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PROMOVER O PENSAMENTO COMPUTACIONAL EM FUTUROS PROFESSORES DE MATEMÁTICA DO ENSINO BÁSICO ATRAVÉS DA APRENDIZAGEM BASEADA EM DESIGN

ENHANCING COMPUTATIONAL THINKING IN PRESERVICE ELEMENTARY MATH TEACHERS THROUGH DESIGN-BASED LEARNING

MEJORANDO EL PENSAMIENTO COMPUTACIONAL EN FUTUROS PROFESORES DE MATEMÁTICAS-EDUCACIÓN PRIMARIA A TRAVÉS DEL APRENDIZAJE BASADO EN EL DESIGN

Pedro Tadeu[1,2] iD *https://orcid.org/0000-0002-0698-400X*
Deniz Kaya[3] iD *https://orcid.org/0000-0002-7804-1772*
Tamer Kutluca[4] iD *https://orcid.org/ 0000-0003-0730-5248*

[1] Instituto Politécnico da Guarda, Guarda, Portugal
[2] Centro de Estudos em Educação e Inovação (CI&DEI), Guarda, Portugal
[3] Nevsehir Hacı Bektaş Veli University, Nevsehir, Turkey
[4] Dicle University, Diyarbakır, Turkey

Pedro Tadeu - ptadeu@ipg.pt | Deniz Kaya - denizkaya@nevsehir.edu.tr | Tamer Kutluca - tkutluca@dicle.edu.tr

Corresponding Author:
Pedro Tadeu
Av. Dr. Francisco Sá Carneiro, Nº50
6300-559 – Guarda - Portugal
ptadeu@ipg.pt

RESUMO

Introdução: O pensamento computacional e a programação são competências essenciais para futuros professores de matemática, promovendo a resolução de problemas e o raciocínio lógico. A integração destas competências na formação de professores exige abordagens inovadoras que envolvam ativamente os futuros docentes. A Aprendizagem Baseada em Design (DBL – Design-Based Learning) surge como uma metodologia promissora, potenciando o pensamento computacional através de processos iterativos de resolução de problemas e de design criativo.

Objetivo: Analisar o impacto de um currículo baseado na Aprendizagem Baseada em Design (DBL) nas competências de pensamento computacional e programação de futuros professores de matemática do ensino básico.

Métodos: Foi utilizado um desenho de investigação misto e baseado em intervenção, envolvendo 40 futuros professores de matemática inscritos num programa de licenciatura. O grupo experimental seguiu um currículo composto por quatro módulos e 24 sessões. Os instrumentos de recolha de dados incluíram a Escala de Pensamento Computacional, a Escala de Autoperceção de Autoeficácia no Ensino do Pensamento Computacional e entrevistas semiestruturadas. Os dados quantitativos foram analisados com Análise Multivariada de Variância (MANOVA) e teste t para amostras independentes, enquanto os dados qualitativos foram tratados através de análise de conteúdo.

Resultados: Os resultados indicam que a abordagem DBL melhorou significativamente as competências de pensamento computacional e programação dos futuros professores. Os participantes referiram ainda que esta metodologia tornou a aprendizagem mais envolvente, interativa e eficaz.

Conclusão: O estudo mostra que a Aprendizagem Baseada em Design é uma abordagem pedagógica eficaz para desenvolver o pensamento computacional no ensino da matemática. A implementação da DBL nos programas de formação de professores pode melhorar a capacidade dos futuros docentes para integrar o pensamento computacional na sua prática letiva.

Palavras-chave: programação; pensamento computacional; Aprendizagem Baseada Design; formação inicial; autoeficácia

ABSTRACT

Introduction: Computational thinking and coding are essential competencies for future mathematics educators, fostering problem-solving and logical reasoning. Integrating these skills into teacher training requires innovative approaches that actively engage preservice teachers. Design-Based Learning (DBL) is a promising methodology that enhances computational thinking through iterative problem-solving and creative design processes.

Objective: Analysing the impact of a Design-Based Learning (DBL) curriculum on preservice elementary mathematics teachers' computational thinking and coding abilities.

Methods: The study employed an intervention-based mixed-methods design with 40 preservice mathematics teachers enrolled in an undergraduate program. The experimental group followed a curriculum consisting of four modules and 24 sessions. Data collection tools included the Computational Thinking Scale, Self-Efficacy Perception Scale towards Teaching Computational Thinking, and semi-structured interviews. Quantitative data were analysed using Multivariate Analysis of Variance (MANOVA) and independent-sample t-tests, while qualitative data were examined through content analysis.

Results: Findings indicate that the DBL approach significantly improved preservice teachers' computational thinking and coding skills. Participants also highlighted that this methodology made learning more engaging, interactive, and effective.

Conclusion: The study shows that Design-Based Learning is a valuable instructional approach for developing computational thinking in mathematics education. Implementing DBL in teacher training programs can enhance future educators' ability to integrate computational thinking into their teaching practices.

Keywords: coding, computational thinking; Design-Based Learning; preservice teacher; self-efficacy

RESUMEN

Introducción: El pensamiento computacional y la programación son competencias esenciales para los futuros docentes de matemáticas, ya que fomentan la resolución de problemas y el razonamiento lógico. Integrar estas habilidades en la formación docente requiere enfoques innovadores que involucren activamente a los futuros profesores. El Aprendizaje Basado en el Diseño (DBL – Design-Based Learning) es una metodología prometedora que mejora el pensamiento computacional mediante procesos iterativos de resolución de problemas y diseño creativo.

Objetivo: Análisis del impacto de un currículo basado en el Aprendizaje Basado en el Diseño (DBL) en las habilidades de pensamiento computacional y programación de los futuros docentes de matemáticas en educación primaria.

Métodos: Se empleó un diseño mixto basado en intervención, con 40 futuros docentes de matemáticas matriculados en un programa de grado. El grupo experimental siguió un currículo compuesto por cuatro módulos y 24 sesiones. Los instrumentos de recopilación de datos incluyeron la Escala de Pensamiento Computacional, la Escala de Autoeficacia Percibida para la Enseñanza del Pensamiento Computacional y entrevistas semiestructuradas. Los datos cuantitativos se analizaron mediante Análisis Multivariante de Varianza (MANOVA) y pruebas t para muestras independientes, mientras que los datos cualitativos se examinaron mediante análisis de contenido.

Resultados: Los hallazgos indican que el enfoque DBL mejoró significativamente las habilidades de pensamiento computacional y programación de los futuros docentes. Además, los participantes destacaron que esta metodología hizo que el aprendizaje fuera más atractivo, interactivo y efectivo.

Conclusión: El estudio muestra que el Aprendizaje Basado en el Diseño es una estrategia didáctica eficaz para desarrollar el pensamiento computacional en la enseñanza de las matemáticas. Implementar DBL en los programas de formación docente puede fortalecer la capacidad de los futuros profesores para integrar el pensamiento computacional en sus prácticas educativas.

