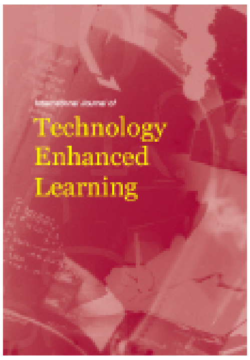

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Unlocking computational thinking: immersive technologies for solving complex problems

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Abstract: Computational thinking (CT) is a key competency in higher education, enhancing abstraction, pattern identification, and algorithm design to address complex problems related to sustainable development goal 10 (SDG10) on reducing inequities. This study employed a quasi-experimental pre-test and post-test design to assess the impact of a training program on 330 students from ITESM (Mexico) and USAC (Guatemala). Through four sessions, students engaged in activities on abstraction, decomposition, pattern recognition, and algorithm design. Results indicated significant improvements in self-perception and problem-solving, though the impact was moderate due to prior exposure to these concepts. While generalisation is limited by sample and context, findings highlight CT's potential as a vital educational tool. Future research should explore early interventions and inclusive strategies to broaden CT's applicability across diverse educational settings.

Keywords: computational thinking; CT; complex thinking; educational innovation; problem-solving; higher education.

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1 Introduction

Scientific literature has reported that computational thinking (CT) skills allow for solving both disciplinary and real-life problems because they are interconnected with other higher cognitive abilities, such as critical thinking, innovation, and creativity (Horton and Hardin, 2021; Silva et al., 2021; Sun et al., 2023), which makes them a highly valued transversal competency in education and the workplace (Bull et al., 2020). However, despite the growing exploration of how to develop these skills, there is still a lack of consensus on measuring them in the resolution of practical situations (George-Reyes et al., 2023).

In higher education, universities need to adopt pedagogical approaches that teach conceptual elements and train practical skills in CT (Gopinath and Santhi, 2021) for students to solve complex problems effectively in their future professions (Gupta and Tiwari, 2022). The importance of this approach derives from the global labour market's accelerating demand for professionals who possess technical knowledge and are capable of applying CT creatively and innovatively to face challenges in multiple disciplines (Herrero-Álvarez et al., 2024).

This article explores the need to measure students' perception of their CT skills and their ability to apply them in real problem-solving. Therefore, the following research question was posed in this study: How does participation in a training experience affect the development of CT skills for problem-solving in university students, examining both their perceptions and the objective demonstration of these skills?

1.1 Problem-solving skills

Problem-solving skills are fundamental in cognitive development and essential in a world that needs people who can deal with rapidly changing environments and solve non-routine problems (Winkler et al., 2021). This refers to the ability to cope with the demands of a complex life using critical thinking, creative thinking, and reasoning (Rodzalan et al., 2020; Açıkgöz et al., 2022; Xiao et al., 2019), which are intrinsically linked to other higher-order skills such as innovation and the use of technologies (Akran et al., 2019; Malik et al., 2022).

With these competencies, the learner combines previously learned knowledge, rules, techniques, skills, and concepts to resolve a new situation (Marin et al., 2024). This multifaceted process involves four key steps: understanding the problem, planning a solution strategy, implementing the planned solution strategy, and verifying the answers found (Nasir and Syartina, 2021). Five stages have also been identified to develop these skills:

1 focusing on problems

2 describing them in concepts related to discipline

3 planning solutions

4 implementing plans

5 evaluating solutions (Doktor, 2016).

Similarly, it has been reported that the process involves understanding the problem, choosing the appropriate concept, and verifying the suitability of the problem with the proposed solution (Hermansyah et al., 2019), as well as procedural frameworks that include identifying and defining the problem, developing the strategy, organising information, allocating resources, monitoring, and evaluating the problem-solving (Lu and Xie 2024).

In education and professions, problem-solving skills are transversally applied to various disciplines, situations, and contexts (Zhong and Xu, 2019). This is especially relevant in the educational setting, where students who master problem-solving can identify the underlying causes of problems, prioritise viable solutions, and collaborate effectively with their peers (Akay, 2023). Developing these skills improves individual ability to face challenges and increases efficiency and collaboration (Karla et al., 2022; Alsmadi et al., 2023).

Studies have suggested that the teaching of problem-solving skills should be initiated from an early age and encouraged throughout life (Gunawan et al., 2020). Some have shown that individuals with strong problem-solving skills can more effectively address challenges (He et al., 2021; Karaoglan, 2022; Lee et al., 2024). The early development of skills can ensure academic and professional success, as children who deploy them tend to be more capable of handling complex problems in their future lives (Cesur, 2020).

Therefore, these types of skills are not limited to a specific discipline; they are transferable and applicable to different contexts (Pennington et al., 2021). For example, engineering skills can be applied to address problems in the field of education; i.e., they are transversal, multidisciplinary, and not limited to solving technical problems. They are also effective in addressing challenges in social sciences and humanities (Zeeshan et al., 2021) where it is necessary to generate decomposition, comprehension, and problem-solving strategies (Rojas et al., 2021; Chouvalova et al., 2022).

1.2 Symbolic systems and problem-solving

The ability to translate complex problems into symbolic representations is critical to addressing challenges in various disciplines, from computer science to social sciences (Piantadosi, 2020). Symbolic systems allow abstract concepts to be represented, manipulated, and communicated through symbols. They are determined by generally accepted conventions (Peirce, 1883), such as language, mathematics, or computer systems. An example of the latter is programming languages, which allow instructions to be written in natural language that computers can translate and execute (Bonet and Geffner, 2019), which facilitates process automation and application development without the need to understand machine language (Garnelo and Shanahan, 2019).

