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CULTURAL AND REGIONAL PERSPECTIVES

Exploring grade and gender differences in computational thinking skills: a Greek primary school study

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Abstract
Computational thinking (CT) skills have become increasingly important in modern education, as they equip students with critical problem-solving skills applicable across various domains. Given the growing emphasis on digital literacy, it is essential to investigate grade- and gender-level differences in CT skills among students to support targeted interventions and to ensure that all students have equal opportunities to succeed in the digital age. This study examined CT skill development among primary school students, taking both grade- and gender-level disparities into account. Using quantitative data from a diverse sample of 517 primary school students, we conducted a comprehensive analysis of their CT scores. The results revealed no significant gender differences in CT scores among primary school students. However, notable age-related disparities emerged, with CT scores rising as students progressed through higher grades. This finding underscores the importance of considering developmental factors in CT education and highlights the need for age-appropriate CT curricula. By investigating both grade- and gender-level differences, this study aims to support educators and policymakers in developing more inclusive and effective strategies for cultivating CT skills among young learners, thereby preparing them for the challenges of the digital age.

Keywords Beginners Computational Thinking Test (BCTt) · Computational thinking (CT) · Primary education · Grade-level disparities · Gender differences · CT assessment tools

Introduction

In one of the most influential works on computational thinking (CT), Wing (2006) defined it as a "universally applicable attitude and skill set everyone, not just computer scientists, would be eager to learn and use" (p. 33), as CT enables students to solve problems that would otherwise be impossible to solve. Wing (2006) argued that in addition to reading,

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writing, and arithmetic, every child must be taught CT. As a result, it is crucial to recognize the value of computing as an interdisciplinary learning tool. However, it is also important not to overlook the social and affective components of students' participation in creating every computational artifact (Lodi & Martini, 2021).

Although numerous approaches have been proposed for incorporating CT into educational curricula, there are fewer suggestions for assessing CT (Babazadeh & Negrini, 2022), while valid and reliable age-tailored assessment tools must be developed (Poulakis & Politis, 2021). Additionally, it is essential to validate gender-fair assessment tools to contribute to closing the gender gap that researchers frequently observe in computing (Hamamsy et al., 2023). The way in which CT skills corresponds to different grades[1] and gender is also currently missing from literature (Angeli & Giannakos, 2020). In summary, it is critical to examine age and gender disparities in the development of CT skills, to support focused interventions, and to promote a more fair and inclusive society where everyone has equal opportunities to prosper in the digital era.

This study aimed to determine if there are developmental and gender-based differences in the CT skills of primary school students, and whether these factors interact to influence CT skills further. Although some previous studies have examined CT sub-dimensions, the present study focuses on overall CT skills to provide a broad understanding of developmental and gender-based differences in Greek primary school students. To explore these issues, we analyzed students' performance based on their grade, which corresponds to "a specific stage of instruction in initial education usually covered during an academic year" (UNESCO Institute for Statistics, 2012, p. 80). Students in the same grade are usually of similar age and each grade represents a distinct stage in primary education with a tailored curriculum, which in Greece is reflected in the Information and Communications Technology (ICT) curriculum (Institute of Educational Policy, 2022), specifically designed to progressively build CT skills by introducing increasingly complex CT concepts at each grade in alignment with students' cognitive development. We begin by introducing the concept of CT and the proposed methods and tools for its assessment. Afterwards, we present the relevant research regarding age and gender differences in the context of CT development. Lastly, we present the results and their discussion, as well as our concluding remarks.

Computational thinking

Although CT became popular after Wing's statements in 2006, it can be traced back to the 1940s, when Polya (1945) described a four-step process for solving mathematical problems that shares many characteristics with various proposed CT concepts and practices. However, the term *CT* first appeared in Papert's (1980) book *Mindstorms* as a mental skill children acquire through programming. Papert also noted that the social and affective components of learning are as significant as the technical ones. Following Wing's statements, a broad academic debate began, during which many definitions of CT were proposed.

In their systematic literature review, Tang et al. (2020) noted that there are two main approaches to defining CT. The first defines CT in terms of programming and computing concepts, while the second includes competencies needed for acquiring both

[1] The term "grade" in this manuscript can be understood equivalently as "class", "cohort" or "year", as per the International Standard Classification of Education (ISCED) by UNESCO (2012).

domain-specific knowledge and general problem-solving skills. Brennan and Resnick (2012) proposed a three-dimensional CT model, which served as a foundation for future CT models and belongs to the first approach to defining CT. They noted that CT is made up of concepts (sequences, loops, parallelisms, events, conditionals, operators, and data), practices (being incremental and iterative, testing and debugging, reusing and remixing, and abstracting and modularizing), and perspectives (expressing, connecting, and questioning). Weintrop et al. (2016), who also influenced future discussions, defined CT in terms of programming and computing concepts and proposed that CT can be divided into four main areas: (a) data practices, (b) modeling and simulation practices, (c) computational problem-solving practices, and (d) systems thinking practices.

Among the most dominant models following the second approach, CSTA & ISTE (2011) proposed that CT is a problem-solving approach that includes, but is not limited to, problem formulation in a way that allows us to solve them using computers and other tools, logical data organization, abstraction, automation through algorithmic thinking, efficient problem solving, and generalization. Several dispositions or attitudes that are crucial CT characteristics promote and improve these problem-solving skills across various settings. Selby and Woolard (2013) conducted a literature review, which resulted in an operational definition stating that CT is not limited to a problem-solving approach. Instead, it can be described as a thought process that incorporates abstraction, decomposition, algorithms, evaluation, and generalization.

Although there are numerous definitions of CT, it has been widely accepted to involve "formulating problems and their solutions in a way that can be effectively executed by an information-processing agent" (Wing, 2011), which can be either a human, a machine, or a combination of the two, in various fields (Grover & Pea, 2018). A recent study by Annamalai et al. (2022) concluded that the most important CT aspects are abstraction, decomposition, debugging and evaluation, algorithms, and generalization, while CT is a significant skill set that enhances general problem-solving skills.

Despite the proliferation of assessment methods aligning with CT models, there is a need for their large-scale validation and application (Cutumisu et al., 2019), as well as their focus on younger students (Poulakis & Politis, 2021). Among the various assessment tools, only a few can be used without depending on a programming environment. The *Computational Thinking Test* (CTt) (Román-González, 2015; Román-González et al., 2017), despite being designed for students between the ages of 10 and 16, has attracted researchers' interest because of its validity and reliability. The Beginners Computational Thinking Test (*BCTt·* Zapata-Cáceres et al., 2020, 2021) was designed with CTt as its foundation and adapted for younger students. It comprises 25 items, divided into six sets, each of which addresses a unique computational concept (sequences, simple loops, nested loops, if–then, if–then-else, and while). BCTt is suitable for students aged 5 to 10, especially the younger ones among them, and it could be used as a pre-test and post-test tool.

