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Do 3–8 Years Old Children Benefit From Computational Thinking Development? A Meta-Analysis

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Abstract

The interest in Computational Thinking (CT) development among young learners increases with the number of studies located in literature. In this study, a meta-analysis was conducted to address two main objectives: (a) the effectiveness of empirical interventions on the development of CT in children aged of 3–8 years; and (b) the variables that influence the effectiveness of the interventions. Following PRISMA procedures, we identified 17 empirical studies with 34 effect sizes and 1665 participants meeting the inclusion criteria from Web of Science database. Overall, we found a statistically significant large effect size (d = .83 [95% CI: 730, .890]; $p < .001$) on the CT development of 3–8 years old children, which provides empirical support for having young children to engage in CT experiences. The effect size was significantly influenced by moderating variables including gender, scaffolding, and education level. Intervention length showed a marginally significant effect. Therefore, educators could refer to the significant moderators when designing tailored interventions for CT development in early childhood education while a call for more empirical studies of CT development in young children is proposed.

Keywords

computational thinking, 3–8 years old, meta-analysis, large effect size

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Introduction

In recent years, the world has witnessed an unprecedented transformation as a result of the rapid growth of computing and digitization. To effectively navigate in the digital age, individuals necessitate core elements of 21st-century skills and digital competence, such as Computational Thinking (CT), creative problem-solving skills, and programming literacy (Nouri et al., 2020). Specifically, CT has been called "the new literacy of the 21st century" (Wing, 2011) and identified as one of the key characteristics of future work environments. As an important capacity for future generations, CT is the vital factor in facilitating students' transition from technology-literate to utilizing computational tools to solve complex and ill-structured problems (Yadav et al., 2016b). This has made CT cross-disciplinary and generalized (National Research Council, 2010; Wing, 2006), and plays a crucial role in a wide range of fields, including mathematics, computational finance, economics etc. (Aksit & Wiebe, 2020; De Santo et al., 2022; Sengupta et al., 2013; Sung & Black, 2020). Studies have been conducted to explore the multifaceted benefits of incorporating CT into early childhood education. According to Wang et al. (2021), engaging children in systematic testing during CT exercises enhanced their problem-solving skills, especially when they made predictions and considered the potential outcomes of different solutions. Participating in CT activities also has the potential to improve executive functions, such as inhibition and planning skills, which are important to the problem-solving procedure (Montuori et al., 2022). Block-based tangible activities are often utilized in CT activities. Such activities aid children in comprehending mathematics. For example, engaging in block play to manipulate and break down cubes that facilitates children's numerical calculations, addition, and subtraction concepts (Krause et al., 2023), and spatial abilities (Kwon et al., 2022) in mathematics. Yang et al. (2023) also found that CT was positively associated with sequencing ability among young children. Furthermore, Lin et al. (2020) discovered that children were capable of transforming abstract cognitive concepts into concrete actions using interactive CT interfaces, strengthening the link between mental processes and physical behaviors. With the potential benefits of CT on young children, CT in early childhood education is becoming more and more common.

Even though Bati (2022) systematically reviewed experimental evidence about CT and found that CT of young children could be enhanced by both plugged and unplugged applications, there is a dearth of meta-analytic studies of early childhood and early elementary education levels. Stamatios (2022) found that ScratchJr had a favorable impact on CT among 5-7-year-old children based on an empirical review. More specifically, McCormick and Hall (2022) conducted a scoping review and determined that physical, tangible kits emerged as the most common tools, with adult scaffolding as the preferred strategy for young children. Nevertheless, there has been a lack of comprehensive quantitative analysis of CT focusing on children between the ages of 3–8. To fill the gap, the purpose of the present study is to synthesize the effect of existing studies of CT practice in early childhood settings in order to provide an informed decision for instructors and researchers to better integrate CT into practice and theory respectively.

Literature Review

Wing (2006) explained that CT was a fundamental skill for everyone and involved mathematical and engineering thinking. Within early childhood education, Bers (2010; 2019) considered CT as problem-solving skills in which young children engage in systematic design and analysis. The concept of coding as a playground is emphasized in which young children learn to code through fun and playful activities. Bers et al. (2022) further clarified the basic CT concepts to include programming elements such as algorithms, decomposition of problems, control structure, representation, hardware and software systems, and debugging. Lavigne et al. (2023) also identified a learning blueprint of CT for young children which includes abstraction, algorithmic thinking, pattern recognition, problem deconstruction, design process, debugging process, and logical reasoning. Sohr et al. (2023) argued that daily life contexts involving moral reasoning may allow young children to engage in CT practice. Therefore, this study considers CT beyond the core concept of coding but rather a multidimensional framework of cognitive thinking processes that involve young children to solve daily life problems which both humans and computers understand.

