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Evaluating the Impact of the DIPEC–STEM Teaching Model on Secondary Students' Computational Thinking: A Quasi-Experimental Study in Colombia

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Abstract. This study examines changes in computational thinking (CT) associated with the implementation of the DIPEC–STEM teaching model in technical upper-secondary education. Using a quantitative, one-group pretest–posttest quasi-experimental design, the intervention was implemented over one academic period in three public institutions in Medellín, Colombia. Participants (N = 130) were selected through non-probabilistic multistage sampling (purposive selection of institutions and convenience sampling of intact classes). CT was measured before and after the intervention using an adapted version of the Computational Thinking Test, assessing four CT dimensions: decomposition, pattern recognition, abstraction, and algorithmic thinking. Pre–post differences were evaluated using paired-samples inferential analysis and effect sizes (Cohen's d). Results indicated a statistically significant improvement in overall CT performance after the intervention, with a large effect (d = 0.8957). Dimension-level effects were strongest for algorithmic thinking (d = 1.22) and pattern recognition (d = 0.76), modest for abstraction (d = 0.28), and slightly negative for decomposition (d = –0.20), evidencing differentiated patterns across CT skills. Additionally, a student perception survey administered to a subsample (n = 31) yielded consistently positive ratings regarding the clarity of the DIPEC–STEM sequence and the usefulness of the activities. Overall, the findings suggest that DIPEC–STEM is associated with meaningful gains in CT—particularly in skills related to algorithmic structuring and pattern analysis—within the constraints of authentic public-school settings.

Keywords: computational thinking; STEM; teaching model; secondary education; quasi-experiment

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1. Introduction

The sudden emergence of computational thinking (CT) as a fundamental skill for 21st-century education has transformed pedagogical discussions about how to teach, what to learn, and for what educational purposes (Borchardt & Roggi, 2017; UNESCO, 2021). This concept, initially popularized by Wing (2006) as a form of thinking applicable beyond programming and computer science, has expanded its scope to become a key component of problem-solving, modeling, abstraction, and decision-making in diverse educational contexts.

Within this framework, school systems have taken on the challenge of integrating CT into curricula, particularly in STEM (Science, Technology, Engineering, and Mathematics) areas, recognizing that its articulation enhances conceptual understanding and knowledge transfer (Lee et al., 2019; Li et al., 2020). Evidence from recent years indicates that learning environments that combine the STEM approach and CT improve academic performance, strengthen analytical skills, and stimulate higher-order thinking (Balladares et al., 2016; Cheng et al., 2023).

In Latin American contexts, the incorporation of CT into primary and secondary education faces additional tensions linked to inequalities in access, resource availability, teacher training, and institutional challenges (Cossío, 2021; Mono, 2023; Motoa, 2019). Although there are national and regional initiatives aimed at promoting digital literacy, the integration of computers remains heterogeneous, fragmented, and conditioned by current policies. In practice, this means that schools—particularly public institutions serving low-income communities—are expected to demonstrate CT outcomes without consistent infrastructure, sustained teacher support, or evidence-based instructional models, which directly affects educational quality and widens opportunity gaps (Enríquez et al., 202; Lopez-Gamboa et al., 2020).

From an international perspective, pedagogical models and frameworks for teaching computer science have evolved toward more comprehensive approaches that include active strategies such as project-based learning, educational programming, and unplugged activities (Enríquez et al., 2021b; Hsu et al., 2018; Kang et al., 2020; Sen et al., 2021). This pedagogical shift is in response to the need to generate meaningful experiences that promote collaborative, context-based problem-solving. Nevertheless, despite the proliferation of conceptual frameworks, important research gaps persist.

First, there is limited quasi-experimental evidence from public secondary settings in Latin America evaluating CT–STEM interventions under authentic constraints. Second, many studies report improvements descriptively but provide insufficient inferential evidence and effect sizes using standardized CT measures. Third, fewer studies report dimension-level outcomes (e.g., decomposition, pattern recognition, abstraction, and algorithmic thinking) together with complementary learner-experience data that help explain how changes occur (Saad & Zainudin, 2022; Tang et al., 2020; Tikva & Tambouris, 2020; Zeng et al., 2023).

In response to this situation, the teaching model known as DIPEC–STEM (Diagnosis, Problem Identification, Solution Planning, Execution, and Closure) has emerged as a proposal focused on teaching practice and aimed at strengthening CT in STEM technical high school students. This model integrates principles of active learning, problem-solving, the STEM approach, and technological mediation, articulating the phases of diagnosis, identification, planning, execution, and closure. However, although its theoretical foundation has been established, it is necessary to evaluate its impact using rigorous methodologies and appropriate instruments empirically. This need is particularly acute in contexts where educational policies require evidence of pedagogical interventions' effectiveness and relevance to diverse student populations.

The purpose of this article is to evaluate the impact of the DIPEC-STEM model on the development of computational thinking in technical secondary school students from three public educational institutions in the city of Medellín, Colombia. Accordingly, the study addresses the following research question: What is the impact of the DIPEC–STEM didactic teaching model on the development of computational thinking in STEM technical upper-secondary students? To this end, we implemented a quasi-experimental design with pre- and post-tests, complemented by a student perception survey. This methodological approach not only allowed us to observe quantitative changes in the skills evaluated but also to understand the pedagogical experience from the students' perspective, which is essential for assessing the model's applicability in real classroom settings (Corrales-Álvarez et al., 2024; Román-González et al., 2017).

