Children and Youth Services Review 118 (2020) 105439

Contents lists available at ScienceDirect

Children and Youth Services Review

journal homepage: www.elsevier.com/locate/childyouth

Computational thinking and academic achievement: A meta-analysis among students

Hao Lei[a], Ming Ming Chiu[b], Feng Li[c,*], Xi Wang[c], Ya-jing Geng[c]

[a] Institute of Curriculum and Instruction, Faculty of Education, East China Normal University, Shanghai, People's Republic of China
[b] Department of Special Education and Counselling, The Education University of Hong Kong, Hong Kong, People's Republic of China
[c] Department of Education Information Technology, Faculty of Education, East China Normal University, Shanghai, People's Republic of China

ARTICLE INFO

Keywords:
Computational thinking
Academic achievement
Meta-analysis
Students

ABSTRACT

This meta-analysis examines whether greater computational thinking is linked to greater academic achievement among students from 1st graders in primary school to 4th year seniors at university. Results from 34 studies showed that computational thinking and academic achievement were positively correlated (0.288). Moderator analysis showed that this correlation was (a) stronger among students in Eastern cultures than Western cultures; (b) strongest among primary school students, less strong among secondary school students, and weakest among undergraduates; (c) stronger among females than males; and (d) strongest when assessing assignment scores; less strong with GPA, course grade, or tests; and weakest with quizzes. Neither subject content (e.g., math, science) nor sampling strategy (e.g., randomized, convenience) moderated the link between computational thinking and academic achievement. In sum, the positive link between computational thinking and academic achievement is moderated by culture, grade, achievement indicators, and gender.

1. Introduction

The advent of computers has influenced curriculum, learning processes, and learning outcomes (Luo, Liu, & Luo, 2019). Specifically, schools are increasingly teaching *computational thinking*, "the thought processes involved in formulating a problem and expressing its solution (s) in such a way that a computer–human or machine—can effectively carry out" (Wing, 2006, p. 33). In the last decade, many countries have incorporated computational thinking into their curricula (e.g., South Korea, Jeong, 2016; Ministry of Education of the People's Republic of China, 2017). Computational thinking's key elements of procedures/algorithms and abstraction help students understand and build systems of understanding that can cut across different academic subjects such as mathematics, science, and language—which in turn can improve student learning outcomes in them (Grover & Pea, 2013).

However, past studies of computational thinking and learning outcomes show mixed results, ranging from slightly negative links to small positive links to large positive links (Doleck, Bazelais, Lemay, Saxena, & Basnet, 2017; Grover, Pea, & Cooper, 2015; Liang & Lin, 2015). Hence, this meta-analysis synthesizes the results of 34 past studies to determine an overall result and to test for significant moderators (culture, grade level, subject content, gender, assessment type, and sampling strategy).

1.1. Computational thinking and academic achievement

Computational thinking aids interpretation, analysis and solution of many problems via abstraction, algorithms, and systemic thinking (Wing, 2011). Abstraction identifies key features and their relations while ignoring irrelevant distractions to represent a problem properly. Algorithms are abstractions of processes that use the problem representation's inputs to execute a sequence of actions and produce an output solution. Applying abstraction and algorithms aids construction of larger systems that help students look beyond the immediate stimuli to see and act on the complex relations inherent in many real-world situations.

These computational thinking processes of abstraction, algorithmic processing, and systemic thinking can aid students' understanding of many academic domains such as mathematics, science and language (Grover & Pea, 2013). In mathematics, students learn to abstract numbers from quantities of objects, apply arithmetic algorithms (e.g., multi-digit multiplication), and build arithmetic systems (subtraction as inverted addition, multiplication as repeated addition, etc.). In science, students abstract the elements of compounds (sugar's atoms: $C_6H_{12}O_6$), apply chemical algorithms (photosynthesis: $6CO_2 + 6H_2O + \text{light} \rightarrow C_6H_{12}O_6 + 6O_2$), and build systems (carbon cycle with photosynthesis, decomposition, respiration, etc.). In language, students learn to abstract

* Corresponding author.
E-mail address: lifengys2001@163.com (F. Li).

https://doi.org/10.1016/j.childyouth.2020.105439
Received 21 June 2020; Received in revised form 1 September 2020; Accepted 1 September 2020
Available online 12 September 2020

words for objects (dog) and parts of speech for words (noun, verb); then, they build algorithms for creating sentences (noun – verb – direct object) and build grammar systems. Hence, students with superior computational thinking in school might show greater academic achievement across domains, compared to other students.

However, past studies show mixed results. For example, Gülmez and Özdener (2015) study showed a significant positive link between students' computational thinking and their academic achievements in information technology, mathematics, Turkish, and English. However, other studies showed no significant link between computational thinking and academic achievement (e.g., Doleck et al., 2017; Miller et al., 2014).

1.2. Factors influencing the relationship between computational thinking and academic achievement

The mixed results of past studies might stem from differences across studies. Hence, we consider differences in culture, grade level, academic subject content, and gender.

1.2.1. Integrated curricula across cultures and grade levels

The link between computational thinking and learning outcomes is likely stronger with integrated curricula (rather than fragmented curricula), which are more likely in collectivist countries (rather than individualistic ones) or lower grade levels. Countries that favor group goals (collectivist) over individual ones often have national integrated curricula (e.g., China, Japan and many Eastern countries, Tanaka, Nishioka, & Ishii, 2016; Zhang & Campbell, 2012), unlike the fragmented curricula of individualistic countries (e.g., Australia, USA, and many Western countries, Savage & O'Connor, 2015). Students learning via integrated curricula across subjects (computer science, mathematics, science…) are more likely to have knowledge and skills acquired in one subject (computer science) affect their learning outcomes in other subjects (mathematics), compared to students learning via fragmented curricula with segregated subjects (Ingram, 2014; Tanaka et al., 2016). Hence, we expect a link between computational thinking and academic achievement to be stronger among students in Eastern countries than those in Western countries.

