condition is in line with the finding that platform-based digital environments significantly increase student engagement compared to direct instruction, as students gain control over their own learning process and are motivated to explore various solution paths (Cirneanu & Moldoveanu, 2024; Alenezi, 2023). Overall, this pedagogical mechanism makes the Koding LIFE platform not just a medium for delivering material, but a learning environment that encourages students to think computationally through direct experience, while preparing students to actively participate in the digital ecosystem of Society 5.0.

The findings of this study align with literature that emphasizes the importance of developing computational thinking from elementary school onward. Computational thinking is a cognitive capacity that can be developed from an early age through coding activities designed appropriately for students' developmental stages (Lodi & Martini, 2021; Wu et al., 2024). Various studies show that application-based, robotics-based, and unplugged coding activities effectively train decomposition, pattern recognition, abstraction, and algorithmic thinking skills, which in turn support higher-order thinking, creativity, collaboration, and cross-disciplinary problem-solving skills that are the demands of the 21st century (Monteiro et al., 2021; Huang & Wang, 2025). In the context of implementation in elementary schools in Boyolali Regency, this study

also revealed several practical challenges, such as teachers' limited information technology background, the lack of interactive coding learning media, and students' perceptions that artificial intelligence concepts are abstract and difficult to understand. The LIFE Coding platform presents a pedagogical solution to these obstacles by providing a structured, interactive, and visualization-based learning environment so that teachers can facilitate coding learning more effectively and students gain a more concrete and exploratory learning experience (Alshammary & Alhalafawy, 2023). Thus, in addition to demonstrating statistical effectiveness in improving computational thinking skills, this platform is also contextually relevant in bridging the gap between the demands of digital-era education and the limitations of implementation in elementary schools, in line with the direction of transformation towards Education 4.0 and Society 5.0 (Adel, 2024; Shenkoya & Kim, 2023).

Despite the significant findings, this study has several limitations that should be acknowledged. First, the use of a quasi-experimental design limits full control over external variables that may influence students' computational thinking development. Second, the study was conducted within a limited geographical scope in Boyolali Regency, which may affect the generalizability of the findings to other educational contexts with different technological infrastructures and teacher competencies. Third, the measurement of computational thinking relied primarily on test-based instruments, which may not fully capture process-oriented and behavioral aspects of computational thinking skills. Therefore, future research is recommended to employ broader samples, experimental designs with stronger control, and mixed-method approaches to obtain a more comprehensive understanding of students' computational thinking development.

Conclusion

This study concludes that the Koding LIFE platform is proven effective in improving elementary school students' computational thinking skills in coding and artificial intelligence learning, with the experimental group showing statistically significant and significantly higher improvements compared to the control group receiving conventional learning. The effectiveness of this platform can be attributed to its ability to provide an interactive, visualization-based, and problem-solving-oriented learning experience, conditions that directly train the core components of computational thinking, namely decomposition, pattern recognition, abstraction, and algorithmic thinking from the elementary school level. Based on these findings, elementary schools are advised to systematically integrate digital platforms such as Koding LIFE into their coding and artificial intelligence curricula, accompanied by ongoing training for teachers to maximize the use of the platform as an effective pedagogical instrument. However, these findings should be interpreted with consideration of the study's limitations, including the restricted geographical scope and the use of a quasi-experimental design. Future research is recommended to explore the effectiveness of this platform on a broader scale, assessing its impact on each sub-component of computational thinking individually, and investigating moderating factors such as teacher technological competence and infrastructure availability that may influence successful implementation in various elementary school contexts.

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