This study contributes to (i) quality education by providing evidence on a structured CT–STEM teaching model implemented in authentic public-school conditions; (ii) education policy by offering empirical results that can inform decisions on scaling and supporting CT interventions in resource-constrained contexts; and (iii) STEM curriculum development by detailing a phased instructional sequence and reporting overall and dimension-level CT outcomes alongside student perceptions of the learning experience.

2. Literature Review

CT has established itself as a key construct in contemporary studies on education and digital literacy (Brennan & Resnick, 2012; Díaz et al., 2020; Wing, 2006). Its earliest formulations, attributed to Papert (1980) within the framework of constructionism, established a relationship between meaningful learning and programming as a means of modeling ideas. Years later, Wing (2006) proposed CT as a cross-cutting skill applicable beyond computational environments, highlighting abstraction, decomposition, and algorithmic design as cognitive processes common to multiple disciplines. Based on these contributions, research has advanced toward conceptual frameworks that seek to delimit its components and characterize its cognitive nature (Grover & Pea, 2013; Shute et al., 2017). In this scenario, it has been proposed that CT is not an exclusively technical skill, but rather a way of structuring problems through logical procedures and systematic models (Motoa, 2019; Papert, 1980).

In parallel with conceptual development, various proposals have sought to organize CT into operational domains for assessment and teaching. Brennan and Resnick (2012), for example, identified dimensions related to concepts, practices, and perspectives, while Lye and Koh (2014) highlighted the need for pedagogical frameworks that connect CT with problem-solving activities in school contexts. These approaches have generated ongoing debate about the definition and scope of CT, as well as its cognitive, disciplinary, and curricular implications.

Interest in teaching CT has led to the emergence of teaching models and integration strategies in primary and secondary education. Several systematic reviews have documented a sustained growth in research focused on developing and strengthening CT through programming, robotics, unplugged activities, and project-based approaches (Hsu et al., 2018; Sen & Kiray, 2021). Lockwood and Mooney (2018) identified an increase in initiatives to embed CT into non-technical subjects, while Buitrago (2022) proposed a framework for its incorporation into STEM domains through modeling, simulation, and data analysis practices. Recent research has also examined the teaching conditions necessary to integrate CT into the classroom, highlighting factors related to training, self-efficacy, and digital skills (Kong et al., 2018; Liu et al., 2024).

Studies show that CT is implemented in K–12 education through three types of approaches: (a) programming as a central focus, (b) activities integrated into other subject areas, and (c) multimodal strategies that combine digital technologies and active methodologies (Kong, 2020; Popat & Starkey, 2019). Although these approaches have enabled the exploration of different forms of mediation, the literature still lacks teaching models with robust empirical validation, especially in school contexts with limited resources or significant sociocultural diversity (Tikva & Tambouris, 2020).

The link between CT and STEM education has received increasing attention in both conceptual reviews and meta-analyses. Li et al. (2020) argue that CT is a valuable component for strengthening interdisciplinary understanding, while Lee et al. (2019) analyze its role from a disciplinary perspective, examining how modeling, analysis, and representation processes connect STEM areas through computational practices. Recent research confirms a moderate positive effect on performance and problem-solving skills when CT is integrated into well-structured STEM activities (Cheng et al., 2023; Li & Oon, 2024). Additional studies indicate that CT-STEM-based interventions require curricular alignment and clarity about pedagogical purposes to sustain learning (Adiyono et al., 2024; Balladares et al., 2016).

CT assessment is another well-established field of research and instruments with varying degrees of validity and reliability have been developed and used in both experimental studies and classroom experiences. Román-González et al. (2017) proposed a standardized test to measure the cognitive skills underlying CT, while Moreno-León et al. (2015) developed automated metrics based on programming projects. Recent systematic reviews have documented the proliferation of instruments designed to measure specific components of CT, while highlighting the need for assessments that are consistent with classroom practices and cultural contexts (Corrales-Álvarez et al., 2024; Ocampo et al., 2024; Tang et al., 2020). These studies have shown that pretest-posttest research designs are frequently used to evaluate CT-oriented pedagogical interventions, as they allow for the estimation of quantitative changes over short implementation periods. Several studies have analyzed initiatives to integrate CT into public educational institutions, highlighting challenges related to infrastructure, curriculum continuity, and teacher training (Cossío, 2021; Mono, 2023). Recent research has explored the incorporation of CT through unplugged activities and STEM projects contextualized in vulnerable environments, identifying advances and pending issues in terms of implementation and sustainability (Enríquez et al., 2021; Lopez-Gamboa et al., 2020).

Likewise, regional reviews have highlighted the absence of empirically validated teaching models in Latin American contexts and the need to generate evidence from quasi-experimental designs (Sarmiento-Bolívar, 2022). On the other hand, some studies have examined the development of computational skills through robotics, programming, and interdisciplinary projects, highlighting significant variations across national policies and institutional strategies (Motoa, 2019; Pereiro et al., 2022).

