Computational Thinking Skills in Engineering Education: Enhancing Academic Achievement Through Innovations, Challenges, and Opportunities

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Abstract **– This study is a meta-analysis that identifies several publications focusing on the effect of computational thinking skills (CTS) on the academic achievement of engineering education students at the higher education level. Publications were sourced from Google Scholar and Scopus metadata using the Publish or Perish application, with a search time range of 2014-2023. Initial analysis was carried out using statistical formulas with Microsoft Excel, and meta-analysis results were generated using JASP software. A total of 6 publications were analyzed to determine how much influence CTS has on students' academic achievement. The results of the analysis provide evidence that the overall effect is 54%, which falls into the medium category. The study highlights that innovation, challenge, and opportunity significantly enhance student learning outcomes by fostering skill development, motivating problem-solving, and encouraging the exploitation of new opportunities.**

These findings offer valuable insights for curriculum developers, educators, and policymakers aiming to incorporate CTS-focused strategies to bolster academic achievement.

Keywords **– Computational thinking skills, engineering education, academic achievement, meta-analysis.**

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1. Introduction

In contemporary society, technology has evolved quickly, having a significant impact on various aspects of daily life. This swift development has changed the way people communicate, work, and learn. Technology simplifies all activities, providing quick and easy access that encourages continuous use. As a result, its adoption has been rapid and widespread globally [1], [2].

This development impacts various life sectors, including social, health, economic, and education [3]. In the social sector, technology is applied in various capacities to monitor trends and social issues (CCTV and smart city technologies). In the health sector, advanced medical devices are equipped with sensors to automatically and accurately detect internal diseases (magnetic resonance imaging, CT scans, ultrasonography devices). In the economic sector, automatic sensors are used to detect economic trends (blockchain, automated trading systems, and mobile banking). In the education sector, advanced technology is used for student learning access and teacher assessments (online collaboration tools, immersive learning, e-books and digital resources, and learning management systems).

Technology now plays a crucial role in all aspects of learning, from planning and implementation to evaluation. Specifically, in the field of engineering education, technology has driven significant changes in how students learn, enhancing the quality of education. This is evidenced by the widespread use of online learning platforms (google classroom, e-learning, zoom meeting), simulation software for practical engineering training (matlab, autocad, augmented and virtual reality), and the incorporation of electronic devices for collaborative projects and assessments (kahoot! and quizziz) [4].

According to numeorus studies, these technological advancements enable more interactive and personalized learning experiences, increase student engagement, and result in better academic outcomes [5]. Furthermore, the ability to access vast resources and connect with experts from around the world enhances the educational experience and prepares students for the demands of today's engineering landscape.

Engineering education is a comprehensive system designed to equip students with specific competencies for careers in fields such as mechanical engineering, automotive engineering, computer engineering, and electronics engineering, among others. In mechanical engineering classes, students apply principles such as fluid dynamics and thermodynamics to design complex systems, including lathe machines with integrated transmission mechanisms. Automotive engineering students employ algorithms related to the internal combustion cycle such as intake, compression, combustion, exhaust, to design and optimize vehicle systems, encompassing powertrains, transmission systems, cooling mechanisms, and exhaust systems. In the realm of computer engineering, students delve into programming languages such as C++, JavaScript, and Python, subsequently abstracting these languages into functional applications. Meanwhile, electronics engineering students deconstruct components like integrated circuits (ICs), resistors, capacitors, and batteries to engineer devices such as flip-flop circuits and other advanced electronic apparatus. This rigorous approach ensures that graduates are well-prepared to meet the demands of modern engineering challenges.

Given these considerations, it is critical that students are equipped with the necessary skills to excel in their respective fields of engineering. One critical skill is computational thinking (CTS). Individuals with CTS are distinguished by their ability to solve problems methodically, using logical and organized steps. Engineering education, by providing a solid foundation in computational thinking, can prepare students to succeed in an ever-changing workplace.

Several previous studies have empirically demonstrated that CTS improves students' academic achievement. For example, computational thinking has been shown to improve learning outcomes in elementary schools [6], [7], middle schools [8], and high schools [9]. Furthermore, CTS contributes to improved learning outcomes in K-12 education [10], technical schools, and higher education institutions [11]. However, these studies cover all educational levels, making it difficult to determine the importance of computational thinking at a specific level. We have chosen to focus solely on the impact of computational thinking skills in higher education. This decision is motivated by universities' critical role in preparing students for a broader range of opportunities compared to primary, secondary, and high school education. Moreover, higher education provides a more nuanced and relevant understanding of how these skills can improve learning outcomes in preparation for the transition to the industrial realm.