Palabras Clave: programación; pensamiento computacional; Aprendizaje Basado en el Diseño; profesor en formación inicial; autoeficacia

INTRODUCTION

While national curricula were previously shaped by modern theories, today a skill-oriented structure is growing in importance due to rapid changes in information dynamics, technological advancements, and digitalization. Despite being in the early stages of the 21st-century digital age, skills such as versatility, analytical thinking, problem-solving, productivity, responsibility, flexibility, autonomy, communication, collaboration, creativity, and digital literacy have become essential for individuals to compete globally and adapt to change (Partnership for 21st Century Skills [P21], 2019). These competencies, aligned with the dynamics of the age, prioritize thinking skills within national educational objectives. One of these priorities is computational thinking (CT) skills, which focus on knowledge production through computer-oriented thinking (Sneider et al., 2014; Wing, 2006, 2008). CT is increasingly recognized as a valuable competence area in contemporary education (Boom et al., 2022; Looi et al., 2024). This phenomenon can be attributed to computers' ability to restructure daily life problems in ways that enhance solution processes (International Society for Technology in Education [ISTE] & Computer Science Teachers Association [CSTA], 2011). While CT skills comprise various components, the core principle is that personal computers have the potential to transform individual lives and enhance thinking and learning processes (Papert, 1980). Thus, understanding and applying the principles of computer science, along with effectively utilizing problem-solving processes, significantly increases the demand for CT skills.

In recent years, CT skills have become increasingly important, particularly within teacher education (ISTE & CSTA, 2011). Equipping preservice mathematics teachers (PMTs) with CT skills is critical for developing their algorithmic thinking and analytical abilities within problem-solving processes (Looi et al., 2024; Wing, 2006). While it is recommended that CT skills be introduced early in education, research on effective methods for imparting these skills, specifically in preparing preservice teachers for this process, remains limited (Avşar, 2023; Grover & Pea, 2013; Israel & Lash, 2020; Kafai et al., 2019; Kaya, 2024; Lockwood & Mooney, 2018; Özyurt & Aslan, 2023; Shute et al., 2017; Yadav et al., 2017). This highlights a gap in the field, particularly regarding the identification and implementation of methods to effectively enhance the CT skills of PMTs (Lye & Koh, 2014; Navarro & de Sousa, 2023; Wing, 2008). Providing CT skills training to PMTs plays a key role in enabling students to develop creative solutions to complex problems and in fostering deeper learning (Ching & Hsu, 2024; Grover & Pea, 2013). Thus, the design-based learning (DBL) approach can significantly contribute to the development of CT.

This situation reveals that there is a gap in the field, especially in terms of determining and implementing methods that will effectively improve the CT skills of PMTs (Lye & Koh, 2014; Navarro & de Sousa, 2023; Wing, 2008). Equipping PMTs with CT skills

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plays a critical role in enabling students to develop creative solutions to complex problems and deepening their learning processes (Grover & Pea, 2013). Therefore, preservice teachers' acquisition of CT skills brings with it the need for a pedagogical approach beyond traditional methods. The acquisition of CT skills by preservice teachers necessitates a pedagogical approach that transcends traditional methods.

This study investigates effect of the DBL approach on the acquisition of CT and self-efficacy perception towards teaching computational thinking (SEPTCT) skills among PMTs and seeks to fill a critical gap in the field. DBL stands out as a powerful method that supports PMTs' creative thinking, problem-solving and algorithmic approach development skills through a structured design process (Harel & Papert, 1991). Given these attributes, DBL is expected to make significant contributions to the acquisition of CT skills among PMTs. In contrast to previous research, this study seeks to facilitate a deeper acquisition of CT skills among preservice teachers through the structured learning environment provided by the DBL approach. The DBL approach encourages preservice teachers to engage in active learning and problem-solving activities, while fostering a hands-on, experiential learning environment beyond traditional teaching methods. Aligned with these objectives, the following research questions (RQs) were designed and answers were sought:

- RQ 1. Does a significant difference exist between the pre-test and post-test scores for CT and SEPTCT among PMTs in the experimental and control groups?
- RQ 2. What effect does the DBL approach have on the CT skills of PMTs?
- RQ 3. What effect does the DBL approach have on the SEPTCT of PMTs?
- RQ 4. What are the opinions of the PMTs in the experimental group regarding the DBL approach?

1.1 Computational Thinking (CT) and Design Based Learning (DBL)

As a crucial component of modern education, CT lays a strong foundation for developing students' problem-solving, analytical and algorithmic thinking skills. Imparting these skills through the teaching process plays a critical role in enabling individuals to devise innovative and systematic solutions to complex problems. To ensure the success of this process, educators must possess in-depth knowledge of CT pedagogy and competence in implementing effective teaching approaches. However, there is limited research on structured approaches for developing CT skills in preservice teachers (Brennan & Resnick, 2012). To accommodate the increasingly computational nature of mathematics, Weintrop et al. (2016) developed a taxonomy organized into four main categories: data handling, modeling and simulation, computational problem-solving, and systems thinking. Research indicates that when CT is taught through these four components, students deepen not only their technical skills but also their conceptual understanding. This structured CT framework offers a clear path for teachers to integrate CT into their lesson plans. Shute et al. (2017) highlight the value of approaches such as game and project-based learning for effective CT introduction in education and emphasize the necessity of process-based evaluation methods. Research demonstrates that CT has a strong relationship with both cognitive and emotional components, such as self-efficacy and motivation. Yadav et al. (2017) highlight CT's role as an interdisciplinary skill in teacher education and recommend project-based learning approaches that incorporate hands-on activities and collaboration to enable preservice teachers to acquire CT skills. Israel and Lash (2020) claim that integrating mathematics with CT strengthens students' systematic problem-solving skills and fosters a deeper understanding of mathematical concepts.

Studies indicate that CT applications deepen mathematical domain knowledge and promote the interaction between computer science and mathematical concepts (Looi et al., 2024; Pei et al., 2018; Ye et al., 2023). Although CT research has been applied across various educational levels, it has been primarily adopted at the K-12 level (Grover & Pea, 2013; Kafai et al., 2019). CT-based approaches to mathematics teaching have become widespread in the K-12 context, fostering DBL research and establishing the concept of "computationally enhanced mathematics education" (Ng & Cui, 2021, p. 848). These studies have enhanced mathematics learning and promoted the integration of CT into engineering, technology, and science education by providing opportunities for real-world and interdisciplinary connections (Ching & Hsu, 2024; Ng & Cui, 2021; Pei et al., 2018; Ye et al., 2023). Following Wing's (2006) introduction of the concept of CT, CT has become increasingly recognized as a fundamental 21st-century skill. Extending beyond digital literacy, CT provides a comprehensive skill set that enhances individuals' abilities to solve complex problems, think algorithmically, and analyze systematically (Brennan & Resnick, 2012; Kafai et al., 2019; P21, 2019; Pei et al., 2018; Ye et al., 2023). With technological advances, CT skills are regarded as an essential competency in fields ranging from education to industry, enabling individuals to develop innovative solutions within these areas. CT serves as a cornerstone in reshaping educational approaches by adding a new dimension to the processes of teaching and learning mathematics (Looi et al., 2024; Weintrop et al., 2016). This skill equips students with problem-solving and analytical thinking skills, facilitating deeper understanding and engagement in mathematics education. CT's integration into mathematics education is rooted in Papert's (1980) vision of developing children's CT skills with the Logo programming language. Papert believed that powerful computational technologies and algorithmic thinking could transform students' learning and argued that CT could play a pivotal role in enhancing problem-solving skills. Weintrop et al. (2016) developed a comprehensive taxonomy to align CT with the increasingly computational nature of contemporary science and mathematics. This classification aims to make CT applicable not only in

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computer science but also in other disciplines, including mathematics, engineering, and science, facilitating the integration of computational skills across various fields.