The Greek version of BCTt (Vourletsis & Politis, 2025), used in our study, has also demonstrated good psychometric properties. In particular, regarding its validity, a panel of experts agreed on the relevance of its items for assessing CT concepts and statistical analyses revealed better model fits for younger students. Furthermore, the adapted scale includes items of varying difficulty, has good discriminatory power, good internal consistency, and consistent and stable results over 2–3 weeks. Overall, the BCTt is a promising tool for assessing CT development in younger primary school students.

Related work

Age and grade differences

The inclusion of CT from early education in modern curricula highlights the importance of investigating differences in CT skills between students of different grades. Coding and programming skills are often linked to cognitive maturity (Kim et al., 2021), while Piaget (1964) proposed the order in which children develop their intellectual abilities decades before the widespread use of computers in everyday life and education. According to Piaget's theory of cognitive development, children progress through four key stages: (a) the sensorimotor stage (0−2 years), where they learn through physical interaction with their environment, (b) the preoperational stage (2−7 years), characterized by symbolic thinking but limited logical reasoning; the concrete operational stage (7−11 years), where children begin to think logically about concrete events but have difficulty with abstract ideas, and (c) the formal operational stage (around 11 years onward), where abstract and logical reasoning become more fully developed. These stages help explain how children's ability to understand increasingly complex concepts, including those related to CT, is influenced by their cognitive development as they mature. In the earlier years of primary education, they are more adept at handling simpler tasks, while the abstract reasoning required for more complex concepts, such as loops and conditionals, develops more completely in the later years.

Building on Piaget's framework, research into CT and robotics further supports this developmental perspective. For example, the systematic review of robotics construction kits (RCKs) by Sullivan and Heffernan (2016) highlighted that younger children are capable of engaging with fundamental aspects of CT, such as sequencing, through manipulative robotic environments. As students progress to upper elementary and middle school, they demonstrate more advanced cognitive abilities, which enhance their programming and engineering knowledge. This development allows older children to improve their understanding of more complex CT tasks. Further evidence of developmental progression is provided by Seiter and Foreman (2013), who introduced the *Progression of Early Computational Thinking* (PECT) Model to assess CT in primary grade students, focusing on procedures and algorithms, problem decomposition, parallelization, abstraction, and data representation. Their study, involving Scratch projects from students in Grades 1 to 6, indicated that as students advanced in age and grade, they demonstrated increased proficiency in tasks like animation, user interaction, and the use of more complex design patterns, highlighting the need for age-appropriate CT curricula.

The developmental trajectory of CT skills continues to be supported by recent studies. For instance, An's (2022) examination of sequencing abilities among 1,234 children aged 5 to 7 revealed that the most rapid development occurred between the ages of 5 and 6, with a less significant improvement from 6 to 7 years. The study also revealed that children at the age of 7 demonstrated significantly stronger sequencing skills than younger students, emphasizing this period as critical for developing such abilities. Similarly, Relkin et al. (2020) explored the developmental progression of CT in their study of 768 first and second graders in a Virginia school district. By using *TechCheck*, an unplugged assessment tool designed to evaluate CT skills in young children aged 5 to 9, focusing on algorithms, modularity, control structures, representation, hardware/software, and debugging, they found that second graders consistently outperformed first graders. Their findings further reinforced the idea of a developmental trajectory, with significant improvements in abstract and logical reasoning over time.

Tsarava et al. (2022) further explored the cognitive foundations of CT in primary education, finding that CT skills are differentially influenced by various cognitive abilities across age groups. Their study involving third and fourth graders showed that CT was positively associated with numerical abilities, verbal reasoning, and non-verbal visuospatial skills. They also observed that while numerical abilities play a more significant role in CT development during early education, this influence diminishes in later stages. Their research emphasizes that CT development in young learners draws on multiple cognitive abilities, further highlighting the need for age-appropriate educational approaches to support CT development.

However, some studies did not find consistent developmental progression across all age groups. Jiang and Wong (2021), who examined both developmental and gender differences in CT skills among 197 students aged 9 to 13, noted significant differences between students in Grade 4 and Grade 6, with older students consistently scoring higher than their younger counterparts. In contrast, Atmatzidou and Dimitriadis (2016), who explored CT skill development through an educational robotics program involving 164 junior high and high vocational students and using written and oral assessment tools, reported that students reached similar levels of CT skills regardless of age. They argued that CT skills may require substantial time to develop properly.

Rijke et al. (2018) conducted research with 200 primary school students aged 6 to 12 years, employing an instructional intervention that included unplugged activities. Their results indicated that the participants' age may impact the development of specific CT skills. In particular, they found that not all students' age groups attained the same level of abstraction skills, as older students performed better than younger students. As students move into later primary and secondary education, researchers offer further insights into how CT skills develop across a broader age range. Korucu et al. (2017) investigated CT skill development in 160 secondary school students aged 10 to 14 and found differences in CT abilities across grades. Specifically, seventh graders scored lower than both sixth and eighth graders, suggesting variability in CT development. Similarly, Polat et al. (2021) implemented a 9-week CT program for 1 h a week with 328 fifth and sixth-grade students (aged 10–12) in Istanbul. They used the Scratch visual programming environment and found that sixth graders performed better than fifth graders, although the effect size was small. This difference was attributed to the fact that the sixth graders participated in more complex Scratch activities than the fifth graders.

In the context of large-scale analyses, Román-González et al. (2017) used CTt to evaluate the CT skills of 1,251 Spanish students in fifth through tenth grade. Statistically significant differences in scores were observed among students of different grades. These differences spanned all possible pairs between grades, supporting the authors' assumption that CT, as a problem-solving ability, is linked to students' cognitive development.

Finally, the findings by Sullivan and Bers (2016) suggest that even very young learners can develop foundational CT skills. More specifically, they explored the development of CT skills among 45 students from kindergarten to second grade (aged 4 to 7) in an eight-week robotics and programming curriculum. They found that older students did not consistently outperform younger students across various activities. However, their conclusion must be considered with caution due to the small sample size and underrepresentation of second graders in their study.