The reviewed literature highlights three needs that remain insufficiently addressed: (1) instructional models for CT–STEM that are empirically tested under real classroom constraints (rather than described conceptually), (2) quasi-experimental evidence using standardized CT instruments that reports both overall and skill-level effects, and (3) studies situated in Latin American public technical secondary education, where infrastructure and teacher preparation conditions differ from those typically reported in the Global North. To address these gaps, the present study evaluates the DIPEC–STEM teaching model using a pretest–posttest quasi-experimental design and complements performance outcomes with student perceptions, thereby providing context-sensitive evidence on CT development in Medellín's public technical STEM programs.

3. Methodology

The study was conducted using a quantitative approach, employing a quasi-experimental one-group pretest-posttest design without a control group. This design is appropriate for educational contexts where random assignment is not possible but estimating changes associated with a teaching intervention over time is necessary (Creswell & Creswell, 2018). The main objective was to evaluate the impact of the DIPEC–STEM teaching model on the development of computational thinking (CT) in technical secondary school students from three public educational institutions. The intervention lasted for one academic period (three months), and the instruments were administered before and after its implementation. The independent variable was the implementation of the DIPEC–STEM instructional intervention during one academic period, and the dependent variable was students' computational thinking performance, operationalized as the overall CT test score and the four dimension-level scores.

3.1 DIPEC–STEM Teaching Model

The DIPEC–STEM model served as the pedagogical framework for this study and was developed to address needs identified in public technical secondary education in Medellín. An empirical characterization informed the development of 30 teachers from public institutions offering STEM-oriented technical programs in the city. This process identified prevalent pedagogical approaches, levels of technological appropriation, common instructional strategies, and recurring barriers to CT integration, which informed the model's structure.

The model articulates three fundamental conceptual axes: CT as a cross-cutting cognitive competence (Brennan & Resnick, 2012; Wing, 2006), the STEM approach as a training paradigm oriented toward interdisciplinary problem solving, and the TPACK framework (Mishra & Koehler, 2006) describing the interaction among technological, pedagogical, and disciplinary knowledge. These references were complemented with socioconstructivist perspectives drawn from Vygotsky (1978), Papert (1980), and Shulman (1986), which collectively supported the articulation of a context-specific instructional model responsive to heterogeneous teacher profiles.

the DIPEC-STEM structure was organized into five sequential phases: diagnosis, problem identification, planning, execution, and closure with each phase is linked to cognitive and pedagogical processes associated with the development of CT. The diagnostic phase collects prior knowledge and initial cognitive pathways, guided by formative assessment (Black & Wiliam, 1998) and Vygotsky's notion of the starting point. Problem identification draws on elements of problem-based learning (Barrows, 1986) to promote the decomposition and recognition of patterns. Planning strengthens algorithmic thinking and strategic anticipation, while execution is based on constructionism, activating processes of experimentation, creation, and modeling. Finally, closure integrates authentic assessment (Wiggins, 1993), metacognitive reflection, and formative feedback, which are key to consolidating learning.

The model includes a system of teaching typologies—traditional, emerging, innovative, and benchmark—derived from the teacher characterization process. These typologies describe variations in pedagogical trajectories, levels of TPACK appropriation, and instructional practices in technical secondary education. Rather than assuming a homogeneous profile, the model incorporates differentiated guidance intended to support progressive appropriation of CT-oriented strategies.

The DIPEC Prompt was designed as a pedagogical reflection tool that guides the analysis, planning, and evaluation of activities across the model's phases. This resource operated as a teacher support mechanism, promoting informed decision-making and the design of teaching experiences aligned with the principles of the CT and the STEM approach. Its structure allowed teachers to identify pedagogical intentions, evaluated disciplinary integration, and reflected on the development of skills such as abstraction, decomposition, algorithms, and pattern recognition.

A Preliminary validation of DIPEC-STEM was conducted with graduate teachers from the Universidad Técnica Particular de Loja (UTPL) in Ecuador through socialization sessions, critical discussion, and activity simulations. This stage enabled an assessment of the model's internal consistency, structural clarity, and operational viability across diverse educational contexts.

For this study, DIPEC–STEM was operationalized through a standard teaching sequence applied in three public institutions in Medellín during the intervention phase. This sequence included problem-solving activities, algorithmic challenges, visual programming, and contextualized projects, ensuring consistency in the application of the model's phases: 1. Diagnosis: Students' prior knowledge and mental representations were explored to establish a cognitive starting point (zone of proximal development). 2. Problem Identification: An authentic situation was presented that required decomposition and pattern recognition, encouraging students to analyze the context before attempting to solve it. 3. Solution Planning: Focused on algorithmic thinking, this phase required designing the logic of the solution (flowcharts, pseudocode) before coding, favoring strategic anticipation. 4. Execution: This corresponded to practical implementation (visual programming, robotics, or prototyping), based on constructionism, where knowledge is consolidated through tangible creation. 5. Closure and Evaluation: This focused on metacognitive reflection and process assessment through rubrics and self-evaluation, allowing students to analyze the efficiency of their own solution.

In this way, the intervention derived from DIPEC-STEM served as the basis for quantitatively evaluating its impact on computational thinking skills through a pretest-posttest design. Across the five DIPEC phases, continuous feedback mechanisms were embedded through brief checkpoints to enable immediate adjustments to activity clarity, accessibility, and alignment between objectives and student work.