The strong relationship between mathematics and CT emphasizes CT's potential for enhancing mathematical skills. The National Research Council [NRC] (2010) report demonstrates that CT aligns with mathematical thinking processes by incorporating key components such as hypothesis generation, data management, abstraction, and debugging. These components provide valuable tools for enhancing mathematical thinking when analyzing complex problems. CT supports the fundamental dynamics of mathematics with skills including algorithmic and algebraic thinking, modeling, and abstraction (Shute et al., 2017). Gadanidis et al. (2017) state that CT establishes a natural connection with mathematics by enabling the discovery of logical structures and modeling abilities. In this context, CT constitutes the epistemological basis of mathematics, enables multidimensional thinking and deepens problem-solving processes (Weintrop et al., 2016; Wing, 2008).

DBL is widely regarded as an effective approach in mathematics education for developing students' problem-solving and analytical thinking skills (Barab & Squire, 2004). This method seeks to ensure that students not only learn abstract mathematical concepts but also develop knowledge and skills applicable to real-world contexts (Kolodner et al., 2003). DBL fosters a more meaningful and interactive learning experience by involving students actively in the problem-solving process, which in turn increases student motivation and learning retention (Gresalfi et al., 2009). DBL is a teaching method that, in the classroom environment, aims to equip students with essential problem-solving skills, such as imagination, creativity, problem visualization, and holistic thinking (Mehalik & Schunn, 2006). With this approach, students have the opportunity to deeply engage in the learning process by learning from their mistakes as they develop their own solutions (Hmelo-Silver, 2004). Unlike traditional instruction, DBL engages students in authentic problem-solving, guiding them to generate, test, and revise solutions. This approach encourages deep cognitive engagement and facilitates pedagogical planning by aligning instruction with students' evolving conceptual understanding and reflective feedback (Kolodner et al., 2003; Mehalik & Schunn, 2006).

2. METHODS

2.1 Research Design

This study adopted a mixed design to assess the effect of a DBL course plan on the CT skills of PMTs. For this purpose, an intervention design, a sophisticated form of mixed-methods approach, was chosen. The purpose of this design is to address a research problem by incorporating qualitative data into the research process through an experiment or intervention trial program (Cresswell, 2014). Consequently, a quasi-experimental study procedure was developed, integrating qualitative data within an experimental intervention design that included a pre and post-test model. The symbolic representation of the design, measured both before and after the experiment, is presented in Table 1.

Table 1 - Symbolic view of quasi-experimental design

Groups	Pre-test	Process	Post-test
Experiment	Q1	X (Training consisting of 24 sessions-Intervention mixed method design)	Q2
Control	Q3	No intervention	Q4

2.2 Participants, Sampling Technique, and Sample Size

The study participants were selected to enable an in-depth examination of both quantitative and qualitative data within the framework of the mixed-method research model. The participant group comprised 40 PMTs enrolled at a state university. The group consisted of 70% females (n=28) and 30% males (n=12). Purposeful maximum diversity sampling was used to determine the study group. The key criteria for inclusion were: (i) age range (20–23), (ii) previous experience with coding or CT activities, (iii) self-reported digital literacy level, and (iv) being enrolled in a mathematics education course taught by one of the researchers. This selection process ensured both instructional relevance and ecological validity within the existing teacher education context. Based on the study criteria, participants were divided equally, with 20 assigned to the experimental group and 20 to the control group.

2.3 Data collection tools and process

The data collection tools consist of the Computational Thinking (CT) (Korkmaz et al., 2017) and Self-Efficacy Perception towards Teaching Computational Thinking (SEPTCT) (Özçınar & Öztürk, 2018) scales, along with a semi-structured interview form. The CT scale consists of 29 items and five sub-factors. The sub-factors are creativity, algorithmic thinking, cooperativity, critical thinking, and problem-solving. Items on the scale are rated on a 5-point Likert scale, ranging from "never" to "always." Confirmatory factor analysis (CFA) confirmed the scale's construct validity, indicating that the five-factor structure aligned with the data set [CMIN/DF=3.23; RMSEA=0.062; GFI=0.91; AGFI=0.90; CFI=0.95; IFI=0.97; SRMR=0.044]. The total Cronbach alpha reliability

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coefficient for the scale was calculated as 0.80 in this study. The SEPTCT scale comprises 31 items and four sub-factors. The sub-factors are problem construction, algorithmic thinking, teaching assessment, and planning and teaching. CFA confirmed the scale's construct validity, indicating that the four-factor structure aligned with the data set [CMIN/DF=4.07; RMSEA=0.13; GFI=0.63; CFI=0.97; NNFI=0.97; SRMR=0.04]. The total Cronbach alpha reliability coefficient for the scale was calculated as 0.82 within this study. Researchers developed a semi-structured interview form to evaluate the effectiveness of the design-based education program for PMTs. This form includes questions exploring PMTs knowledge, practices, and perceptions regarding coding and CT. Two experts were consulted for language and content validity, and revisions were made accordingly. A sample question is: "What do you think are the contributions of CT and coding education?" The design-based processes in the study involve assessing participants' current knowledge and skills, expectations from the training program, modules, courses, practice activities, digital, written, and visual materials used in the training, a pilot application with a small group, planned scope and content for the target audience, and the program's overall effectiveness (see Figure 1).
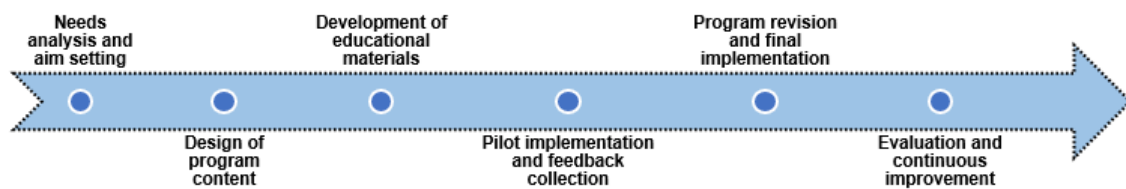

Figure 1 - Process for design-based education program

The design-based teaching approach includes four modules and 24 sessions (see Table 2). Based on reflective and social cluster formation, the educational theoretical framework incorporates Shulman and Shulman's (2009) model of "fostering a community of learners", Schön's (1983) concept of "reflective practitioners", and Vygotsky's (1934/1986) social development theory. The activities presented in Table 2 incorporate CT-rich educational content, including group sharing, collaborative learning, brainstorming, conversation circles, synectics, focus group interviews, and tutorial discussions. Individual studies showcase original designs developed from participants' group experiences.