People use symbolic systems to organise and process information efficiently (Deacon, 1997). Verbal language is the best representation of this as it symbolises the primary means of expressing our ideas and emotions, allowing the transfer of knowledge (Elleström, 2022), regardless of whether others share the same cultural or linguistic context. This ability to transcend individual and cultural barriers through symbols makes symbolic systems powerful tools in human communication (Neto, 2020).

Some studies have shown that symbolic systems are crucial in problem-solving in mathematics and technologies (Güner and Erbay, 2021; Andrews-Todd et al., 2023). For example, symbolic representation is indispensable for constructing mental representations of a mathematical problem, making it easier to identify its key features and formulate solutions (Lee et al., 2020). On the other hand, these systems can be understood as informational constructions incorporating signs and symbols (Tsvetkov, 2020) and are used in artificial intelligence to develop intelligent agents that combine symbolic reasoning with neural processing (Silver and Mitchell, 2023).

In education, symbolic systems are fundamental for developing abstract thinking and problem-solving (Santoro et al., 2021). In their first school experiences, students learn to use symbols to represent different types of ideas for various purposes (Melton et al., 2022). These systems are not exclusively used in a disciplinary area or a specific topic; a student who learns mathematics uses this knowledge to solve tasks in that discipline and can also apply it to solve problems in other subjects (Schwartz et al., 2021).

Students' ability to adapt symbolic systems in different knowledge domains is crucial for their general cognitive development (Planer, 2019). Its use in education facilitates understanding abstract concepts and improves the ability to think critically and adapt to new situations (Fernback, 2019). Thus, symbolic systems are not limited to resolving specific problems but are fundamental in contextually planning and applying symbolic actions, such as developing CT (Acosta et al., 2023).

This ability to generalise is essential for generating new knowledge and adapting to novel situations (Tanneberg and Gienger, 2023). Symbolic systems, therefore, facilitate communication and are indispensable for individuals' deep learning and a comprehensive understanding of the world around them, allowing them to interpret, organise, and transmit information effectively across disciplines and situations (Hitzler et al., 2020).

1.3 Computational thinking as a symbolic system

It has been affirmed that CT skills are increasingly decisive in the training of students (Adell et al., 2019), as they positively impact cognitive processes (Adler et al., 2023) and promote self-efficacy in various ways such as problem-solving, decision-making, and research skills (Araujo et al., 2019), which are required for success in the current educational systems (Çoklar and Akçay, 2018).

CT is a cognitive ability that involves solving problems using computer science concepts and techniques (George-Reyes et al., 2023). It is understood as a symbolic system because it facilitates the understanding and resolution of problems by developing a series of cognitive skills, such as abstraction, decomposition, pattern identification, and the creation of algorithms (George-Reyes, 2023). These skills allow students to conceptualise problems using symbols and rules that can be manipulated to find practical solutions (Stella et al., 2020; Oteniya et al., 2020).

Integrating CT as a symbolic system in education facilitates the development of critical skills such as the ability to break down complex problems into more manageable parts, design efficient algorithms, and employ symbolic models to find effective solutions, making it essential to meet the growing demands for knowledge in an ever-evolving world (Angeli and Giannakos, 2020). In addition, it prepares students for a work environment increasingly impacted by digital technologies and emerging applications (Bati and İkbal Yetişir, 2021), one being artificial intelligence (Celik, 203).

Symbolic systems are powerful tools for developing CT (Hashimoto et al., 2020), allowing individuals to abstract complex concepts and represent them simply. Abstraction in CT relies on the ability of symbolic systems to create representations that capture only the essential features of a problem, omitting irrelevant details (Qian and Choi, 2023). This process is necessary because it allows students to focus on the most critical aspects of a problem for a more precise and manageable understanding.

Pattern identification is another core aspect of CT reinforced by symbolic systems that provide a framework for individuals to identify these schemas, which is essential for creating efficient and effective algorithms (Purwasih and Dahlan, 2024). Symbols and logical structures make it possible to recognise similarities and regularities in different datasets or situations by seeing patterns and behaviours that can be useful in making informed decisions based on previous experiences, which is critical for solving problems (Lee and Malyn-Smith, 2020).

Algorithm design particularly benefits from symbolic systems, which provide a common language for accurately and clearly expressing the steps needed to solve a problem (Chen et al., 2021). Algorithms, ordered sequences of instructions, can be conceived and optimised through symbols and notations that facilitate their understanding and application (George-Reyes, 2023). Symbolic systems allow algorithms to be documented, shared, and improved by different people, creating more robust and efficient solutions (Ellis et al., 2020).

Finally, by allowing a complex problem to be decomposed into more manageable parts, symbolic systems provide a structure that enables each component to be approached systematically and orderly (He-Yueya et al., 2023). This not only facilitates the understanding of the problem entirely but also allows for identifying and solving sub-problems, thus optimising the resolution process. More efficient and effective solutions can be developed through decomposition, focusing on accurately solving each part of the problem (George-Reyes et al., 2023).

Therefore, it can be said that knowledge of CT is built based on a deep understanding of the dimensions that compose it and the symbols that represent it. Technology facilitates the process of learning and teaching CT skills. However, it is essential to understand that CT is an inherent human capacity that transcends using technology. Applying CT trains a versatile cognitive competency versatility that can be applied transversally to all disciplines, from the sciences to the humanities, enriching how problems are approached and solved in any context.

2 Method

2.1 Research design

This quantitative and comparative study focused on two aspects: first, to know the students' perception of their CT skills to solve problems; secondly, to analyse their abilities to choose the right solution when facing a problem related to Sustainable Development Goal 10 (reduction of inequities) presented in a case study. The data collection phase employed a quasi-experimental design (Althubaiti and Althubaiti, 2024) in a pre-test and a post-test. This approach is consistent with other studies that used quasi-experimental models to assess the impact of educational interventions on the development of specific skills (Cohen et al., 2018).

