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Does Gender Influence the Learning Process of Computational Thinking in Secondary Education?

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ABSTRACT

The gender gap in STEM disciplines both in the workplace and in university education is still a reality. Computational thinking (CT) is deeply related to these disciplines. CT is fundamental to problem-solving and critical thinking, skills that are core to STEM disciplines. CT involves skills like algorithmic thinking, pattern recognition, and abstraction, all of which are necessary for tasks in fields such as engineering, computer science, mathematics, and science. It is important to understand gender differences, if any, in the acquisition of CT skills, so that we can develop more effective teaching strategies for all. This study analyses the gender differences in the development of CT skills (measured with a standard test) in 149 students of a Spanish secondary school, in three courses between 12 and 14 years old, before and after classroom work sessions with a 3D robotics simulator. In the empirical evidence a relevant a priori gender difference was detected in the first course, likely related with prior experiences on computer programming, but boys and girls finish the first year with similar CT levels. Disparate results appear for second year (male students improve more) and third year (female students improve more) which demands further study.

1 | Introduction

The term computational thinking has entered the educational vocabulary quickly and effectively. And it has done so not only in the technology or computer science environment; today no one doubts that the skills associated with computational thinking such as abstraction, decomposition, feature extraction or algorithmic thinking are of enormous value in any discipline [1]. Because of the growing importance given to computational thinking, more and more research is being done on the acquisition of these skills by schoolchildren of different ages, from infants [1] to university students [2]. Much research is also directed at determining what factors influence the acquisition of computational thinking [3, 4].

There is a broad consensus regarding the close relationship between computational thinking skills and programming [5]. The term Computational Thinking (CT) has been employed since Papert [6] defined it in the inaugural issue of Mathematics Education. In Repenning et al. work [7] the CT process is synthesized in three phases: problem formulation, solution expression and execution and evaluation. In the last decade, there has been an increasing interest on the benefits that CT provides to children and there has been an effort to define designs of Computer Science curricula [4]. Many of these CT experiences are being designed around programming, and especially block-based programming environments such as Scratch, Alice, Blockly, MIT App Inventor, among others.

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While computational thinking can be developed in various ways, research suggests that robotics is an effective approach. This is due to its ability to enhance CT skills [8–10]. Educational robotics (ER) provide a suitable platform for developing skills in a fun and meaningful way. They also offer opportunities to engage with a range of disciplines, including science, technology, engineering, and mathematics (STEM), literacy, social studies, dance, music, and arts [11, 12]. ER can be used to teach specific content in a domain, such as engineering, or more commonly, as construction and programming tools to promote problem-solving and CT [9].

Simulators have been a part of robot research and development for some time. However, due to the COVID-19 pandemic, there has been a growing interest in using simulators for educational robotics [13]. While simulators cannot fully replace robots, they do assist teachers in their work. For instance, the quantity of physical robots in the classroom can be decreased if students use a simulator [14, 15]. They can download their program to the robot only when it is sufficiently mature and debugged. This approach also enables online or blended learning, where each student can work with the simulator from home, among other benefits.

Despite initiatives to increase the presence of women in the STEM field, there is still a significant gender gap [16]. Women make up about one-third of the STEM workforce in United States. In 2019, women accounted for 48% of life scientists and 65% of social scientists but only 35% of physical scientists, 26% of computer and mathematical scientists, and 16% of engineers. The distribution of women who earned degrees in Science and Engineering fields was similar to their distribution among STEM occupations at the bachelor's degree level or higher [17]. In this context, it is particularly important to examine the mechanisms that influence this gender inequality in science and engineering. Technical self-efficacy is one of the factors that researchers have found to be gender biased [18]. It is therefore worth asking whether this gender gap in STEM is replicated in the acquisition of computational thinking.