Table 2 - Integrated course plan designed for PSMT

Module	Week	Session	Duration	Course Activity	Educational Content
Module 1 **Coding Training**	1st Week	1	10 min	CCD	Definition of coding
		2	10 min	CCD	Concepts related to coding
		3	10 min	RCD	The importance and necessity of coding education
		4	10 min	RCD	Reasons for coding skills in terms of 21st-century skills
		5	20 min	RID	The nature of coding skills
		6	30 min	RCD	Basic information about the coding process
Module 2 **Computational Thinking Training**	2nd Week	7	10 min	CCD	Definition of CT
		8	10 min	CCD	CT education and its importance
		9	10 min	RCD	Problem-solving in the context of CT
		10	20 min	RCD	Components of CT
		11	20 min	RID	Dimensions of CT
		12	20 min	RID	CT processes
Module 3 **Teaching Coding and Computational Thinking**	3rd-4th Weeks	13	20 min	CCD	CT in light of instructional approaches
		14	20 min	CCD	Developmentally appropriate applications
		15	20 min	RCD	Coding and CT in the context of constructivism
		16	30 min	RCD	Positive technological development
		17	45 min	RID	Activities unplugged-1
		18	45 min	RID	Activities unplugged-2
Module 4 **Developing Activities for Computational Thinking**	5th-6th-7th-8th Weeks	19	45 min	CCD	Algorithm design (signs, constants, variables, loops etc.)
		20	45 min	CCD	Separation (character, graphic, scenario, etc.)
		21	45 min	RID	Abstraction (code blocks, subjective designs)
		22	45 min	RID	Pattern recognition (sequential operations, loops)
		23	45 min	RID	Data processing (expressions, predicates), debugging
		24	45 min	RID	Modeling (modularity) (real object, image and event)

Note: CCD: Communal Cluster Discourses RCD: Reflective Cluster Discourses RID: Reflective Individual Discourses

2.4 Data analysis

A normality analysis was first conducted for the quantitative data analysis. Given the sample size, Shapiro-Wilk test results were examined, confirming a normal data distribution (p>0.05). In addition, the skewness and kurtosis values of the measurement tools were examined. The skewness and kurtosis values of the CT scale and its sub-factors ranged from -0.078 to 0.298, while those of the SEPTCT scale and its sub-factors ranged from 0.050 to -0.300. Values within the ±1.50 range for skewness and kurtosis indicate that the data are normally distributed (Tabachnick & Fidell, 2013). The homogeneity of variances was assessed using Levene's test, and the homogeneity of the variance-covariance matrix was examined with Box's M test. Furthermore, independent samples t-test, multifactor analysis of variance (MANOVA) for repeated measures, and descriptive statistics were used in evaluating the quantitative data. Content analysis was used to analyze the qualitative data. Descriptive statistics and t-test results based on the preliminary measurements of students in the experimental and control groups are presented in Table 3. According to the table, there is no significant difference between the pre-test total score averages of preservice teachers in the experimental and control groups for both the CT ($t_{(38)}$=0.210, p>0.05) and the SEPTCT ($t_{(38)}$=-0.242, p>0.05) scales. Additionally, no significant difference was found in the pre-test average scores across the scales' sub-dimensions (p>0.05).

Table 3 - T-test results for the pre-test scores of the experimental and control groups

Scales	Dimension	Groups	N	$\bar{X}$	SD	MD	df	t	p
Computational Thinking	Creativity	Experiment	20	3.71	0.51	-0.037	38	-0.264	0.793
		Control	20	3.75	0.37				
	Algorithmic thinking	Experiment	20	3.57	0.51	0.125	38	0.730	0.470
		Control	20	3.45	0.56				
	Cooperativity	Experiment	20	3.88	0.78	0.050	38	0.232	0.818
		Control	20	3.83	0.55				
	Critical thinking	Experiment	20	3.59	0.80	0.040	38	0.179	0.859
		Control	20	3.55	0.60				
	Problem-solving	Experiment	20	3.88	0.37	-0.041	38	-0.389	0.700
		Control	20	3.92	0.29				
Grand Total	CT Skills (Total)	Experiment	20	3.72	0.37	0.020	38	0.210	0.834
		Control	20	3.70	0.22				
Self-Efficacy Perception towards Teaching Computational Thinking	Teaching algorithmic thinking	Experiment	20	3.83	0.47	-0.025	38	-0.185	0.854
		Control	20	3.85	0.37				
	Teaching evaluation	Experiment	20	3.70	0.62	0.050	38	0.283	0.779
		Control	20	3.65	0.48				
	Course planning and teaching methods	Experiment	20	3.65	0.52	0.035	38	0.262	0.795
		Control	20	3.61	0.30				
	Teaching problem-posing	Experiment	20	3.89	0.28	-0.060	38	-0.564	0.576
		Control	20	3.95	0.37				
Grand Total	SEPTCT (Total)	Experiment	20	3.80	0.31	-0.020	38	-0.242	0.810
		Control	20	3.82	0.22				

Note. SD: Standard Deviation; MD: Mean Difference; df: Degrees of Freedom

2.5 Ethical consideration

The participants were informed about the study's purpose, the topics to be measured, and the benefits provided. Participation was voluntary, and they were informed that they could withdraw from the study at any time or request detailed information. Additionally, they were told that some questions might be uncomfortable and that no monetary compensation would be provided for participation. This research was carried out with the permission of Nevşehir Hacı Bektaş Veli University Publication Ethics Board with the decision numbered 2023.11.265 dated 27.09.2023.

3. RESULTS

Following (Table 4), we present the results of the post-test applied to the group and the discussion and conclusions of this research.

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Table 4 - T-test results for the post-test scores of the experimental and control groups

Scales	Dimension	Groups	N	$\overline{X}$	SD	MD	df	t	p
Computational Thinking	Creativity	Experiment	20	4.20	0.38	0.331	38	2.916	0.006**
		Control	20	3.86	0.32				
	Algorithmic thinking	Experiment	20	3.96	0.39	0.333	38	2.591	0.013*
		Control	20	3.63	0.42				
	Cooperativity	Experiment	20	4.31	0.50	0.375	38	2.360	0.024*
		Control	20	3.93	0.49				
	Critical thinking	Experiment	20	4.03	0.39	0.270	38	2.109	0.042*
		Control	20	3.76	0.41				
	Problem-solving	Experiment	20	4.40	0.41	0.350	38	3.206	0.003**
		Control	20	4.05	0.25				
Grand Total	CT Skills (Total)	Experiment	20	4.17	0.16	0.331	38	5.871	0.000***
		Control	20	3.84	0.18				
Self-Efficacy Perception towards Teaching Computational Thinking	Teaching algorithmic thinking	Experiment	20	4.32	0.47	0.275	38	2.134	0.039*
		Control	20	4.05	0.32				
	Teaching evaluation	Experiment	20	4.31	0.50	0.500	38	3.778	0.001**
		Control	20	3.81	0.31				
	Course planning and teaching methods	Experiment	20	4.07	0.50	0.307	38	2.330	0.025*
		Control	20	3.76	0.31				
	Teaching problem-posing	Experiment	20	4.22	0.29	0.246	38	2.377	0.023*
		Control	20	3.97	0.35				
Grand Total	SEPTCT (Total)	Experiment	20	4.21	0.23	0.290	38	4.519	0.000***
		Control	20	3.92	0.16				

An examination of Table 4 reveals a significant difference in the CT post-test scores between preservice teachers in the experimental and control groups ($t_{(38)}$=5.871, p<0.001). Examining the CT scale's sub-factors, significant differences emerged in the post-test scores for creativity (t(38)=2.916, p<0.01), algorithmic thinking ($t_{(38)}$=2.591, p<0.05), cooperativity ($t_{(38)}$=2.360, p<0.05), critical thinking ($t_{(38)}$=2.109, p<0.05), and problem-solving ($t_{(38)}$=3.206, p<0.01). A significant difference was found between the experimental and control group scores on the SEPTCT scale in the post-test ($t_{(38)}$=4.519, p<0.001). In the SEPTCT scale's sub-factors, significant differences were observed in the post-test scores for the dimensions of teaching algorithmic thinking ($t_{(38)}$=2.134, p<0.05), teaching evaluation ($t_{(38)}$=3.778, p<0.01), course planning and teaching methods ($t_{(38)}$=2.330, p<0.05), and teaching problem-posing ($t_{(38)}$=2.377, p<0.05).