Gender disparities

Studies exploring the impact of gender on the development of CT skills in students have produced varying outcomes. Research examining younger students tends to show minimal or no gender differences in CT skills. Del Olmo-Muñoz et al. (2020) suggested that gender did not significantly affect the development of CT skills, but noted its influence on motivation toward CT instruction. Their study involved 84 s-grade students in a quasi-experimental study with a control and an experimental group, using unplugged and plugged-in instruction respectively, followed by plugged-in instruction for both groups. Relkin et al. (2020), in a study of 768 first- and second-grade students using the TechCheck assessment tool, also found no significant gender-based disparities in CT skills. In contrast, An (2022) examined 1,234 children aged 5 to 7 and found significant gender differences in sequencing ability, with girls demonstrating higher sequencing abilities than boys. Sullivan and Bers (2013) worked with 53 kindergarten students on a six-lesson robotics program and found few statistically significant gender differences, except for boys scoring higher in tasks like the proper attachment of robotic parts and the concept of conditionals. Subsequent pilot research by the same authors (Sullivan & Bers, 2016) with 45 students from ages 4 to 7 reported no statistically significant differences between boys and girls regarding robotics and simple programming tasks but found that boys outperformed girls in more advanced tasks like repeat loops with sensor parameters.

Additional research has explored gender differences in CT through the use of robotics and programming environments. Papadakis et al. (2016), working with kindergarten students using ScratchJr, found no significant gender-related impact on CT-related tasks. Angeli and Valanides (2020) emphasized the importance of designing gender-inclusive CT content for young learners. Their study, involving 50 kindergarten children working with Bee-Bot, found no significant gender differences in programming skills. However, Angeli and Georgiou (2023) identified gender effects in CT dimensions like sequences and decomposition among 170 children aged 5 to 6.

As students progress to secondary education, gender-based disparities in CT skills may become more pronounced (Ardito et al., 2020). For example, Polat et al. (2021) studied 328 fifth and sixth grade (aged 10–12) students and discovered that boys outperformed girls in CT skills. However, the effect size was small, suggesting that the gender gap may be narrowing. Differences in some CT subscales are attributed to boys' greater interest in technical issues at younger ages. Mouza et al. (2020), after analyzing both quantitative and qualitative data from 238 students in Grades 4 to 6 over the course of 2.5 years, observed differences in CT outcomes between genders at the beginning and end of an after-school CT program. They attributed this difference to the boys' possible greater prior experience with computers, referred to as the "experience gap" (Mouza et al., 2020, p. 1050), but no significant differences in gain scores were found between boys and girls. On the other hand, Atmatzidou and Dimitriadis (2016) found that males and females have the same level of CT skills. However, in some cases, girls seemed to need additional practice to attain the same level of skill as boys. Similarly, Korucu et al. (2017) found no statistically significant differences in CT skills between 160 students aged 10 to 14, nor did Alsancak (2020) between 722 secondary school male and female students.

Large-scale analyses have also contributed to understanding gender differences in CT skills. Hubwieser and Muhling (2015) analyzed the data from 38,873 German Bebras

CT contest participants, including students aged 10 to 19, and concluded that boys generally performed better than girls. Román-González et al. (2017) revealed statistically significant differences in scores between boys and girls in fifth to tenth grades, albeit with a small effect size. The mean scores were higher in the group of boys in the seventh grade or above. The authors noted that as the grades increased, a gender gap was also developing regarding the CT skills measured by CTt.

The relationship between age and gender adds another layer of complexity to the development of CT skills. The results of the study conducted by Jiang and Wong (2021), who investigated both age and gender differences in CT skills of 197 students aged 9 to 13 years, revealed that throughout the development of CT skills, the participants' gender is not an influential factor. However, Rijke et al. (2018) discovered that after 9.5 years, female students outperformed males in abstraction tasks, indicating that gender disparities may emerge in specific CT dimensions as students grow older.

Methods

Research questions

Our study aimed to investigate how CT skills evolve as students progress through the early stages of primary education, specifically focusing on Grades 1, 2, and 3. We examined the potential influence of gender on this developmental trajectory and explored any possible interaction between grade and gender in shaping CT skills. We utilized the data collected during the psychometric validation of the Greek adaptation of the BCTt (Vourletsis & Politis, 2025), a process that demonstrated its reliability and validity as a tool for assessing CT skills among students in Grades 1 through 3.

In the Greek primary education system, the ICT curriculum (Institute of Educational Policy, 2022) is designed to progressively build CT skills as students develop cognitively. The curriculum for Grade 1 focuses on foundational concepts, such as basic algorithms and sequences related to real-life scenarios. By Grade 2, students engage with more advanced topics such as loops and algorithmic sequences, while Grade 3 introduces more complex skills, including debugging, trial-and-error approaches, and problem decomposition. This structured progression is expected to influence the development of CT skills across these grades, and grades were treated as an independent variable in the data analysis, reflecting distinct stages of cognitive and CT skill development rather than merely time spent in school.

In this context, our study addressed the following research objectives:

(1) Do students in Grades 1, 2, and 3 have different levels of CT skills?
(2) Do male and female students in Grades 1, 2, and 3 have different levels of CT skills?
(3) How do grade and gender collectively influence the CT skills of students in Grades 1, 2, and 3?

By addressing key research questions, this study provided valuable insights into the development of CT skills among young learners and enhanced our understanding of the potential factors that can influence these skills, which are regarded as essential to meet the challenges of the twenty-first century.

Participants

We employed a two-stage probability sampling approach to obtain a representative sample of primary school students aged 6 to 10 (grades 1 to 4). The chosen grades were strategically selected to examine early CT development but were also aligned with our data collection tool (BCTt) which is specifically designed and validated for use with students aged 5 to 10. During the first stage of the sampling approach, we implemented a probability proportional to size (PPS) random sampling technique. This approach can be useful with sampling units of different sizes, where the size of each unit corresponds to its inclusion probability (Cheung, 2014). We began by sorting the 13 Regional Directorates of Primary and Secondary Education in Greece according to the number of schools they supervise and randomly selecting the Attica Regional Directorate among them. Following the selection of the Regional Directorate, we proceeded to the second stage of the sampling process, and we employed a simple random sampling (SRS) approach, in which the sampling units are selected randomly with equal probability from the population (Singh, 2003). As a result, we randomly selected five schools from the list of primary schools supervised by the Attica Regional Directorate.