Factors Affecting the Impact of CT Practices on 3–8 years Old Children

Previous studies (Hong, 2023; Lei et al., 2020; Lu et al., 2023; Sun et al., 2021) have identified factors that may account for differences in the effect of CT across studies. These factors include:

Region

Discrepancies may be due to variations in culture and economic conditions among countries. For example, Lei et al. (2020) found that the relationship between CT and academic achievement was stronger among students in Eastern cultures than in Western cultures due to the national integrated curricula. Studies in different countries have been located so it is interesting to explore if region is a possible factor to explain the CT practices in young children.

Sample Size

Sample size moderates the impact of educational robots on K-12 students' CT (Hong, 2023). Sun et al. (2023) who investigated the effect of game-based CT activities also had similar finding. The small and medium-sized sample seem to have a greater impact on CT development.

Gender

The effect of CT intervention on young children seems to be better for boys than girls. For example, Sullivan and Bers (2013; 2016) found that boys outperformed girls in attaching robotic materials properly and programming knowledge using the If statement, the repeat, and the loop structure. Angeli and Georgiou (2023) also found that boys outperformed girls in CT at all learning stages. However, Montuori et al. (2022) revealed that girls performed better in terms of time and acurracy in CT activities. Furthermore, Angeli and Valanides (2020) demonstrated a statistically significant interaction effect between gender and scaffolding among 5-6-year-old children, suggesting that boys and girls derived varying benefits from different instructional strategies. Given the inconsistent findings, it is imperative for stakeholders to address the question regarding potential gender disparities in the acquisition of CT through early intervention. Hence, this study examines gender as a moderator to emphasize the significance of efficacious early intervention of CT.

Education Level

Educational level is considered a moderator in other studies but with inconsistent findings. For example, Sun et al. (2023) found that primary students benefited more in terms of game-based CT activities. Hong (2023) revealed that educational robots have a better effect on CT development for kindergarteners than primary school students. Merino-Armero et al. (2022) could not find any difference between kindergarten and elementary groups.

Teacher Training

One of the challenges of CT in early childhood education is teachers' capacity to design and plan CT practices for young children. Many kindergarten teachers lack the academic background in coding, so they often feel incapable of implementing CT in the curriculum (Mouza et al., 2018; Yadav et al., 2016a). However, professional development opportunities in terms of intensive workshops or teacher education programs help teachers to gain knowledge, skills, and confidence in designing appropriate CT experiences for students (Chan, 2021; Kong & Wang, 2020). Thus, it is relevant to explore whether teacher training is a factor that affects the level of CT development in young children.

Scaffolding

Various scaffoldings techniques have been employed to foster CT development in young children. Xu et al. (2022) categorized scaffoldings into teacher support, resource support and technical support corresponding to embodied activities such as bodily movements (Kwon et al., 2022), story (Yang et al., 2023), cardboard and floor mat

(Angeli & Valanides, 2020) respectively. In these studies, scaffolding could enhance the acquisition of CT in children, leading to improved efficiency in the learning process. Nevertheless, some findings raise concerns regarding the validity of the scaffolding. Angeli and Georgiou (2023) identified only noteworthy interaction effects between various scaffolding strategies and gender in relation to children's sequencing and deconstruction abilities. Nam et al. (2019) scaffolded children's computational thought process with worksheets, a paper-based cognitive tool, but no comparable results demonstrating the efficacy of scaffolding were presented. A recent study found no statistically significant difference between CT scores of two groups using cognitive control strategies to monitor and reflect problem-solving (Wang et al., 2022). Hence, the extent to which these scaffolding strategies provide greater support compared to traditional learning methods remained uncertain. For this reason, our study investigates the degree to which scaffolding influences CT learning in young children.

Learning Environments

The CT practice for children between 3 to 8 involves different developmentally appropriate learning environments such as visual programming platforms (Chou, 2020; Yang et al., 2023), educational robots (Yang et al., 2023), and unplugged activities, such as storytelling or child literacy activities (Lavigne et al., 2020; Lee & Junoh, 2019). Kindergarteners aged 5–6 are capable of coping with graphical software, acquiring basic programming and mathematical concepts, developing social skills, and practicing solving problems through computers (Fessakis et al., 2013). By integrating ScratchJr with storytelling, children could develop key digital literacy skills, numeracy, and science concepts within traditional early childhood curriculum themes (Papadakis et al., 2016; Stamatios, 2022). For tangible educational robotics, Kazakoff et al. (2013) and Bers et al. (2019) found that three-year-old children possessed the ability to comprehend CT concepts through robotic activities. Bers (2021) stated that robots had the affordance to offer preschoolers an unconstrained embodied learning experience, making them a developmentally appropriate way of introducing young children to CT. The incorporation of unplugged activities has a positive impact on the development of CT skills for second-grade students (del Olmo-Muñoz et al., 2020).