Within a country, a single teacher for all courses and an integrated curriculum is most likely in primary (elementary) school, less likely in secondary (high) school and least likely at university (Moss, Godinho, & Chao, 2019; VanTassel-Baska & Wood, 2010). As computational thinking is more likely to influence learning outcomes in integrated curricula, this link is likely strongest in primary school, especially when each student only has one teacher. This link is likely less strong in secondary school when a student has many teachers. Lastly, this link is likely weakest at university, where many students can choose from a buffet of courses. Indeed, the results of several studies suggest that computational thinking and academic achievement are more strongly linked at lower grade levels than higher ones (Olatoye, Akintunde, & Yakasi, 2010; Lishinski, Yadav, Enbody, & Good, 2016; Doleck et al., 2017).

1.2.2. Academic subject content

Student learning outcomes in closely-related academic subjects resemble one another more than those in distantly related ones (Kastberg, Chan, & Murray, 2016). As computational thinking is more closely related to some subjects (e.g., mathematics) than others (e.g., history), the link between computational thinking and academic achievement is likely stronger in closely-related subjects (mathematics) than distantly-related subjects (history). Indeed, some studies show that computational thinking's correlation with mathematics achievement far exceeds its correlation with history achievement ($0.74 \gg 0.17$; Gras, Bordoy, Ballesta, & Berna, 2010; Korkmaz, 2012).

1.2.3. Gender

As males have more positive attitudes toward computers and technology than females do (see meta-analysis by Cai, Fan, & Du, 2017), males are more likely than females to informally learn about them outside of school (Boeren, 2011). Hence, males' informal learning of computational thinking outside of school reduces the value of formally learning it in school (*substitution* effect, Mankiw, 2020). In contrast, females are less likely to informally learn computational thinking, so formally learning it in school likely yields greater impact on their academic learning outcomes. Hence, the link between computational thinking and academic achievement is likely stronger for females than for males, as shown in a few studies (Doleck et al., 2017; Haddad & Kalaani, 2015).

1.3. The purpose of this study

This meta-analysis synthesizes the results of past studies on computational thinking and academic achievement. Specifically, this study (a) determines the overall effect size for the link between computational thinking and academic achievement and (b) tests whether this link differs across culture, grade level, academic subject, or gender. We also test for differences in sampling design (e.g., randomized, convenience) and measures of academic achievement (quiz score, test score, assignment score, course grade, and grade point average).

2. Methods

2.1. Literature search

To locate studies on computational thinking and academic achievement, we systematically searched the literature via electronic databases, including Web of science, Google Scholar, Springer, Taylor & Francis, EBSCO, and ScienceDirect. Indexed keywords included computational thinking and academic achievement (academic achievement, academic performance, students' performance, students' achievement, students' success). If full-text articles were not available online, we obtained them from our university library. All articles available to us were written in English. We used inclusion criteria to filter the collected studies.

2.2. Inclusion criteria

We included articles that fit these criteria: (a) analyzed the relation between computational thinking and students' academic achievement, (b) measured students' computational thinking, (c) measured academic achievement via grade point average (GPA), examination score, course grade, quiz, assignment grade, or other indicators, (d) specified a sample size, and (e) reported the correlation coefficient r between computational thinking and academic achievement (or a β-value, t or F-value that could be transformed into r)..

2.3. Coding

Two researchers separately screened the literature for suitable studies (see Fig. 1), had acceptable inter-rater reliability (Cronbach's $\alpha = 0.891$), and consensually resolved differences via discussion. Eventually, 22 articles fit the inclusion criteria, and 7 had multiple samples for a total of 34 independent studies. We considered the following variables: author(s) and publication year, proportion of male participants, grade levels, culture, subjects, indicators of academic achievements, number of participants, and r effect size. The following criteria guided coding procedure (see Table 1): (a) effect sizes were recorded for each independent sample within a study; (b) if a study reported the correlation between multiple components of computational thinking (e.g., algorithmic thinking, problem solving) and academic achievement, we used their mean effect size rather than separate

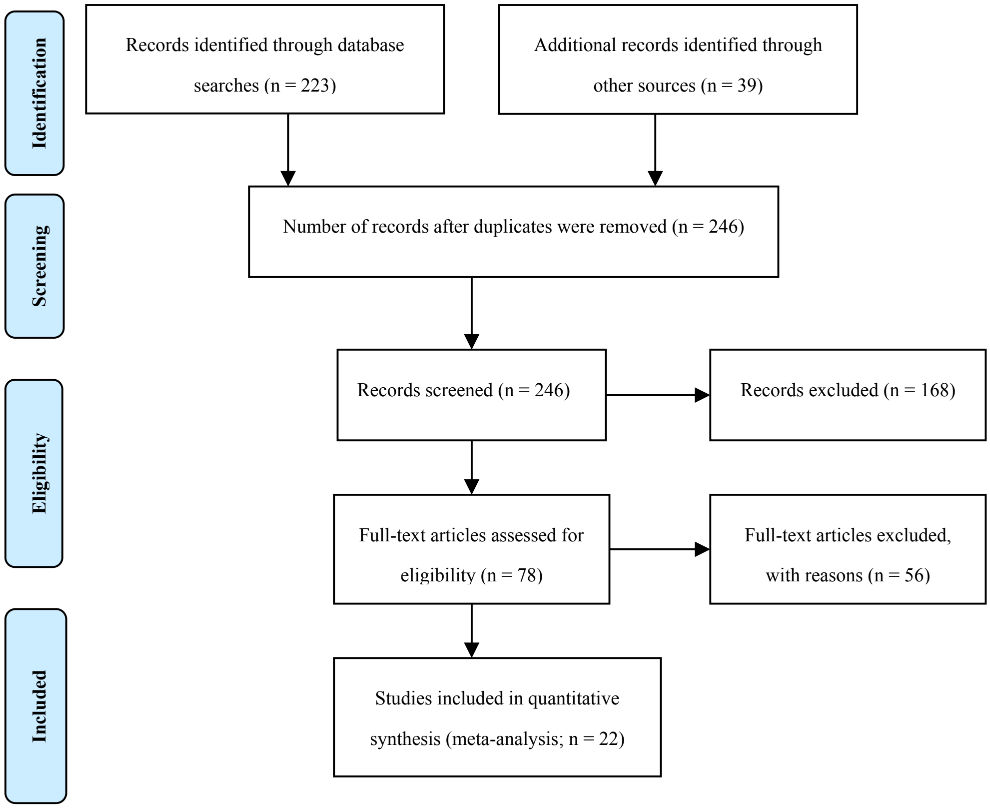

Fig. 1. PRISMA 2009 flow diagram.