To determine the appropriate sample size, we followed recommendations from the literature. We need to note that there is no absolute consensus regarding the sample size required for factor analysis and scale validation. Sample sizes of at least 200–300 participants, or 10 participants per scale item, are recommended for factor analysis (Boateng et al., 2018). Additionally, Tsang et al. (2017) suggest that a respondent-to-item ratio between 5:1 and 30:1 is generally acceptable. Given that our 25-item BCTt scale required a sufficient sample size for rigorous psychometric analysis, we aimed to adhere to established guidelines suggesting a respondent-to-item ratio between 5:1 and 30:1. Furthermore, while ensuring that the sample size was sufficient for factor analysis during the psychometric validation, we calculated the Kaiser–Meyer–Olkin (KMO) Measure of Sampling Adequacy (Arafat et al., 2016).

Initially, our initial sample comprised 673 students: 294 males and 379 females. However, we observed a ceiling effect during the analysis of student scores by grade, particularly among Grade 4 students, as approximately 17% of them achieved the highest score on the scale. This percentage exceeded the common threshold of 15% of respondents achieving the lowest or highest possible score for floor and ceiling effect respectively (Terwee et al., 2007), causing us to exclude the Grade 4 students (66 males and 90 females) from the final sample. The final sample comprised 517 students (see Table 1).

Table 1 Student distribution by grade and gender

Grade	Males	Females	Total	% Males	% Females
1	63	97	160	39.4	60.6
2	77	95	172	44.8	55.2
3	88	97	185	47.6	52.4
Total	228	289	517	44.1	55.9

Data collection and analysis

Data collection adhered to ethical guidelines and took place in May and June 2022. To ensure consistent administration and minimize potential biases, the author was the sole administrator for the test. The author administered the BCTt scale to the participating students, providing detailed instructions and examples for each concept included in the scale, as outlined in the original BCTt protocol. Digital presentations were used to deliver instructions and examples to all students, aiming to provide a standardized learning environment. Students were allowed to ask questions during the test, while the author provided individual explanations focusing solely on the mechanics of the questions, without offering hints or clues about the correct answers. The 25-item scale assessed students' CT skills in sequences, loops (simple and nested), and conditionals (if–then, if–then-else, and while). Students required 35 (Grade 3) to 55 min (Grades 1 and 2) to complete the test. Immediately afterwards, we used a spreadsheet and coded the students' responses with a value of 1 for the correct answers and a value of 0 for the wrong answers.

To address our research questions, we employed a two-way ANOVA and a multiple linear regression analysis. The two-way ANOVA is frequently used to investigate possible interaction effects between two independent variables on a continuous dependent variable (Kim, 2014). We used it to investigate the possible interaction effect between students' grades and gender (independent variables) on their CT score (dependent variable) but also the main effects, specifically how each factor (grade and gender) independently influenced CT scores. Before conducting the test, we ensured that the required assumptions were met: the CT score was measured continuously and the independent variables included at least two independent groups. Furthermore, there were no significant outliers and the distributions of the scores were approximately normal for each cell (including grade and gender combinations). The assumption of homogeneity of variances was violated, but the ratio of the largest to the smallest group variance was less than 3, which permits the use of two-way ANOVA (Jaccard, 1998). Finally, we calculated the partial eta squared (η_p^2) coefficient and reported the effect size, which was interpreted similarly to the eta squared (η^2) coefficient. Cohen (1977) stated that a small effect size typically falls in the range of $\eta^2 < 0.06$, a medium effect size is observed when $0.06 \le \eta^2 < 0.14$, and a large effect size is evident when $\eta^2 \ge 0.14$.

To further explore the potential interaction between grade and gender on CT skills, we conducted a multiple linear regression analysis. This analysis offered several additional benefits, such as the quantification of effects, thus indicating how much CT scores change with each unit increase in grade and whether gender has a measurable impact (Mason & Perreault, 1991). Additionally, it provided insights into the proportion of variance in CT scores explained by grade and gender, and evaluated the overall fit of the model. To conduct the analysis, we ensured that the required assumptions regarding the study design were met. The CT score (dependent variable) was measured at the continuous level, while the independent variables (grade and gender) were treated as nominal variables. To assess the independence of residuals, we calculated a Durbin-Watson statistic of 1.64, which suggests that the independence assumption was met, as a value between 1.5 and 2.5, ideally close to 2.0, indicates independence (Turner, 2019). We also found a linear relationship between the dependent variable and each of our independent variables, and also between the dependent variable and the independent variables collectively, through the visual inspection of the partial regression plots and the scatterplot of studentized residuals against predicted values, respectively. The latter was also used to inspect homoscedasticity of residuals. Afterwards, we ensured that our independent values were not highly correlated with each other (multicollinearity), there were no significant outliers, high leverage points or highly influential points, and that the residuals (errors) were approximately normally distributed (Sarstedt & Mooi, 2019). Finally, we calculated the multiple correlation coefficient (*R*), the percentage of variance explained (R^2 and adjusted R^2), and the statistical significance of the overall model. The value of R ranges from 0 to 1, where higher values indicate higher predictability of the dependent variable from the independent variables, while the value of R^2 is between 0.02 and 0.13 for a weak effect size, between 0.13 and 0.26 for a moderate and greater than 0.26 for a large effect size (Cohen, 1977). According to Sarstedt and Mooi (2019), values of 0.10 are normal in cross-sectional data in exploratory research.

Results

Grade-level differences

From a developmental perspective, we examined the main effect of grade on CT scores, conducting a two-way ANOVA using unweighted marginal means, given the unbalanced design of the study with differing numbers of students across grades. The analysis revealed a statistically significant main effect of grade on CT scores, $F(2, 511) = 21.127$, $p < .001$, $\eta_p^2 = 0.08$. The effect size was moderate, indicating that differences in CT scores among students of different grade are meaningful. The unweighted marginal means for CT scores were 12.47 ($SE = 0.465$) for Grade 1, 13.50 ($SE = 0.441$) for Grade 2, and 16.36 ($SE = 0.423$) for Grade 3. These means (see Table 2) represent the estimated average CT scores for each grade group.

All pairwise comparisons were conducted (see Table 3), with p-values being Bonferroni-adjusted. Grade 3 students were associated with a mean CT score of 3.88, 95% CI [2.37, 5.39] points higher than that of Grade 1 students, $p < .001$, and 2.86, 95% CI [1.39, 4.33] points higher than that of Grade 2 students, $p < .001$. These findings indicate a statistically significant increase in CT scores as students advance from Grade 1 to Grade 3.