3.2 Study Design and Structure

This study followed a one-group pretest–posttest quasi-experimental design represented as O_1 – X – O_2, where O_1 denotes the baseline CT measurement (pretest), X corresponds to the DIPEC–STEM intervention, and O_2 denotes the post-intervention CT measurement (posttest). The design was implemented in three stages. First pretest was administered to establish participants' initial CT level. Second, teachers implemented the DIPEC–STEM intervention over consecutive weeks integrated into regular class sessions. Finally, a posttest was administeredunder conditions comparable to the pretest to estimate changes associated with the intervention.

Because the Media Técnica curriculum required all participating classes to receive the intervention during the same academic term, a separate control group was not feasible. Accordingly, the study employed a one-group pretest–posttest design, which is common when institutional constraints prevent group manipulation (Tang et al., 2020). Therefore, the appropriate classification is a one-group pretest–posttest quasi-experimental design, rather than a time-series design.

Control of extraneous variables. Several procedures were implemented to reduce potential confounding influences. Participants were drawn from grades 10–11 within public STEM-oriented technical secondary programs, which limited variability in educational level and institutional type. The intervention was implemented concurrently during the same academic term across the three institutions using a standardized instructional sequence, and pretest/posttest administrations followed standardized protocols (same instructions, comparable timing, and similar classroom conditions). Although socioeconomic differences are inherent to public-school contexts, all participating institutions served predominantly low-income communities, supporting contextual comparability. Variables such as peer and parental support were not directly measured and therefore could not be fully controlled; this is acknowledged as a limitation when interpreting pre–post changes.

3.3 Population and Sample

The study population consisted of secondary and technical secondary education students from three public educational institutions in the city of Medellín, Colombia. These institutions had a heterogeneous socioeconomic composition (the majority are low-income families). This context adequately represented the conditions of urban public education in the country and allowed the study results to be placed within a geographical and social framework relevant to international discussion.

The participants were in grades 10 and 11, with ages ranging from approximately 13 to 16. In addition, the participating institutions offer technical secondary programs that integrate elements of the STEM approach, facilitating the articulation of the DIPEC-STEM teaching model with existing curricular practices. The study used a non-probabilistic multistage sampling approach. First, institutions were selected through purposive (criterion-based) sampling, considering: (a) public schools offering STEM-oriented technical secondary education, (b) willingness to participate, and (c) feasibility for implementing the intervention and standardized assessments. Second, within each institution, participants were selected through convenience sampling of intact classes, including students enrolled in the courses where the intervention was implemented.

The sample was non-probabilistic and consisted of 130 students enrolled in the courses where the intervention was implemented during the corresponding academic period. Participation was voluntary, with guardians signing informed consent forms and underage students signing assent forms. To ensure the comparability of the results, cases that did not complete both the pretest and posttest were excluded from the analysis. In addition, four teachers from the institutions involved participated, receiving initial training in the DIPEC–STEM Model and subsequently designing activities aligned with its phases and pedagogical principles.

Despite natural differences among the institutions (technological resources, teaching materials, and group size), the three educational centers share structural and organizational characteristics typical of urban public education in Medellín. This allowed the intervention to be implemented in a relatively homogeneous manner, replicating activities, teaching sequences, times, and conditions for applying the instruments. Institution 1 (74 students) was implemented by two teachers across intact classroom groups, while Institutions 2 (26 students) and 3 (30 students) were each implemented by one teacher. Thus, the intervention was delivered at the classroom level rather than to a single combined cohort of 130 students.

3.4 Information Collection Instruments

To measure the development of computational thinking, the study employed an adaptation of the Computational Thinking Test (CTT), an instrument with evidence of criterion validity widely used in CT research (Román-González et al., 2015). This instrument assessed components such as abstraction, patterns, logical reasoning, and algorithms using multiple-choice items tailored to participants' school level. The adaptation consisted of language adjustments and contextualized examples, while maintaining the central conceptual structure.

Both test administrations were conducted in person during supervised sessions. Standardized instructions were used, comparable time allocation, and similar classroom conditions across the three institutions. The posttest followed the same administration protocol as the pretest to ensure measurement comparability. In addition to the test, a perception survey was designed to gather students' perceptions of the intervention, the clarity of the activities, and their understanding of concepts related to CT and the STEM approach. The items were organized in a five-point Likert format, and two STEM education specialists reviewed the questionnaire to ensure clarity and consistency. The expert review focused on item clarity, content alignment with the intended constructs, and wording appropriateness for the target grade level; minor revisions were made to improve readability and reduce ambiguity.

Before implementation, both instruments underwent a content validation process through expert review and a pilot test with a group of 20 students not participating in the study, resulting in minor revisions to improve clarity and reduce ambiguity.

3.5 Implementation Procedure

The study was implemented through a standardized sequence of procedures to ensure methodological consistency across the three participating institutions. First, a preparatory phase was conducted in which the research team introduced the study to school administrators, participating teachers, and student groups, clarifying the study objectives, implementation scope, roles, and data-collection logistics. Subsequently, ethical requirements were addressed by obtaining written informed consent from parents or legal guardians and assent from underage students in accordance with institutional guidelines. The intervention was not delivered to a single large cohort; it was implemented in intact classroom groups across three institutions and facilitated by four teachers within regular class conditions.