Table 1
Studies included in the meta-analysis.

Name (year)	Sample	Achievement measure	Region	Grade	Male%	Subject	Sampling[a]	JADAD
Alyahya and Alotaibi (2019)	46	Quiz	Western	Middle	N	Math	1	3
Ambrosio, Almeida, Macedo, and Franco (2014)	12	Course grade	Western	University	0.5	Overall	2	4
Ambrosio et al. (2014)	12	Test score	Western	University	0.5	Overall	2	4
Ceylan and Kesici (2017)	53	Quiz	Western	Elementary	0.472	Computer	2	4
Chongo, Osman, and Nayan (2020)	128	Course grade	Eastern	Middle	0.445	Math	1	4
Doleck et al. (2017)	104	GPA	Western	University	0.481	Overall	1	4
Durak and Saritepeci (2018)	156	Quiz	Western	Mixed	0.546	Math	1	3
Durak and Saritepeci (2018)	156	Quiz	Western	Mixed	0.546	Science	1	4
Durak and Saritepeci (2018)	156	Quiz	Western	Mixed	0.546	Computer	1	3
Grover et al. (2015)	28	Assignment grade	Western	Middle	0.714	Computer	1	3
Gülmez and Özdener (2015)	84	GPA	Western	Elementary	0.5	Overall	2	3
Haddad and Kalaani (2015)	982	GPA	Western	University	0.95	Overall	1	3
Haddad and Kalaani (2015)	982	Course grade	Western	University	0.95	Computer	1	4
Kuo and Hsu (2020)	52	Quiz	Eastern	Middle	0.519	Computer	2	4
Lee, Jung, and Park (2017)	86	Quiz	Eastern	Elementary	0.57	Overall	2	4
Li (2012)	48	quiz	Eastern	Elementary	0.5	Math	2	4
Mindetbay, Bokhove, and Woollard (2019)	775	Quiz	Western	Middle	0.708	Math	1	4
Mindetbay et al. (2019)	775	Quiz	Western	Middle	0.708	Computer	1	3
ML, Andrade, and MR (2019)	32	Course grade	Western	Mixed	N	Math	2	4
Özgür (2020)	405	Course grade	Western	Mixed	0.489	Math	1	3
Özgür (2020)	405	Course grade	Western	Mixed	0.489	Science	1	3
Özgür (2020)	405	Course grade	Western	Mixed	0.489	Computer	1	4
Peteranetz, Wang, Shell, Flanigan, and Soh (2018)	815	GPA	Western	University	N	Computer	1	3
Rodrigues, Andrade, and Campos (2016)	149	Test score	Western	Middle	N	Math	2	4
Rodrigues et al. (2016)	149	Test score	Western	Middle	N	Language	2	4
Rodrigues et al. (2016)	149	Test score	Western	Middle	N	Human	2	4
Rodrigues et al. (2016)	149	Test score	Western	Middle	N	Science	2	4
Román-González, Pérez-González, Moreno-León, and Robles (2018)	138	GPA	Western	Middle	0.704	Computer	2	4
Román-González et al. (2018)	138	GPA	Western	Middle	0.704	Math	2	3
Román-González et al. (2018)	138	GPA	Western	Middle	0.704	Language	2	3
Shell, Hazley, Soh, Ingraham, and Ramsay (2013)	175	Course grade	Western	University	0.863	Computer	1	4
Shell et al. (2014)	155	GPA	Western	University	0.807	Overall	1	3
Sırakaya (2020)	722	Quiz	Western	Middle	0.506	Computer	1	4
Xia, Zhang, Liu, and Guo (2020)	187	Course grade	Eastern	Middle	N	Math	1	3

Note: a, 1 = Convenience sample; 2 = Randomized sample/Stratified sample.

Table 2
Random-model of the correlation between computational thinking and academic achievement.

k	N	r	95% CI for g	Homogeneity test			Tau-squared			Test of null (two tailed)	
				Q(r)	p	I^2	Tau^2	SE	Tau	Z-Value	p
34	8946	0.288	[0.235, 0.340]	203.872	0.00	83.813	0.021	0.008	0.144	10.073***	< 0.001

*** $p < .001$.

effect sizes; (c) if a study reported the correlation between computational thinking and academic achievements of different subjects such as math and computer, we encoded them separately, (d) if a study reported a correlation between computational thinking and academic achievement in the same subject area at different time periods, we used their mean effect size rather than separate effect sizes, and (e) if an independent sample provided multiple effect sizes for subsample characteristics, we used the effect size for the full sample.

After using meta-analysis principles to complete the coding (Lipsey & Wilson, 2001), we calculated effect sizes between computational thinking and academic achievement for each sample. We tested whether the association between students' computational thinking and academic achievement were moderated by (a) culture; (b) grade; (c) academic subject; (d) gender; (e) achievement indicators; or (f) sampling. Studies were coded for culture based on the location of the study participants: (a) *Eastern* for participants in Asian countries, or (b) *Western* for participants from Australian, European and North American countries. (No such studies at this time were conducted in Africa or Latin America.) Academic subjects were coded as *computer*, *language*, *math*, *science*, *social science*, or *overall*. Grade level was coded as *elementary school*, *middle school*, *university*, or *mixed* (if the study included at least two of these categories of participants). The academic achievement measures were coded as *assignment grade*, *course grade*, *test score*, *GPA*, or *quiz*. Sampling was coded as *convenience sample*, *randomized sample*, or *stratified sample*. Gender was coded as the proportion of *female* participants.