Table 2 Unweighted marginal means, standard errors, and 95% confidence intervals for CT scores by grade

Estimates				
Dependent variable: CT score				
Grade	Mean	Std. error	95% Confidence interval	
			Lower bound	Upper bound
1	12.47	.465	11.561	13.388
2	13.50	.441	12.630	14.362
3	16.36	.423	15.524	17.186

Table 3 Pairwise comparisons of CT scores across grades with bonferroni adjustment

Pairwise comparisons

Dependent variable: CT score

(I) Grade	(J) Grade	Mean difference (I-J)	Std. error	Sig[b]	95% Confidence interval for difference[b]	
					Lower bound	Upper bound
1	2	– 1.022	.641	.334	– 2.561	.517
	3	– 3.881*	.629	< .001	– 5.391	– 2.371
2	1	1.022	.641	.334	– .517	2.561
	3	– 2.859*	.611	< .001	– 4.326	– 1.392
3	1	3.881*	.629	< .001	2.371	5.391
	2	2.859*	.611	< .001	1.392	4.326

Based on estimated marginal means

*The mean difference is significant at the .05 level

[b]Adjustment for multiple comparisons: Bonferroni

Gender disparities

We also conducted the two-way ANOVA using unweighted marginal means, to examine the main effect of gender on CT scores. The analysis revealed that there was no statistically significant main effect of gender on CT scores, $F(1, 511) = 0.149$, $p = .700$, $\eta_p^2 = 0.00$, indicating that CT scores did not differ significantly between male ($M = 14.21$, $SE = 0.384$) and female students ($M = 14.01$, $SE = 0.338$). The value of the effect size indicated that there was no meaningful difference in CT scores between male and female primary school students. Overall, these results suggest that, when controlling for grade, gender does not have a meaningful impact on the CT skills of students in Grades 1, 2, and 3.

Collective influence of grade and gender

First, we conducted a two-way ANOVA to examine the effects of grade and gender on the CT skills of students. We found that the interaction effect between grade and gender on CT score was not statistically significant, $F(2, 511) = 0.008$, $p = .992$, $\eta_p^2 = 0.00$). The effect size for the interaction effect is negligible, indicating that the interaction between grade and gender has no practical significance in explaining the variation in CT scores among students of different grade and gender. Overall, this suggests that the effect of grade on CT skills is consistent across both genders, without any significant interaction (Fig. 1).

While the two-way ANOVA allowed us to assess the effects of grade and gender on the students' CT skills, the multiple regression analysis provided a quantification of the independent variables' effects on the dependent variable and insights into the overall fit of the model. Using grade and gender as predictors of CT scores, the regression model was statistically significant, $F\ (2, 514) = 20.381$, $p < .001$, indicating that grade and gender together significantly predict the variance in CT scores. The Multiple Correlation Coefficient (R) value was 0.271, reflecting a weak correlation between the observed and predicted CT scores, thus a weak linear association between the dependent variable and the independent variables. The R^2 value was 0.073, indicating that approximately

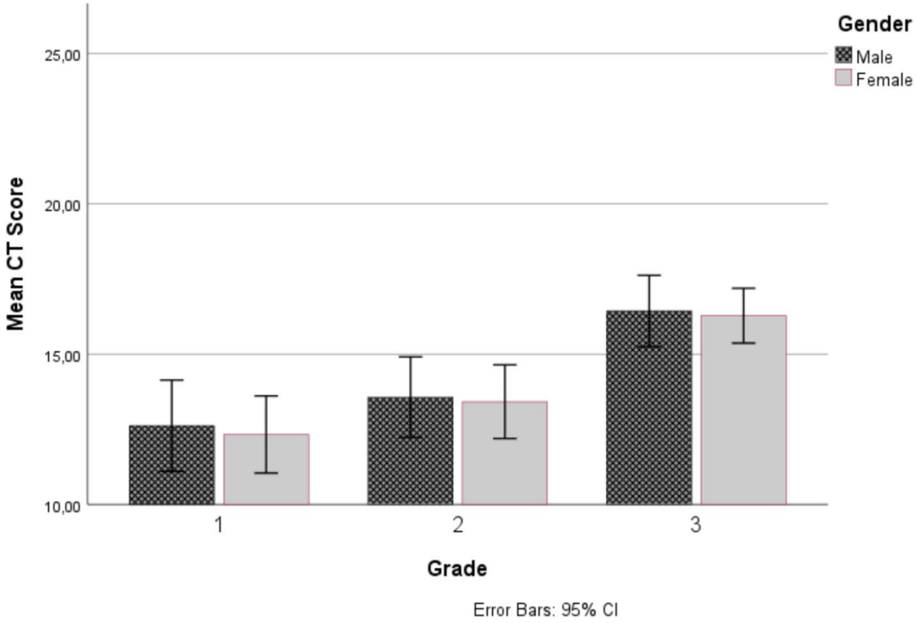

Fig. 1 Clustered Bar (Mean) of CT scores by grade and gender

7.3% of the variance in CT scores can be explained by the independent variables. The Adjusted R^2 value was 0.070, indicating that approximately 7.0% of the variance in CT scores is explained by the predictors (grade and gender), after adjusting for the number of predictors in the model. This suggests that, although the model explains some of the variance in CT scores, a substantial proportion remains unexplained, possibly due to other factors not included in the model. The unstandardized coefficient (B) for grade was significant with value 1.968, suggesting that for each additional grade level, the CT score increases by approximately 1.968, holding gender constant. Additional details, such as the standard errors and 95% confidence intervals for the regression coefficients, are provided in Tables 4 and 5.