2.2 Participants

The study was developed to determine the perception and effectiveness of applying CT skills for SDG 10-related problem-solving. A workshop addressed this topic through a digital educational platform (https://e4cct.mx), aiming to offer a digital ecosystem emulating real-world environments to develop and evaluate problem-solving through abstraction, decomposition, pattern identification, and algorithm design in training experiences oriented toward sustainable development goals (SDGs) (Tecnológico de Monterrey, 2024).

Three hundred thirty students enrolled in various faculties of the Instituto Tecnológico y de Estudios Superiores de Monterrey, Mexico (ITESM, also known as Tecnológico de Monterrey) and the University of San Carlos in Guatemala participated in a workshop from February to March 2024. The non-probabilistic convenience sample comprised voluntary participants (Shi and Cheung, 2024). Table 1 shows the distribution by gender and university.

Table 1 Participant distribution

University	*N*	*%*	*Men*	*Women*
ITESM	193	58.59	88	105
USAC	137	41.51	82	55
	330	100	170 (51.52%)	160 (48.48%)

2.3 Workshop design

The extracurricular training experience was delivered in four sixty-minute sessions based on conceptual knowledge of the components of CT and its application in resolving case-study problems related to SDG 10. Table 2 shows the students' training experience using the E4CCT platform.

The topics covered four primary training elements: abstraction, decomposition, algorithm design, and pattern identification in four progressive learning levels. The first level introduced participants to the course objective. The basic level presented the fundamental concepts, allowing participants to understand the essential definitions and principles. The intermediate level deepened the understanding of these concepts through activities that required identifying and manipulating them in various contexts. Finally, the complex level focused on applying concepts to solve complex problems, integrating the skills acquired in real situations. Table 2 summarises the session contents.

Table 2 Topics of the training experience in scientific entrepreneurship

Training experience: scientific entrepreneurship				
Topic	*Element 1*	*Element 2*	*Element 3*	*Element 4*
1	Introduction and objectives	Video 1	Explanatory content	Pre-test
2	Video 2	Explanatory content	Infographic to know more	Case study 1 (concepts)
3	Video 3	Explanatory content	Automatic assessment	Case study 2 (application)
4	Explanatory content	Co-creation activity	Explanatory content	Case study 3 (application to ODS 10)

2.4 Data collection process

Information was gathered using the *CT-Complex: Horizons of CT Questionnaire for the Resolution of Complex Problems*. It comprised two sections: the first was a Likert-type scale with four response options:

1 strongly disagree

2 disagree

3 agree

4 strongly agree.

which measures the self-assessment of CT skills (abstraction, decomposition, pattern identification, and design of algorithms). Table 3 shows the dimensions and items of the instrument.

The instrument's reliability was evaluated using Cronbach's alpha coefficient, obtaining values in the pretest of 0.8920 for Tec and 0.9254 for USAC and in the posttest of 0.9010 for Tec and 0.9395 for USAC. These coefficients indicate good to excellent internal consistency across both institutions, affirming the questionnaire's reliability. Table 4 shows the differences in scores, highlighting that, in Abstraction, the difference between Tec and USAC decreased from 0.1194 in the pretest to 0.0840 in the post-test. In Pattern Identification, the difference decreased from 0.1157 to 0.0805. The reductions indicate convergence in the results at both universities, reducing the initial disparities.

Table 3 Dimensions and items of the CT-complex instrument

Dimension	*Code*	*Item*
Abstraction	A1	I can identify the essential components of a complex problem, ignoring the irrelevant details
	A2	I find it easy to simplify complex problems to make them more manageable
	A3	I often create simplified models or representations of real systems to understand how they work
	A4	I can explain complex concepts simply to people without prior knowledge of the subject
	A5	I regularly use examples or metaphors to present complicated ideas
	A6	I believe the ability to abstract is essential to solve problems in various areas
	A7	I can determine the most relevant data or aspects when faced with a broad information set
Pattern identification	B1	I readily recognise similarities and differences when comparing objects or situations
	B2	I can identify trends in datasets, even if they are complex
	B3	I usually predict future behaviours or outcomes based on previously observed patterns
	B4	I find underlying patterns in seemingly disordered or random problems
	B5	I use patterns identified in one situation to solve problems in another context
	B6	I can classify information based on common characteristics
	B7	I regularly look for patterns or regularities as a first step in understanding a new problem
	B8	I believe that pattern identification is crucial for learning and problem-solving
Design of algorithms	C1	I can design clear and logical sequential steps to solve problems
	C2	I am comfortable creating step-by-step solutions that other people or computers can follow
	C3	I tend to think, 'If this, then that,' to plan how to approach tasks or problems
	C4	I can optimise processes by simplifying or eliminating unnecessary steps
	C5	I regularly break down complex tasks into smaller, more manageable pieces
	C6	When I face a problem, I automatically think of possible algorithms to solve it
	C7	I consider algorithm design to be an essential skill in solving everyday problems
	C8	I can adapt or modify existing algorithms to improve their efficiency or applicability to new problems