2.4. Assessment of study quality

We assessed the quality of each study with the revised Jadad Scale, scoring them from lowest (=0) to highest (=5; Borenstein et al., 2005). Describing the randomization process in detail yielded two points, while simply mentioning it yielded one point. Also, describing the double-blind implementation in detail yielded two points, while mentioning it yielded one point. Specifying the number of lost or withdrawn participants yielded one point. High-quality studies had scores above two. The scores of all 22 articles exceeded two, indicating that they were all high-quality studies.

2.5. Effect size computation

This meta-analysis used the Pearson correlation coefficient *r* of each study for its effect size (Borenstein, Hedges, Higgins, & Rothstein, 2005). As the study sample sizes differed substantially, we applied the Fisher Z-transformation with weights based on study sample sizes to compute the final *r* and 95% confidence intervals ($Z = 0.5 * \ln[(1 + r)/(1 - r)]$; variance of Z: $V_Z = 1/(n - 3)$; standard error of Z: $SE_z = 1/(n - 3)^{0.5}$.

2.6. Heterogeneity test

We tested whether the mean effect sizes of the studies differed significantly (*homogeneity* test) via Cochrane's Q and I^2 (Huedo-Medina, Sánchez-Meca, Marín-Martínez, & Botella, 2006). If I^2 exceeds 75, the effect sizes show significant heterogeneity; in this case, a random-effects model is more suitable than a fixed-effects model for this meta-analysis (in a random-effects model, the selected studies are treated as random samples from a larger population to help generalize the findings (Lim et al., 2019). Substantial heterogeneity indicates the need for moderation tests.

2.7. Evaluation of publication bias

We assessed the risk of publication bias with a funnel chart, fail-safe number (Nfs, Khoury et al., 2013), and Egger's linear regression. Nfs is the minimum number of additional studies with non-significant results that would render a non-significant overall result for this meta-analysis. When Nfs is less than 5 k + 10 (k = number of original studies), the danger of publication bias is substantial (Rothstein et al., 2005). If Egger's linear regression yields a non-significnat intercept near 0, the possibility of publication bias is low (Egger, Smith, Schneider, & Minder, 1997); See results in Table 2 and Fig. 3.

2.8. Data analysis

After obtaining the effect value *r*, we used Comprehensive Meta-Analysis 3.3 (CMA 3.3) for the meta-analysis. A random-effects model calculated the homogeneity test and mean effect. Averaged weighted (within- and between-inverse variance weights) correlation coefficients of independent samples were used to compute mean effect sizes. When the homogeneity test is significant ($Q_{Bet} > 0.05$), showing substantial variance in effect sizes, moderators were tested: culture, grade level, academic subject, gender, achievement measure, and sampling.

3. Results

3.1. Results of literature retrieval and description of the data

The flow and results of the literature retrieval are shown in Fig. 1 (see Section 2.1.2 for criteria details). As noted above, all effect sizes on the relation between computational thinking and academic achievement from 34 independent samples met our study criteria. A total of 8946 participants were involved in these studies, and the numbers of participants in each of study ranged from 12 to 982. The basic characteristics of these independent samples are presented in Table 1. The correlations between computational thinking and academic achievement varied widely in these 34 studies.

3.2. Effect size and the homogeneity test

The homogeneity test for computational thinking and academic achievement showed significant heterogeneity ($Q = 203.872$, $p < 0.001$, $I^2 = 83.813$; see Table 2), which required a *random* model (Lipsey & Wilson, 2001). Overall, computational thinking was significantly positively correlated with students' academic achievement ($r = 0.288$; 95% CI: 0.235–0.340; $Z = 10.073$; $p < 0.001$). A forest plot intuitively describes the effect sizes (see Fig. 2).

3.3. Assessment of publication bias

The funnel plot, fail-safe *Nfs*, and Egger's regression all showed no publication bias. The funnel plot showed that the 34 effects were

Study name	Correlation	Lower limit	Upper limit	Z-Value	p-Value
1.000	0.669	0.470	0.803	5.305	0.000
2.000	0.373	-0.256	0.780	1.176	0.240
3.000	0.252	-0.376	0.722	0.773	0.440
4.000	0.206	-0.068	0.451	1.478	0.139
5.000	0.322	0.157	0.469	3.733	0.000
6.000	-0.010	-0.202	0.183	-0.101	0.920
7.000	0.192	0.036	0.339	2.405	0.016
8.000	0.208	0.053	0.354	2.611	0.009
9.000	0.100	-0.058	0.253	1.241	0.215
10.000	0.661	0.382	0.830	3.973	0.000
11.000	0.550	0.380	0.684	5.565	0.000
12.000	0.401	0.347	0.452	13.293	0.000
13.000	0.289	0.231	0.345	9.308	0.000
14.000	0.181	0.085	0.274	3.669	0.000
15.000	0.158	0.062	0.252	3.195	0.001
16.000	0.117	0.020	0.212	2.357	0.018
17.000	0.221	-0.055	0.466	1.573	0.116
18.000	0.250	0.040	0.439	2.327	0.020
19.000	0.601	0.382	0.756	4.660	0.000
20.000	0.180	0.111	0.247	5.056	0.000
21.000	0.070	-0.000	0.140	1.948	0.051
22.000	0.232	0.166	0.296	6.734	0.000
23.000	0.440	0.300	0.561	5.706	0.000
24.000	0.120	-0.042	0.275	1.457	0.145
25.000	0.060	-0.102	0.219	0.726	0.468
26.000	0.250	0.093	0.395	3.086	0.002
27.000	0.432	0.286	0.559	5.372	0.000
28.000	0.355	0.200	0.493	4.312	0.000
29.000	0.421	0.273	0.549	5.216	0.000
30.000	0.350	0.213	0.474	4.793	0.000
31.000	0.350	0.204	0.481	4.505	0.000
32.000	0.110	0.037	0.182	2.962	0.003
33.000	0.570	0.276	0.766	3.487	0.000
34.000	0.559	0.452	0.650	8.564	0.000