Table 5 - Results of multivariate analysis of variance on mean scores of CT

Effect	Test	Value	F	Hypothesis df	Error df	p	η_p^2	Power
Intercept	Pillai's Trace	0.998	4009.48	5.00	34.00	0.000***	0.998	1.000
	Wilks' Lambda	0.002	4009.48	5.00	34.00	0.000***	0.998	1.000
	Hotelling's Trace	589.63	4009.48	5.00	34.00	0.000***	0.998	1.000
	Roy's Largest Root	589.63	4009.48	5.00	34.00	0.000***	0.998	1.000
Group	Pillai's Trace	0.505	6.938	5.00	34.00	0.000***	0.505	0.995
	Wilks' Lambda	0.495	6.938	5.00	34.00	0.000***	0.505	0.995
	Hotelling's Trace	1.020	6.938	5.00	34.00	0.000***	0.505	0.995
	Roy's Largest Root	1.020	6.938	5.00	34.00	0.000***	0.505	0.995

The MANOVA analysis in Table 5 indicates a statistically significant difference in CT score averages between the experimental and control groups of preservice teachers. A statistically significant difference was found at both within-group ($F_{(5-34)}$=4009.48, $p<0.001$, λ=0.002, η_p^2=0.998) and between-group levels ($F_{(5-34)}$=6.938, $p<0.001$, λ=0.495, η_p^2=0.505). These differences indicate a high level of effect.

Table 6 - CT impact test results

Source	Dependent variable	Sum of squares	df	F	p	η_p^2	Observed power
Computational Thinking	Creativity	1.097	1	8.505	0.006**	0.183	0.811
	Algorithmic thinking	1.111	1	6.714	0.013*	0.150	0.714
	Cooperativity	1.406	1	5.570	0.024*	0.128	0.633
	Critical thinking	0.729	1	4.447	0.042*	0.105	0.538
	Problem-solving	1.225	1	10.281	0.003**	0.213	0.878

The dependent variables in Table 6 reveal statistically significant differences across all CT sub-dimensions between preservice teachers in the experimental and control groups. Specifically, the dimensions of creativity ($F_{(1-38)}$=8.505, $p<0.01$, η_p^2=0.183), algorithmic thinking ($F_{(1-38)}$=6.714, $p<0.05$, η_p^2=0.150), cooperativity ($F_{(1-38)}$=5.570, $p<0.05$, η_p^2=0.128), critical thinking ($F_{(1-38)}$=4.447, $p<0.05$, η_p^2=0.105), and problem-solving ($F_{(1-38)}$=10.281, $p<0.01$, η_p^2=0.213) all demonstrate statistically significant differences. These differences indicate high to medium effect sizes.

Table 7 - Results of multivariate analysis of variance on mean scores of SEPTCT

Effect	Test	Value	F	Hypothesis df	Error df	p	η_p^2	Power
Intercept	Pillai's Trace	0.998	4002.86	4.00	35.00	0.000***	0.998	1.000
	Wilks' Lambda	0.002	4002.86	4.00	35.00	0.000***	0.998	1.000
	Hotelling's Trace	457.47	4002.86	4.00	35.00	0.000***	0.998	1.000
	Roy's Largest Root	457.47	4002.86	4.00	35.00	0.000***	0.998	1.000
Group	Pillai's Trace	0.439	6.844	4.00	35.00	0.000***	0.439	0.986
	Wilks' Lambda	0.561	6.844	4.00	35.00	0.000***	0.439	0.986
	Hotelling's Trace	0.782	6.844	4.00	35.00	0.000***	0.439	0.986
	Roy's Largest Root	0.782	6.844	4.00	35.00	0.000***	0.439	0.986

The MANOVA analysis in Table 7 indicates a statistically significant difference in SEPTCT score averages between the experimental and control groups of preservice teachers. A statistically significant difference was found at both within-group ($F_{(4-35)}$=4002.86, $p<0.001$, λ=0.002, η_p^2=0.998) and between-group levels ($F_{(4-35)}$=6.844, $p<0.001$, λ=0.561, η_p^2=0.439). These differences indicate a high level of effect.

Table 8 - SEPTCT impact test results

Source	Dependent variable	Sum of squares	df	F	p	η_p^2	Observed power
Self-Efficacy Perception towards Teaching Computational Thinking	Teaching algorithmic thinking	0.756	1	4.554	0.039*	0.107	0.548
	Teaching evaluation	2.500	1	14.274	0.001**	0.273	0.957
	Course planning and teaching methods	0.943	1	5.429	0.025*	0.125	0.622
	Teaching problem-posing	0.608	1	5.648	0.023*	0.129	0.639

The dependent variables in Table 8 reveal statistically significant differences across all SEPTCT sub-dimensions between the experimental and control groups of preservice teachers. Specifically, the sub-dimensions of teaching algorithmic thinking ($F_{(1-38)}$=4.554, $p<0.05$, η_p^2=0.107), teaching evaluation ($F_{(1-38)}$=14.274, $p<0.01$, η_p^2=0.273), course planning and teaching methods ($F_{(1-38)}$=5.429, $p<0.05$, η_p^2=0.125), and teaching problem-posing ($F_{(1-38)}$=5.648, $p<0.05$, η_p^2=0.129) demonstrate statistically significant differences. These differences indicate high to medium effect sizes.
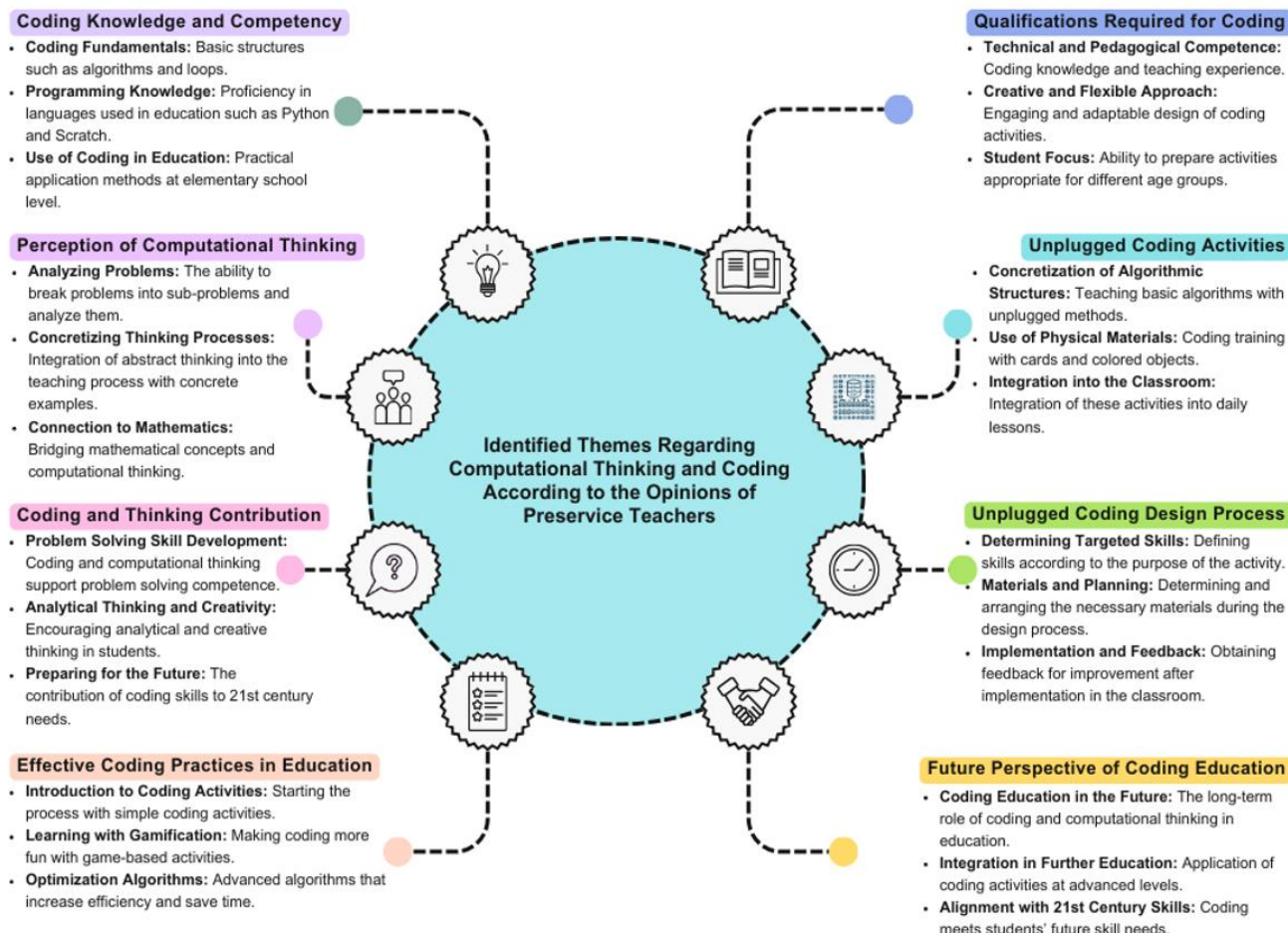
Figure 2 - Themes determined according to the opinions of preservice teachers