Therefore, this study seeks to uncover the extent of this influence, encapsulated within a meta-analysis aimed at providing a clearer understanding of how computational thinking skills (CTS) impact the academic achievement of engineering students at the higher education. By analyzing data from various previous publications, this study aims to determine the magnitude of the effect of CTS on student academic achievement. Additionally, we endeavor to unveil insights into how innovation, challenge, and opportunity within each publication influence student learning outcomes. The findings of this study are expected to offer deeper insights into the relationship between CTS and academic achievement, as well as provide recommendations for educational policies to be more effective.

1.1. Literature Review

Seymour Papert introduced the concept of "computational thinking" (CT) between 1980 and 1996 [12]. Papert suggested that all children should learn to use computers to improve their intellectual abilities. This aims to sharpen their thinking so they can think quickly, similar to how computers operate [13]. Papert's recommendation stemmed from his collaboration with Piaget in 1965, where he observed that children develop their intellectual abilities through self-directed, structured learning. This is not to diminish the value of teacher-led instruction, but rather to emphasize that self-initiated learning fosters a deeper and more meaningful understanding.

In March 2006, Jeanette Wing reintroduced the concept of computational thinking [14], [15]. This abilities involve fundamental computer science concepts in order to solve problems, design systems, and understand human behavior.

Since then, this skill set has evolved in response to changing times, and many people now recognize it as computational thinking skills (CTS) due to its inclusion of various competencies.

Academics worldwide have extensively researched CTS, particularly within the realm of engineering education. These investigations seek to identify the various factors that contribute to the enhancement of these skills among students. Furthermore, they aim to ascertain the most effective pedagogical strategies for fostering the development of computational thinking abilities in this discipline. The findings reveal that critical factors for improving these skills in students include digital literacy and metacognitive awarness [16], [17]. Furthermore, the most efficacious teaching methodologies for fostering CTS are problem-based learning (PBL) and project-based learning (PjBL) [18], [19]. Problem-based learning underscores the importance of problem-solving throughout the educational journey, encouraging students to independently tackle and resolve issues. Conversely, project-based learning requires students to develop innovative products pertinent to their specific fields of study.

Both methodologies promote critical thinking and practical application, which are indispensable for mastering computational thinking skills in engineering education.

These skills are inextricably linked to engineering education because it requires students to solve problems, develop innovations, design and build complex systems, analyze and evaluate data, and apply theoretical knowledge to real-world scenarios [20].

This principle transcends the confines of computer engineering, extending its relevance across the spectrum of engineering disciplines, including mechanical, automotive, civil, electrical, electronics, and beyond. This demand emphasizes the importance of students in engineering education having the necessary skills to complete these tasks. Generally, CTS consist of several key components, including abstraction, algorithms, decomposition, and pattern recognition [21], [22], [23]. These components are frequently regarded as fundamental to the development of computational skills, constituting the core of skills that must be mastered. CTS's scope expands over time. According to Ha Chu Chang) [25] individuals with strong CTS master 19 different skills.