Table 4 Unweighted marginal means, standard errors, and 95% confidence intervals for CT scores by gender

Estimates				
Dependent variable: CT score				
Gender	Mean	Std. error	95% Confidence interval	
			Lower bound	Upper bound
Male	14.21	.384	13.45	14.96
Female	14.01	.338	13.35	14.67

Table 5 Multiple regression results for CT scores

CT score	*B*	95% CI for B		SE *B*	β	R^2	ΔR^2
		LL	*UL*				
Model						.07	.07
Constant	10.442*	8.32	12.57	1.08			
Grade	1.968*	1.36	2.58	.31	.27		
Gender	− .183	− 1.19	.82	.51	− .02		

Model = "Enter" method in SPSS Statistics, B = unstandardized regression coefficient, CI = confidence interval, *IL* = lower limit, *UL* = upper limit, *SE B* = standard error of the coefficient, β = standardized coefficient, R^2 = coefficient of determination, ΔR^2 = adjusted R^2

*$p < .001$

Discussion

Our study investigated grade-level differences and gender disparities in CT skills among primary school students. Although the literature highlights differences in sub-dimensions of CT, the current study took a holistic approach, focusing on overall CT skills. Our findings included significant differences in CT scores among students in different primary school grades, strongly supporting the notion of a developmental trajectory in CT skills. As we mentioned, the Greek ICT curriculum is structured to progressively build CT skills from foundational concepts in Grade 1 to more advanced skills in Grade 3, which aligns with the observed developmental trajectory. These findings also align with Piaget's (1964) theory of cognitive development, which suggests that as children advance through distinct stages of cognitive maturity, their ability to understand increasingly complex concepts also improves. As students progressed from Grade 1, representing the initial stage of primary school, to Grade 3, there was a statistically significant increase in mean CT scores. Grade 3 students exhibited the highest CT scores, with a substantial difference compared to Grade 1 and Grade 2 students.

According to Piaget's (1964) theory, younger students in Grade 1 may still be in the late preoperational or early concrete operational stage, where they can think logically about concrete events but have difficulties with abstract reasoning. By Grade 3, children have typically reached the concrete operational stage, which allows for improved logical thinking and handling of more complex CT tasks. Our results support the notion that as students advance in their primary school education, there is a noticeable improvement in their CT skills, as found by other researchers (An, 2022; Jiang & Wong, 2021; Polat et al., 2021; Relkin et al., 2020; Rijke et al., 2018). The effect size was moderate, underscoring meaningful grade-related differences. Overall, our findings are consistent with the idea that cognitive maturity contributes to the progression of CT skills, as proposed by Piaget (1964) and supported by educational research (Román-González et al., 2017; Seiter & Foreman, 2013).

It is noteworthy that the curriculum for ICT in Greece aligns with the observed grade-level differences in CT skills. The curriculum emphasizes deeper modelling and more complex CT skills in Grade 3 compared to the foundational skills taught in Grades 1 and 2. This alignment between curriculum complexity and developmental stages might contribute to the observed increase in CT scores between Grades 2 and 3. Students in Grade 3, exposed to more advanced CT concepts, might experience a greater developmental leap in their CT skills compared to the foundational skills learned in Grades 1 and 2. This idea is further supported by Tsarava et al. (2022), who found that CT skills are differentially influenced by various cognitive abilities, including numerical, verbal, and visuospatial reasoning, which develop progressively as children grow older. Beyond curriculum and individual variations, other factors not directly measured in this study might also influence CT development.

Overall, the grade-level differences observed in our study emphasized the importance of considering students' educational stages when assessing and fostering CT skills. As CT skills become increasingly integral to modern curricula, recognizing these grade-related disparities is essential for tailoring educational strategies to promote CT skill development effectively. Future research could use a continuous measure of age across a broader age range, possibly allowing for a more comprehensive examination of this developmental trajectory and comparisons between primary and secondary school students.

In the context of investigating gender disparities in CT skills among primary school students, our study provided findings that both align with and diverge from existing literature. Our findings did not reveal significant gender differences in CT scores among primary school students. This result is consistent with those of prior research regarding kindergarten (Angeli & Valanides, 2020; Papadakis et al., 2016) and older students (Alsancak, 2020; Del Olmo-Muñoz et al., 2020). However, many studies that found gender disparities in kindergarten and primary school levels revealed that either the effect size was small (Polat et al., 2021; Román-González et al., 2017) or the disparities regarded specific or advanced CT skills (Sullivan & Bers, 2013, 2016). In conclusion, our findings contribute to the ongoing discourse on gender disparities in CT skills among primary school students and support the notion of the narrowing of the gender gap. Furthermore, we emphasize the need for continued exploration of gender-related differences in CT skills, considering the potential influence of various factors such as age, educational context, and the specific CT skills being assessed.

Our study also contributes to the limited literature on grade-gender interaction in CT skill development among primary school students. We found no significant interaction between grade and gender in CT skill development and our multiple regression analysis indicated that grade and gender together predict the variance in CT scores, albeit weakly. Grade had a significant impact, with older students showing higher CT scores, while gender had no practical effect on CT scores, aligning with some literature (Jiang & Wong, 2021), but differing from Rijke et al. (2018), who found age-related gender differences in specific CT skills after the age of 9.5 years.

Finally, our results have implications for educational strategies and interventions aimed at enhancing CT skills across different grades. However, it is crucial to acknowledge the cross-sectional nature of our study, which may have restricted our ability to detect subtle effects. Moreover, our data came from multiple schools and classrooms, introducing potential variance due to differences in teaching methods and classroom environments. A hierarchical (multi-level) linear regression could account for this nested structure, but our sample size did not meet the required criteria for such an analysis. Future research should aim to include a larger sample size and utilize hierarchical models to better understand the impact of classroom and school-level differences on CT skills.

Conclusions

In this study, our primary aim was to investigate age- and gender-related disparities in CT skills among primary school students. Regarding age-related differences, our study found a significant increase in CT scores as students progressed from lower to higher grades, reflecting the cognitive growth that allows them to handle more complex computational tasks. This finding aligns with a developmental perspective and is consistent with prior research, suggesting that CT skills develop with cognitive maturity and educational advancement. Gender differences, on the other hand, were not significant in our findings, aligning with previous research on both younger and older students, indicating that gender disparities in CT skills may not be a prominent issue in primary education. However, gender-related variations in CT skills frequently depend on the specific skills assessed and the age groups studied.

In conclusion, our study underscored the importance of considering both age- and gender-related factors in understanding CT skill development among primary school students. While age-related improvements in CT skills highlight the need for strategies tailored to students' developmental stages, gender disparities may not be a significant concern at this level. This research contributes to the ongoing dialogue on CT skill development, offering insights that can guide more inclusive and effective educational approaches in primary schools. However, it is important to note that the cross-sectional nature of this study limits the ability to infer causality and the sample characteristics may affect the generalizability of the findings. Data were also collected across multiple schools and classrooms, limiting the use of a multilevel model. Future research could further investigate the relationship between gender, age, and CT skills, considering additional contextual factors and individual differences among students. By addressing them, educators and policymakers could possibly better support the cultivation of CT skills in primary school students, thus preparing them for success in an increasingly digital and complex world.