In this article, we present both diachronic and synchronic gender differences in the acquisition of computational thinking skills measured through a study with 149 students between first and third secondary school grade from one public high school in the Community of Madrid. We measured the scores obtained in a standard CT test before and after working on these skills in the classroom using a robotics simulator for 1 month (approximately six sessions of work in the classroom). We pose three research questions:

1. **RQ1**: Do 12–14 year-old students' CT skills improve after working with a robotics simulator?
2. **RQ2**: Are there differences between the different ages in terms of the CT starting level and the level acquired after the intervention?
3. **RQ3**: Are there differences in the acquisition of CT skills by gender?

2 | Related Work

Regarding Computational Thinking and gender differences, while gender gaps in STEM disciplines are apparent at all levels of education, they become more pronounced as the education level increases [19]. As stated in the UNESCO report, we need to understand and target the specific barriers that keep female students out of STEM disciplines. This knowledge will teach us how to stimulate their interest from the earliest years, to combat stereotypes, to train teachers to encourage girls to pursue STEM subjects and to choose STEM careers.

Despite all the efforts made in recent years investigating the reasons for these gender differences in the choice of STEAM careers, many questions remain. At what age do these differences begin to be perceived? Is there a real gender gap in learning STEM disciplines? Is there a negative self-perception of girls about their performance in these subjects? What factors influence this negative perception?

In this scenario, we can find that most of the studies found in the literature focus on different aspects related to computational thinking. These studies mainly analyse computer science areas such as robotics and computer programming and the students' attitudes towards them [5]. Moreover, authors also have evaluated the influence on the use of physical devices [2] or the perception of self-efficacy in learning programming [20], considering gender as an aspect to be added to these studies. In [21], the authors found that students' interest and self-efficacy in STEM careers were significantly higher in male than in female students. Using a questionnaire, they explore the factors that lead to this difference in Chinese culture and the gender differences in the relationship with these factors. They analyse environmental factors, STEM self-efficacy, perceptions of STEM careers and interest in STEM careers.

Sevilla et al. [22] examine the persistence in STEM programs trying to identify whether exposure to STEM courses within the academic or vocational tracks translates into fewer gender differences in STEM higher education. They found that although exposure to STEM courses during the precollege years is the most effective way to encourage STEM career choice, it does not appear to influence career continuation in later years.

There is also some research focused on gender differences in the acquisition of skills related to computational thinking (decomposition, abstraction, algorithmic thinking, and pattern recognition). There are some studies that report no gender differences in CT skills, such as [23], which examined the grouping effect in 8–11 year old Idaho students in CT and robotics adquisition or [24]. This study examined gender differences in coding performance before and after implementing a 24-lesson visual programming curriculum using ScratchJr in first grade learners. The authors found that gender had no effect on either CT acquisition robotics performance or coding proficiency. In a study of 128 participants in Malaysia [25], the authors found that while the relationship between CT skills and mathematics achievement was statistically significant, there were no significant gender differences in CT skills.

However, there are other studies in the literature that show appreciable gender differences in skills related to computational thinking and programming or attitudes towards robotics and programming in boys and girls. The results in [26] showed that CT performance of boys was higher than that of girls.

In the literature, learners' prior attitudes towards programming and robotics have been analyzed and considered key to explaining differences in performance between students, even at a very early age, as in [27]. The authors found that, among boys and girls aged 4–7, boys liked building things more than girls, but both genders liked robotics equally. No gender differences were found in construction, technological concepts, or basic programming. In advanced programming tasks for their age (e.g., loops with sensors), boys showed better results than girls.

In the case of older students (aged 10–13) the situation is similar. Boys perform slightly better than girls, as reported in [5] in computational thinking. This better performance is linked to a more positive attitude of boys towards programming. When analyzing in detail the process of acquiring these skills, as they do in [28], it is observed that girls focus on planning and reflection processes while boys focus on more functional aspects.

With such disparate results, it seems important to continue research both to understand whether gender does indeed influence the acquisition of CT skills and, if so, what factors explain this difference and how to act on these factors to reduce the gender gap. A good understanding of the existence of gender differences in the acquisition of CT skills and an analysis of the causes is also fundamental to be able to establish mechanisms or guidelines, as proposed in [29], to reduce the gender gap in the acquisition of CT. In our case, the focus of our study is dual, on the one hand diachronic, looking at differences in the acquisition of CT skills across different ages. On the other hand, we also study the gender differences in the acquisition of CT.