Statistics for each study

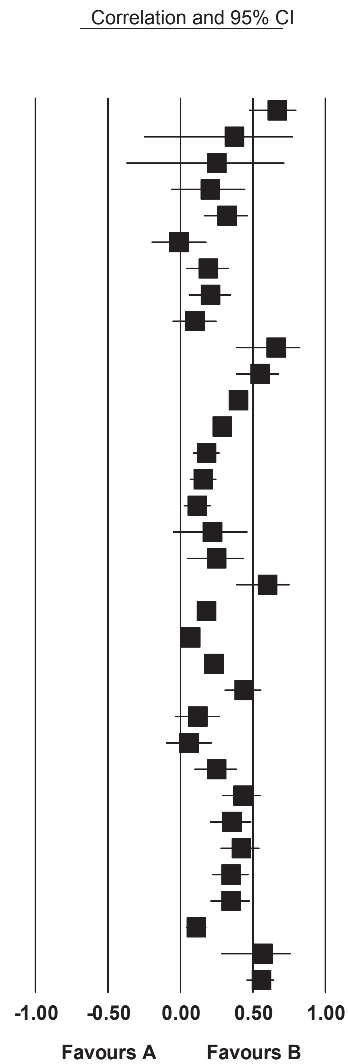

Fig. 2. Forest plot for the random-effects model.

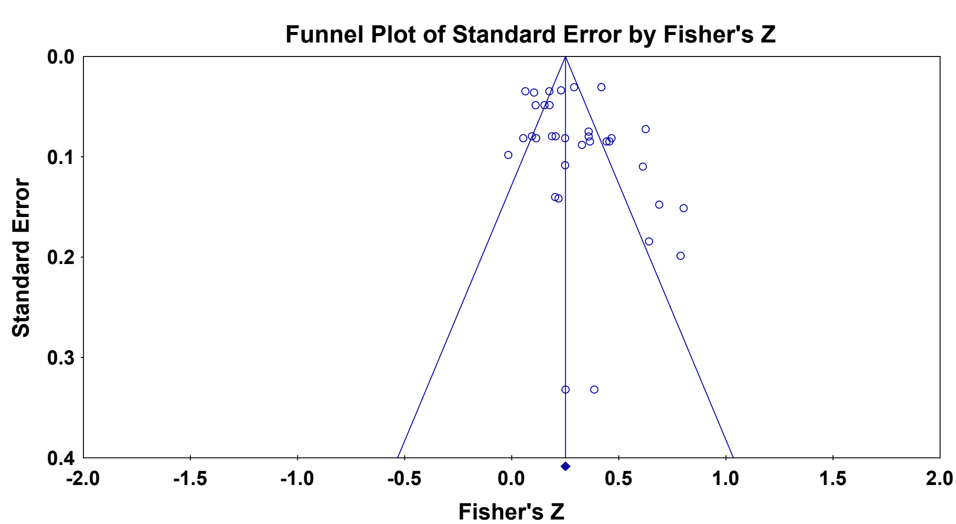

Fig. 3. Funnel plot of the effect sizes of the beta between computational thinking and academic achievement.

Table 3
The relationship between computational thinking and students' academic achievement: Univariate analysis of variance for moderator variables (categorical variables).

	Between-group effect(Q_{BET})	k	r	SE	95% CI for g	Homogeneity test within each group(Q_W)	I^2
Culture	6.315*						
Eastern		5	0.407	0.033	[0.275, 0.525]	16.049***	75.075
Western		27	0.281	0.008	[0.224, 0.336]	137.281***	81.061
Others		2	0.125	0.009	[−0.063, 0.305]	4.831*	79.299
Subjects	7.299						
Math		10	0.388	0.024	[0.289, 0.478]	64.963***	86.146
Overall		6	0.297	0.042	[0.137, 0.442]	18.822***	73.435
Language		2	0.276	0.076	[0.042, 0.481]	7.561**	86.775
Computers		12	0.253	0.012	[0.160, 0.341]	97.184***	88.681
Science		3	0.203	0.041	[0.016, 0.377]	1.070	0.000
Social science		1	0.060	0.000	[−0.272, 0.380]	0.000	1.000
Grade	9.255*						
Elementary school		5	0.437	0.040	[0.292, 0.563]	12.153***	67.087
Middle school		15	0.307	0.019	[0.231, 0.379]	115.744***	87.904
University		8	0.284	0.008	[0.175, 0.386]	28.684***	75.597
Mixed		6	0.159	0.002	[0.040, 0.273]	2.053	0.000
Achievement indicators	10.391*						
Assignment		1	0.661	0.000	[0.320, 0.850]	0.000	0.000
Course grade		9	0.300	0.014	[0.206, 0.387]	48.377***	83.463
Test		6	0.291	0.040	[0.162, 0.409]	28.180***	82.257
GPA		8	0.346	0.014	[0.253, 0.433]	38.026***	81.591
Quiz		10	0.193	0.005	[0.100, 0.282]	22.715***	60.387
Sampling	2.327						
Randomized sample/Stratified sample		15	0.341	0.014	[0.255, 0.421]	42.686***	67.202
Convenience sample		19	0.257	0.009	[0.189, 0.322]	149.164***	87.933

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

symmetrically distributed on both sides of the mean with respect to sample size. Also, Nfs = 4,534, far greater than the comparison criteria of 180 (=5 × 34 + 10 = 5 k + 10; Card, 2011, p. 270). Lastly, Egger's regression showed no significant bias ($t_{(32)}$ = 1.874; $p = .069 > 0.05$).