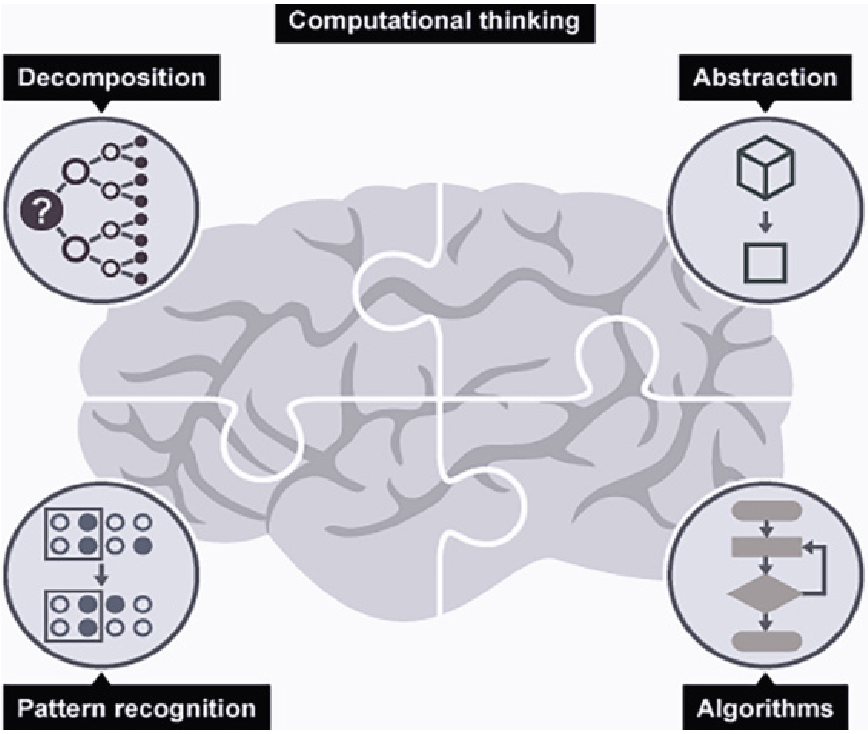

Figure 1. Basic components of CTS [24]

Table 1. Classification of (CTS) based on

No.	Category	Skills	Definition	Resources
1	Data management	Data analysis	Examining, interpreting, and transforming data to extract meaningful insights.	[26], [27]
		Data collection	Gathering information or data from various sources to use for analysis.	[28]
		Data representation	Representing information or data in a format that is easy for humans to understand and interpret.	[29], [30]
2	Problem solving and strategy	Algorithm design	Creating efficient methods for solving problems.	[31]
		Modelling	Creating abstract representations of real-world systems, processes, or phenomena.	[32], [33]
		Problem solving	Identifying, analyzing, and finding solutions to complex challenges.	[34], [35], [7]
		Simulation	Creating a model or virtual representation of a real-world system, process, or phenomenon.	[36]
		Transformation	Thinking refers to the process of converting data from one format, structure, or state to another.	[37], [38]
3	Logical thinking and pattern	Conditional logic	Making decisions based on specific conditions.	[39], [40]
		Error detection	Identifying and flagging mistakes, inconsistencies, or anomalies in data or code.	[41]
		Pattern generalization	Identifying common patterns or trends in specific examples and apply them more broadly to new or different situations.	[42]
		Pattern recognition	Observing and interpreting data to find consistent features or similarities across different sets of information.	[43], [44]
3	Abstraction and decomposition	Abstraction	Reducing complexity by focusing on the essential characteristics of something while ignoring the irrelevant details.	[45], [46]
		Decomposition	Breaking down complex problems or tasks into smaller, more manageable parts.	[47], [48], [49]
		Parallelization	Dividing a problem into smaller, independent tasks that can be executed simultaneously.	[47]
4	Automation and efficiency	Automation	Using technology to perform tasks with minimal human intervention.	[50], [51]
		Efficiency	Optimization of processes, algorithms, and code to achieve desired outcomes with minimal resource usage, such as time, memory, and computing power.	[52]
5	Connection and visualization	Connection	Establishing links or relationships between different data sets, concepts, or systems to gain insights or create integrated solutions.	[53], [54]
		Visualization	Representing data or information in graphical or visual formats, such as charts, graphs, maps, or diagrams.	[55]

Table 1 presents specific categories of CTS, offering a broader perspective on the scope and complexity of these skills. Each category is interrelated. Data management involves processing raw data into meaningful information, problem-solving and strategy focus on resolving and predicting relationships within specific and complex problems to find optimal solutions, logical thinking and pattern prioritizes logical and rational thinking in every task, abstraction and decomposition group problems into descriptive forms for easier analysis, automation and efficacy aim for effectiveness and efficiency in tasks, while connection and visualization relate to the ability to link various datasets or concepts and represent them visually.

2. Methodology

The methodology of this study consists of three main components. Firstly, formulating the research questions that will serve as the central focus in guiding the objectives and contributions of this study. Secondly, conducting a thorough and comprehensive literature review of publications relevant to the research topic. This process entails identifying, selecting, and evaluating information sources related to the analyzed theme. Lastly, it involves the application of precise and meticulous statistical analysis techniques to interpret the collected data and reveal significant findings related to the research questions.

2.1. Reserach Question

Based on the background previously outlined, we formulated the research question using the PICO framework [56]: students in engineering education (P), the implementation of computational thinking skills (CTS) integrated with learning technologies (I), methods of instruction without the integration of computational thinking skills (CTS) or traditional teaching methods (C), and student academic achievement (O).