Assessment Tools

Merino-Amero et al. (2022) found that the assessment tool is a moderator in K-12 CT education. The existing literature shows that computer and paper-pencil are the two mainly adopted assessment tools in CT practice for children between 3 to 8 years old. For example, children dragged and dropped their responses in the coding platform to illustrate their coding ability (Arfé et al., 2019) while they arranged the sequence of a story using cards (Nam et al., 2019).

Intervention Length

Intervention length is a potential factor that may explain the CT practices on young children. Merino-Amero et al. (2022) and Lu et al. (2023) found that short intervention has a better effect. Cheng et al. (2023) and Montuori et al. (2024) found that both long and short interventions have an impact.

Research Questions

In order to provide a quantitative impact of CT intervention on young children. The following two research questions guided the current study:

(1) What was the overall effect of interventions on cultivating 3-8 year-old children's CT development?
(2) Which factors affected children's CT development?

Method

Literature Search and Study Selection

Relevant studies were retrieved from the Web of Science (WoS) for its representative of major databases and publications with high quality (Kumpulainen & Seppänen, 2022; Li et al., 2018) in February 2023. The search terms were constructed by Boolean logic as follows: ("children" OR "early childhood") AND ("computational thinking") AND ("programming" OR "robotic" OR "robot" OR "tangible" OR "unplugged").

Figure 1 presented the PRISMA Flowchart, which included the process of selecting studies for this meta-analysis. During the search process, the 'WoS' database was used to find relevant studies. A total of 1272 articles were identified during the initial search. After screening duplicates, 558 articles were left.

To filter irrelevant articles, the following criterion was adopted:

(a) All participants were between three and eight years old;
(b) Studies needed to test the effect of interventions on CT in a quasi-experimental group design;
(c) Studies reported Cohen's *d* on CT with and without intervention, or at least can be calculated based on the available statistical information (M, N, SD, t-value, and F-value) provided in the article;
(d) Studies involving samples of students with specific learning disabilities or clinical conditions were excluded;
(e) Studies published in journals;
(f) Studies were written in English.

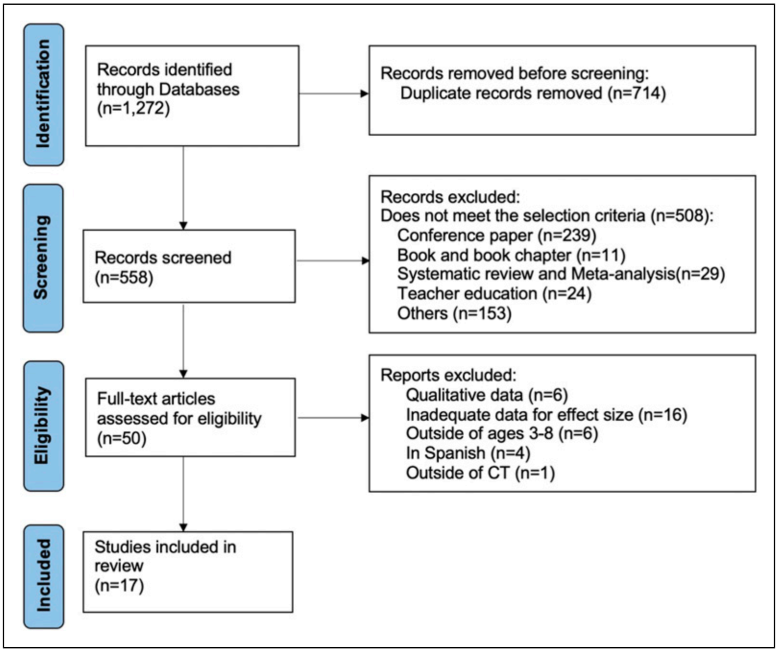

Figure 1. PRISMA flow diagram.

Only the articles that reached the above six criteria were selected. The selection process is consistent with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Page et al., 2021). 50 articles reaching eligibility were chosen. Finally, only 17 full-text articles were included in the meta-analysis.

Coding of Study Characteristics

The following information was retrieved from the selected studies: (1) name of the author; (2) publication year; (3) region; (4) sample size; (5) gender; (6) education level; (7) scaffolding; (8) learning environments; (9) assessment tools; (10) intervention length; (11) effect size. Each article is coded based on the 11 characteristics listed above. Some variables such as author, and publication year are used for identification purposes and the 'effect size' variable is to record the effect of intervention for the quasi-experimental study based on Cohen's d. The remaining codes are for the moderator analysis.

The above characteristics of the selected articles were coded independently by three experienced and well-trained coders who were from the background of early childhood education, technology education, and language education respectively. All coders had reached the prerequisite of conducting reviews (Lipsey & Wilson, 2001). First, the three independent coders coded three random identical articles from 17 inclusive studies to reach internal coder reliability. Second, three coders coded the remaining 14 articles individually and reached a 95% absolute consensus. Thirdly, the final coding result was gained after discussion among the three coders on any differences.