3.4. Moderator analysis

The homogeneity test showed substantial differences among effect sizes, indicating the need to explore potential moderators. We tested culture, grade level, academic subject, gender, academic achievement measure and sampling design (see Table 1).

3.4.1. Culture

The homogeneity test showed significant heterogeneity in effect sizes of computational thinking on academic achievement across cultures (Q_{BET} = 6.315, df = 1, $p < .01$; see Table 3). The correlation between computational thinking and academic achievement was significant for both Eastern countries (r = 0.407, 95% CI = 0.275…0.525) and Western countries (r = 0.281, 95% CI = 0.224…0.336) but significantly stronger in Eastern ones (0.407 > 0.281).

3.4.2. Grade level

The effect sizes of computational thinking on academic achievement showed significant heterogeneity across grade levels (Q_{BET} = 9.255, df = 3, $p < .05$). Their effect sizes were significant at all grade levels: largest for primary school students (r = 0.437, 95% CI = 0.292…0.563), smaller for secondary school students (r = 0.307, 95% CI = 0.231…0.379), and smallest for undergraduates (r = 0.284, 95% CI = 0.175…0.386).

3.4.3. Achievement indicators

The effect sizes of computational thinking on academic achievement showed significant heterogeneity across achievement measures (Q_{BET} = 10.391, df = 4, $p < .05$). The effect sizes for all measures were significant, but largest for assignments (r = 0.661, 95% CI = 0.320…0.850), smaller for GPA (r = 0.346, 95% CI = 0.253…0.433), course grade (r = 0.300, 95% CI = 0.206…0.387), and test score (r = 0.291, 95% CI = 0.162…0.409); and smallest for quiz score (r = 0.193, 95% CI = 0.100…0.282).

3.5. Academic subjects and sampling

The effect sizes of computational thinking on academic achievement did not show significant heterogeneity across academic subjects (computers, language, math, science, social science or overall: Q_{BET} = 7.299, df = 5, $p > .05$) or sampling design (convenience sample, randomized sample /stratified sample: Q_{BET} = 2.327, df = 1, $p > .05$). These results indicate that neither academic subject nor sampling design moderates the relation between computational thinking and students' academic achievement.

Table 4
Univariate regression analysis of continuous variables (random-effect model).

	Parameter	Estimate	SE	Z-value	95%CI for b
Male (%)	β_0	0.047	0.116	0.409	[−0.179, 0.274]
	β_1	0.352	0.177	1.990	[0.005, 0.698]
	Q_{Model} (1, k = 26) = 3.961, $P < .05$				

3.5.1. Gender

To examine whether gender moderated the effect sizes between computational thinking and academic achievement, the *g* effect size was meta-regressed onto the percentage of female participants in each sample. The results (Q_{Model} [1, k = 26] = 3.961, $p < .05$; see Table 4) showed that gender moderated the link between computational thinking and academic achievement. The effect sizes of the correlation between computational thinking and academic achievement for an extrapolated all-female sample ($r = 0.399$) were expected to be much stronger than those for an extrapolated all-male sample ($r = 0.047$).

4. Discussion

This meta-analysis of 34 studies showed an overall medium positive correlation between computational thinking and academic achievement. Furthermore, culture, grade level, gender, and achievement measure moderated this link.

4.1. The relationship between computational thinking and academic achievement

The medium positive correlation between computational thinking and academic achievement across subjects is consistent with the view that learning computational thinking aids learning outcomes. This result lends credence to the idea that the abstraction, algorithmic, and systemic aspects of computation support learning across multiple academic subjects (Grover & Pea, 2013) and suggests that educators study whether systemic incorporation of computation thinking into school curricula enhances learning outcomes for most students.

4.2. Moderating effects

Culture, grade, achievement measure, and gender moderated the link between computational thinking and academic achievement. By contrast, academic subject and sampling design did not moderate this link.

4.2.1. Integrated curricula across cultures and across grade levels

The stronger link between computational thinking and academic achievement in Eastern cultures than Western cultures is consistent with the greater integration of academic subjects within a curriculum in the former than in the latter (Savage & O'Connor, 2015; Tanaka et al., 2016; Zhang & Campbell, 2012). Hence, our finding of a greater link between learning computational thinking and academic achievement in Eastern countries than in Western countries is consistent with the view that the impact of computational thinking across academic subjects is greater with integrated curricula (in many collectivist Eastern cultures) than with fragmented curricula (in many individualistic Western cultures).

The link between computational thinking and academic achievement was strongest among primary school students, less strong among secondary school students, and weakest among university students. This result is consistent with the greater curricula integration of academic subjects in lower grade levels: greater curriculum coherence of being taught by a single teacher in many primary schools, less curriculum coherence when taught by several teachers in many secondary schools, and curricula fragmentation when students can choose from many university courses (Moss et al., 2019; VanTassel-Baska & Wood, 2010).

Together, these findings suggest that students with integrated curricula might benefit more than other students from learning computational thinking. Furthermore, these findings suggest that scholars explicitly study whether integrating computational thinking more closely with other academic subjects improves students' learning outcomes in these subjects.

4.2.2. Gender

The stronger link between computational thinking and academic achievement among females than among males is consistent with the *substitution* effect (Mankiw, 2020) of informal learning of computational thinking for its formal learning in school. This result suggests that females benefit more than males from learning computational thinking in school via greater academic achievement because they have worse attitudes toward computers and technology (Cai et al., 2017) and hence less likely to informally learn computational thinking outside of school (Boeren, 2011). In contrast, as males have better attitudes toward computers and are more likely to informally learn computational thinking, its impact on their academic achievement was smaller, as expected. This stronger link for females than for males suggests that educators study whether intervening to encourage more females to learn computational thinking in school (or requiring all students to do so) enhances their learning outcomes across academic subjects.

4.3. Other variables

This study also found that achievement measure moderated the link between computational thinking and academic achievement. Meanwhile, academic subject content and sampling strategy did not moderate this link.