RQ1: Is an instructional method focused on the development of computational thinking skills (I) more effective for engineering education students (P) compared to traditional methods (C), as measured by student learning outcomes (O)?

Additionally, to understand the impact of innovations, challenges, and opportunities on academic achievement, we propose the following research question:

RQ2: How do innovations, challenges, and opportunities (C) in the development of computational thinking skills (I) influence the academic achievement (O) of engineering education students (P)?

3. Data Collection and Review Process

The entire set of publications was collected from Google Scholar and Scopus metadata using the keywords "computational thinking skills" AND "technology" AND "engineering education" with the assistance of the Publish or Perish software. The search for articles was conducted using inclusion criteria, which comprised articles that aligned with predetermined requirements and research objectives. Exclusion criteria were also applied, focusing on articles that did not meet specific requirements [57]. The criteria in the inclusion process include:

I1: All articles discussing the application of computational thinking skills in engineering education published between 2014 and 2023.

I2: Articles with experimental methods that include both experimental and control groups, as well as pre-test and post-test scores available for each group.

I3: Articles providing sample size (N), mean (M), and standard deviation (SD) values.

I4: Articles integrating technology with computational thinking skills.

Following the selection of the chosen publications, we proceeded with exclusions:

E1: Articles not written in English.

E2: Articles lacking the required data completeness for analysis. Additionally, articles with unclearly presented methods and data analysis were excluded.

To facilitate the retrieval and screening of articles according to the aforementioned criteria, we utilized the PRISMA method. This method enabled us to organize and report the search results more transparently, thereby ensuring that the analyzed articles met the established inclusion criteria.

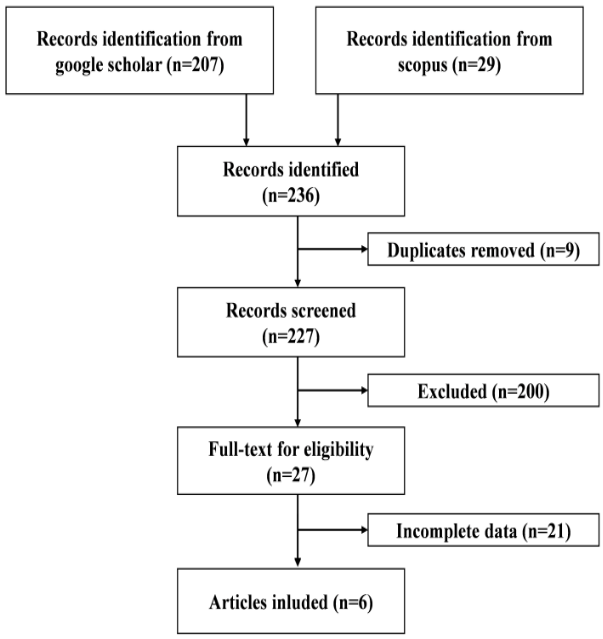

Figure 2. Research procedures using the PRISMA method

4. Data Analysis

The analysis was conducted using the meta-analysis method with a random-effects model, employing JASP software. Prior to analysis, the data were organized in terms of sample size (N), mean (M), and standard deviation (SD). Initial analysis was performed using Microsoft Excel to calculate additional details such as effect size and standard error.

Specific mathematical formulas were utilized to compute the effect size and standard error.

$$g = \frac{x_e + x_c}{\sqrt{\frac{(n_e-1)\,Se^2 + (n_c-1)\,Sc^2}{n-2}}} \quad (1)$$

$$SEg = \sqrt{\left(\frac{n_e+n_c}{n_e.n_c}\right) + \frac{g^2}{2(n-2)}} \quad (2)$$

Description:
g = effect size
Seg = standar error
xe and xc = mean of experimental and control group
Se and Sc = standar deviation of experimental and control group
n, ne and nc = total of samples, and number of samples in the experimental and control group.

5. Results

After adhering to the PRISMA guidelines, which encompass the stages of identification, screening, eligibility assessment, and inclusion (Figure 2), we excluded 9 duplicate articles. Subsequently, we meticulously reviewed each of the remaining 227 articles. Our screening process involved a thorough examination of the titles and abstracts, followed by a detailed assessment of the data pertinent to our study. Consequently, from the initial 227 articles, we selected 6 that aligned with the criteria and objectives of this research.