Quality Assessment

The quality assessment (Table A1 in the Appendix A) was evaluated by the same three coders independently. The discussion among the three authors resolved the differences in scoring. The quality of the included studies in this meta-analysis was assessed based on the Study Design and Implementation Assessment Device (Study DIAD) provided by Cooper (2017). The rubric to examine the methodological quality of studies included four categories (fit between concepts and operations, clarity of causal inference, generality of findings, and precision of outcome estimation) with eight composite questions retrieved from the Study DIAD (Cooper, 2017). The assessment tool had eight items in four categories, which were "yes or no" questions. "Yes" was for 1 point, and "no" was for zero point. The evaluation score was calculated by dividing the total score by the total number of items (eight items), followed by converting the score into a percentage. Overall, the methodological evaluation scores of the included studies ranged from 87.5% to 100%. The mean quality of the studies in this meta-analysis was .94, representing that the overall study reached 94% of the Study DIAD requirement. This indicated that the quality of the inclusive studies was good.

Data Analysis

All data analyses were conducted by using the R 4.0.0 (R Core Team, 2020) with the *"Metaphor" package* (Viechtbauer, 2010). Studies were detected and excluded as an outlier by the *altimeter* package with the function "meta-outliers" if the standard residual exceeded 3 (Lin et al., 2017; Viechtbauer & Cheung, 2010).

Heterogeneity was evaluated by the Cochrane Q statistical test, which was an indicator for detecting the existence of unexplained heterogeneity (Higgins et al., 2003). Publication bias was examined through Begg's rank correlation test (Egger et al., 1997) and the symmetry of the funnel plot (Duval & Tweedie, 2000).

To remove the dependence of certain values that should exist independently (e.g., the effect size, observation value, and error term in the same study), multi-level meta-analysis was adopted (Van den Noortgate et al., 2013). A three-level random-effects meta-analysis model was adopted to decompose the variance from different sources, including the sample of subjects for each experiment within effect sizes (Level 1), effect sizes within studies (Level 2), and effect sizes between studies (Level 3). This method has been validated for articles containing multiple sample sizes and effect sizes, allowing for a more precise analysis at all three levels (Van den Noortgate et al., 2013).

Results

Characteristics of the Included Studies

Characteristics of the included studies were shown in Table 1. All studies included in this meta-analysis were published between 2019 and 2023. In all 17 studies, there were 25 independent sample studies and 35 effect sizes. A total of 1665 samples were covered. Out of the total, 52% of the participants were affiliated with the kindergarten level, while the remaining 48% were enrolled in the first and second year of primary school. The samples of the interventions were from several countries, namely Asia (53%), Europe (29%), and the Americas (18%). Nine studies (53%) are mainly in the kindergarten level while eight studies (47%) are in early elementary level. Only seven studies (41%) mentioned that teachers receive training on CT. Four studies (24%) used scaffolding techniques to facilitate children's learning experience. The predominant learning environment of the included studies was educational robot (47%). Graphical programming platform was employed in a proportion of 26%. Only two studies (11%) incorporated unplugged activity and three studies (16%) included hybrid environment. Two studies (Yadav & Chakraborty, 2023; Yang et al., 2023) used two different learning environments at the same time. Ten studies (59%) have computer-assisted assessment tools while seven studies (41%) used paper and pencil to collect children's responses. The intervention length of the studies ranges between .3 to 9 hours.

Outlier Detection

One of the effect sizes in the work of Angeli and Valanides (2020) was found to be significantly different from other studies with standard residuals over 3. Therefore, one of the effect sizes in Angeli and Valanides (2020) was removed from the subsequent data analysis as an outlier and no outlier had been detected in the remaining data analysis (Figure 2). There were 17 studies with 34 effect sizes after removing the outlier to be included in the following overall analysis and moderator analysis.

The Overall Effect of Interventions on Cultivating 3–8 years Old Children's CT Development

As Figure 3 showed, among 17 studies that assessed the effect of intervention on CT, 34 effect sizes ranged from .007 to 6.805. The overall effect was found to be .83 (95% CI: .730, .890).

We tested whether the mean effect sizes of the studies differed significantly (homogeneity test) via Cochrane's Q and I^2. If I^2 exceeded 75, the effect sizes showed significant heterogeneity (Melsen et al., 2013). In this case, a random effects model was more suitable than a fixed-effects model for this meta-analysis. In a random-effects model, the selected studies were treated as random samples from a

Table 1. Characteristics of the Included Studies in the Meta-Analysis.

