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Computational Thinking in Mathematics Instruction Integrated to STEAM Education: A Systematic Review and Meta-Analysis

Suparman Suparman [1], Dadang Juandi [1], Turmudi Turmudi [1], Bambang Avip Priatna Martadiputra [1], Yullys Helsa [2], Masniladevi Masniladevi [2], Dea Stivani Suherman [2]

[1] *Department of Mathematics Education, Universitas Pendidikan Indonesia, Bandung 41054, Indonesia*
[2] *Department of Elementary Education, Universitas Negeri Padang, Padang 25173, Indonesia*

Abstract **– In the early 2000s, computational thinking (CT) has emerged as an essential skill, and combining mathematics teaching with STEAM education is seen as an effective strategy to improve CT abilities. Over the past few decades, research on this educational strategy has increased significantly. This study evaluates the impact of STEAM-based mathematics teaching on CT skills among students and investigates major factors that contribute to their CT development. A meta-analytic review was conducted, encompassing 43 empirical studies listed in Scopus and published between 2017 and 2023. These studies included data from 7,807 students and produced 80 effect size estimates for analysis. By applying Q Cochrane and Z tests using CMA v.4 software, the results demonstrated a significant, moderately positive impact on students' CT skills. Additionally, variables such as duration of intervention, ICT utilization, and the type of mathematical content were found to significantly influence CT outcomes, while factors like educational level and learning setting did not. The implications for mathematics education are explored in depth.**

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Corresponding author: Dadang Juandi,
Department of Mathematics Education, Universitas Pendidikan Indonesia, Bandung 41054, Indonesia.
Email: dadang.juandi@upi.edu

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1. Introduction

The swift and advanced progression of science and technology in the 21st century requires individuals, particularly students, to adjust to new challenges across sectors such as education, business, healthcare, and industry. Addressing these challenges often involves programming abilities, a foundational aspect of computer science [1]. As programming becomes increasingly vital, educators are more frequently tasked with fostering computational thinking (CT), an essential subject in global educational technology discussions [2], [3], [4], [5], [6]. Molina-Ayuso *et al.* [7] describe CT as a multifaceted ability that enables students to tackle complex issues in areas such as engineering, mathematics, science, technology, and the arts. Therefore, prioritizing the cultivation of CT within educational contexts, especially in learning environments, is crucial.

Many studies describe CT as a structured approach to problem-solving that includes efficient and effective methods, such as algorithm design, pattern recognition, abstraction, and decomposition, all of which are foundational in computer science [8], [9], [10], [11], [12]. CT is particularly relevant to mathematics, often referred to as the "language of sciences," where mathematical thinking activities inherently require CT skills. Studies indicate a positive relation between students' CT skills and their success in mathematics, suggesting that as students' CT skills improve, so does their performance in mathematics, and the relationship works in both directions [13], [14], [15], [16]. Despite its importance, several studies reveal that students' CT achievement remains suboptimal, with many exhibiting low CT proficiency [17], [18], [19], [20], [21].

Consequently, effective interventions in math learning environments are needed to improve CT skills. Enhancing students' mathematics achievement through improved computational thinking (CT) skills can be achieved by creating structured learning environments. Methods such as problem-based learning, discovery learning, and project-based learning are particularly effective in building advanced problem-solving skills [22], [23], [24]. Since complex problem-solving is fundamental to CT [7], these teaching strategies are highly suitable for nurturing CT skills in mathematics. Additionally, incorporating science, technology, engineering, art, and mathematics (STEAM) into math education can further support CT skill development. Research demonstrates that STEAM education significantly benefits students' CT acquisition [17], [25], [26], [27], [28], providing a solid foundation for the idea that STEAM-based math instruction can strengthen CT within math classrooms.

From 2004 to 2023, numerous empirical studies indicated that math instruction integrated with STEAM education positively impacts students’ CT acquisition [29], [30], [31], [32], [33]. However, other studies report insufficient evidence to conclude a significant effect on CT achievement [46], [47], [48], [49], [50], and some even indicate negative impacts [54], [55], [56]. This variation suggests that the impact of STEAM-based math instruction on CT skills is inconsistent.

Over the last two decades, quantitative studies have yielded mixed results: Some report moderate effects of STEAM-integrated math instruction on CT achievement [33], [34], [35], [36], [37], while others report strong effects [39], [42], [43]. In contrast, a number of studies indicate modest effects [46], 49], [52], and others show weak effects [57], [58]. This range of findings reflects the diverse outcomes of STEAM-integrated math instruction on students’ CT skills, suggesting a need to examine factors that may account for these differences, such as intervention duration, class size, educational level, learning environment, ICT use, and content focus.

Meta-analysis - A quantitative method that synthesizes findings across relevant empirical studies by using effect sizes as data [59], [61] can provide a clearer picture of the varying effects of STEAM-integrated math instruction on CT achievement. This approach also facilitates analysis of critical factors that may contribute to differences in students’ CT outcomes.