Table 2. Data recapitulation

Study	Author (year)	Experiment Group			Control Group			g	SEg
		N	M	SD	N	M	SD		
1	Shell, *et al*., (2015), [58]	90	7,47	2,56	90	6,14	3,01	0,47	0,15
2	Magana, *et al*., (2016), [59]	14	58,92	23,22	14	35,71	25,41	0,93	0,39
3	Mendoza *et al*, (2023), [60]	88	7,38	2,44	88	5,62	2,45	0,72	0,16
4	Wang, *et al*., (2022), [61]	65	3,87	0,66	39	3,77	0,60	0,16	0,20
5	Congo, *et al*., (2021) , [62]	15	47,53	12,66	16	46,06	8,24	0,13	0,36
6	Liu, *et al*., (2023), [63]	176	4,35	0,55	165	3,93	0,66	0,69	0,11

Table 2 compiles data extracted from the reviewed articles, presenting details such as sample size (N), mean (M), and standard deviation (SD) for both experimental and control groups, along with effect size (g) and standard error (SEg) for each article. This dataset facilitates a thorough analysis to ascertain whether the implementation of a learning intervention in the experimental group yielded statistically significant outcomes compared to the control group without the intervention. The dataset derived from Microsoft Excel analysis, encompassing effect size and standard error, serves as the primary dataset for subsequent meta-analysis using the JASP framework. The overarching aim is to discern the substantial influence of computational thinking skills on student learning outcomes.

5.1. Heterogeneity Test

In this study, a random-effects model was employed to address the heterogeneity present among the studies under analysis. This model recognizes that the true effect size may differ across various studies due to differences in conditions, populations, or methodologies.

By accounting for this variability in the analysis, the random-effects model offers a more inclusive estimate of the effect size, capturing the wider spectrum of potential outcomes across the included studies [64]. Additionally, it evaluates the significant variation between the groups or conditions being compared [65]. A random-effects hedge model was utilized in this study.

Table 3. Heterogeneity test

Fixed and Random Effects	Q	df	P
Omnibus test of model coefficients	26.689	1	<0.001
Test of residual heterogeneity	9.062	5	<0.107

The results of the meta-analysis test indicate a statistically significant effect based on the Omnibus test of model coefficients. The value of Q is 26.689 with 1 degree of freedom (df), and the p-value is less than 0.001, indicating strong evidence to support the model used.

Meanwhile, the test of residual heterogeneity shows no significant heterogeneity among the analyzed studies.

The value of Q is 9.062 with 5 degrees of freedom (df), and the p-value is 0.107, which is greater than the significance threshold of 0.05 [66]. These results indicate that the studies are sufficiently consistent, and their findings can be validly combined in the meta-analysis.

5.2. Summary Effect

RQ1: Is an instructional method focused on the development of computational thinking skills (I) more effective for engineering education students (P) compared to traditional methods (C), as measured by student learning outcomes (O)?

The summary effect size test in a meta-analysis aims to provide a single, synthesized estimate of the average impact of an intervention or relationship between variables across a sample of studies. This offers a comprehensive view of the overall effect of the measured variable, accounting for differences in study contexts and methodologies. By utilizing a random-effects model, the meta-analysis acknowledges potential variations among the studies and seeks to generalize findings beyond individual results [67], [68].

In the context of this meta-analysis, the random-effects model was employed to determine whether there is a significant positive relationship between the implementation of computational thinking skills and the enhancement of students' learning outcomes in engineering education. The results of the analysis are presented in Table 4.

Table 4. Summary effect

				95% Confidence Interval	
Estimate	Standard Error	z	p	Lower	Upper
0.587	0.104	5.166	< .001	0.333	0.741

Based on Table 4, the random-effects model demonstrated a statistically significant positive impact between computational thinking skills (CTS) and students' academic achievement. The effect size of CTS fell into the medium category (rRE = 0.537). This interpretation was based on Cohen (2013), where effect sizes of 0.1 are considered small, 0.5 medium, and 0.8 large. The forest plot illustrating these findings is presented in Figure 3.