Studies (Year)	Region	*N (males/ females)*	Level	Teacher training	Scaffolding	Learning environments	Assessment tools	Intervention length
Arfé et al. (2019)	Europe	76 (37/39); 38 (21/17)	Primary	Yes	No	Graphical programming platform	Computer-assisted	8 hours
Chiazzese et al. (2019)	Europe	46 (29/17)	Primary	Yes	No	Hybrid environment	Computer-assisted	8 hours
Nam et al. (2019)	Asia	53 (32/21)	Kindergarten	No	Yes	Educational robot	Paper-pencil	12 hours
Angeli and Valanides (2020)	Europe	25 (12/13)	Kindergarten	No	Yes	Educational robot	Paper-pencil	1.3 hours
Chou (2020)	Asia	11 (5/6)	Primary	No	No	Graphical programming platform	Computer-assisted	8 weeks
Relkin et al. (2021)	Americas	342 (162/178)	Primary	Yes	No	Educational robot	Computer-assisted	15 hours
Gerosa et al. (2022)	Americas	51 (33/18)	Kindergarten	No	No	Educational robot	Paper-pencil	5 hours
Kwon et al. (2022)	Americas	44 (26/18)	Primary	No	No	Educational robot	Paper-pencil	3.3 hours
Montuori et al. (2022)	Europe	109 (64/45)	Primary	Yes	No	Graphical programming platform	Computer-assisted	8 hours
Wang et al. (2022)	Asia	79 (40/39); 33 (21/12)	Kindergarten	No	Yes	Educational robot	Paper-pencil	N/A
Yang et al. (2022a)	Asia	18 (5/13)	Kindergarten	Yes	No	Educational robot	Computer-assisted	3.5 hours
Yang et al. (2022b)	Asia	54 (26/28); 47 (23/24)	Kindergarten	Yes	No	Unplugged activity	Computer-assisted	N/A

(continued)

Table 1. (continued)

Studies (Year)	Region	*N (males/ females)*	Level	Teacher training	Scaffolding	Learning environments	Assessment tools	Intervention length
Zhan et al. (2022)	Asia	48 (33/15)	Primary	No	No	Hybrid environment	Computer-assisted	9 hours
Angeli and Georgiou (2023)	Europe	110 (67/43); 118 (61/57)	Kindergarten	No	Yes	Educational robot	Computer-assisted	.3 hours
Canbeldek and Isikoglu (2023)	Asia	80 (*N*/A)	Kindergarten	No	No	Hybrid environment	Paper-pencil	13.5 hours
Yadav and Chakraborty (2023)	Asia	79 (*N*/A); 80 (*N*/A)	Primary	No	No	Graphical programming platform; unplugged activity	Paper-pencil	8 hours
Yang et al. (2023)	Asia	64 (*N*/A); 60 (*N*/A)	Kindergarten	Yes	No	Educational robot; graphical programming platform	Computer-assisted	5.25 hours

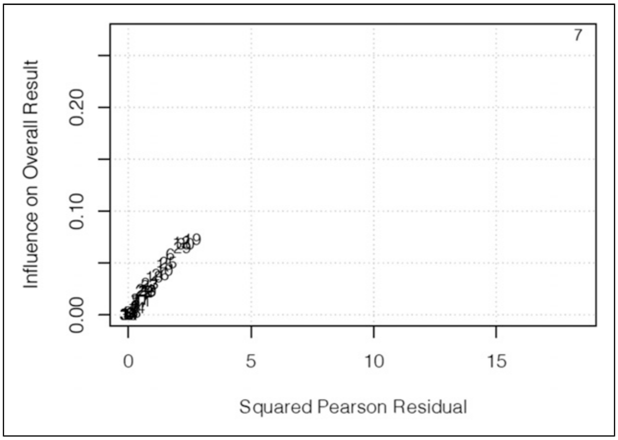

Figure 2. Baujat plot.

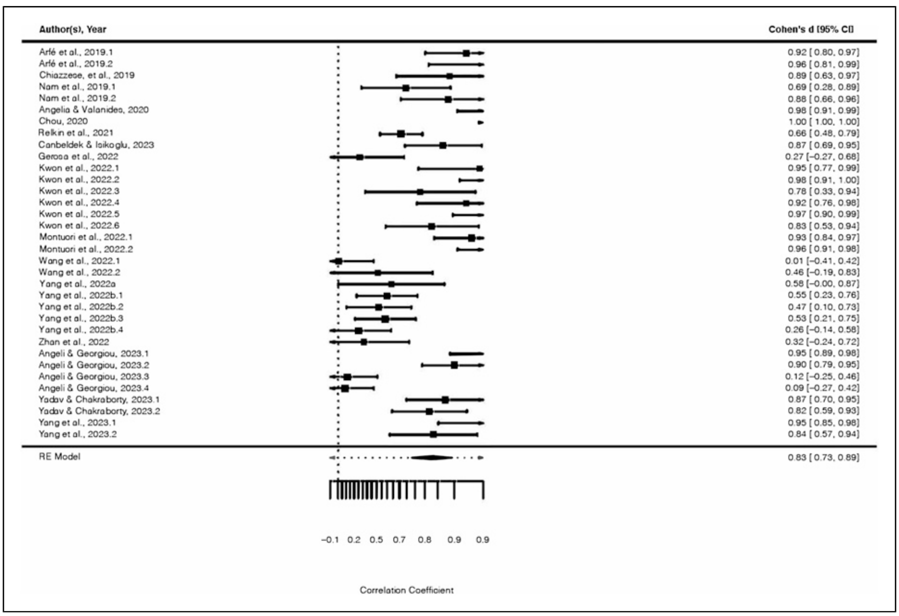

Figure 3. Forest plot for all samples.

larger population to help generalize the findings (Lin et al., 2017). The I^2 was 88.26, which indicated a high heterogeneity. In addition, significant heterogeneity existed among effect sizes (Q (df = 33) = 249.236, p < .0001) which suggested a further moderator analysis is needed.