Although some systematic reviews have provided overviews of CT studies within mathematics education [62], [63], [64], [65], [66], [67], and various meta-analyses have explored CT interventions more broadly [60], [68], [69], [70], [71], [72], this study employs meta-analysis specifically to address the inconsistent effects of STEAM-enhanced math instruction on CT abilities and to identify factors that may affect students’ CT achievement in these settings.

This study examines and synthesizes the results of previous research on computational thinking (CT) within the context of STEAM-based mathematics instruction. The primary objectives are to evaluate the impact of this instructional method on students' CT development and to explore the factors that may contribute to differences in student outcomes. Particularly, the meta-analytic review seeks to answer the following questions:

1. What is the effect size of STEAM-integrated mathematics instruction on students' CT development?
2. Does this teaching method produce a significant positive impact on students' CT abilities?
3. How do variables such as class size, duration of the treatment, participant demographics, educational level, learning environment, use of ICT, and mathematical content influence CT outcomes in STEAM-integrated mathematics instruction?

2. Theoretical Framework

In this section, some theoretical frameworks are explained, including computational thinking, mathematics instruction, STEAM education, and substantial factors. Each of theoretical framework is discussed in detail in the following subsection.

2.1. Computational Thinking

CT is defined as a complex problem-solving method, primarily for students in educational settings around the world. The concept of "computational thinking" was first presented by Papert in 1980 as a foundational skill in computer science [42], [50]. Later, Wing broadened CT’s popularity in 2006, defining it as a cognitive process for approaching problems, especially in the context of computer science [1], [26], [74], [75], [77], [78], [79], [80]. Combining insights from multiple sources, CT is understood as a methodical approach to problem-solving that involves structured steps such as abstraction, pattern recognition, decomposition, and algorithm - fundamental concepts in computer science [9], [10], [11], [12]. Wing [12] outlines these stages as follows: (1) Decomposition – dividing complex problems into smaller, more manageable components; (2) Pattern Recognition – detecting recurring patterns; (3) Abstraction – concentrating on key, relevant details; and (4) Algorithm – executing a series of organized steps or instructions.

Further, Fry *et al.* [5] identify five components of CT within the Australian Mathematics Curriculum: (1) Decomposition – breaking down problems; (2) Abstraction – isolating important data; (3) Pattern Recognition – analyzing and identifying data patterns; (4) Algorithm – creating sequential steps to solve a problem; and (5) Generalization – applying solutions to similar problems. Brennan and Resnick [8] also describe CT as having three dimensions: Computational practices, perspectives, and concepts. In a similar vein, Grover and Pea [9] highlight key CT concepts such as logical and algorithmic reasoning, pattern recognition, abstraction, evaluation, and automation. Several indicators of CT, including debugging, critical and algorithmic thinking, problem-solving, data analysis, and generalization are also identified by the International Society for Technology in Education (ISTE) [20], [34], [36], [37], [40]. The National Research Council (NRC) offers similar indicators, such as representation, data analysis, algorithm creation, collaboration, and evaluation [28]. These frameworks and indicators have been adopted in 57 documents included in this meta-analytic review to assess CT achievements.

2.2. Mathematics Instruction and STEAM Education

Incorporating STEAM into mathematics education is designed to improve students' computational thinking (CT) abilities. Different mathematics learning environments integrate information and communication technology (ICT) within the STEAM framework, focusing on a constructive approach to learning. Constructive learning is an educational perspective that encourages students to actively build knowledge through creative and reflective processes [83], [84], [85], [86], [87]. This approach assumes that students actively create understanding by engaging in problem-solving and decision-making [6], [88].

STEAM-based learning in mathematics often follows a structured process: Asking questions to identify a problem, imagining possible solutions, planning a product through detailed sketches, and creating and testing the solution [89], [90], [91]. Several technologies, including robotics, Scratch, virtual reality, Arduino, math labs, and educational games, support this approach to enhance CT skills. These tools are frequently employed in the 57 documents reviewed in this paper to boost CT achievements in mathematics within a STEAM framework.

2.3. Substantial Factors

Substantial factors refer to moderating variables that can influence the dependent variable independently of the main independent variable. In this study, in addition to examining the impact of STEAM-integrated mathematics instruction on students' CT, several moderating variables are analyzed for their potential effect on CT achievement. Lipsey and Wilson [92] argue that substantial factors closely relate to both independent and dependent variables. In this context, variables such as treatment duration, participant, class size, educational level, learning environment, ICT use, and mathematics content may contribute to differences in students' CT outcomes.

Specifically, factors like mathematics content, participant demographics, and educational level relate to CT, while variables like intervention duration, learning environment, ICT, and class size relate to STEAM-integrated mathematics instruction. Helsa *et al.* [60] found that class size, educational level, participant characteristics, and ICT use can impact CT outcomes in interventions, while Ye *et al.* [74] identified intervention duration, learning environment, and subject content as factors influencing students' CT skill variations. Thus, these factors are examined here for their potential role in explaining differences in students' CT achievement within STEAM-integrated mathematics instruction.