Regarding Computational Thinking and Robotics, CT may be taught and learned using robots. In fact, educational robotics (ER) is widely extended as a way to teach STEM skills [9, 30], including CT, and a nice and efficient way to introduce children to technology basic concepts. The combination of ER and CT has been widely explored with students of different ages, from elementary school [31] to primary education [8] and secondary education [10]. A comprehensive literature review on the combination of Robotics and CT can be found in [32, 33].

Physical robots are naturally compelling and awaken the students' curiosity and motivation. Many successful robots are used in the ER, such as WeDo, Mindstorms EV3, or Spike from LEGO; Mbot from Makeblock; Thymio and Edison programmable robots. Beyond physical robots, virtual robots have also been explored [34] in the last few years. Simulated robots keep the potential for learning while providing some practical advantages such as cheaper cost, no need for maintenance, and anywhere-anytime availability. There are several tools for teaching robotics with simulated robots: OpenRoberta, GearsBot, and CoderZ to mention a few. An interesting comparison between physical and virtual robots can be found in [35].

After their two studies with US elementary and high school students, Witherspoon et al. [36] stated that participating in a directed programming curriculum, in which virtual robots are programmed, develops CT knowledge and skills. The same conclusion, that the use of simulated 3D robots significantly helps when developing students' CT, was found in the experimental quantitative evidence of [10] with secondary education students.

3 | Theoretical Framework

Grasping the neuroscientific distinctions between genders is essential. The hippocampus, responsible for memory and language, matures quicker and is more substantial in girls than in boys [37]. Conversely, the cerebral cortex in boys, which is pivotal for spatial understanding, is more developed than in girls. These neurological variances influence both the development of skills and learning methodologies across genders. Boys tend to learn more effectively through physical activity and visual stimuli but may struggle with sustaining attention over extended periods. Girls, on the other hand, excel in cooperative tasks but could benefit from enhanced training in spatial abilities. In essence, the learning preferences can be encapsulated as such: girls are naturally inclined towards auditory learning and stationary tasks such as art projects, enjoying the exchange of ideas, whereas boys are drawn to autonomous, tactile activities that they can direct [38].

There are notable gender imbalances within the realms of STEM, particularly with a lower representation of women in the computer science sector [39]. The absence of encouraging educational encounters throughout the learning journey often deters women from pursuing careers in computer science [40]. This reluctance is compounded by various intricate elements, such as apprehension about participating in programming classes or prevailing stereotypes regarding career options in the tech industry [41]. Over recent years, the presence of women in the tech world has seen a marked decline [42], with a disproportionately small number of women embarking on computer science vocations. To foster a sense of empowerment among girls in the context of interdisciplinary education, it is crucial to implement teaching strategies that promote gender balance.

To enhance the engagement of young women in the field of computing and to impart CT abilities, it has been proposed that robotics be utilized as a teaching tool [43]. Robotics serves as a multidisciplinary platform, offering a versatile educational setting in which learners can apply principles from STEM alongside distinct programming languages to tackle computational challenges [9]. Furthermore, engaging in robotics can potentially shift the perceptions of female students about the computing domain and act as an intervention strategy to maintain their enthusiasm through middle school and beyond [36]. Research by Tselegkaridis and Sapounidis [44] indicates that girls who engage in robotics-related programs and activities tend to pursue STEM-related fields in college.

4 | Methods

4.1 | Research Context and Participants

The study presented in this article was carried out in the secondary school IES El Álamo during the second term of the

2022–2023 school year. IES El Álamo is located in El Álamo a municipality on the southwest of the Community of Madrid, Spain. It is an emerging municipality with a population of 10, 123 registered inhabitants. The school has around 400 students. The sociocultural level of a high percentage of the families is medium and medium-low. The two fundamental features of IES El Álamo seem to be diversity and multiculturalism.

One hundred and forty-nine students between first and third secondary school grade, from different classes, participated in this study. The selected age range considers students before they have to make their first subject choices, thus avoiding the bias of conducting the study with students who have already demonstrated their affinity or liking for programming or science by choosing it as a subject.