Figure 2 presents themes on the current situation based on preservice teachers' opinions. Specifically, preservice teachers' opinions were organised into eight themes, each containing three categories. The categories are coding knowledge and competency, perception of CT, coding and thinking contribution, effective coding practices in education, qualifications required for coding, unplugged coding activities, unplugged coding design, and future perspectives on coding education. Sample participant statements for each category are presented in Figure 3.
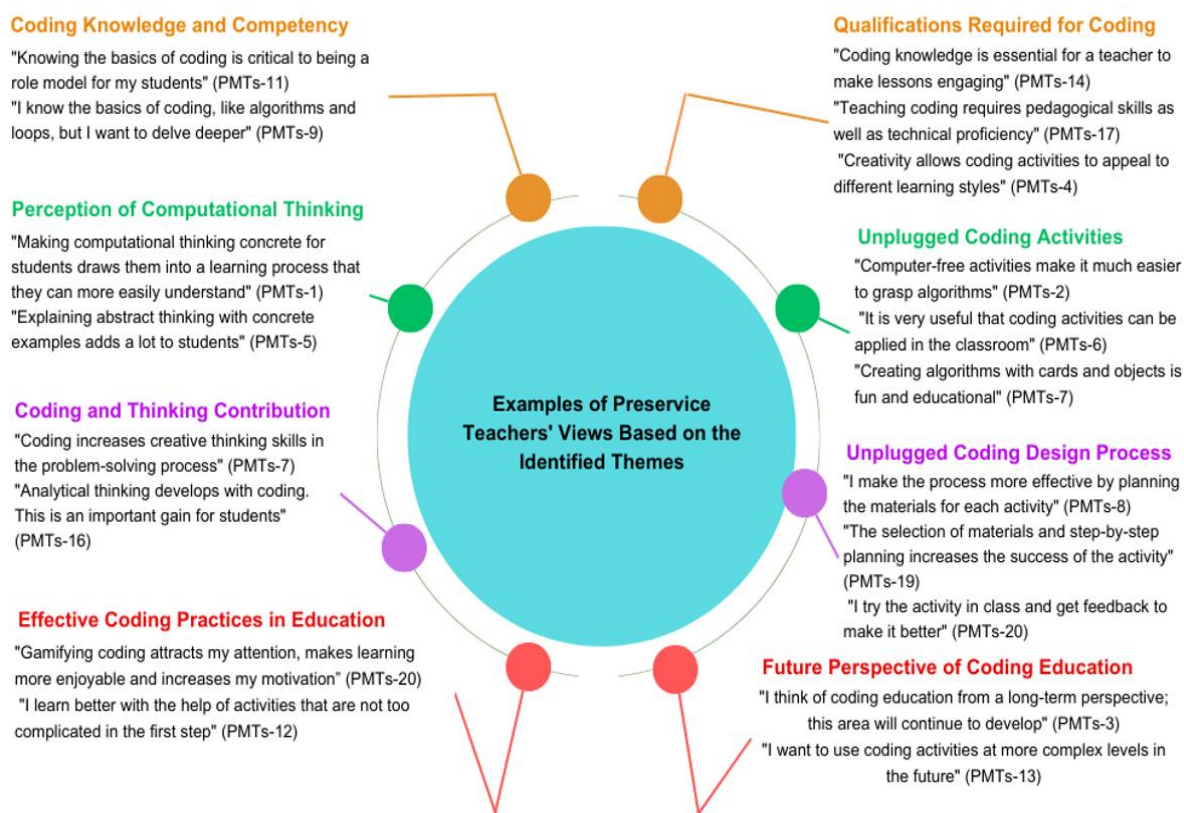
Figure 3 - Examples from the views of preservice teachers

A general evaluation of preservice teachers' opinions in Figure 3 suggests that supporting design-based CT instruction enhances candidates' pedagogical approaches and strengthens their inclination towards CT processes. Additionally, coding knowledge encourages deeper learning, supports abstract thought, and fosters creative and analytical thinking. It increases motivation by making learning enjoyable, adding interest to lessons, and enhancing pedagogical skills. Furthermore, coding knowledge offers an innovative perspective on diverse learning styles, facilitates comprehension of algorithms, improves process efficiency, and is anticipated to become increasingly essential in the future.

4. DISCUSSION

This study comprehensively investigated the effect of the DBL approach on preservice teachers' CT skills and their self-confidence in teaching these skills. The findings show that DBL is highly effective in developing preservice teachers' CT skills and enhancing their competence in teaching these skills.

The post-test CT skill scores of preservice teachers in the experimental group were significantly higher than the control group's scores. CT skills were analysed in the sub-dimensions of creativity, algorithmic thinking, cooperativity, critical thinking, and problem-solving, with significant differences favouring the experimental group in each dimension. These results validate DBL's contribution to individuals' thinking and problem-solving skills, as shown in studies by Barab and Squire (2004) and Brennan and Resnick (2012). In particular, improving algorithmic thinking and problem-solving skills suggests that DBL significantly enhances PMTs' systematic thinking and approach to problem-solving processes. The effect of DBL in education lies in its encouragement of creative and innovative thought processes. Grover and Pea (2013) stated that teachers require support in CT education, their competence in this area should be enhanced, and they should be provided with the necessary tools and materials for CT instruction. This study offers guidance on integrating CT more effectively with pedagogical strategies and curriculum in elementary teacher education programs to enhance PMTs' CT proficiency. It highlights the need for strategies to help preservice teachers acquire these skills while enhancing their self-confidence and pedagogical competence. Development in the creativity and critical thinking sub-dimensions indicates that DBL promotes both problem-solving skills and the ability to explore diverse solution methods. DBL encourages more active participation from preservice teachers in the learning process and fosters the development of innovative strategies in teaching (Avşar, 2023; Israel & Lash, 2020).