3. Method

In this section, some information is explained comprehensively, including research design, inclusion criteria, literature search, document selection, data extraction, and data analysis. Each of information is discussed in detail in the following subsection.

3.1. Research Design

This study employed a systematic review to analyze recent research. A comprehensive review was conducted on a wide range of empirical and secondary sources concerning CT and the integration of STEAM education into mathematics instruction. Additionally, meta-analysis—a set of quantitative methods utilizing effect sizes [93], [94], [95], [96], was applied to evaluate the effect of STEAM-integrated math instruction on students' CT acquisition. The study also investigated variables such as participant, educational level, treatment duration, class size, learning environment, ICT usage, and mathematical content, all of which could potentially affect CT outcomes.

As outlined by Jesson *et al.* [97], a systematic review follows several steps: (1) defining the research question, (2) setting inclusion and exclusion criteria, (3) performing an extensive document search, (4) selecting pertinent documents, (5) extracting the data, (6) analyzing the data, and (7) interpreting the findings and preparing the report. Each stage of this systematic review is explained in detail in the following sections.

3.2. Inclusion Criteria

To narrow the scope of the study, specific inclusion criteria were defined. First, each document title needed to include the keywords "computational thinking" AND "mathematics." Second, the documents had to be conference papers or journal articles written in English, from reputable journals or conference proceedings. Third, the documents had to be published between 2004 and 2023 and span relevant disciplines, including social sciences, computer science, mathematics, arts and humanities, or interdisciplinary fields. Fourth, the sample population covered students from various global regions—Asia, America, Europe, Africa, and Australia—and educational levels from preschool through university. Fifth, the intervention had to involve STEAM-integrated math instruction, such as math, programming, or robotics education. Sixth, traditional math instruction served as a comparator. Seventh, the outcome assessed was computational thinking, while the eighth criterion specified a quasi-experimental design. Ninth, documents needed to report sufficient statistical data to calculate effect sizes. Any documents failing to meet these criteria were excluded in the selection phase.

3.3. Literature Search

The Scopus database was used to locate studies related to CT and STEAM-based mathematics instruction. Scopus is recognized as a credible, extensive repository of scientific literature [98], [99]. A search using the keywords "computational thinking" and "mathematics" was performed on November 15, 2023, at 11:59 PM, identifying 948 documents published between 1970 and 2023. These included articles, conference papers, book chapters, reviews, and editorials in various languages. Documents were then filtered according to the inclusion criteria.

3.4. Document Selection

A four-step procedure was employed to systematically select documents [100], [101]. The process for selecting documents is illustrated in Figure 1.