After permissions were secured, the Computational Thinking Test (CTT) was administered as the pretest in face-to-face, proctored sessions. To maximize comparability across sites, administration conditions were standardized (identical instructions, equivalent time allocation, and similar classroom environments). Following baseline measurement, the DIPEC–STEM intervention was implemented over consecutive weeks within regular class periods during the academic term. Teachers delivered the planned instructional sequence aligned with the five DIPEC phases (Diagnosis, Problem Identification, Solution Planning, Execution, and Closure), integrating active-learning strategies and digital tools.

The intervention included guided activities, computational challenges, and contextualized projects designed to elicit computational thinking practices. The intervention was delivered by the trained schoolteachers, not by the researchers. Teacher training was conducted to ensure procedural consistency across institutions, including a shared understanding of the DIPEC phases, common instructional materials, and standardized assessment administration.

At the conclusion of the intervention period, students completed the posttest under procedures equivalent to those used in the pretest to support measurement equivalence. Immediately thereafter, participants responded to the student perception survey, which captured their evaluations of the clarity, organization, and perceived usefulness of the learning activities. This sequential procedure ensured that outcome measures reflected learning conditions comparable across institutions and aligned with the study's quasi-experimental pretest–posttest structure.

3.6 Ethical Considerations
The study complied with the ethical principles of educational research. The institutional bioethics committee approved the study, which was carried out, ensuring data confidentiality, participant anonymity, and voluntary participation. No personal data were associated with the results during statistical analysis, and information was handled in accordance with current data protection regulations. Parents and students applied the respective informed consent and assent forms.

3.7 Data Analysis
Data were analyzed using descriptive and inferential procedures. For pretest and posttest CT scores, measures of central tendency and dispersion (means and standard deviations) were computed and score distributions were examined to characterize changes between measurement occasions. To test whether the observed pre–post differences were statistically significant, a paired-samples (related-samples) t-test was conducted. The magnitude of change was estimated using Cohen's d for paired designs, and mean differences were reported to support interpretation of practical relevance.

Skill-level results (decomposition, pattern recognition, abstraction, and algorithmic thinking) were summarized using descriptive statistics and effect size estimates to characterize differential patterns across CT dimensions. Student perception survey responses were analyzed descriptively using item means, standard deviations, and response distributions to summarize students' perceptions (n = 31). All analyses were performed in Python to generate standardized tables and graphical representations.

4. Results and Findings

This chapter reports the quantitative findings derived from the instruments applied before and after implementing DIPEC–STEM. In line with the study objective and research question, the results prioritize inferential evidence (paired-samples test and effect size) to evaluate whether observed changes are statistically reliable and educationally meaningful. Descriptive statistics and score distributions are presented as complementary information to illustrate the direction and variability of change.

4.1 Overall Pretest and Posttest

A total of 130 students completed both the pretest and the posttest. Table 1 summarizes the descriptive statistics for the overall CT test score. The pretest mean was 6.99 (SD = 2.18), and the posttest mean increased to 9.83 (SD = 2.42). The mean difference (posttest – pretest) was 2.84 points (SD = 3.17), indicating a general improvement in performance after the intervention.

Table 1: Descriptive statistics for the pretest, posttest, and difference

statistical	Pretest	Postest	Difference
Count	130	130	130
Mean	6.99	9.83	2.84
Std	2.18	2.42	3.17

These descriptive results indicate an upward shift in central tendency, with slightly greater dispersion in the posttest, which is common in heterogeneous educational contexts.

4.2 Distribution of Scores

To determine whether the observed improvement in total CT scores was statistically reliable, a paired-samples t-test was conducted (Table 2). Results indicated a statistically significant increase from pretest to posttest, $t(129) = 10.212$, $p < .001$, supporting that the observed difference is unlikely to be due to chance within this sample.

To quantify the magnitude of the change, Cohen's d for paired designs (d_n or d_z) was computed, yielding ** d = 0.896**, which is typically interpreted as a large effect. Therefore, the results support not only statistical significance but also educational relevance of the observed improvement in the overall CT score.

Table 2: Results of the Student's t-test for related samples between pretest and posttest

Statistical	value
Pretest Average	6.99
Posttest Average	9.83
Mean Difference	2.84
T (129)	10.212
p	<.001
Cohen's d	0.8957

4.3 Results of Computational Thinking Skill

To provide a more detailed understanding of how DIPEC–STEM influenced CT, results were examined across the four CT dimensions: decomposition, pattern recognition, abstraction, and algorithmic thinking.

Table 3 presents descriptive statistics (means, standard deviations, and mean differences) and effect sizes for each CT dimension. In three of the four skills, the posttest mean exceeded the pretest mean. The largest descriptive increase was observed in algorithmic thinking ($\Delta = 1.85$; $d = 1.22$), followed by pattern recognition ($\Delta = 0.94$; $d = 0.76$). Abstraction showed a smaller increase ($\Delta = 0.28$; $d = 0.28$). In contrast, decomposition showed a slight decrease ($\Delta = -0.25$; $d = -0.20$).