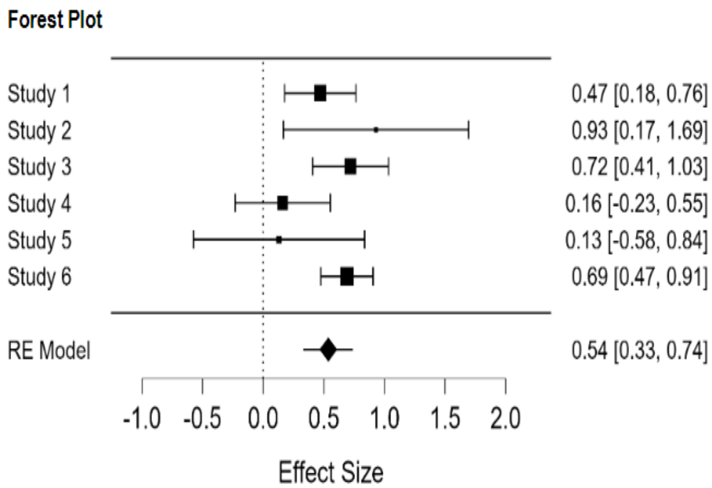

Figure 3. Forest plot

Figure 3 displays the results of the analysis of 6 publications on computational thinking skills (CTS) and student learning outcomes, indicating an estimated effect size of 0.54 or 54%. This finding suggests a significant relationship between CTS and student learning outcomes. The effect size of 0.54 reflects a moderate impact, indicating that improvements in students' CTS abilities have the potential to substantially enhance their learning outcomes.

6. Publication Bias

The funnel plot, Egger's regression, and fail-safe N were utilized to evaluate publication bias. The funnel plot (Figure 4) serves as a graphical tool to illustrate the relationship between effect size and study precision. Ideally, in the absence of publication bias, the plot should resemble an inverted funnel, with studies symmetrically distributed around the overall effect size. Any asymmetry in the plot may indicate potential publication bias.

Egger's regression, on the other hand, is a statistical test that examines the relationship between effect size and study precision . A significant result in this test may suggest the presence of publication bias, quantifying the extent of bias by analyzing the degree of asymmetry in the funnel plot.

Additionally, fail-safe N is a calculation used to estimate the number of unpublished or missing studies with null results that would need to be added to significantly alter the overall effect size. A high fail-safe N indicates that the meta-analysis results are robust and less likely to be influenced by potential missing studies.

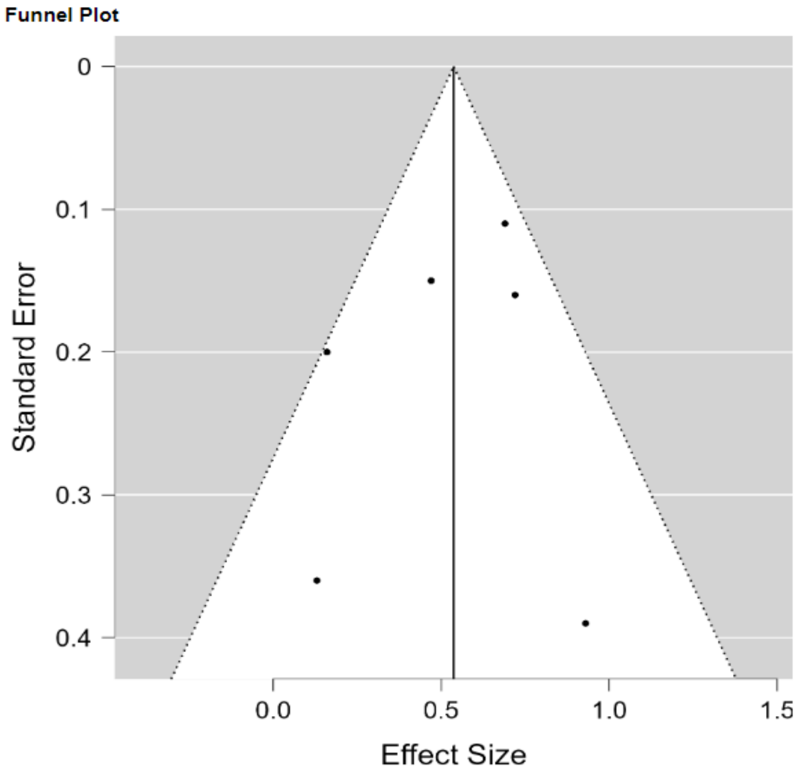

Figure 4. Funnel plot

Figure 4 depicts that the funnel plot derived from the analysis exhibited a tendency towards symmetry [70]. The distribution of the analyzed studies appeared to be even, indicating no publication bias in the meta-analysis. Fail-safe N and Egger's Test were conducted to further enhance the comprehensiveness of the data and complement the findings.