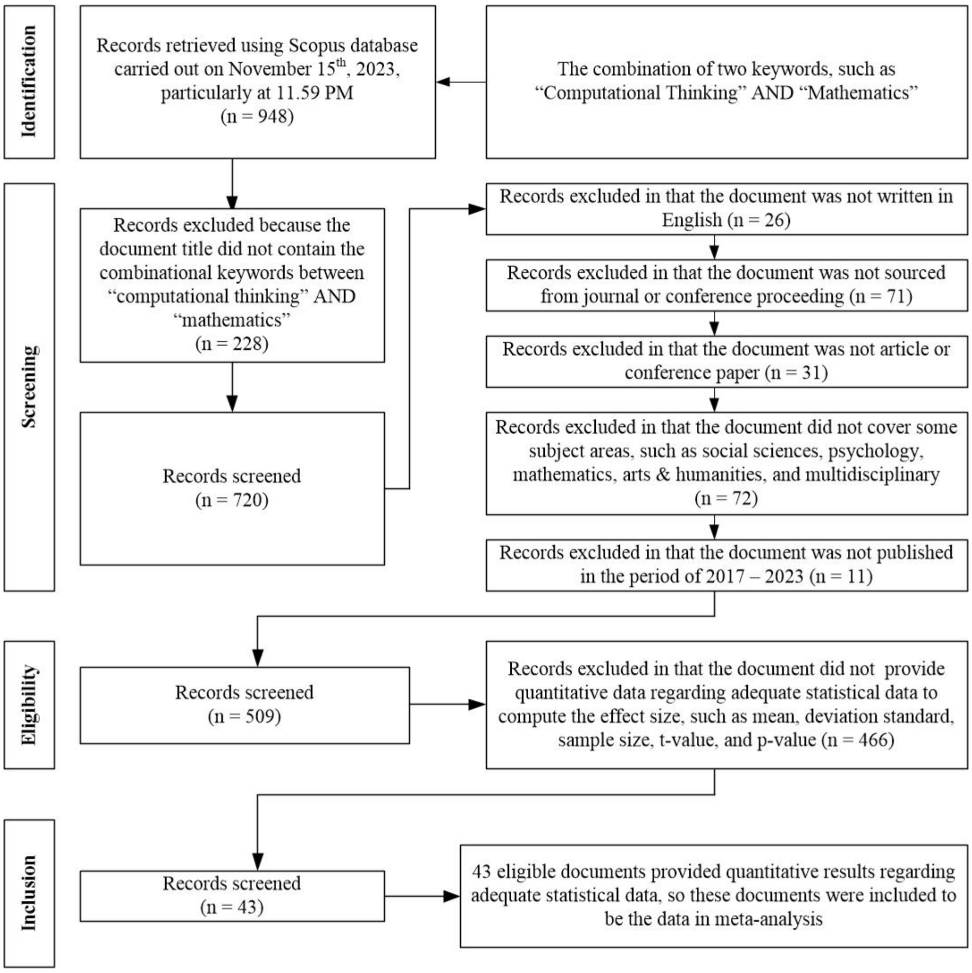

Figure 1. The systematic process of document selection

3.5. Data Extraction

From the initial pool, 43 documents meeting the eligibility criteria were selected and entered into a coding sheet. The sheet included information such as author, research approach, design, participants, instruments, quantitative results, relevant factors, document type, source type, publication details, and access information (DOI or URL). Key details included authorship, methodology, sample size, CT assessment components, learning environment, ICT use, and mathematical content.

These documents provided statistical data and information on factors like class size, intervention duration, educational level, participants, learning environment, ICT, and mathematical content, ultimately contributing 80 effect size units and involving 7,807 participants across educational level.

To ensure data quality, two meta-analysis experts and two qualitative meta-synthesis experts verified and validated the data. Following the re-coding and review of the coding sheet, coding consistency between coders was evaluated using Cohen's Kappa test, [102]. As seen in Table 1, the Kappa values indicate that coding agreement was between moderate and almost perfect, with all items showing significant values below 0.05, demonstrating strong data reliability and validity [103], [105], [106].

Table 1. The results of Cohen's Kappa test

Coding Item	Kappa Value	Agreement Level	Sig. Value
Mean of Experiment Group	0.923	Almost Perfect	0.009
Dev. Std. of Experiment Group	0.912	Almost Perfect	0.009
Sample Size of Experiment Group	0.927	Almost Perfect	0.009
Mean of Control Group	0.957	Almost Perfect	0.008
Dev. Std. of Control Group	0.943	Almost Perfect	0.008
Sample Size of Control Group	0.952	Almost Perfect	0.008
T-value	0.962	Almost Perfect	0.007
P-value	0.969	Almost Perfect	0.007
Class Capacity	0.899	Strong	0.011
Intervention Duration	0.822	Strong	0.018
Educational Level	0.845	Strong	0.017
Participant	0.831	Strong	0.017
Learning Environment	0.889	Strong	0.011
ICT	0.872	Strong	0.011
Mathematical Content	0.867	Strong	0.012

3.6. Data Analysis

A random-effects model was applied in this meta-analytic review, which involved calculating the estimated effect size, conducting a publication bias analysis, performing sensitivity analysis, and applying the Z test and Q Cochrane test. This model was chosen for its suitability in handling diverse study characteristics, including differences in participants, educational levels, instruments, intervention duration, learning environment, class size, and ICT interventions [105]. Hedges' equation was used to compute effect sizes, suitable for smaller sample sizes [93]. As outlined by Pigott [95], the formula for Hedges' equation is:

$$g = \frac{\overline{x_1} - \overline{x_2}}{\sqrt{\frac{(n_1 - 1)S_1^2 + (n_2 - 1)S_2^2}{n_1 + n_2 - 2}}} \times \left(1 - \frac{3}{4df - 1}\right)$$

The effect size was categorized based on the g value as follows: 0.00–0.20 (Weak), 0.21–0.50 (Modest), 0.51–1.00 (Moderate), and >1.00 (Strong). The Z test was used to assess the significance of STEAM-based mathematics instruction on CT development, while the Q Cochrane test evaluated the influence of seven key factors on CT variability. Using funnel plots and the trim-and-fill test, publication bias was evaluated [59], [60], [100]. To verify the stability of the data and identify any outliers that could affect the results, sensitivity analysis was performed [104].

The "one study removed" feature in CMA software was utilized to perform this sensitivity analysis, ensuring the reliability of the dataset [105].

4. Results

This meta-analysis covered key areas including sensitivity analysis, publication bias, estimated effect size, and subgroup analysis. Each of these elements is explored in detail in the following subsections.

4.1. Sensitivity Analysis and Publication Bias

To evaluate potential publication bias, the distribution of effect sizes was analyzed using a funnel plot.