Moderator Analysis - Factors Affecting Children's CT Development

Table 2 showed the moderator analysis results from the effect of the intervention on CT. There were four statistically significant moderators, Males with F (18, 15) = 3.041 (p = .017), Females with F (18, 15) = 3.041 (p = .017), Level with F (1, 32) = 4.206 (p = .049), and Scaffolding with F (1, 32) = 46.076 (p < .001). In addition, there was one moderator (Intervention Length with F (2, 31) = 3.135 (p = .058) was marginally significant. The rest of the moderators were found nonsignificant.

In terms of gender, the significant moderating results revealed that both male and female students gained equal benefits from the interventions to develop their CT. As for education level, although interventions were effective for both students at kindergarten and primary school, kindergarten-level students achieved better performance than those in primary school. In addition, providing students with scaffolding was better than those without such interventions to enhance CT. This indicates that scaffolding was a useful support for helping young children develop CT. With regard to intervention length, the shorter time had the potential to optimize interventions to cultivate students' CT than the longer time. Although the moderating result for intervention length was marginally significant, a growing trend existed among researchers to consider effects of marginal significance as an indicative of supporting evidence for a hypothesis (Pritschet et al., 2016). This study also took consideration of the marginally significant moderator when interpreting the result for moderator analysis. As for assessment tools, there was no significant difference between assessments collected through computer and paper-pencil.

Publication Bias

A meta-analysis is biased if the sample literature was not representative of the overall status of research in the field, affecting its accuracy and reliability (Rothstein et al., 2005). All of the studies examined in this paper were from published peer-reviewed articles. Due to the exclusion of unpublished studies from the study, the effect size derived may not reflect the actual situation. In addition, works with large effect sizes were more likely to be published. Hence, it was essential for meta-analyses to examine the presence of publication bias within the dataset. It was common to use the funnel plot to test publication bias, where the abscissa was the effect size, and the ordinate was the standard error.

In Figure 4, it was evident that the majority of the effect sizes fell within the middle and upper effective areas of the funnel plot and were fairly evenly distributed on both sides of the average effect size, suggesting a small publication bias (Egger et al., 1997). The symmetry of the Funnel Plot showed no publication bias for the effect of intervention on CT (Kendall's tau = .346, p = .004). Thus, the overall findings of our meta-analysis could be accepted.

Table 2. Moderator Analyses for Studies Reporting the Effect of Intervention on CT.

Moderator variables	# Studies	# ES	β_0 (95% CI)	β_1 (95% CI)	*F (df1, df2)*	Level 2 variance	Level 3 variance
Region					.705 (2, 31)	.217	.396
Asia	13	16	1.093 (.555; 1.632)				
Europe	8	10	.463 (−.418; 1.344)	−.630			
Americas	4	8	−.075 (−1.117; .967)	−1.168			
Sample size					2.736 (2, 31)	.238	.277
<30	5	9	1.996 (1.206; 2.786)				
30–60	10	13	−1.061 (−1.990; −.133)	−3.057			
>60	10	12	−.889 (−1.823; .045)	−2.885			
Gender							
Male	19	29	1.699 (1.060; 2.338)***	−.328 (−1.155; .498)	3.041 (18, 15)*	.233	.000***
Female	19	29	1.717 (1.114; 2.320)***	−.346 (1.145; .453)	3.041 (18, 15)*	.233	.000***
Education level					4.206 (1, 32)*	.260	.179
Kindergarten	13	18	.913 (.496; 1.330)***				
Primary	12	16	.628 (.004; 1.251)*	−.285			
Teacher training					.004 (1, 32)	.224	.428
Yes	11	13	1.210 (.604; 1.816)				
No	14	21	.026 (−.774; .826)	−1.184			
Scaffolding					46.076 (1, 32)***	.005	1.281
Yes	5	7	2.387 (1.718; 3.056)***				
No	20	27	−1.404 (−1.826; −.983)***	−3.791			

(continued)

Table 2. (continued)