The study further reveals that the DBL approach increases PMTs' self-confidence in teaching CT. Preservice teachers in the experimental group obtained significantly higher scores than the control group in the sub-dimensions of algorithmic thinking,

evaluation, course planning, teaching methods, and problem-posing. This finding supports researchers' findings on student competencies and pedagogical development (Boom et al., 2022; Kolodner et al., 2003; Lockwood & Mooney, 2018; Looi et al., 2024; Navarro & de Sousa, 2023; Shute et al., 2017; Shulman & Shulman, 2009). The increase in PMTs' self-confidence enhances their competence in teaching CT skills, supports the effective use of teaching strategies, and improves their management of educational processes for students. Improvement in assessment and lesson planning shows that DBL strengthens PMTs' skills in structuring their teaching processes and enables them to anticipate potential difficulties better. Therefore, DBL can be considered an important tool for developing preservice teachers' teaching competencies and pedagogical strategies (Avşar, 2023; Pei et al., 2018). The study's findings align with previous literature emphasising the synergy between DBL and CT development (Grover & Pea, 2013; Kolodner et al., 2003). In particular, the impact on pedagogical self-efficacy echoes findings by Navarro and de Sousa (2023), who noted that hands-on design activities empower teachers to translate CT into classroom practice.

Effect analyses reveal a high effect size in both CT skills and teaching confidence in CT between the experimental and control groups. These significant differences within and between groups demonstrate that DBL is an effective model for teaching and developing CT skills (Hmelo-Silver, 2004; Papert, 1980). The DBL approach supports the development of advanced cognitive processes such as abstract thinking, analytical problem solving, and collaborative learning in PMTs. Additionally, these findings show that DBL is effective in knowledge acquisition and in fostering in-depth understanding through the teaching process. The high effect sizes in the creativity and problem-solving dimensions reveal that the thinking skills cultivated by PMTs through DBL receive strong support (Navarro & de Sousa, 2023). These results confirm DBL as an effective method for equipping students with a broad range of problem-solving and critical thinking skills. While the results strongly support the effectiveness of DBL, it is important to consider whether the improvements are solely attributable to the methodology itself. Alternative explanations, such as increased instructor attention, participant motivation, or the novelty of the experience, could also have contributed. Thus, future studies should control for this potential confound.

Evaluations of PMTs' opinions show that design-based CT teaching enhances their pedagogical skills and aptitude for CT processes. PMTs' views highlight the positive effects of the DBL approach in education and suggest that DBL, an innovative approach to developing pedagogical and technical skills in preservice teachers, should be more widely integrated into educational programs. The themes identified from participant responses, particularly those emphasising collaboration and reflection, mirror the improvements observed in cooperativity and critical thinking subdimensions. This convergence strengthens the internal validity of the results and supports the interpretation that DBL influenced both skills and pedagogical perspectives.

4.1. Limitations and implications for future research

Although the study's findings revealed significant results, the research has limitations. Firstly, the study was conducted with a specific sample of PMTs. This limitation restricts the generalizability of the findings and indicates the need for similar studies in groups with diverse demographic or geographic characteristics. The DBL method used in this study was implemented as an additional activity to preservice teachers' existing education programs. However, fully integrating such an intervention into the curriculum may depend on student density, institutional resources, and educators' capacity to apply this method. Similar studies with larger sample groups across various education levels (primary school, middle school, high school, etc.) would be beneficial following future research recommendations.

Additionally, evaluating preservice teachers' teaching performance after acquiring CT skills is crucial. This is an important research area for examining the impact of DBL on classroom teaching processes. As technology rapidly evolves, digital tools and environments available for DBL-based CT teaching are expected to diversify. Integrating digital tools into teaching processes and examining their effects on the effectiveness of DBL represent valuable areas of investigation for future studies. Such studies can enhance preservice teachers' digital literacy and pedagogical technology skills by exploring more effective ways to incorporate technology in education. Nevertheless, this research has virtues and implications for the future, allowing the group of researchers to further develop in CT.

CONCLUSION

This study confirms the effectiveness of the DBL approach in enhancing CT skills and teaching self-confidence among preservice teachers. The findings demonstrate that DBL supports a broad range of cognitive and pedagogical competencies, from creativity and algorithmic thinking to lesson planning and instructional design.

DBL provides knowledge acquisition and facilitates deep understanding and active engagement in learning. The significant gains in both technical and pedagogical aspects highlight the potential of DBL to transform teacher education and better prepare future educators for the demands of 21st-century classrooms.

The alignment between quantitative data and qualitative insights reinforces the validity of the findings. By integrating DBL into elementary teacher training programs, institutions can promote more innovative, reflective, and effective teaching practices. As the educational landscape continues to develop, adopting approaches like DBL will be essential for equipping teachers to foster CT skills in increasingly complex learning environments.

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AUTHORS' CONTRIBUTION

Conceptualization, P.T., D.K. and T.K.; data curation, P.T., D.K. and T.K.; formal analysis P.T., D.K. and T.K.; funding acquisition, P.T., D.K. and T.K.; investigation, P.T., D.K. and T.K.; methodology, P.T., D.K. and T.K.; project administration, P.T., D.K. and T.K.; resources, P.T., D.K. and T.K.; software, P.T., D.K. and T.K.; supervision, P.T., D.K. and T.K.; validation, P.T., D.K. and T.K.; visualization, P.T., D.K. and T.K.; writing-original draft, P.T., D.K. and T.K.; writing-review and editing, P.T., D.K. and T.K.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

REFERENCES

Avşar, M. (2023). *Supporting preschool teachers' computational thinking skills: The effect of design-based in-service training* [Tese de doutoramento, Hacettepe University]. Council of Higher Education National Thesis Center.

Barab, S., & Squire, K. (2004). Design-based research: Putting a stake in the ground. *The Journal of the Learning Sciences, 13*(1), 1–14. https://doi.org/10.1207/s15327809jls1301_1

Boom, K. D., Bower, M., Siemon, J., & Arguel, A. (2022). Relationships between computational thinking and the quality of computer programs. *Education and Information Technologies, 27*(6), 8289–8310. https://doi.org/10.1007/s10639-022-10921-z

Brennan, K., & Resnick, M. (2012). New frameworks for studying and assessing the development of computational thinking. In *Proceedings of the 2012 Annual Meeting of the American Educational Research Association* (pp. 1–25). American Educational Research Association. https://web.media.mit.edu/~kbrennan/files/Brennan_Resnick_AERA2012_CT.pdf

Ching, Y. H., & Hsu, Y. C. (2024). Educational robotics for developing computational thinking in young learners: A systematic review. *TechTrends, 68*(3), 423–434. https://doi.org/10.1007/s11528-023-00841-1

Creswell, J. W. (2014). *A concise introduction to mixed methods research*. SAGE Publications.