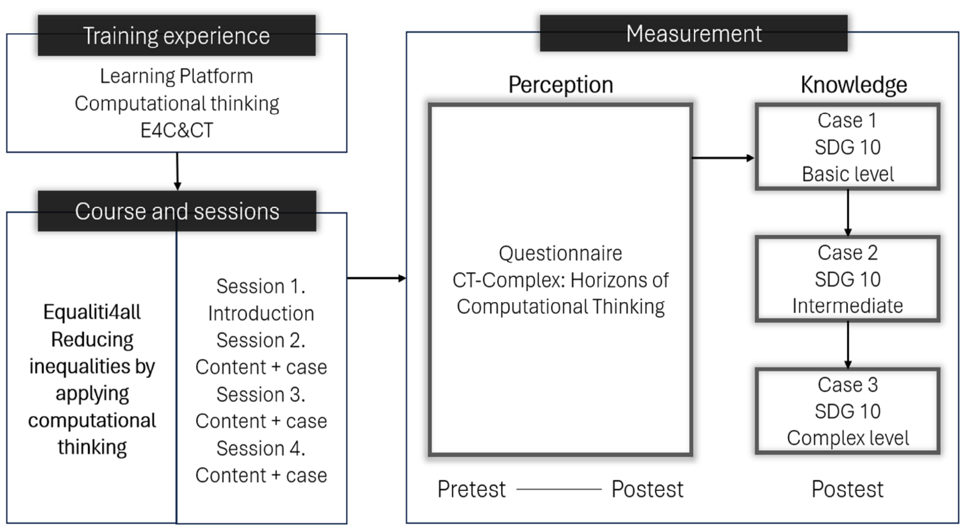
Table 3 Dimensions and items of the CT-complex instrument (continued)

Dimension	*Code*	*Item*
Decomposition	D1	When faced with a large project, my first instinct is to break it down into smaller, more manageable parts
	D2	I can identify sub-problems within a complex problem to facilitate its resolution
	D3	When faced with a challenge, I usually organise tasks into components or stages
	D4	I find it helpful to break tasks down into smaller steps to avoid feeling overwhelmed
	D5	I regularly assign priorities to sub-tasks within a project to improve efficiency
	D6	I can maintain an overview of the project while working on its individual components
	D7	I consider decomposition a key strategy for handling complex or long-term projects
	D8	I often use diagrams or lists to organise and visualise the parts of a problem or project

Table 4 Pre-test and post-test Cronbach's alpha

	Pretest			*Post-test*		
Dimension	*Tec*	*USAC*	*Difference*	*Tec*	*USAC*	*Difference*
Abstraction	0.7846	0.9040	0.1194	0.8498	0.9338	0.0840
Pattern identification	0.7599	0.8756	0.1157	0.8388	0.9193	0.0805
Algorithm design	0.8181	0.8969	0.0788	0.8878	0.9306	0.0428
Decomposition	0.8145	0.8941	0.0796	0.8683	0.9387	0.0704

Figure 1 Training experience structure and measurement



The second section consisted of a series of case studies that had to be analysed, developed, and evaluated via the four dimensions of CT. Each case had four questions, each with three possible answers, with only one being correct. Students had thirty minutes to read the case, analyse it, and choose the most appropriate answer. This section of the instrument was validated by 16 experts, attaining an Aiken's V coefficient of 0.8731 for general reliability, which can be considered high (Aiken, 1980). Figure 1 shows the strategy for solving the case studies.

2.5 Data analysis

The following analyses were derived from the first section of the instrument:

1. graphs of individual values at the universities (TEC and USAC) in the pre-test and post-test to visualise the differences in the scores obtained by the students in the different dimensions of CT and evaluate the changes
2. Dispersion graphs by age and gender to analyse possible correlations between these variables and the scores attained in the pre-test and post-test
3. Pearson correlation graphs for each university, which allowed measuring the relationships between the different dimensions (abstraction, pattern identification, algorithms, and decomposition) both in the pre-test and the post-test.

For the second section, a detailed comparison of the percentages of correct and incorrect answers before and after the workshop was performed using the McNemar test. This analysis made it possible to identify significant changes in student performance. A positive change was indicated when an incorrect answer in the pre-test was transformed into a correct one in the post-test, reflecting improved learning. On the other hand, a negative change was defined when a correct answer in the pretest became incorrect in the post-test, evidencing a possible regression.

2.6 Ethics

All information provided by the participants was collected with their consent (https://comiteinstitucionaletica.tec.mx/es/formatos). The implementation was regulated and approved by the Tecnológico de Monterrey Ethics Committee-IFE-2024-001 and supervised by the interdisciplinary research group R4C with the technical support of the Writing Lab of the Institute for the Future of Education at Tecnológico de Monterrey, Mexico. All the information recovered was protected per the criteria established in the Federal Law on the Protection of Personal Data in Possession of Private Parties in force in Mexico.

3 Results

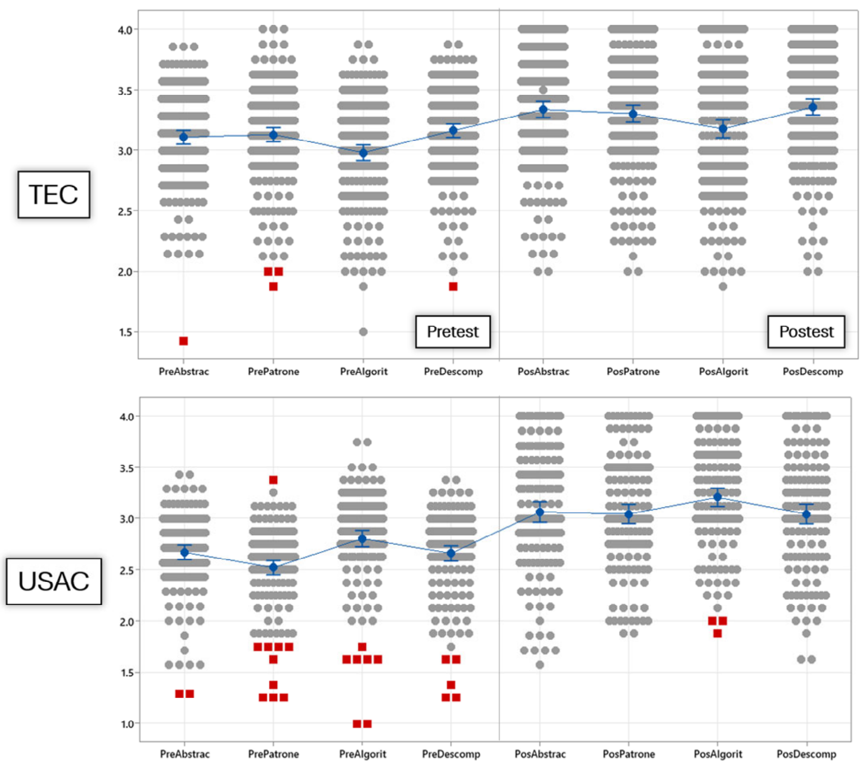
3.1 Computational thinking skills self-assessment