References

Alsancak, D. (2020). Investigating computational thinking skills based on different variables and determining the predictor variables. *Participatory Educational Research, 7*(2), 102–114. https://doi.org/10.17275/per.20.22.7.2

An, M. (2022). CTST: Development and validation of an sequence ability in computational thinking in early childhood education. In *Proceedings of the 5th International Conference on Big Data and Education* (pp. 241–247). https://doi.org/10.1145/3524383.3524445

Angeli, C., & Georgiou, K. (2023). Investigating the effects of gender and scaffolding in developing preschool children's computational thinking during problem-solving with Bee-Bots. *Frontiers in Education*. https://doi.org/10.3389/feduc.2022.757627

Angeli, C., & Giannakos, M. (2020). Computational thinking education: Issues and challenges. *Computers in Human Behavior*. https://doi.org/10.1016/j.chb.2019.106185

Angeli, C., & Valanides, N. (2020). Developing young children's computational thinking with educational robotics: An interaction effect between gender and scaffolding strategy. *Computers in Human Behavior*. https://doi.org/10.1016/j.chb.2019.03.018

Annamalai, S., Che Omar, A., & Abdul Salam, S. N. (2022). Review of computational thinking models in various learning fields. *International Journal of Education, Psychology and Counseling, 7*(48), 562–574. https://doi.org/10.35631/ijepc.748042

Arafat, S., Chowdhury, H., Qusar, M., & Hafez, M. (2016). Cross cultural adaptation and psychometric validation of research instruments: A methodological review. *Journal of Behavioral Health, 5*(3), 129. https://doi.org/10.5455/jbh.20160615121755

Ardito, G., Czerkawski, B., & Scollins, L. (2020). Learning computational thinking together: Effects of gender differences in collaborative middle school robotics program. *TechTrends, 64*(3), 373–387. https://doi.org/10.1007/s11528-019-00461-8

Atmatzidou, S., & Demetriadis, S. (2016). Advancing students' computational thinking skills through educational robotics: A study on age and gender relevant differences. *Robotics and Autonomous Systems, 75*, 661–670. https://doi.org/10.1016/j.robot.2015.10.008

Babazadeh, M., & Negrini, L. (2022). How is computational thinking assessed in European K-12 education? A systematic review. *International Journal of Computer Science Education in Schools, 5*(4), 3–19. https://doi.org/10.21585/ijcses.v5i4.138

Boateng, G. O., Neilands, T. B., Frongillo, E. A., Melgar-Quiñonez, H. R., & Young, S. L. (2018). Best practices for developing and validating scales for health, social, and behavioral research: A primer. *Frontiers in Public Health*. https://doi.org/10.3389/fpubh.2018.00149

Brennan K, & Resnick, M. (2012). New frameworks for studying and assessing the development of computational thinking. In *Proceedings of the annual American educational research association meeting*, pp. 1–25. Vancouver, Canada. https://web.media.mit.edu/~kbrennan/files/Brennan_Resnick_AERA2012_CT.pdf

Cheung, A. K. L. (2014). Probability proportional sampling. In A. C. Michalos (Ed.), *Encyclopedia of quality of life and well-being research* (pp. 5069–5071). Springer.

Cohen, J. (1977). *Statistical power analysis for the behavioral sciences*. Lawrence Erlbaum Associates Inc.

CSTA & ISTE. (2011). *Operational definition of computational thinking for K–12 education*. https://cdn.iste.org/www-root/Computational_Thinking_Operational_Definition_ISTE.pdf

Cutumisu, M., Adams, C., & Lu, C. (2019). A Scoping review of empirical research on recent computational thinking assessments. *Journal of Science Education and Technology, 28*(6), 651–676. https://doi.org/10.1007/s10956-019-09799-3

Del Olmo-Muñoz, J., Cózar-Gutiérrez, R., & González-Calero, J. A. (2020). Computational thinking through unplugged activities in early years of primary education. *Computers & Education, 150*, 103832. https://doi.org/10.1016/j.compedu.2020.103832

Grover, S., & Pea, R. (2018). Computational thinking: A competency whose time has come. In S. Sentence, E. Barendsen, & C. Schulte (Eds.), *Computer science education: Perspectives on teaching and learning in school* (pp. 19–38). Bloomsbury Academic.

Hamamsy, L.E., Zapata-Cáceres, M., Martín-Barroso, E., Mondada, F., Dehler-Zufferey, J., Bruno, B., & Román-González, M. (2023). The competent Computational Thinking test (cCTt): A valid, reliable and gender-fair test for longitudinal CT studies in grades 3–6. *ArXiv.* https://arxiv.org/abs/2305.19526

Hubwieser, P., & Muhling, A. (2015). Investigating the psychometric structure of bebras contest: Towards measuring computational thinking skills. In *2015 International Conference on Learning and Teaching in Computing and Engineering* (pp. 62–69). https://doi.org/10.1109/latice.2015.19

Institute of Educational Policy (2022). Πρόγραμμα Σπουδών για το Μάθημα Πληροφορική και Τεχνολογίες της Πληροφορίας και Επικοινωνιών Δημοτικού [Curriculum for Informatics and Information and Communications Technology for Primary School]. https://www.iep.edu.gr/el/nea-ps-provoli.

Jaccard, J. (1998). *Interaction effects in factorial analysis of variance*. SAGE Publications Inc.

Jiang, S., & Wong, G. K. W. (2021). Exploring age and gender differences of computational thinkers in primary school: A developmental perspective. *Journal of Computer Assisted Learning, 38*(1), 60–75. https://doi.org/10.1111/jcal.12591

Kim, H. S., Kim, S., Na, W., & Lee, W. J. (2021). Extending computational thinking into information and communication technology literacy measurement. *ACM Transactions on Computing Education, 21*(1), 1–25. https://doi.org/10.1145/3427596

Kim, H. Y. (2014). Statistical notes for clinical researchers: Two-way analysis of variance (ANOVA)-exploring possible interaction between factors. *Restorative Dentistry & Endodontics, 39*(2), 143. https://doi.org/10.5395/rde.2014.39.2.143

Korucu, A. T., Gencturk, A. T., & Gundogdu, M. M. (2017). Examination of the computational thinking skills of students. *Journal of Learning and Teaching in Digital Age, 2*(1), 11–19.