The link between computational thinking and academic achievement was significant and positive regardless of the achievement measure, though it was strongest when assessing assignment scores; less strong with GPA, course grade, or tests; and weakest with quizzes. Hence, researchers conducting future studies should design their academic achievement measures carefully, and might consider triangulating multiple measures. In all the studies within this meta-analysis, assignment scores were externally determined, whereas teachers assigned test scores, quiz scores, course grades, and GPAs. Future studies can examine the possible causes of these moderation effects, including whether external versus teacher scoring is relevant.

Academic subject content did not significantly moderate the link between computational thinking and academic achievement. However, only the numbers of studies of computer achievement and mathematics achievement exceeded three. After more studies with different academic subjects, future meta-analyses can test this potential moderation effect with greater accuracy.

Lastly, sampling design did not significantly moderate the link between computational thinking and academic achievement. This result is also consistent with the results showing no publication bias.

5. Limitations and future research directions

The limitations of this meta-analysis include its small sample, English language publications, and absence of experimental studies. This meta-analysis only included 34 independent samples. As more such studies accumulate, future meta-analyses can yield results with greater accuracy and test a greater range of moderators. Also, this meta-analysis examined the searchable literature published in English, so future studies can expand the language range of the literature search to include Chinese, Japanese, Spanish Russian, and so on. Too few studies examined in this meta-analysis used controlled experimental designs to test for moderation effects. As controlled experiments are the gold standard for intervention effects, future studies of computational thinking and academic achievement can use such designs, which would inform subsequent meta-analyses.

Funding

This research was supported by the National Social Science Foundation for Education of China (CFA180249).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

All authors read and approved the manuscript.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.childyouth.2020.105439.

References

Alyahya, D. M., & Alotaibi, A. M. (2019). Computational thinking skills and its impact on TIMSS achievement: An instructional design approach. *Issues and Trends in Learning Technologies, 7*(1).

Ambrosio, A. P., Almeida, L. S., Macedo, J., & Franco, A. H. R. (2014). Exploring core cognitive skills of computational thinking.

Boeren, E. (2011). Gender differences in formal, non-formal and informal adult learning. *Studies in Continuing Education, 33*(3), 333–346.

Borenstein, M., Hedges, L., Higgins, J., & Rothstein, H. (2005). Comprehensive meta-analysis (version 3.3) (p. 104). Englewood, NJ: Biostat.

Cai, Z., Fan, X., & Du, J. (2017). Gender and attitudes toward technology use: A meta-analysis. *Computers & Education, 105*, 1–13.

Ceylan, V. K., & Kesici, A. E. (2017). Effect of blended learning to academic achievement. *Journal of Human Sciences, 14*(1), 308–320.

Chongo, S., Osman, K., & Nayan, N. A. (2020). Level of computational thinking skills among secondary science student: Variation across gender and mathematics achievement. *Science Education International, 31*(2), 159–163.

Doleck, T., Bazelais, P., Lemay, D. J., Saxena, A., & Basnet, R. B. (2017). Algorithmic thinking, cooperativity, creativity, critical thinking, and problem solving: Exploring the relationship between computational thinking skills and academic performance. *Journal of Computers in Education, 4*(4), 355–369.

Durak, H. Y., & Saritepeci, M. (2018). Analysis of the relation between computational thinking skills and various variables with the structural equation model. *Computers in Education, 116*, 191–202.

Egger, M., Smith, G. D., Schneider, M., & Minder, C. (1997). Bias in meta-analysis detected by a simple graphical test. *British Medical Journal, 315*, 629–634.

Gras, R. M. L., Bordoy, M., Ballesta, G. J., & Berna, J. C. (2010). Creativity, intelectual abilities and response styles: Implications for academic performance in the secondary school. *Anales De Psicologia, 26*(2), 212–219.

Grover, S., & Pea, R. (2013). Computational thinking in K–12: A review of the state of the field. *Educational Researcher, 42*(1), 38–43.

Grover, S., Pea, R., & Cooper, S. (2015). "Systems of assessments" for deeper learning of computational thinking in K-12. In Proceedings of the 2015 annual meeting of the American educational research association (pp. 15–20).

Gülmez, I., & Özdener, N. (2015). Academic achievement in computer programming instruction and effects of the use of visualization tools; at the elementary school level. *British Journal of Education, Society & Behavioural Science, 11*(1), 1–18.

Haddad, R. J., & Kalaani, Y. (2015). Can computational thinking predict academic performance? *2015 IEEE integrated STEM education conference* (pp. 225–229). IEEE.

Huedo-Medina, T. B., Sánchez-Meca, J., Marín-Martínez, F., & Botella, J. (2006). Assessing heterogeneity in meta-analysis: Q statistic or I^2 index? *Psychological Methods, 11*(2), 193–206.

Ingram, J. B. (2014). *Curriculum integration and lifelong education: A contribution to the improvement of school curricula, Vol. 6*. Elsevier.

Jeong, Y. (2016). Needs analysis of software education curriculum at national universities of education for the 2015 revised national curriculum. *Journal of The Korean Association of Information Education, 20*(1), 83–92.

Kastberg, D., Chan, J. Y., & Murray, G. (2016). *Performance of US 15-year-old students in science, reading, and mathematics literacy in an international context: First Look at PISA 2015*. NCES 2017-048National Center for Education Statistics.

Khoury, B., Lecomte, T., Fortin, G., Masse, M., Therien, P., Bouchard, V., & Hofmann, S. G. (2013). Mindfulness-based therapy: A comprehensive meta-analysis. *Clinical Psychology Review, 33*, 763–771.

Korkmaz, Ö. (2012). The impact of critical thinking and logico-mathematical intelligence on algorithmic design skills. *Journal of Educational Computing Research, 46*(2), 173–193.

Kuo, W. C., & Hsu, T. C. (2020). Learning computational thinking without a computer: How computational participation happens in a computational thinking board game. *The Asia-Pacific Education Researcher, 29*(1), 67–83.