Figure 2 compares the results between the pre-test and post-test, showing differences in the means and the dispersion of the data (standard deviations) and the outliers. TEC students scored higher in the four dimensions evaluated in the pre-test and post-test. In abstraction, the TEC pre-test mean was approximately 3.1 and 2.67 at USAC, suggesting that the students began with a slightly higher level of CT knowledge.

Regarding the data dispersion, the USAC students had more variability in the scores. In the abstraction dimension, the standard deviation in the pretest was 0.41 for USAC versus 0.39 for TEC. The higher dispersion indicates that the USAC students had more heterogeneity in their skills before participating in the experience; this difference was slightly reduced in the post-test, suggesting a light leveling of their abilities.

Regarding the outlier data, many red dots are observed in all dimensions among USAC students, all at the lowest levels of the scale. In contrast, TEC students had fewer outliers, which indicates greater consistency in the scores. However, after participating in the workshop, the number of outliers decreased in all four dimensions, both at TEC and USAC, suggesting an overall improvement in student performance and a reduction in disparity between them.

Figure 2 Graph of individual values at Tec and USAC (see online version for colours)



Notably, although both groups improved in the post-test, the differences in the means between TEC and USAC remained. For example, in the abstraction dimension, the mean post-test for TEC was 3.34 and 3.06 for USAC. Although these differences declined slightly from the pretest, TEC students maintained an overall advantage. This may be due to differences in pedagogical approaches or the students' level of familiarity with the topic before participating in the formative experience.

Figure 3 Dispersion graphs by age and gender at the universities (see online version for colours)

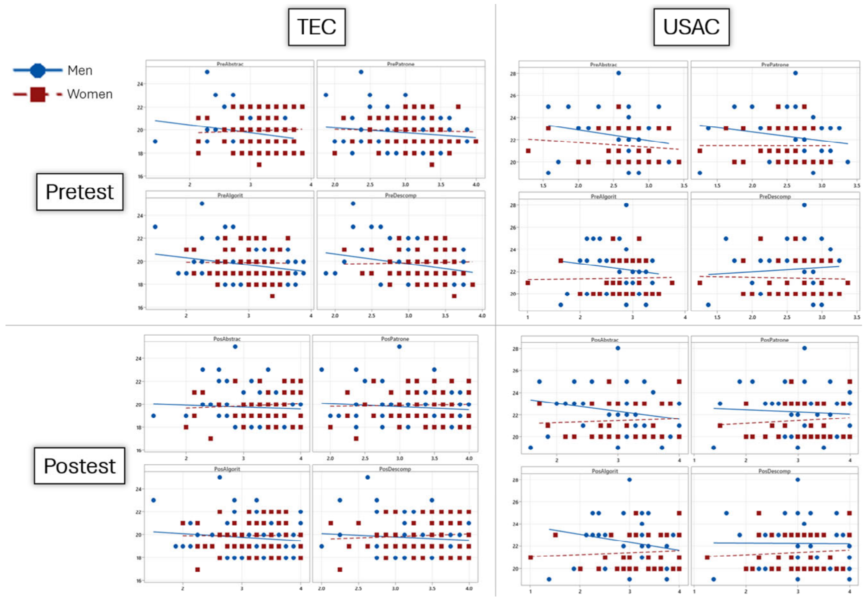


Figure 4 Cross-dimensional correlational analysis (Tec) (see online version for colours)