According to the fail-safe N criteria ($N > 5k + 10$, where k = number of original studies) [66], with $k = 6$, the threshold for N was 40. The results indicated that $N = 107$, surpassing the threshold of 40 significantly. The significance level was set at 0.05, with an observed p-value of less than 0.001. This high fail-safe N suggests that the findings of the meta-analysis are robust and unlikely to be overturned [71].

Egger's regression was also conducted to enhance the comprehensiveness of the data [72], [70], [73]. The test necessitated a p-value greater than 0.05, and the observed p-value was 0.922, confirming the absence of publication bias in these studies. These results collectively bolster the reliability and validity of the meta-analysis findings, indicating that the overall conclusions drawn from the studies are robust and trustworthy.

7. Innovations, Challenges, and Opportunities

RQ2: How do innovations, challenges, and opportunities (C) in the development of computational thinking skills (I) influence the academic achievement (O) of engineering education students (P)?

Table 5. Innovation, challenge, and opportunity in the implmentation of CTS

Study	Author (year)	Innovation	Callenge	Oportunity
1	Shell, et al., (2015), [58]	Implementation of computational creativity exercises (CCE) integrated into the IC2Think project.	• Some students still have low competencies. • Students hindered in completing their projects. • Students require more practice and courses for projects.	Improvement and optimization of better project outcomes.
2	Magana, et al., (2016), [59]	Introduction of authentic learning integrated with computational modules.	• Resistance to curriculum changes. • Lack of support from faculty unfamiliar with this teaching approach. • Insufficient resources to support the implementation of relevant modules.	• Enhancement of students' abilities in solving real-world problems. • Improvement of understanding and balance between theoretical concepts and practical application.
3	Mendoza & Sotomayor, (2023), [60]	Implementation of educational interventions informed by computational thinking design (CTD).	• Existence of a gap in students' understanding of CTD. • Need for appropriate assessment tools for teachers to measure students' academic achievements.	• Enhancement of learning quality with the CTD system. • Recognition of the importance of computation in education.
4	Wang, et al., (2022), [61]	Implementation of computational thinking concepts with visual artificial intelligence in education.	• It requires a significant amount of time to implement AI conceptualized with computational thinking skills. • The complexity of AI is difficult to comprehend.	• Reducing dropout rates for students. • Facilitating students from different educational backgrounds to learn AI more easily.
5	Congo, et al., (2021), [62]	Integration of computational thinking skills concepts with scratch programming.	• Limited time for project introduction and understanding. • Students' difficulty in visualizing abstract concepts.	• Utilizing scratch programming enhances students' critical thinking skills. • Improvement in understanding visual materials.
6	Liu, et al., (2023), [63]	Integration of educational technology and artificial intelligence in education.	• The complexity of technology with tools that are difficult for students to understand. • Tools that are difficult to comprehend in technology and artificial intelligence lead to students' lack of concentration and involvement in learning.	• Increased patience and concentration of students to understand a new technology. • Creation of an interactive learning environment.

Table 5 illustrates several innovations that have been implemented and integrated with the concept of CTS. Innovations are predominantly dominated by the integration of CTS and artificial intelligence. Additionally, there are several challenges to be faced in integrating CTS with technology, such as a lack of resources in terms of both teaching skills and facilities, the complexity of technology that is difficult for students to grasp, and the time-consuming nature of implementation.

Alongside these challenges, there are also opportunities to be gained.

For instance, the complexity of technology can encourage students to learn and base their problem-solving skills on complex issues, seeking ways to resolve them. This is also part of CTS. If this skill is continuously nurtured, it will make students more critical. This, indirectly, will also impact their academic achievements.

8. Discussion

This study aims to statistically depict the influence of computational thinking skills (CTS) on students' learning outcomes at the higher education level. Although CTS has been introduced for the past 40 years [74], we conducted a search for publications covering the last 10 years in the hope of providing a current report on the topic. Furthermore, focusing on topics discussed in recent years will offer a more relevant understanding of the current situation.