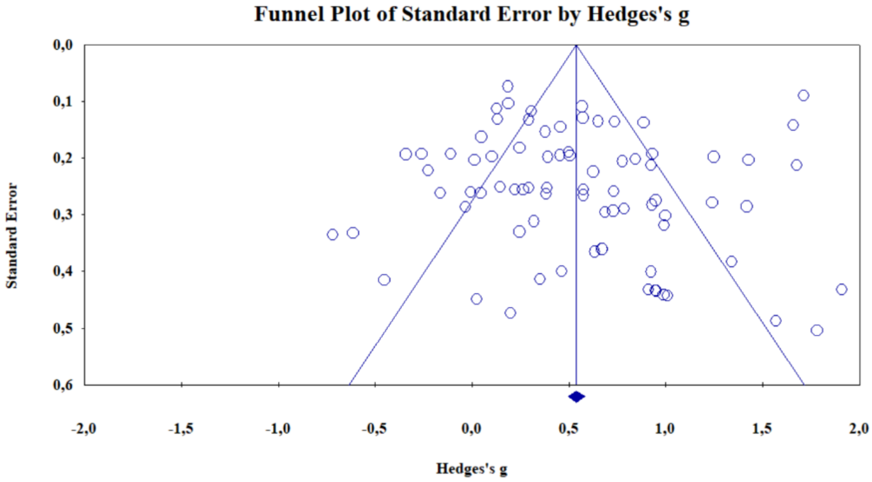

Figure 2. The distribution of effect size data in the funnel plot

According to Figure 2, the effect size data seems to be symmetrically distributed in the funnel plot. To verify this symmetry, a trim-and-fill test was performed.

Table 2. The results of fill and trim test

	Studies Trimmed	Effect Size in g	Lower Limit	Upper Limit	Q-value
Observed Values		0.550	0.427	0.674	579.634
Adjusted Values	0	0.550	0.427	0.674	579.634

As demonstrated in Table 2, no data needed to be removed from either side, reinforcing the symmetry of the plot and suggesting that there is no publication bias in the data.

To further evaluate sensitivity, a sensitivity analysis was conducted by inspecting outliers within the range of the lowest and highest effect sizes.

Using the "one study removed" feature in the CMA software, the analysis revealed a lowest effect size of 0.527 and a highest of 0.564, with an estimated mean of 0.551 across the 80 effect size data points. Since this estimated mean fall within the interval of 0.527 to 0.564, no outliers were identified. This suggests the data does not exhibit sensitivity due to variations in data quantity. According to Bernard *et al.* [105], if the estimated mean lies within the interval of the lowest and highest effect sizes, changes in data quantity do not indicate sensitivity.

4.2. Summarization and Estimation of Effect Size

This meta-analysis included 43 documents, generating 80 effect size units involving 12,746 students. These effect sizes varied in direction, significance, and strength (Table 3).

Table 3. The results of calculations of effect size

Document	Effect Size in g Unit	P-value
[35], b	0.568 [0.354; 0.782]	0.000
[4]	-0.227 [-0.663; 0.209]	0.308
[2]	0.391 [0.002; 0.780]	0.049
[7]	0.049 [-0.271; 0.369]	0.765
[58]	0.103 [-0.285; 0.491]	0.603
[48]	0.128 [-0.094; 0.350]	0.258
[19], a	0.293 [-0.202; 0.788]	0.246
[19], b	0.144 [-0.349; 0.637]	0.567
[22]	0.013 [-0.386; 0.412]	0.949
[24]	-0.034 [-0.597; 0.528]	0.905
[25], a	0.222 [-0.279; 0.724]	0.384
[25], b	1.419 [0.859; 1.979]	0.000
[25], c	1.240 [0.694; 1.787]	0.000
[51]	0.673 [-0.034; 1.380]	0.062
[56], a	0.576 [0.055; 1.097]	0.030