Table 3: Descriptive results by CT skill (pretest vs. posttest)

CT Skill	Pretest M	Pretest SD	Posttest M	Posttest SD	Δ (Post–Pre)	Cohen's d
Decomposition	3.15	0.66	2.90	1.03	-0.25	-0.20
Pattern recognition	2.08	0.96	3.02	0.87	0.94	0.76
Abstraction	0.64	0.62	0.92	0.74	0.28	0.28
Algorithmic thinking	1.31	0.93	3.16	1.17	1.85	1.22

Because descriptive patterns alone are insufficient to demonstrate intervention-related impact, paired-samples t-tests were conducted for each CT dimension. Effect sizes were estimated using Cohen's d for paired designs. Table 4 summarizes the inferential evidence.

Table 4: Paired-samples t-tests and effect sizes by CT skill (n = 130; df = 129)

CT Skill	t(129)	p	Cohen's d (paired)
Decomposition	-2.231	.027	-0.196
Pattern recognition	8.648	< .001	0.758
Abstraction	3.194	.002	0.280
Algorithmic thinking	13.902	< .001	1.219

Inferential results indicate statistically reliable gains in algorithmic thinking, pattern recognition, and abstraction, with the largest effect in algorithmic thinking. Importantly, the decline in decomposition was also statistically significant (** p = .027**) but the magnitude of the effect was small (d ≈ −0.20), suggesting that the reduction—although reliable—was limited in size.

To support interpretation across CT dimensions, performance levels were classified using an achievement-rate criterion. For each skill, students' raw scores were converted to the percentage of the maximum possible score for that skill (based on the number of items allocated to each dimension), and categorized as low (< 40%), moderate (40–69%), or high (≥ 70%). These thresholds were used to describe performance patterns descriptively rather than as normative benchmarks.

4.4 Distribution of Scores

Figures 1–3 provide a visual check of the distributions, showing a rightward shift in posttest scores and predominantly positive pre–post differences, consistent with the inferential results reported below.

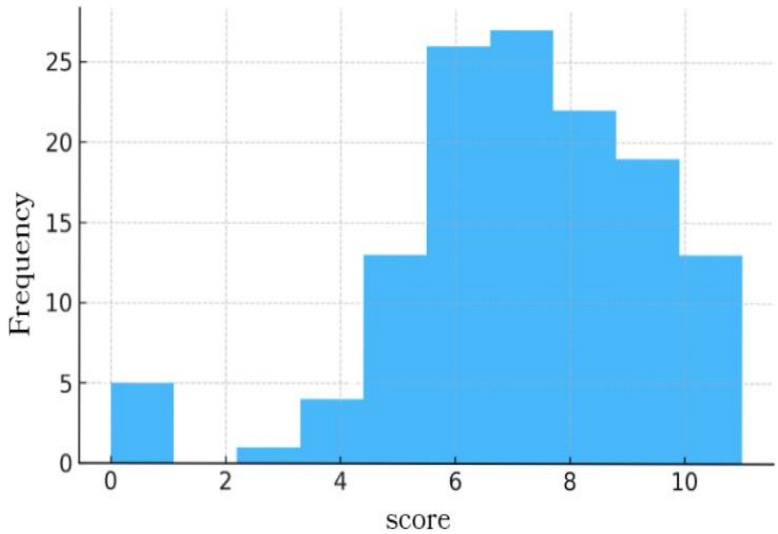

Figure 1: Distribution of pretest scores

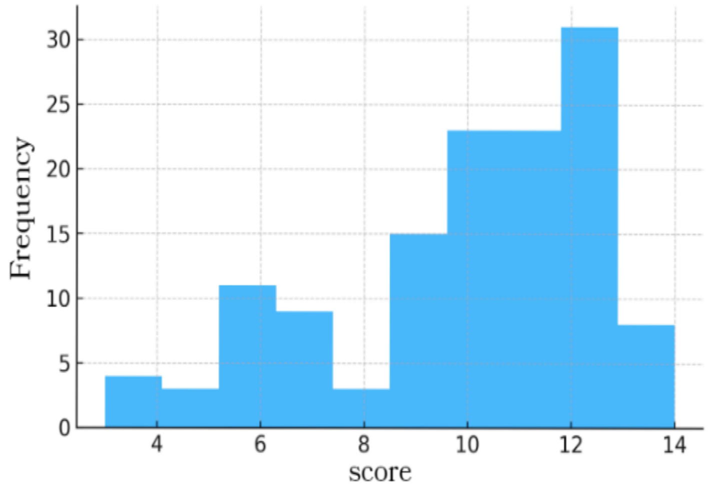

Figure 2: Distribution of posttest scores

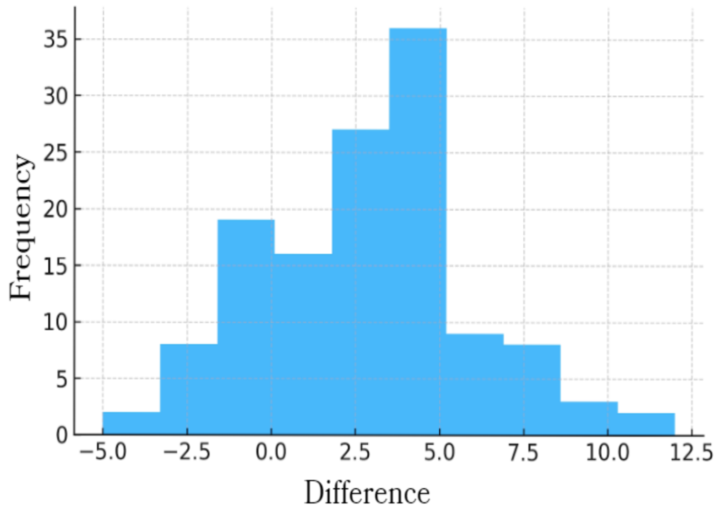

Figure 3: Distribution of the difference between posttest and pretest

4.5 Results of the Student Perception Survey

In addition, a perception survey was administered to 31 students who participated in implementing the DIPEC–STEM model, to assess their perceptions of the process clarity, understanding of the activities, and perceived usefulness of the approach. The instrument used a five-point Likert scale, which was subsequently recoded to values from 1 to 5 for analysis.