Moderator variables	# Studies	# ES	β_0 (95% CI)	β_1 (95% CI)	*F (df1, df2)*	Level 2 variance	Level 3 variance
Learning environments					1.902 (3, 30)	.307	.145
Unplugged activity	2	3	.834 (−.006; 1.674)				
Educational robot	15	21	.222 (−.653; 1.096)	−.612			
Graphical programming platform	7	7	.975 (−.033; 1.983)	.141			
Hybrid	3	3	.184 (−1.022; 1.389)	−.650			
Assessment tools					.010 (1, 32)	.235	.378
Computer-assisted	15	18	1.232 (.770; 1.695)				
Paper-pencil	11	16	−.030 (−.640; .580)	−1.262			
Intervention length					3.135 (2, 31)	.248	.164
<6 hours	9	15	1.218 (.767; 1.668) ***				
≥6 hours	12	13	.262 (−.395; .919)	−.956			

Note. # Studies = Number of independent studies; # ES = Number of effect sizes; CI = Confidence interval; Level 2 variance = Variance in effect sizes within studies; Level 3 variance = Variance in effect sizes between studies.

*$p < .05$.

***$p < .001$.

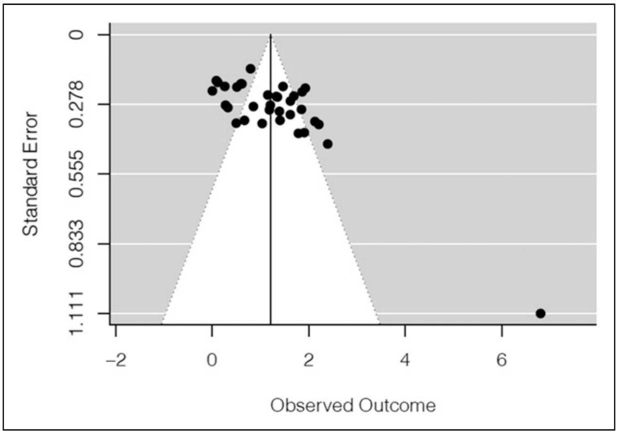

Figure 4. Funnel plot.

Discussion

First and foremost, this meta-analysis of 17 studies with 34 effect sizes showed an overall effect of .83 on CT for 3–8 years old children, which could be regarded as a large effect (Hedges & Olkin, 1985). This result was generally consistent with existing studies that various interventions had a large effect size on CT in K-12 education (Cheng et al., 2023; Merino-Armero et al., 2022; Xu et al., 2022). In other words, through the appropriate interventions, it was possible for young children to develop CT with large effect size as students in K-12. The results showed that the effect size differed significantly due to different moderators which may provide more specific guidance on promoting CT development for young children in the future.

Moderators

Results showed that some factors namely gender, education level, scaffolding and intervention length moderated children's CT development. Other factors such as region, sample size, gender, teacher training, learning environments and assessment tools did not moderate children's CT development.

Gender

This study found that boys and girls gained equally from the treatments. This contrasted with the finding of Lei and collaborators (2020). They showed a stronger link between CT and academic achievement among girls than boys through first primary graders to fourth university seniors. It was possible that CT might exert a more pronounced influence on females as they went into adolescence. Hence, this study affirmed the significance of early intervention, thereby encouraging the stakeholders to actively participate in early intervention efforts. Although the overall gender disparity in young children might be minimal, Sullivan and Bers (2016) had shown that there still existed a gender disparity in the acquisition of advanced CT skills. It is important to recognize early intervention in fostering equitable development of CT for young children due to their gender-based variations.

Education Level

This study demonstrated that kindergarten education level had a statistically significant effect when compared to the early primary education level. This finding is endorsed by Hong (2023) but contrasted with others (Merino-Armero et al., 2022; Sun et al., 2021). The integrated nature of the curriculum in kindergarten may be a reason to explain the current finding (Aldemir & Kermani, 2017; Fantuzzo et al., 2011) and young children if supported appropriately are able to learn CT (Kazakoff & Bers, 2014; Strawhacker & Bers, 2018). Subsequently, this study provided evidence in favour of the feasibility of CT intervention during the early stages, highlighting the potential for CT to be effective in younger children.

Scaffolding

Scaffolding appeared to have a statistically significant effect on young children's CT learning. Scaffolding is an integral part of the learning experience of young learners because it has the potential to improve learning outcomes (Belland, 2014), a validity that extends to the CT education. Overall, this study highlighted the importance of scaffolding for young children's CT learning. Through K-12 practices, Xu et al. (2022) concluded that support from teachers had a greater impact than technical tools and resources. To date, scaffolding techniques for CT learning in young children have predominantly been technical and resource-based. There seemed to be a deficiency in teacher support during the CT implementation. As Wang et al. (2021) showed, CT was often taught to young children by researchers or research assistants in after-school and summer enrichment programs. Fewer opportunities might result in a lack of pedagogical knowledge and confidence in applying concepts or practices of CT in education (Brennan & Resnick, 2012). By providing teachers with the necessary training and support, stakeholders could better understand the impact of scaffolding on student learning. In light of our apparent evidence that scaffolding could enhance children's CT development, future researchers are encouraged to focus on scaffolding. Specifically with regard to assistance for educators, including training in pedagogical strategies, familiarity with learning environments, and instruction in CT-related knowledge.