[56], b	0.384 [-0.134; 0.902]	0.146
[56], c	0.949 [0.410; 1.488]	0.001
[56], d	-0.164 [-0.678; 0.350]	0.532
[56], e	-0.008 [-0.518; 0.503]	0.977
[56], f	0.045 [-0.468; 0.558]	0.865
[54], a	1.010 [0.142; 1.878]	0.023
[54], b	1.783 [0.795; 2.771]	0.000
[54], c	-0.718 [-1.375; -0.061]	0.032
[54], d	0.989 [0.123; 1.855]	0.025
[54], e	1.568 [0.612; 2.524]	0.001
[54], f	-0.614 [-1,266; 0.037]	0.065
[45]	0.926 [0.509; 1.343]	0.000
[36]	0.687 [0.107; 1.267]	0.020
[3]	0.245 [-0.402; 0.893]	0.458
[53]	0.187 [-0.016; 0.391]	0.071
[31], a	0.499 [0.127; 0.871]	0.009
[31], b	1.677 [1.259; 2.095]	0.000
[34]	0.845 [0.449; 1.241]	0.000
[120], a	0.992 [0.368; 1.617]	0.002
[120], b	0.633 [-0.083; 1.349]	0.083
[52]	0.464 [-0.319; 1.248]	0.246
[43], b	1.340 [0.589; 2.091]	0.000
[33]	0.784 [0.217; 1.351]	0.007
[41]	0.626 [0.186; 1.067]	0.005
[49]	0.263 [-0.238; 0.765]	0.303
[51]	0.672 [-0.035; 1.379]	0.062
[35], a	1.713 [1.536; 1.891]	0.000
[39]	1.658 [1.379; 1.937]	0.000
[40]	0.777 [0.373; 1.180]	0.000
[37]	0.932 [0.554; 1.309]	0.000
[27]	0.925 [0.139; 1.711]	0.021
[50], a	0.293 [0.033; 0.553]	0.027
[50], b	0.737 [0.469; 1.004]	0.000
[50], c	0.886 [0.614; 1.157]	0.000
[50], d	0.650 [0.384; 0.915]	0.000
[50], e	0.131 [-0.128; 0.390]	0.321
[106], a	0.023 [-0.857; 0.903]	0.959
[106], b	0.198 [-0.731; 1.127]	0.676
[106], c	0.352 [-0.458; 1.163]	0.394
[42], a	0.246 [-0.111; 0.603]	0.177
[42], b	1.428 [1.030; 1.827]	0.000
[42], c	1.249 [0.860; 1.638]	0.000
[47], a	0.576 [0.074; 1.078]	0.025
[47], b	0.733 [0.225; 1.242]	0.005
[47], c	0.387 [-0.109; 0.884]	0.126
[46]	0.320 [-0.291; 0.932]	0.305
[32], a	0.456 [0.170; 0.741]	0.002
[32], b	0.307 [0.076; 0.539]	0.009
[38], a	0.573 [0.319; 0.827]	0.000
[38], b	0.184 [0.039; 0.330]	0.013
[43], a	0.730 [0.155; 1.305]	0.013
[29]	0.928 [0.374; 1.482]	0.001
[30]	0.379 [0.077; 0.681]	0.014
[14]	1.909 [1.062; 2.757]	0.000
[16], a	0.505 [0.122; 0.889]	0.010
[16], b	0.505 [0.122; 0.889]	0.010
[16], c	0.455 [0.073; 0.838]	0.010
[16], d	-0.110 [-0.488; 0.268]	0.569
[16], e	-0.341 [-0.721; 0.040]	0.079
[16], f	-0.260 [-0.639; 0.119]	0.179
[28], a	0.952 [0.100; 1.804]	0.028
[28], b	0.946 [0.094; 1.797]	0.029
[28], c	0.911 [0.064; 1.759]	0.035
[28], d	-0.453 [-1.268; 0.362]	0.276
[44]	0.998 [0.407; 1.589]	0.001
Estimated Effect Size	0.551 [0.427; 0.674]	0.000

The effect sizes presented in Table 3 indicate that of the 43 eligible documents, seven produced two effect size units each (e.g., [19], [31], [32], [35], [38]).

Additionally, four documents generated three effect size units [25], [42], [47], [106], one document produced four [30], one produced five [50], and three produced six effect size units [16], [54], [56].

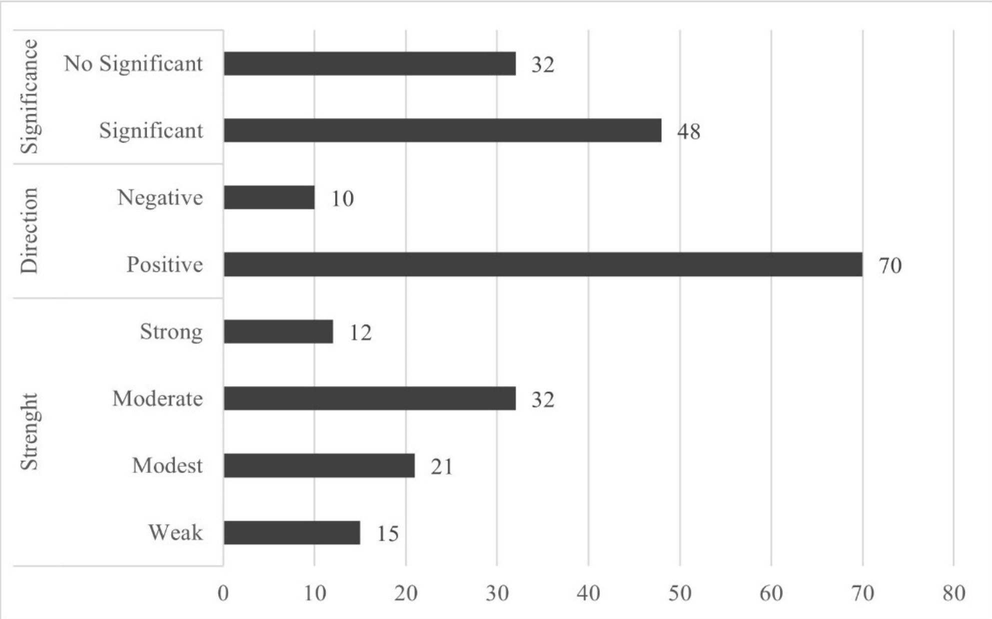

Figure 3. The frequency distribution of effect size data in the perspective of strength, direction, and significance

Effect sizes were then categorized by direction, significance, and strength, as shown in Figure 3.

According to Figure 3, the effect sizes, based on significance, consisted of 40% non-significant and 60% significant values. In terms of direction, 12.5% were negative, while 87.5% were positive. When viewed by strength, 18.75% were weak, 26.25% modest, 40% moderate, and 15% strong. This suggests that the effect size data is predominantly significant, positive, and moderate. Table 3 further shows that the average effect size of the 80 data units was 0.551, indicating a moderately positive effect of STEAM-integrated mathematics instruction on students' computational thinking (CT).