The descriptive statistics are presented in Table 5, which shows that the means per item ranged from 4.27 to 4.90, with low standard deviations, indicating a relatively homogeneous distribution of responses within the group. The highest scores corresponded to statements about understanding the model, the usefulness of the activities, and the perception that the DIPEC-STEM approach clearly addressed the content. No item had a mean below 4, indicating that, within the responding group, no negative or neutral perceptions of the intervention were identified. These values indicate that the students who responded to the instrument consistently valued aspects of the project's organization, the clarity of the activities, and the overall understanding of the approach.

Table 5: Descriptive statistics from the student perception survey

	count	mean	std
The activities of the DIPEC–STEM project were organized in a clear and easy-to-follow manner.	31	4.451613	0.567962
The work we did in class followed a logical sequence that helped me learn.	31	4.741935	0.444803
I knew what I had to do at each stage of the project because the instructions were clear.	31	4.322581	0.540808
In this project, I was able to see how science, technology, engineering, and mathematics are related to solving a problem.	31	4.419355	0.564163
The activities of the DIPEC-STEM project helped me to think like a scientist or engineer.	31	4.483871	0.569852
I felt that using technology and programming was an essential part of what we were learning.	31	4.677419	0.475191
I felt motivated to actively participate in the project.	31	4.645161	0.486373
I found the activities interesting and fun.	31	4.612903	0.558416
Working with computational thinking made me feel more curious to learn.	31	4.612903	0.558416
I liked the way we learned using the DIPEC-STEM model.	31	4.612903	0.558416

5. Discussion

The present study examined changes in students' computational thinking (CT) following the implementation of the DIPEC–STEM model in three public technical secondary schools in Medellín. Overall findings indicated a statistically significant pre–post improvement in total CT scores with a large effect size, and survey responses suggested that students perceived the intervention as clearly organized and useful for learning. Taken together, these results support the educational value of structured CT–STEM interventions in authentic school settings and contribute evidence from a Latin American public-school context, where inequalities in resources and heterogeneous learner profiles often complicate implementation.

Beyond the overall gain, the dimension-level pattern provides a nuanced view of DIPEC–STEM's influence on CT as a multidimensional construct. Strong improvements were observed in algorithmic thinking and pattern recognition, a smaller improvement emerged in abstraction, and decomposition showed a slight decline. Similar patterns of differential growth across CT dimensions have been reported in the literature, reinforcing the need to interpret CT outcomes at both global and component levels rather than assuming uniform effects (Brennan & Resnick, 2012; Román-González et al., 2017).

5.1 Theoretical Implications

These findings can be interpreted through Vygotsky's sociocultural theory, particularly the roles of mediation, scaffolding, and the zone of proximal development (ZPD). DIPEC–STEM begins with a diagnostic phase that establishes students' starting point and supports instruction aligned with an appropriate ZPD. Subsequent phases provide structured mediation through teacher facilitation, task sequencing, and representational tools, supporting the gradual internalization of problem-solving strategies. From this perspective, the observed gains are consistent with the view that higher mental functions develop through socially mediated activity and progressively become self-regulated cognitive processes.

From an instructional-design standpoint, DIPEC–STEM can be conceptualized as a phase-based scaffolding cycle that operationalizes CT development within STEM problem solving. The strong improvement in algorithmic thinking is theoretically coherent with structured learning experiences that foreground sequencing, rule-based reasoning, and explicit solution planning—elements repeatedly linked to CT growth in STEM-oriented and project-based designs (Lee et al., 2019; Lopez-Gamboa et al., 2020; Lye & Koh, 2014). Likewise, the increase in pattern recognition aligns with the conceptual centrality of identifying regularities and relationships as a foundational CT process (Brennan & Resnick, 2012; Lee et al., 2019), and it is consistent with evidence that CT skills can be strengthened when STEM tasks make patterns visible and actionable through guided inquiry and iterative practice (Kong et al., 2020; Shute et al., 2017).

In contrast, abstraction showed more modest progress, as theoretically expected, because abstraction often requires extended exposure across multiple problem-solving cycles and opportunities to generalize across context conditions not always fully realized within a single academic term (Buitrago et al., 2022; Lopez-Gamboa et al., 2020). The small decline in decomposition suggests that decomposition may be particularly sensitive to task demands and measurement characteristics, or that students' strategic shifts toward algorithmic structuring may temporarily affect how they segment problems.

Prior work has reported fluctuations in decomposition when it depends on complementary CT processes and when item difficulty or interpretation varies across administrations (Román-González et al., 2017). This finding therefore refines learning-theory expectations by highlighting that CT components may respond differently to the same instructional sequence and may require targeted scaffolds to ensure balanced development.