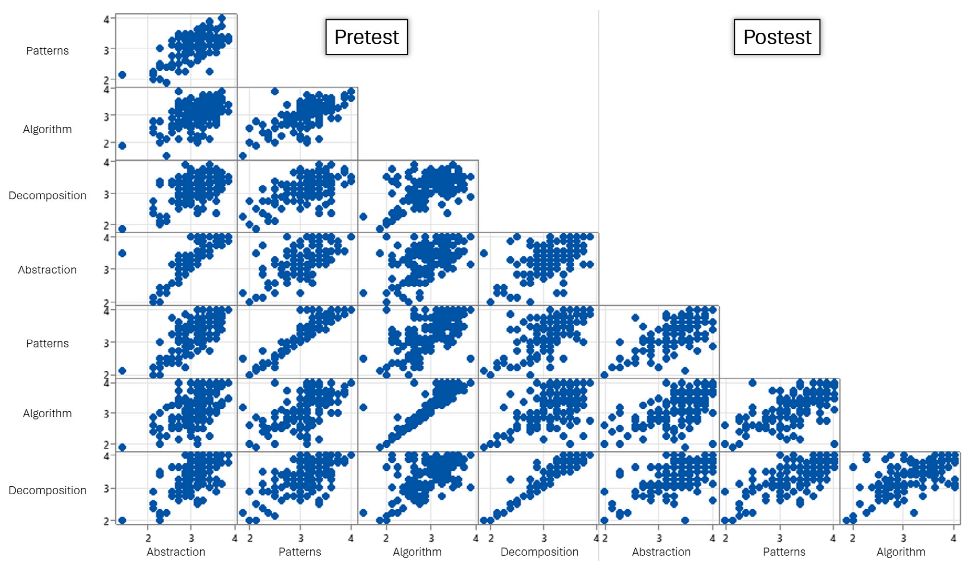


Figure 3 shows a dispersion analysis by gender and age where, in the case of TEC, men presented a slightly downward trend in abstraction in the pretest, with a trend line revealing a reduction in scores as age increases. In contrast, TEC women maintained a more uniform distribution with no downward trend, suggesting less variability by age. The USAC dispersion is more remarkable. In the pretest, women's scores concentrated in the lower ranges in dimensions such as algorithm design; in contrast, men display a markedly downward trend in abstraction among younger students.

The scores converged in the post-test at TEC and USAC, with less dispersion in general. At TEC, men improved in abstraction, where scores stabilised between 3.0 and 3.5, with less dispersion by age. Women improved in decomposition, with scores between 2.5 and 3.5; in the pre-test, many of their scores were below 3.0. At USAC, men had a more stable trend in the post-test, with an almost horizontal line in the algorithm design and abstraction dimensions.

Although the dispersion decreased in the post-test, the differences in the means persisted between the two universities; in the abstraction dimension, the mean in the post-test for TEC men stabilised at around 3.2, while for USAC men, it remained around 2.5. For TEC women, the abstraction mean was approximately 3.1 and 2.7 for USAC women. These data indicate that although the workshop helped to level the dispersion of skills in general, institutional and gender differences persisted.

Figure 5 Cross-dimensional correlational analysis (USAC) (see online version for colours)

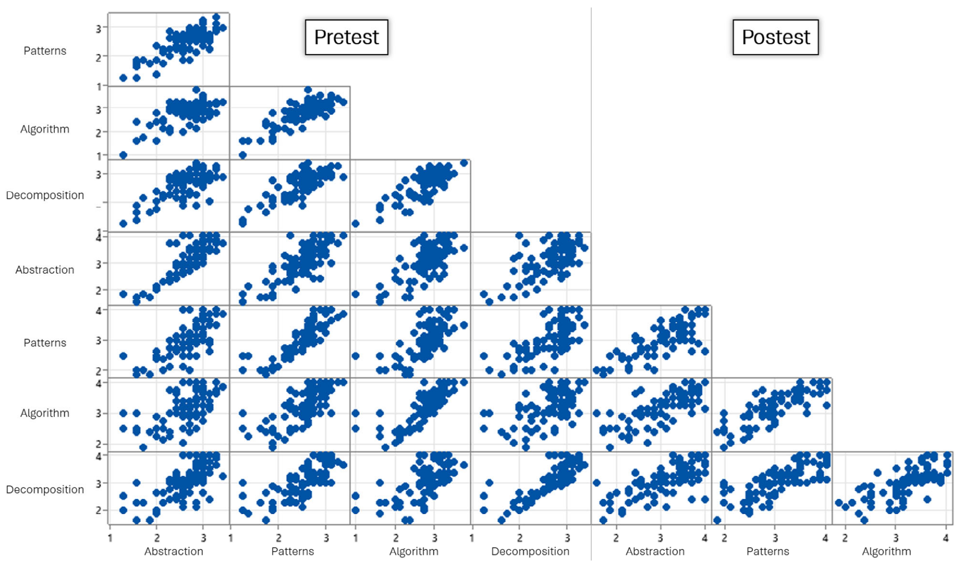


Figure 4 shows a correlational analysis with strong correlations at Tec. In the pretest, there is a high correlation between abstraction and pattern identification (0.654) and between pattern identification and algorithms (0.612), suggesting that students who attained high pattern identification scores also tended toward high scores in abstraction and algorithm design. The correlation between abstraction and decomposition in the pretest was 0.565, indicating a moderate relationship between these two skills, suggesting that students who are good at identifying the essential components of a problem can also break it down into more manageable parts. The lowest correlation in the pretest (0.462) was between decomposition and algorithm design, which could imply that students find it more challenging to apply their decomposition skills to algorithm design.

Regarding USAC, correlations were also strong in the pretest, the highest between pattern identification and algorithm design (0.779), followed by the relationship between pattern design and decomposition (0.772). This suggests that students who initially perceive themselves as having good abilities to identify patterns also perform better in constructing algorithms and decomposing problems. As shown in Figure 5, the correlation between abstraction and pattern identification in the pretest was 0.768, reflecting a strong connection between the ability to identify the essential elements of a problem and recognising recurring patterns. In addition, the correlations between abstraction and algorithm design (0.680) and abstraction and decomposition (0.694) indicate that students who abstract complex concepts tend to perform better in the other dimensions of CT. The lowest correlation in the pretest (0.734 between algorithms and decomposition) suggests that some students faced difficulties applying decomposition skills in creating algorithms before participating in the formative experience.