All the participants were previously informed and the tests were completely voluntary and anonymous.

4.2 | Materials: Kibotics Web Platform

Kibotics is an innovative online learning system for learning computational thinking and educational robotics. It is mainly designed for primary and secondary education students, all levels before university. It supports robot programming in Scratch language (Blockly variant) and in Python text language. It includes an online 3D robot simulator and it also supports common real robots such as LEGO EV3, Makeblock mbot or Tello Drone.

The Kibotics typical webpage for robot programming shows a block-based code editor and a 3D robot scenario as shown in Figure 1. The robot runs the Scratch program and moves accordingly in the 3D scene. In the editor the child may build her program dragging and dropping blocks from the palette. The 3D scene can be seen from a fixed observation position, from the bird-eye view or from the onboard robot camera. The web page provides several debugging tools as a console, the map, the sensor viewer and the robot teleoperator.

The website provides several courses which include robot programming challenges (exercises, didactic units) to the students, and presents computational thinking concepts (variables, conditionals, loops, functions, etc.) in the context of robots that have to perform a task (following a line, avoiding obstacles, cleaning a room…), with their sensors and actuators. It follows the pedagogical learn-by-doing approach, with practical exercises to teach how to get sensor data from the software program, how to send commands to the robot motors from the software program, and how to combine them in several robotics applications. The participants used version 3.8 of the platform.

4.2.1 | Bump and Go Exercise

In this didactic unit the robot has to wander around a house with walls and furniture around (a table, a coach, etc.) without hitting any obstacle (Figure 2). It has a distance sensor looking ahead which measures the distances to the nearest objects in the left, front, and right areas. The robot has two motors for