Gadanidis, G., Hughes, J., Minniti, L., & White, B. (2017). Computational thinking, grade 1 students and the binomial theorem. *Digital Experiences in Mathematics Education, 3*(2), 77–96. https://doi.org/10.1007/s40751-016-0019-3

Gresalfi, M., Barab, S., Siyahhan, S., & Christensen, T. (2009). Virtual worlds, conceptual understanding, and me: Designing for consequential engagement. *On the Horizon, 17*(1), 21–34. https://doi.org/10.1108/10748120910936126

Grover, S., & Pea, R. (2013). Computational thinking in K–12: A review of the state of the field. *Educational Researcher, 42*(1), 38–43. https://doi.org/10.3102/0013189X12463051

Harel, I., & Papert, S. (Eds.). (1991). *Constructionism*. Ablex Publishing. https://www.researchgate.net/publication/220040743_Constructionism

Hmelo-Silver, C. E. (2004). *Problem-based learning: What and how do students learn? Educational Psychology Review, 16*(3), 235–266. https://doi.org/10.1023/B:EDPR.0000034022.16470.f3

International Society for Technology in Education, & Computer Science Teachers Association. (2011). *Operational definition of computational thinking for K–12 education*. https://cdn.iste.org/www-root/Computational_Thinking_Operational_Definition_ISTE.pdf

Israel, M., & Lash, T. (2020). From classroom lessons to exploratory learning progressions: Mathematics + computational thinking. *Interactive Learning Environments, 28*, 362–382. https://doi.org/10.1080/10494820.2019.1674879

Kafai, Y., Proctor, C., & Lui, D. (2019). From theory bias to theory dialogue: Embracing cognitive, situated and critical framings of computational thinking for K–12 CS education. In *Proceedings of the 2019 ACM Conference on International Computing Education Research* (pp. 101–109). ACM. https://doi.org/10.1145/3291279.3339400

Kaya, D. (2024). Computational thinking from the past to the present: A retrospective using bibliometric analysis. *Hacettepe University Journal of Education, 39*(2), 195–219. https://doi.org/10.16986/HUJE.2024.520

Kolodner, J. L., Camp, P. J., Crismond, D., Fasse, B., Gray, J., Holbrook, J., Puntambekar, S., & Ryan, M. (2003). Problem-based learning meets case-based reasoning in the middle-school science classroom: Putting learning by design™ into practice. *Journal of the Learning Sciences, 12*(4), 495–547. https://doi.org/10.1207/S15327809JLS1204_2

Korkmaz, Ö., Çakir, R., & Özden, M. Y. (2017). A validity and reliability study of the computational thinking scales (CTS). *Computers in Human Behavior, 72*, 558–569. https://doi.org/10.1016/j.chb.2017.01.005

Lockwood, J., & Mooney, A. (2018). Computational thinking in secondary education: Where does it fit? A systematic literary review. *International Journal of Computer Science Education in Schools, 2*(1), 41–60. https://doi.org/10.21585/ijcses.v2i1.26

Looi, C. K., Chan, S. W., Wu, L., Huang, W., Kim, M. S., & Sun, D. (2024). Exploring computational thinking in the context of mathematics learning in secondary schools: Dispositions, engagement and learning performance. *International Journal of Science and Mathematics Education, 22*, 993–1011. https://doi.org/10.1007/s10763-023-10419-1

Lye, S. Y., & Koh, J. H. L. (2014). Review on teaching and learning of computational thinking through programming: What is next for K–12. *Computers in Human Behavior, 41*(4), 51–61. https://doi.org/10.1016/j.chb.2014.09.012

Mehalik, M. M., & Schunn, C. (2006). What constitutes good design? A review of empirical studies of design processes. *International Journal of Engineering Education, 22*(3), 519–532.

National Research Council. (2010). *Report of a workshop on the scope and nature of computational thinking*. National Academies Press. https://doi.org/10.17226/12840

Navarro, E. R., & de Sousa, M. d. C. (2023). The concept of computational thinking in mathematics education. *Journal of Mathematics and Science Teacher, 3*(2), 1–11. https://doi.org/10.29333/mathsciteacher/13630

Ng, O. L., & Cui, Z. (2021). Examining primary students' mathematical problem-solving in a programming context: Towards computationally enhanced mathematics education. *ZDM Mathematics Education, 53*(4), 847–860. https://doi.org/10.1007/s11858-020-01200-7

Özçınar, H., & Öztürk, E. (2018). The scale of self-efficacy perception towards teaching computational thinking: A validity and reliability study. *Pamukkale University Journal of Social Sciences Institute, 30*, 173–195. https://doi.org/10.5505/pausbed.2018.82574

Özyurt, Ö., & Aslan, A. (2023). A broad view of the problem-based learning field based on machine learning: A large-scale study based on topic modeling. *International e-Journal of Educational Studies, 7*(15), 608–626. https://doi.org/10.31458/iejes.1320491

Papert, S. (1980). *Mindstorms: Children, computers, and powerful ideas*. Basic Books.

Partnership for 21st Century Skills. (2019). *Framework for 21st century learning*. https://www.battelleforkids.org/networks/p21/frameworks-resources

Pei, C., Weintrop, D., & Wilensky, U. (2018). Cultivating computational thinking practices and mathematical habits of mind in Lattice Land. *Mathematical Thinking and Learning, 20*(1), 75–89. https://doi.org/10.1080/10986065.2018.1403543

Schön, D. A. (1983). *The reflective practitioner: How professionals think in action*. Basic Books.

Shute, V., Sun, C., & Asbell-Clarke, J. (2017). Demystifying computational thinking. *Educational Research Review, 22*, 142–158. https://doi.org/10.1016/j.edurev.2017.09.003

Shulman, L. S., & Shulman, J. H. (2009). How and what teachers learn: A shifting perspective. *Journal of Education, 189*(1–2), 1–8. https://doi.org/10.1177/0022057409189001-202

Sneider, C., Stephenson, C., Schafer, B., & Flick, L. (2014). Computational thinking in high school science classrooms. *The Science Teacher, 81*(5), 10–15. https://doi.org/10.2505/4/tst14_081_05_53

Tabachnick, B. G., & Fidell, L. S. (2013). *Using multivariate statistics* (6th ed.). Pearson Publishing.

Vygotsky, L. S. (1986). *Thought and language.* The MIT Press. (Original work published 1934)

Weintrop, D., Beheshti, E., Horn, M., Orton, K., Jona, K., Trouille, L., & Wilensky, U. (2016). Defining computational thinking for mathematics and science classrooms. *Journal of Science Education and Technology, 25*(1), 127–147. https://doi.org/10.1007/s10956-015-9581-5

Wing, J. M. (2006). Computational thinking. *Communications of the ACM, 49*(3), 33–35. https://doi.org/10.1145/1118178.1118215

Wing, J. M. (2008). Computational thinking and thinking about computing. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 366*(1881), 3717–3725. https://doi.org/10.1098/rsta.2008.0118

Yadav, A., Stephenson, C., & Hong, H. (2017). Computational thinking for teacher education. *Communications of the ACM, 60*(4), 55–62. https://doi.org/10.1145/2994591

Ye, H., Liang, B., Ng, O. L., & Chai, C. S. (2023). Integration of computational thinking in K–12 mathematics education: A systematic review on CT-based mathematics instruction and student learning. *International Journal of STEM Education, 10*(1), 1–26. https://doi.org/10.1186/s40594-023-00396-w