After undergoing a rigorous selection process for the chosen publications, out of the 236 articles considered, 6 articles were deemed fitting for the scope and context of this research. Subsequently, an analysis was conducted to obtain the statistical results of this study, revealing that the influence of CTS on the academic achievement of engineering students in higher education is 54%. This result is considered significant, as more than half of the factors affecting academic achievement from the contribution of CTS. This indicates that the higher the level of computational thinking among students in managing and synthesizing learning, the higher their academic achievement. Additionally, no publication bias was found in the selected articles, ensuring the robustness and reliability of the study's findings. This emphasizes the critical importance of incorporating CTS into engineering curricula to improve student success and academic performance.

Furthermore, each publication was analyzed to gather information regarding the innovations, challenges, and opportunities (Table 5) influencing the implementation of CTS on academic achievement. The analysis revealed that CTS is predominantly integrated with various cutting-edge technologies [75]. Innovations proposed include the implementation of computational creativity exercises (CCE) integrated into the IC2Think project, the introduction of authentic learning integrated with computational modules, the implementation of education interventions informed by computational thinking design (CTD), the application of computational thinking concepts with visual artificial intelligence in learning, the integration of computational thinking skills with scratch programming, and the integration of educational technology and artificial intelligence in education. Additionally, several challenges were identified, both from students themselves and from educators and faculties. These challenges include difficulties in understanding the complexity of technology combined with CTS (using AI-based technology with too many confusing features and tools). Some studies stade that the more complex the technology, the more difficult its adoption by users [76], [77].

This may hinder the adoption of new technology by students. Furthermore, educators still lack mastery of existing technology. They require extensive practice to learn and understand the innovations they teach, resulting in wasted time. Moreover, institutions and governments still inadequately facilitate the need for this integration. The lack of support from faculties unfamiliar with this teaching approach will impede the acceleration of understanding and the improvement of CTS. However, amidst the myriad challenges, there are numerous opportunities to be seized. These opportunities include learning more from the complexity of technology, optimizing project outcomes, enhancing students' ability to solve real-world problems, improving the understanding and balance of theoretical concepts with practice, recognizing the importance of computation in education, increasing students' patience and concentration to understand new technology, and creating an interactive learning environment.

The integration of innovations with CTS will encourage students to think and strive for further advancement [78]. Creative students will not be content with stagnation in the innovations they use; instead, they will continually strive to enhance them [79], [80]. For instance, if the educational application they are using only presents topics through static images and abstract text, students with computational thinking skills will endeavor to make the application more concrete. They might transform it into a virtual reality experience with animations, making the learning material more tangible and interactive. This exemplifies the essence of computational thinking, where innovations are designed to facilitate a deeper understanding of a subject. This will provide impetus to continuously engage in critical thinking and complete projects within the innovations they create. At this stage, they employ computational thinking: abstraction, decomposition, pattern recognition, logical thinking, and other skills to solve and dissect challenges faced, seeking optimal solutions. Behind every challenge lies curiosity, compelling students to persistently question and search for answers. This not only tests students' abilities but also ignites and reveals their latent capabilities, acquired through perseverance and consistent effort.

Furthermore, the integration of CTS with cutting-edge innovations creates opportunities for students to envision future goals and strive to achieve them. This fosters ambition and competition among students to attain these objectives, resulting in a sense of fulfillment upon accomplishment. Consequently, it also boosts satisfaction and confidence in their abilities.

Therefore, CTS contributes to all aspects of innovation, challenges, and opportunities in enhancing student academic outcomes and achievements. CTS plays a role in fostering innovation, navigating challenges, and leveraging opportunities to strengthen ambitions and achieve satisfying results in learning. This situation is expected to create a positive and sustainable cycle, impacting academic outcomes as evidenced by the analysis of the influence of CTS on learning outcomes, which yields a positive effect.

9. Conclusion

This study has analyzed 6 publications related to computational thinking skills (CTS) and student academic achievement. Overall, CTS has a 54% influence on student academic achievement, falling into the medium category. This means that these skills significantly contribute to students' academic performance, although other factors, accounting for 46%, also play a role, although they are not specifically detailed in this study. Furthermore, the integration of CTS presents various impacts in terms of innovation, challenges, and opportunities. Innovation leads students to adapt to new technologies, challenges ignite a fighting spirit to solve existing problems, and opportunities serve as targets to strive for and capitalize on.

We recommend that future research explore other potential factors influencing the implementation of computational thinking skills on academic achievement, such as government policy factors, environmental factors, and students' readiness to accept innovation and technology at the engineering education level.

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