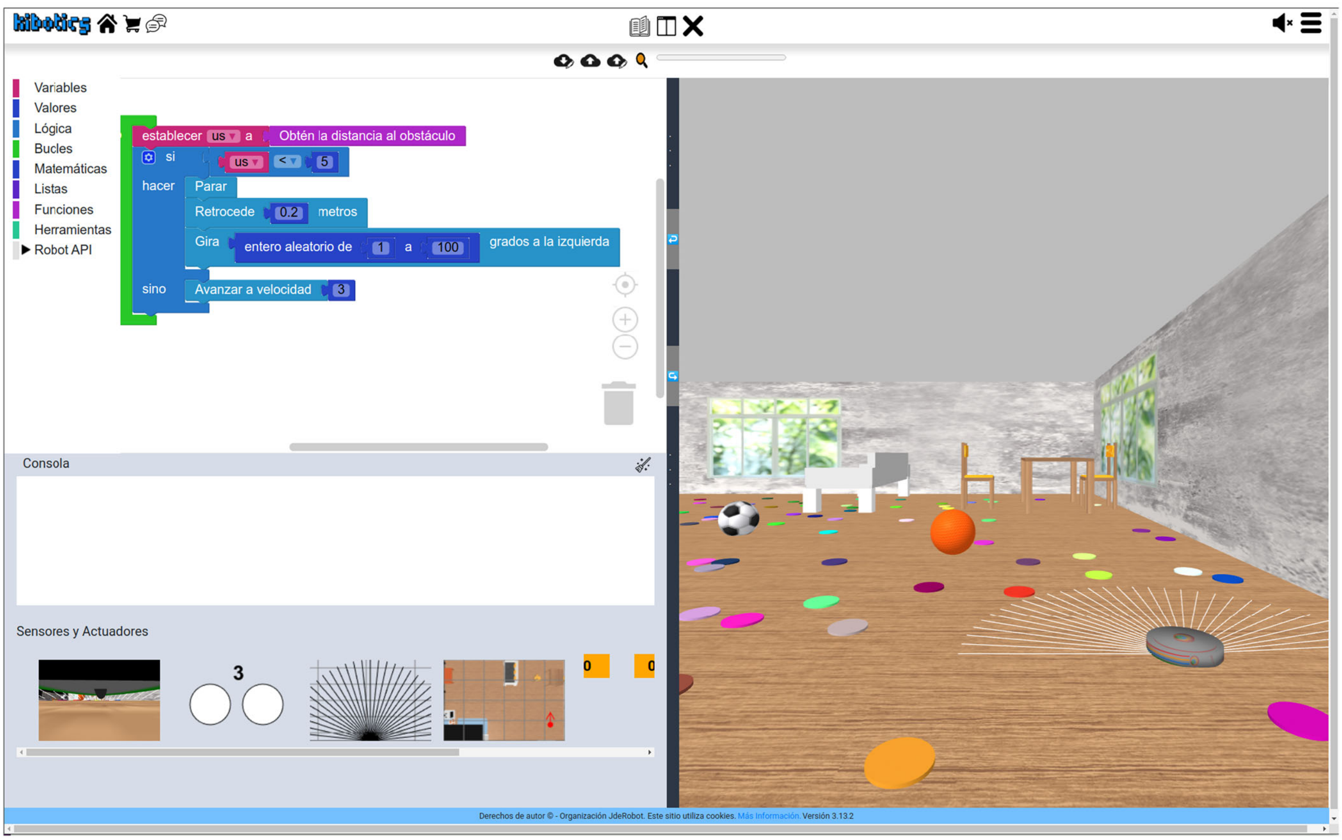

FIGURE 1 | The robot programming and execution panel at Kibotics: code editor (left) and 3D robot scenario (right).

differential drive, one on its left side and the other one on its right side. The robot can be receive position commands (such as rotate 30°, advance 30 cm) or speed commands (linear speed or rotation speed).

4.2.2 | Follow Line Exercise

In this didactic unit the robot has to follow a black line in the floor and complete one lap of a circuit (Figure 3). It has two infrared sensors looking downwards so it may distinguish between being completely over the black line (black–black), in its left side (white–black), right side (black–white) or completely outside the line (white–white). The motors are the same as in the Bump & Go challenge. This exercise is designed to teach the robot control loop, which sends different motors commands depending of the position of the robot relative to the black line as measured by the IR sensors.

4.3 | Research Design

The main objective of this study was to explore the differences between boys and girls in the acquisition of the skills associated with computational thinking. To this end, we planned some work sessions with the Kibotics 3D simulator as part of the "Technology, Programming and Robotics" subject taught in the first, second, and third years of a secondary school (7th, 8th, and 9th grade) in the Community of Madrid. All interventions lasted for six sessions of 2 h each, with one session per week. Two sessions were dedicated to performing the tests (pretest and posttest), while two other sessions were dedicated to the exercise described in Section 4.2.1, and the remaining two sessions were dedicated to the exercise described in Section 4.2.2 of this document.

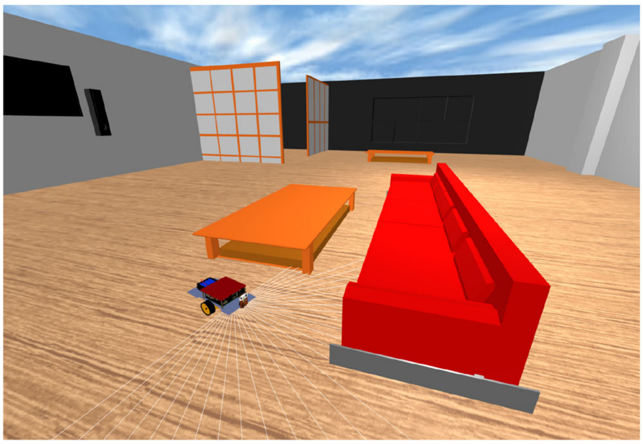

FIGURE 2 | Bump & go exercise.

FIGURE 3 | Follow line exercise.

Having participants from different year groups also allows us to analyse the results taking into account not only gender differences but also age differences.

To be able to answer the research question in greater detail and to explore the effect of working with Kibotics in the classroom, the students who participated in the research should answer the extended CT test (see Section 4.4) both before starting the didactic units and at the end of them. Table 1 shows the number of participants in each course who answered the pre-intervention (pre-test) and post-intervention (Posttest) test. The pretest also included the question: Have you ever had a computer programming class?, in which participants reported whether they had taken programming classes before the study.