Intervention Length

This study showed that the intervention length of less than 6 hours was better for young children. This is supported by various studies (Hong, 2023; Lu et al., 2023; Merino-Armero et al., 2022; Sun et al., 2021) but contrasted with the findings of

Lai and Wong (2022) and Xu et al. (2022). The current finding may be due to the novelty effect of the intervention and the operational measure of CT as Sun et al. (2021) warned that many experimental studies were short and there was a negative moderating trend on intervention length. Xu et al. (2022) doubted the possibility and effect of developing CT, a problem-solving ability, within a short duration. The diverse outcomes call for more empirical studies of CT in early childhood education in order to validate the current findings.

Conclusion and Implication

This study enhances the field of computational thinking education for young children with empirical evidence using meta-analysis. In addition to the confirmation of providing young children with CT experience, this study identified factors that may enhance the instructional design. Researchers and practitioners involved in or concerned with early childhood education needed to address the issue of how to optimize the design of CT instruction for children and enhance the acquisition of CT skills for young children. From a practical standpoint, the findings of this study yielded valuable insights on the factors within the intervention that were more likely to foster the growth of CT in young children, as well as strategies for implementing the intervention more effectively. This study provided empirical evidence about the importance of scaffolding, indicating to both researchers and practitioners that scaffolding instruction could be a highly successful means of promoting the CT development. There was no gender difference in young children, which encourages early intervention to reduce gender differences in future learning. Children in kindergarten showed greater CT improvement than those in grades 1 and 2, highlighting the efficacy and value of early intervention. However, more empirical studies are needed to determine the moderating effect of intervention length. Therefore, instructors and researchers were encouraged to determine the effective combination of intervention features based on their own needs and respective situations to achieve CT education outcomes.

Limitations

For this study, some limitations needed to be noted. First, this study examined the searchable literature published in English, future studies can expand the language range to Spanish, Japanese, Chinese, and so on. Secondly, there was a lack of a precise definition of CT (Brennan & Resnick, 2012; Grover & Pea, 2013) and diversity of assessment instruments. These two issues had the benefit while also hindering the refinement of the results, such as the need to validate and integrate future assessment tools in order to compare results obtained using the same criteria. Third, the dimensional information regarding the moderator categorizations was limited. Future studies could detail and enrich more moderator variables.

Appendix A

Table A1. Quality Assessment.

Author(s) and year	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Total	Quality, %
Arfé et al. (2019)	1	1	1	0	1	1	1	1	7	87.5
Chiazzese et al. (2019)	1	1	1	1	1	1	1	1	8	100
Nam et al. (2019)	1	1	1	1	1	1	1	1	8	100
Angeli and Valanides (2020)	1	1	0	1	1	1	1	1	7	87.5
Chou (2020)	1	1	0	1	1	1	1	1	7	87.5
Relkin et al. (2021)	1	1	1	1	1	1	1	1	8	100
Canbeldek & Isikoglu (2023)	1	1	1	1	1	1	1	1	8	100
Gerosa et al. (2022)	1	1	1	1	1	1	1	1	8	100
Kwon et al. (2022)	1	1	0	1	1	1	1	1	7	87.5
Montuori et al. (2022)	1	1	0	1	1	1	1	1	7	87.5
Wang et al. (2022)	1	1	1	0	1	1	1	1	7	87.5
Yang et al. (2022a)	1	1	0	1	1	1	1	1	7	87.5
Yang et al. (2022b)	1	1	0	1	1	1	1	1	7	87.5
Zhan et al. (2022)	1	1	1	1	1	1	1	1	8	100
Angeli and Georgiou (2023)	1	1	1	1	1	1	1	1	8	100
Yadav and Chakraborty (2023)	1	1	1	1	1	1	1	1	8	100
Yang et al. (2023)	1	1	1	1	1	1	1	1	8	100

Category 1: Fit between concepts and operations

Q1 Were the participants treated in a way that is consistent with the definition of the intervention?

Q2 Were the outcomes measured in a way that is consistent with the proposed effects of the intervention?

Category 2: Clarity of causal inference

Q3 Were the participants in the group receiving the intervention comparable to the participants in the comparison group?

Q4 Was the study free of events that happened at the same time as the intervention that confused its effect?

Category 3: Generality of findings

Q5 Did the study include variation on participants, settings, and outcomes representative of the intended beneficiaries?

Q6 Was the intervention tested for its effect within important subgroups of participants, settings, and outcomes?

Category 4: Precision of outcome estimation

Q7 Were effect sizes and their standard errors accurately estimated?
Q8 Were statistical tests adequately reported?

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