5.2 Practical Implications

The results have practical implications for CT pedagogy and STEM curriculum implementation. First, the significant improvements in overall CT and the large effects observed in algorithmic thinking and pattern recognition indicate that

DIPEC–STEM offers an actionable structure for classroom practice. By requiring explicit planning and stepwise solution construction, the model aligns with evidence that project-based and technology-mediated learning environments can enhance CT when pedagogical structure is clear and tasks are meaningfully sequenced (Grover & Pea, 2013; Lopez-Gamboa et al., 2020; Papert, 1980).

Second, student perception data suggest that learners valued the intervention's clarity, organization, and coherence, which is pedagogically relevant in heterogeneous classrooms. Prior studies have shown that clear task structure, explicit pedagogical purpose, and coherent sequencing can foster engagement and support participation in CT–STEM learning activities, especially where students' prior experience is uneven (Buitrago et al., 2022; Enríquez et al., 2021b; Motoa, 2019). In this sense, DIPEC–STEM may be particularly useful in public-school contexts where instructional routines and transparent expectations help stabilize learning processes (Bautista & Hernández, 2020; Lopez-Gamboa et al., 2020).

Third, the differential pattern across CT dimensions provides concrete guidance for refinement of instructional practice. While DIPEC–STEM appears especially effective for structuring algorithmic and pattern-based reasoning, future classroom implementations should strengthen supports for abstraction and decomposition. Such adjustments would align with recommendations in CT education to design supports that make invisible thinking processes visible and assessable across dimensions (Brennan & Resnick, 2012; Shute et al., 2017).

5.3 Contributions to Instructional Design Theory and CT Pedagogy

DIPEC–STEM contributes to instructional design theory and CT pedagogy in at least three ways relative to existing CT–STEM proposals. First, it formalizes a five-phase sequence that structures problem solving as an instructional cycle rather than a set of loosely connected activities, thereby offering a replicable design logic for CT integration in STEM contexts (Angeli et al., 2021; Weintrop et al., 2016). Second, it incorporates the DIPEC Prompt as an explicit mediational tool that supports step-by-step scaffolding across phases, helping learners connect disciplinary knowledge and computational practices—an integration challenge highlighted in recent CT–STEM work (Li & Oon, 2024; Saad & Zainudin, 2022).

Third, the model includes teaching typologies that guide how instructional roles and supports may vary across phases, addressing a practical gap in many frameworks that describe what students should do but offer limited guidance on how teaching should adapt through the learning cycle (Román-González et al., 2017; Saad & Zainudin, 2022; Weintrop et al., 2016). Together, these elements position DIPEC–STEM as a design-oriented contribution that links pedagogical structure, mediational supports, and measurable CT outcomes.

5.4 Research Implications, Limitations, and Future Directions

Several research implications follow from these findings. First, the statistically significant and large pre–post improvement in overall CT suggests that practice-oriented didactic models such as DIPEC–STEM warrant further testing through stronger designs (e.g., controlled quasi-experiments or longitudinal implementations) to strengthen causal claims and examine the persistence of learning gains. Second, the differentiated effects across CT dimensions underscore the importance of analyzing CT as a multidimensional construct and refining intervention components to better target skills that showed weaker change, particularly abstraction and decomposition, including item-level analyses to assess whether measurement demands influence these patterns (Román-González et al., 2017). Third, the results highlight the value of reporting both statistical significance and effect sizes and incorporating complementary process data to explain how and why gains occur in authentic school conditions.

This study also has limitations. The one-group pretest–posttest design does not fully rule out alternative explanations for change, and the perception survey was administered to a subsample, so those findings should be interpreted as complementary rather than fully representative. Finally, because the study was conducted in public technical secondary schools in Medellín, additional multi-site replications across diverse Latin American contexts are needed to evaluate generalizability and to identify contextual factors (resources, teacher profiles, and curricular constraints) that may moderate the effectiveness of CT–STEM interventions.

6. Conclusion

This study addressed the research objective of evaluating the impact of the DIPEC–STEM teaching model on technical secondary students' computational thinking (CT) in three public schools in Medellín. Results showed a statistically significant pre–post improvement in overall CT with a large effect size, with the strongest gains observed in algorithmic thinking and pattern recognition, a smaller improvement in abstraction, and a small decline in decomposition. In parallel, students' perceptions of the intervention were consistently positive, highlighting the clarity, sequencing, and perceived usefulness of the DIPEC–STEM activities.

These findings indicate that CT development in public technical secondary education is supported not merely by the presence of technology, but by the intentional instructional design of structured learning experiences that connect diagnosis, problem identification, planning, execution, and closure with specific cognitive processes. At the same time, the differential pattern across CT dimensions suggests the need to refine instructional supports aimed at abstraction and decomposition to ensure more balanced skill development.

Future research should replicate these findings using stronger designs (e.g., controlled quasi-experiments), incorporate longitudinal follow-ups to examine sustainability, and extend implementation to other educational levels and contexts. Overall, this study contributes evidence that a structured CT–STEM instructional model can be feasible and effective in resource-constrained settings, offering a practical and transferable pathway to strengthen STEM education in developing countries.

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