With a Z-test significance value below 0.05, this result confirms that the STEAM-integrated approach significantly enhances students' CT, making it an effective educational intervention.

4.3. Subgroup Analysis

To examine how factors such as class size, educational level, intervention duration, participants, learning environment, ICT use, and mathematical content influence students' CT in STEAM-integrated mathematics instruction, a Q Cochrane test was performed (Table 4).

Table 4. The results of Q Cochrane test

Substantial Factor	Groups	Effect Size in g Unit	P-value
Educational Level	Pre-School	0.653	0.059
	Elementary School	0.426	
	Junior High School	0.848	
	Senior High School	0.788	
	College/University	0.427	
Intervention Duration	2 Weeks	0.634	0.045
	3 Weeks	0.718	
	4 Weeks	0.535	
	5 Weeks	0.575	
	6 Weeks	0.737	
	7 Weeks	0.786	
	8 Weeks	0.663	
	9 Weeks	0.218	
	10 Weeks	0.538	
	12 Weeks	0.308	
	15 Weeks	0.320	
	16 Weeks	1.340	
	24 Weeks	0.926	
	48 Weeks	0.125	
Learning Environment	Mathematics Education	0.483	0.188
	Programming Education	0.400	
	Robotics Education	0.769	
	STEAM Education	0.935	
	STEM Education	0.666	
ICT	Arduino	0.581	0.020
	Digital Application	0.396	
	Game Application	-0.054	
	Math Laboratory	0.391	
	No ICT	0.515	
	Robotics	0.700	
	Scratch	0.415	
	Virtual Reality	1.346	
Mathematical Content	Algebra	0.587	0.000
	Combinational Content	0.596	
	Geometry	0.499	
	Number & Operation	0.588	
	Probability & Statistics	-0.236	

As seen in Table 4, factors such as intervention duration, participants, ICT use, and mathematical content significantly influence students' CT, as indicated by p-values below 0.05. Conversely, class size, intervention duration, and learning environment showed p-values above 0.05, suggesting insufficient evidence to conclude that these factors significantly impact CT outcomes.

5. Discussion

This part discusses the effectiveness of mathematics instruction integrated to STEAM education on the achievement of students' CT skills, the difference of students' CT skills in mathematics instruction integrated to STEAM education, implications to mathematics education, and limitations and suggestions. Each part is explained in the following subpart.

5.1. The Effectiveness of Mathematics Instruction Integrated to STEAM Education on the Achievement of Students' CT

This study demonstrates that mathematics instruction combined with STEAM education has a moderately positive effect on enhancing students' CT skills, with an estimated effect size of 0.551 based on 80 data points. Supporting studies similarly show that programming education contributes moderately to CT skill development in students [72], [73], [81]. Other studies indicate that game-based learning and CT interventions also moderately enhance students' CT [70], [71], [74], [82]. Additionally, Cheng *et al.* [69] found that STEM education positively affects students' CT skills, and Hwang and Hwang [76] reported similar effects from software education. These findings collectively suggest that CT interventions, like STEAM-integrated mathematics instruction, positively impact CT skills.

The results also indicate that STEAM-integrated mathematics instruction significantly enhances students' CT skills, affirming its effectiveness in supporting CT development. Numerous related studies highlight that intervention like programming education, game-based learning, and STEM education, alongside tools such as Scratch and other computer-based activities, positively affect students' CT outcomes [81], [82], [107], [108]. These consistent results suggest that STEAM-integrated mathematics instruction is effective in promoting CT skill acquisition over recent decades.

CT is closely connected to mathematics, the fundamental language of science, as solving mathematical problems often requires CT.

Previous research has identified a positive relationship between students' CT abilities and their performance in mathematics [13], [14], [15], [16], [39].

Therefore, promoting CT skills is crucial in mathematics education, particularly through approaches. These approaches cultivate complex problem-solving abilities, aligning with CT's focus on tackling intricate challenges [7]. Incorporating STEAM into mathematics instruction may further enhance CT, as shown by this study and related research indicating STEAM's significant positive impact on CT.

Many instructional models in mathematics, including cooperative, problem-based, and inquiry-based learning, offer constructivist benefits, focusing on students actively constructing knowledge through reflection and creativity [35], [83], [84], [85]. Integrating these models with STEAM's problem-solving approach fosters a deeper understanding and decision-making skills [86], [87], [88]. Technology tools like robotics, Scratch, virtual reality, Arduino, and math labs further boost CT skills in mathematics under a STEAM framework [71], [73]. Thus, integrating STEAM into math education is logically sound for optimizing CT skill development.

5.2. The Difference of Students' CT Achievement in Mathematics Instruction Integrated to STEAM Education

This study identifies certain factors—such as intervention duration, participant demographics, ICT, and specific mathematical content, that significantly influence CT skill outcomes in STEAM-integrated mathematics instruction. However, variables like class size and learning environment showed no significant impact. Each of these factors is discussed further below.