Lee, J., Jung, Y., & Park, H. (2017). Gender differences in computational thinking, creativity, and academic interest on elementary SW education. *Journal of The Korean Association of Information Education, 21*(4), 381–391.

Li, J. F. (2012). *Research on the differences in mathematical computational thinking among Yi ethnic rural pupils.* Doctoral dissertationSouthwest University.

Liang, C., & Lin, W.-S. (2015). The interplay of creativity, imagination, personality traits, and academic performance. *Imagination Cognition and Personality, 34*(3), 270–290.

Lim, K. S., Wong, C. H., McIntyre, R. S., Wang, J., Zhang, Z., Tran, B. X., & Ho, R. C. (2019). Global lifetime and 12-month prevalence of suicidal behavior, deliberate self-harm and non-suicidal self-injury in children and adolescents between 1989 and 2018: A meta-analysis. *International Journal of Environmental Research and Public Health, 16*(22), 4581.

Lipsey, M. W., & Wilson, D. B. (2001). *Practical meta-analysis.* Thousand Oaks, CA: Sage.

Lishinski, A., Yadav, A., Enbody, R., & Good, J. (2016). The influence of problem solving abilities on students' performance on different assessment tasks in CS1. *Proceedings of the 47th ACM technical symposium on computing science education* (pp. 329–334). .

Luo, H., Liu, J., & Luo, Y. (2019). The necessary mental literacy in the era of artificial intelligence: Computational thinking. *Modern Educational Technology, 29*, 26–33.

Mankiw, N. G. (2020). *Principles of economics.* Boston: Cengage Learning.

Miller, L. D., Soh, L. K., Chiriacescu, V., Ingraham, E., Shell, D. F., & Hazley, M. P. (2014). Integrating computational and creative thinking to improve learning and performance in CS1. *Proceedings of the 45th ACM technical symposium on Computer science education* (pp. 475–480). .

Mindetbay, Y., Bokhove, C., & Woollard, J. (2019). What is the relationship between students' computational thinking performance and school achievement? *International Journal of Computer Science Education in Schools,* 3–19.

Ministry of Education of the People's Republic of China (2017). *Curriculum standard of information technology for senior high school.* Beijing: People's Education Press.

ML, S. I., Andrade, W. L., & MR, S. L. (2019). Analyzing the effect of computational thinking on mathematics through educational robotics. *2019 IEEE Frontiers in Education Conference (FIE)* (pp. 1–7). IEEE.

Moss, J., Godinho, S. C., & Chao, E. (2019). Enacting the Australian Curriculum: Primary and secondary teachers' approaches to integrating the curriculum. *Australian Journal of Teacher Education, 44*(3), 2. https://doi.org/10.14221/ajte.2018v44n3.2.

Olatoye, R. A., Akintunde, S. O., & Yakasi, M. I. (2010). Emotional intelligence, creativity and academic achievement of business administration students. *Electronic Journal of Research in Educational Psychology, 8*(21), 763–786.

Özgür, H. (2020). Relationships between computational thinking skills, ways of thinking and demographic variables: A structural equation modeling. *International Journal of Research in Education and Science, 6*(2), 299–314.

Peteranetz, M. S., Wang, S., Shell, D. F., Flanigan, A. E., & Soh, L. K. (2018). Examining the impact of computational creativity exercises on college computer science students' learning, achievement, self-efficacy, and creativity. *Proceedings of the 49th ACM technical symposium on computer science education* (pp. 155–160). .

Rodrigues, R. S., Andrade, W. L., & Campos, L. M. S. (2016). Can Computational Thinking help me? A quantitative study of its effects on education. *2016 IEEE Frontiers in Education Conference (FIE)* (pp. 1–8). IEEE.

Román-González, M., Pérez-González, J.-C., Moreno-León, J., & Robles, G. (2018). Can computational talent be detected? Predictive validity of the Computational Thinking Test. *International Journal of Child-Computer Interaction, 18*, 47–58.

Rothstein, H. R., Sutton, A. J., & Borenstein, M. (Eds.). (2005). *Publication bias in meta-analysis: Prevention, assessment and adjustments*. Sussex, England: Wiley.

Savage, G. C., & O'Connor, K. (2015). National agendas in global times: Curriculum reforms in Australia and the USA since the 1980s. *Journal of Education Policy, 30*(5), 609–630.

Shell, D. F., Hazley, M. P., Soh, L.-K., Ingraham, E., & Ramsay, S. (2013). Associations of students' creativity, motivation, and self-regulation with learning and achievement in college computer science courses. *2013 IEEE Frontiers in Education Conference (FIE)* (pp. 1637–1643). .

Shell, D. F., Hazley, M. P., Soh, L. K., Miller, L. D., Chiriacescu, V., & Ingraham, E. (2014). Improving learning of computational thinking using computational creativity exercises in a college CSI computer science course for engineers. *2014 IEEE Frontiers in Education Conference (FIE) Proceedings* (pp. 1–7). IEEE.

Sırakaya, D. A. (2020). Investigating computational thinking skills based on different variables and determining the predictor variables. *Participatory Educational Research, 7*(2), 102–114.

Tanaka, K., Nishioka, K., & Ishii, T. (2016). *Curriculum, instruction and assessment in Japan: Beyond lesson study.* Taylor & Francis.

VanTassel-Baska, J., & Wood, S. (2010). The integrated curriculum model (ICM). *Learning and Individual Differences, 20*(4), 345–357.

Wing, J. (2011). Research notebook: Computational thinking—What and why. *The Link Magazine,* 6.

Wing, J. M. (2006). Computational thinking. *Communications of the ACM, 49*(3), 33–35.

Xia, X. G., Zhang, W. L., Liu, B., & Guo, J. (2020). The influence of programming software and academic level on the development of junior high school students' computational thinking. *Digital Education, 006*(002), 70–75.

Zhang, D., & Campbell, T. (2012). An exploration of the potential impact of the integrated experiential learning curriculum in Beijing China. *International Journal of Science Education, 34*(7), 1093–1123.