3.2 Application of computational thinking skills

Table 7 presents the pre-test-post-test results in the three case studies of the Tec students. For case 1, the Chi-square test showed a Pearson value of 17.420 with a p-value of 0.043, indicating statistically significant differences between the pre-and post-test responses. The Cramer's V-squared coefficient, with a value of 0.0074827, means a minimal effect, suggesting that although the differences were significant, the magnitude of change was not that large. However, it can be stated that the workshop impacted the students' performance. In the abstraction dimension, 111 students improved from incorrect to correct (–+), a considerable improvement. For the other dimensions, the number of students who improved (–+) was also high, with 105, 118, and 99 students, respectively. The number of students who maintained a correct answer before and after the intervention (++) was considerably lower than those who improved, indicating that the workshop was more effective for those who did not initially master the skills.

In Case 2, the value of Cramer's V-squared is even lower (0.003631), indicating a smaller effect size compared to Case 1. The Chi-squared value for Pearson is 8.538 with a p-value of 0.482, which means that the differences in the pre-and post-test responses were not statistically significant. Although students improved their answers from incorrect to correct (–+), this improvement was insufficient to demonstrate a significant change in overall performance.

In Case 3, Cramer's V-squared was 0.0061929, indicating a slight improvement in effect size compared to Case 2, but still small. The Chi-squared test yielded a Pearson value of 9.056 with a p-value of 0.432, again indicating that the differences between the pre-test and post-test were not statistically significant. Although there are visible improvements in all dimensions, with many students moving from incorrect to correct answers on the post-test (–+), the low effect size suggests that the intervention had a positive, but not drastic, impact on the assessed skills.

Table 8 presents the distribution of pre-and post-test responses of the USAC students, revealing that for Case 1, a Pearson coefficient of 10.181 was obtained with a p-value of 0.336, indicating that the differences were not statistically significant. Although there was an improvement in the number of students who went from incorrect to correct (–+) responses in this dimension (79), the size of the effect, as indicated by Cramer's V-squared of 0.0061929, was small, suggesting that although there were improvements, they were not impactful enough to be statistically relevant.

Table 7 Distribution of TEC pre- and post-test responses

	+–	–+	++	––	*Chi-squared*	
Case 1		*Cramer's V squared = 0.0074827*			*Pearson*	*p-value*
Abstraction	11	111	43	29	17.420	0.043
Patterns	17	105	49	23		
Algorithms	5	118	56	15		
Decomposition	14	99	62	19		
Case 2		*Cramer's V squared = 0.003631*				
Abstraction	9	101	68	16	8.538	0.482
Patterns	7	93	74	20		
Algorithms	6	87	80	21		
Decomposition	11	77	87	19		
Case 3		*Cramer's V squared = 0.0061929*				
Abstraction	9	101	68	16	9.056	0.432
Patterns	7	93	74	20		
Algorithms	6	87	80	21		
Decomposition	11	107	57	19		

Notes: +– = Students who answered correctly in the pre-test and incorrectly in the post-test.
–+Students who answered incorrectly in the pre-test and correctly in the post-test.
++ = Students who answered correctly in pre-test and post-test.
– – = Students who answered incorrectly in pre-test and post-test.

Table 8 Distribution of USAC pre- and post-test responses

	+–	–+	++	– –	*Chi-squared*	
					Pearson	*p-value*
Case 1		*Cramer's V squared = 0.0061929*				
Abstraction	8	79	31	19	10.181	0.336
Patterns	12	75	35	15		
Algorithms	4	81	41	11		
Decomposition	10	70	44	13		
Case 2		*Cramer's V squared = 0.003251*				
Abstraction	6	72	48	11	5.631	0.776
Patterns	5	66	53	13		
Algorithms	4	57	62	14		
Decomposition	8	62	54	13		
Case 3		*Cramer's V squared = 0.0040391*				
Abstraction	6	77	43	11	6.641	0.675
Patterns	5	66	53	13		
Algorithms	4	62	57	14		
Decomposition	8	72	44	13		

Notes: +– = Students who answered correctly in the pre-test and incorrectly in the post-test.
–+Students who answered incorrectly in the pre-test and correctly in the post-test.
++ = Students who answered correctly in pre-test and post-test.
– – = Students who answered incorrectly in pre-test and post-test.

In Case 2, the situation was similar. The test yielded a Pearson value of 5.631 with a p-value of 0.776, indicating once again that there was no statistically significant difference between the results of the pre-test and post-test; the value of Cramer's V-squared (0.003251) suggests that the impact of the intervention on this dimension was minimal. This is consistent across all dimensions of Case 2, where the number of students who improved is remarkable, but the lack of statistical significance implies that the observed changes might not be due to participating in the training experience.

Case 3 follows the same pattern, with a Pearson coefficient of 6.641 and a p-value of 0.675, again indicating no significant differences between the pre-test and the post-test. Although the students improved their answers, the size of the effect, measured by Cramer's V-squared of 0.0040391, was small, reinforcing the idea that the workshop did not generate a substantial change in the skills assessed. Despite the results, a consistent trend is observed across all dimensions and cases: an improvement in the number of students going from incorrect to correct (– +), indicating that the intervention positively impacted some students, although not with statistical significance.

4 Discussion

The results comparing TEC and USAC students in both the pre-test and the post-test suggest that the initial differences in CT skills diminished after participating in the training experience. According to previous studies (Garnelo and Shanahan, 2019; George-Reyes et al., 2023), CT, understood as a transversal competency, allows students to address complex problems through abstraction, pattern identification, and algorithm design. In this research, the TEC students' baseline had higher means in all the dimensions assessed, coinciding with studies that indicate that prior exposure to these skills influences their development (Bull et al., 2020; Gupta and Tiwari, 2022).

Moreover, the intervention made it possible to close the gap between the two institutions, showing a convergence in the scores, suggesting that the training experience effectively leveled competencies. The findings highlight that CT can be seen as a symbolic system, a perspective defended by authors such as George-Reyes (2023) and Piantadosi (2020). The fact that students improved their self-perception of CT suggests that this process involves manipulating symbols and creating abstract representations of the problem to be solved.