Lodi, M., & Martini, S. (2021). Computational thinking, between papert and wing. *Science & Education, 30*(4), 883–908. https://doi.org/10.1007/s11191-021-00202-5

Mason, C. H., & Perreault, W. D. (1991). Collinearity, power, and interpretation of multiple regression analysis. *Journal of Marketing Research, 28*(3), 268–280. https://doi.org/10.1177/002224379102800302

Mouza, C., Pan, Y.-C., Yang, H., & Pollock, L. (2020). A multiyear investigation of student computational thinking concepts, practices, and perspectives in an after-school computing program. *Journal of Educational Computing Research, 58*(5), 1029–1056. https://doi.org/10.1177/0735633120905605

Papadakis, S., Kalogiannakis, M., & Zaranis, N. (2016). Developing fundamental programming concepts and computational thinking with ScratchJr in preschool education: A case study. *International Journal of Mobile Learning and Organisation, 10*(3), 187–202. https://doi.org/10.1504/ijmlo.2016.077867

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

Piaget, J. (1964). Cognitive development in children: Development and learning. *Journal of Research in Science Teaching, 2*, 176–186. https://doi.org/10.1002/tea.3660020306

Polat, E., Hopcan, S., Kucuk, S., & Sisman, B. (2021). A comprehensive assessment of secondary school students' computational thinking skills. *British Journal of Educational Technology, 52*(5), 1965–1980. https://doi.org/10.1111/bjet.13092

Polya, G. (1945). *How to solve it*. Princeton University Press. https://doi.org/10.1515/9781400828678

Poulakis, E., & Politis, P. (2021). Computational thinking assessment: Literature review. In T. Tsiatsos, S. Demetriadis, A. Mikropoulos, & V. Dagdilelis (Eds.), *Research on E-Learning and ICT in education* (pp. 11–128). Springer.

Relkin, E., de Ruiter, L., & Bers, M. U. (2020). TechCheck: Development and validation of an unplugged assessment of computational thinking in early childhood education. *Journal of Science Education and Technology, 29*(4), 482–498. https://doi.org/10.1007/s10956-020-09831-x

Rijke, W. J., Bollen, L., Eysink, T. H. S., & Tolboom, J. L. J. (2018). Computational thinking in primary school: An examination of abstraction and decomposition in different age groups. *Informatics in Education, 17*(1), 77–92. https://doi.org/10.15388/infedu.2018.05

Román-González, M. (2015). Computational thinking test: Design guidelines and content validation. In *EDULEARN15 Proceedings* (pp. 2436–2444). IATED. https://library.iated.org/view/ROMANGONZALEZ2015COM

Román-González, M., Pérez-González, J.-C., & Jiménez-Fernández, C. (2017). Which cognitive abilities underlie computational thinking? Criterion validity of the computational thinking test. *Computers in Human Behavior, 72*, 678–691. https://doi.org/10.1016/j.chb.2016.08.047

Sarstedt, M., & Mooi, E. (2019). A concise guide to market research. *Springer Texts in Business and Economics*. https://doi.org/10.1007/978-3-662-56707-4_7

Seiter, L., & Foreman, B. (2013). Modeling the learning progressions of computational thinking of primary grade students. In *Proceedings of the Ninth Annual International ACM Conference on International Computing Education Research* (pp. 59–66). https://doi.org/10.1145/2493394.2493403

Selby, C., & Woollard, J. (2013). Computational thinking: The developing definition. https://eprints.soton.ac.uk/356481/1/Selby_Woollard_bg_soton_eprints.pdf

Singh, S. (2003). Simple random sampling. *Advanced sampling theory with applications* (pp. 71–136). Springer.

Sullivan, A., & Bers, M. U. (2013). Gender differences in kindergarteners' robotics and programming achievement. *International Journal of Technology and Design Education, 23*, 691–702. https://doi.org/10.1007/s10798-012-9210-z

Sullivan, A., & Bers, M. U. (2016). Girls, boys, and bots: gender differences in young children's performance on robotics and programming tasks. *Journal of Information Technology Education Innovations in Practice, 15*, 145–165. https://doi.org/10.28945/3547

Sullivan, F. R., & Heffernan, J. (2016). Robotic construction kits as computational manipulatives for learning in the STEM disciplines. *Journal of Research on Technology in Education, 48*(2), 105–128. https://doi.org/10.1080/15391523.2016.1146563

Tang, X., Yin, Y., Lin, Q., Hadad, R., & Zhai, X. (2020). Assessing computational thinking: A systematic review of empirical studies. *Computers & Education*. https://doi.org/10.1016/j.compedu.2019.103798

Terwee, C. B., Bot, S. D. M., de Boer, M. R., van der Windt, D. A. W. M., Knol, D. L., Dekker, J., Bouter, L. M., & de Vet, H. C. W. (2007). Quality criteria were proposed for measurement properties of health status questionnaires. *Journal of Clinical Epidemiology, 60*(1), 34–42. https://doi.org/10.1016/j.jclinepi.2006.03.012

Tsang, S., Royse, C., & Terkawi, A. (2017). Guidelines for developing, translating, and validating a questionnaire in perioperative and pain medicine. *Saudi Journal of Anaesthesia, 11*(5), 80. https://doi.org/10.4103/sja.sja_203_17

Tsarava, K., Moeller, K., Román-González, M., Golle, J., Leifheit, L., Butz, M. V., & Ninaus, M. (2022). A cognitive definition of computational thinking in primary education. *Computers & Education, 179*, 104425. https://doi.org/10.1016/j.compedu.2021.104425

Turner, P. (2019). Critical values for the Durbin-Watson test in large samples. *Applied Economics Letters, 27*(18), 1495–1499. https://doi.org/10.1080/13504851.2019.1691711

UNESCO Institute for Statistics. (2012). *International standard classification of education: ISCED 2011*. https://doi.org/10.15220/978-92-9189-123-8-en

Vourletsis, I., & Politis, P. (2025). Greek translation cultural adaptation and psychometric validation of beginners computational thinking test (BCTt). *Education and Information Technologies, 30*(2), 2211–2235. https://doi.org/10.1007/s10639-024-12887-6

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. (2011). Research notebook: Computational thinking—What and why? *The link magazine.* https://www.cs.cmu.edu/link/research-notebook-computational-thinking-what-and-why.

Zapata-Cáceres, M. Martín-Barroso, E., & Román-González, M. (2021). BCTt: Beginners Computational Thinking Test. In *Understanding computing education (Vol 1). Proceedings of the Raspberry Pi Foundation Research Seminar series*. www.rpf.io/seminar-proceedings-2020

Zapata-Cáceres, M., Martín-Barroso, E., & Román-González, M. (2020). Computational thinking test for beginners: Design and content validation. *2020 IEEE Global Engineering Education Conference (EDUCON)*. https://doi.org/10.1109/educon45650.2020.9125368

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