5.2.1. Educational Level

Educational level did not have a significant effect on CT skills in STEAM-integrated mathematics instruction. Supporting studies confirm that educational level generally does not affect CT outcomes in interventions such as unplugged activities, programming, or STEM and software education [73], [74], [76], [81], [109]. This approach positively impacts CT skills across levels, with moderate effects noted in pre-school ($g = 0.653$), junior high ($g = 0.848$), and senior high ($g = 0.788$) students, while elementary ($g = 0.426$) and college ($g = 0.427$) students saw modest improvements. The highest impact appeared in junior high, suggesting that STEAM-integrated instruction may be particularly effective for this group.

5.2.2. Intervention Duration

Intervention durations, ranging from 2 to 48 weeks, significantly affected CT skill acquisition. Prior studies on programming, STEM, and software education also confirm that intervention duration influences CT development [69], [70], [72], [73], [76]. Notably, a 16-week intervention produced the strongest CT improvement (g = 1.340). Comparatively, shorter (2–15 weeks) and longer (24–48 weeks) durations had less impact, indicating 16 weeks may be an optimal duration for maximizing CT gains.

5.2.3. Learning Environment

This factor, including environments like mathematics, programming, robotics, STEAM, and STEM education, showed no significant differentiation in CT skill outcomes. Other studies similarly report that different learning settings do not distinctly impact CT outcomes [69], [71], [73], [76]. Nonetheless, STEAM education environments displayed the highest effect (g = 0.935), followed by STEM and robotics education, while programming and mathematics education had more modest impacts, suggesting STEAM's unique effectiveness in fostering CT.

5.2.4. ICT

ICT type (e.g., Arduino, digital applications, robotics, Scratch) played a significant role in CT skill outcomes. Relevant studies support ICT's role in differentiating CT achievements [70], [71], [72]. Virtual reality, for instance, had the highest impact (g = 1.346), while game applications yielded weaker effects (g = 0.054). This suggests that ICT tools like virtual reality may be more effective in promoting CT within STEAM-integrated math education.

5.2.5. Mathematics Content

Mathematics content areas, including algebra, geometry, and probability have significantly influenced CT skill development. Prior research corroborates that specific content areas impact CT acquisition [70], [72]. This study found that integrating multiple content areas had the highest effect (g = 0.596), indicating that combining various mathematical topics may be particularly effective for enhancing CT skills.

5.3. Implications to Mathematics Education

This review demonstrates that CT interventions, such as mathematics instruction integrated with STEAM education, have a moderate positive impact on students' CT development.

Furthermore, this instructional method has proven effective in improving students' CT achievements over the past two decades. Various learning models can be utilized within this approach. When these models are integrated with STEAM education—a teaching method aimed at enhancing students' problem-solving and decision-making skills, they yield even more positive effects on students' CT achievements [71], [73]. As a result, this instructional approach is recommended for use in mathematics education to enhance CT skills among students.

Furthermore, the intervention of mathematics instruction integrated STEAM education during 16 weeks on the achievement of students' CT is more effective than the intervention of mathematics instruction integrated STEAM education during 2 - 15 weeks and 24 – 48 weeks on the achievement of students' CT. Consequently, to optimize the achievement of students' CT, the implementation of this instructional approach should be conducted during 16 weeks as a relatively ideal intervention duration in mathematics learning activities.

The intervention of mathematics instruction integrated STEAM education using virtual reality is more effective in optimizing students' CT than using Arduino, digital application, game application, math laboratory, no ICT, robotics, and Scratch. This implies that the implementation of this instructional approach should be performed using the technology of virtual reality as a relative ideal ICT in mathematics education to optimize the achievement of students' CT. The intervention of mathematics instruction integrated STEAM education is more effective in optimizing students' CT in the combination among contents than optimizing students' CT skills in algebra, geometry, number and operation, and probability and statistics. Therefore, when designing CT assessment tools, researchers focusing on CT skills in mathematics education should integrate mathematics content. This process requires the inclusion of advanced mathematical content.

5.4. Limitations and Suggestions

Some limitations in this meta-analysis should be noted. Access to certain documents was restricted, and statistical information necessary for effect size computation was often lacking. Future researchers are encouraged to directly request access from authors and seek comprehensive data for analysis. Extending data collection periods to retrieve additional statistical data from authors via email or other contact methods may also be beneficial.

6. Conclusion

This study deduces that STEAM-integrated mathematics instruction has positive moderate effect ($g = 0.551$) on the achievement of students' CT skills. Moreover, mathematics instruction using STEAM approach significantly affects students' computational thinking (CT) skills. Factors such as the duration of the intervention, use of ICT, content area, and participant demographics play a significant role in affecting the achievement of students' CT skills. It means that these factors cause the differences of students' CT skills. However, other factors, such as class size and learning environment did not show significant role on the achievement of students' CT skills. It means that these factors do not cause the difference of students' CT skills. This approach holds promise for CT skill development in mathematics education.

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