This symbolic ability, which includes simplifying complex problems in manageable models, is critical for logical reasoning and algorithm development. However, there are still doubts about the universality of CT as a symbolic system, given that its application may depend on the educational context. This can be verified by analysing the variability observed in the USAC students' pre-test results, which could indicate that access to and familiarity with these symbolic systems, such as the use of algorithms or the abstraction of problems, were not homogeneous (George-Reyes et al., 2023).

Figure 3's scatter plots reveal differences between the two universities, both in the pre-test and the post-test. The analysis of CT skills by age and gender revealed that younger students tended toward higher scores in abstraction, pattern identification, algorithm design, and decomposition. This confirms that CT, when taught from an early age, has the potential to become a powerful symbolic system for solving problems in various domains (Piantadosi, 2020); it coincides with the idea that its early teaching fosters the development of higher cognitive abilities, like decomposition and pattern identification (Bull et al., 2020; Lee et al., 2020).

On the other hand, after participating in the training experience, the correlations between the dimensions increased significantly, indicating that students better integrated the different CT skills. Figures 4 and 5 show students' improved abilities to abstract problems while identifying relevant patterns, essential for success in complex tasks (Bull et al., 2020). The strengthening of correlations after the intervention also indicated more cohesion in developing CT skills, which function as an integrated symbolic system (George-Reyes et al., 2023).

The formative experience improved individual scores and consolidated the correlations between the dimensions. For example, the correlation of 0.905 between algorithms and pattern identification in the post-test suggests that students acquired the ability to identify patterns and translate them into practical algorithms, which is a primary outcome of teaching CT as a symbolic system for solving problems by manipulating symbols and logical structures (Garnelo and Shanahan, 2019).

Together, these correlations reveal that when taught effectively, CT can be integrated into a robust symbolic framework that allows students to tackle problems more efficiently. The increases in correlations after the workshop reinforce the importance of teaching these skills simultaneously, as their joint development enhances students' ability to face interdisciplinary challenges. As suggested by previous studies, CT should be taught not just as a set of individual skills but as an interconnected system where abstraction, decomposition, pattern identification, and algorithm design work in synergy to improve overall problem-solving performance (Gupta and Tiwari, 2022).

Finally, the results of the analyses shown in Tables 7 and 8 show that although there were significant improvements in some dimensions, such as abstraction in Case 1 with a p-value of 0.043, the overall impact of the intervention was moderate, as indicated by Cramer's V-squared coefficient of 0.0074827, which means a small change effect. This finding is consistent with studies suggesting that pedagogical interventions in CT can improve specific skills, but require a more comprehensive approach to maximise their effectiveness (Bull et al., 2020; George-Reyes et al., 2023). In other cases, such as Case 2, no significant differences were observed, suggesting that some students failed to consolidate skills such as abstraction, probably due to not integrating the dimensions assessed, a crucial factor for success in the development of CT (Piantadosi, 2020; Gupta and Tiwari, 2022).

5 Conclusions

This research highlights the relevance of CT as a transversal and symbolic competency that facilitates the resolution of complex problems, especially in the context of the SDGs. It demonstrates that CT helps to structure problems effectively and promotes critical skills, such as abstraction and algorithm design, which are essential in education and professional life. By focusing on the applicability of these skills in higher education students, the study provides empirical evidence of the importance of integrating them into formative experiences that prepare students to face multidisciplinary challenges.

The main findings suggest that when implemented appropriately, CT improves students' ability to identify patterns, decompose problems, and construct logical solutions using algorithms. The training experience showed that, although the TEC students began with an advantage in the pretest, the experience significantly leveled their skills with their peers at USAC. In addition, the correlation analysis showed that the four dimensions of CT were integrated into a cohesive symbolic framework, enhancing the students' ability to face complex problems. These results reaffirm the potential of CT as an essential educational tool that acts in synergy to strengthen transversal competencies.

Additionally, the training experience improved the students' individual scores and strengthened the correlations between the different dimensions of CT. Higher correlations in the post-test indicate that students developed an interrelated skill set, reinforcing the idea that CT should be approached holistically. In particular, improvements in abstraction, pattern identification, and algorithms suggest that these skills are closely linked and that their simultaneous development can boost performance in solving complex problems.

The study revealed limitations in that the formative experience, although effective, only moderately impacted some dimensions, as indicated by the small effect size determined by the chi-squared tests and Cramer's V-squared in some case studies. Likewise, the sample was limited to two universities, restricting the results' generalisation. Additionally, the differences observed in the students' familiarity and previous exposure to CT concepts may have influenced the results, especially in the pretest. These limitations suggest the need to explore a broader approach with a more inclusive framework for future research.

From these results, several lines of potential research emerge that could expand knowledge about CT. It would be beneficial to investigate how different pedagogical methods and cultural contexts influence the acquisition of CT skills, exploring whether these skills develop similarly in other educational and sociocultural settings. It is also suggested to examine the impact of early interventions on developing these competencies and integrating advanced technological tools, such as augmented reality or artificial intelligence, to enhance the teaching-learning process in CT.

Finally, this study reaffirms the relevance of CT as a competency that transcends disciplines and contexts. Although the results show significant improvement in developing critical skills, it is crucial to continue research on how to structure educational programs that promote CT holistically and make them accessible to all students. With an integrated and adaptable approach, CT can be a powerful tool for learning and personal and professional growth, opening up new possibilities in education and contributing to the fulfillment of global goals such as SDG 10.

Declarations

All authors declare that they have no conflicts of interest.

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