The intervention was planned to be executed during the second quarter of the 2022–2023 school year with the following steps:

1. The project was presented to the teachers along with an introduction to the use of the Kibotics simulator.
2. High school teachers tested the simulator with the educational center's equipment.
3. Teachers selected the Kibotics exercises they prefer to use in their classroom. The teachers decided to use the didactic units *FollowLine* with IR sensor and *Bump & Go* with distance sensor.
4. Before the students started to use Kibotics they fullfilled the expanded computational thinking test (see 4.4).
5. Students worked during five sessions with Kibotics in the school.
6. Students completed again the expanded CT test.

4.4 | Measuring Instruments

To assess the degree of acquisition of computational thinking skills, we have used the computational thinking test (CTt) proposed in [45]. This test is one of the most popular block-based assessment tools [5, 46], as it is not tied to any specific subject or programming language. CTt employs a multiple-choice question format. It is one of the few validated assessment tools and its

TABLE 1 | Study participants.

	Participants	
2*Grade	**Pretest**	**Posttest**
First (7th grade)	17	15
Second (8th grade)	76	70
Third (9th grade)	56	22

design is informed by the practical guide of the international standards for psychological and educational testing with application in middle school [47]. Furthermore, the test has been validated for students between the ages of 12 and 14, which is the age range of the students participating in our study, although its use can be extended 2 years downward and 2 years upward.

We have also added six questions taken from Bebras Contest to assess more complex CT skills that we expect to find especially in older students. Bebras International Contest is a competition born in Lithuania in 2003 which aims to promote the interest and excellence of primary and secondary students around the world in the field of Computer Science from a CT perspective [48]. Although Bebras is not a CT assessment tool (the exercises vary from year to year) some of its proposed exercises are used for this purpose [49, 50]. The Bebras questions selected to be part of our test are:

- Candy Maze (Bebras UK 2017)
- Robot (Bebras UK 2017)
- Segwey (Bebras UK 2016)
- Bike paths (Bebras UK 2016)
- Robot exit (Bebras UK 2016)
- Tunnels of the Homestead dam (Bebras UK 2017)

In summary, both before the beginning of the Kibotics sessions and at the end of the sessions, students fill an anonymous test consisting of the following parts:

1. Data on gender, course and device used
2. CTt with 24 questions
3. 6 questions from Bebras
4. Three self-assessment questions:
   - How well do you think you did in the test?
   - How good do you think you are with computers and computing?
   - Have you ever had a computer programming class?

TABLE 2 | Comparison between pre and posttest for different grades (p-value).

Grade	p value
First	0.001
Second	0.169
Third	0.56

5 | Results and Discussion

5.1 | CT Skills Acquisition at Different Ages

In this section we will address the research questions RQ1 and RQ2:

1. **RQ1**: Do 12–14 year-old students' CT skills improve after working with the 3D robotics simulator?
2. **RQ2**: Are there differences between the different ages in terms of the CT starting level and the level acquired after the intervention?

To answer these research questions we assessed the differences in the acquisition of CT skills using the extended CT test [45] before and after the intervention. Although statistically significant differences were only found between the pretest and posttest results in the first year (as shown in Table 2), it can be seen in the graphs of Figure 4a–c, that in the 3 years the curve with the posttest results is shifted to the right with respect to that of the pretest. Although the intervention did not produce statistically significant improvements in the results of the second and third year students, the posttest score is not worse than in the pretest. One explanation for this results could be a possible plateau effect, where students have already reached a certain level of computational thinking skills, making further improvement more challenging. Additionally, external factors such as student engagement, the length of the intervention, or differences in instructional approaches could have contributed to the variation in results across different cohorts. This highlights the need for tailored interventions that consider the unique characteristics of each academic year.

5.1.1 | Pretest Analysis

The results of the pre-intervention test provide information about the starting level of students in each grade in terms of CT.

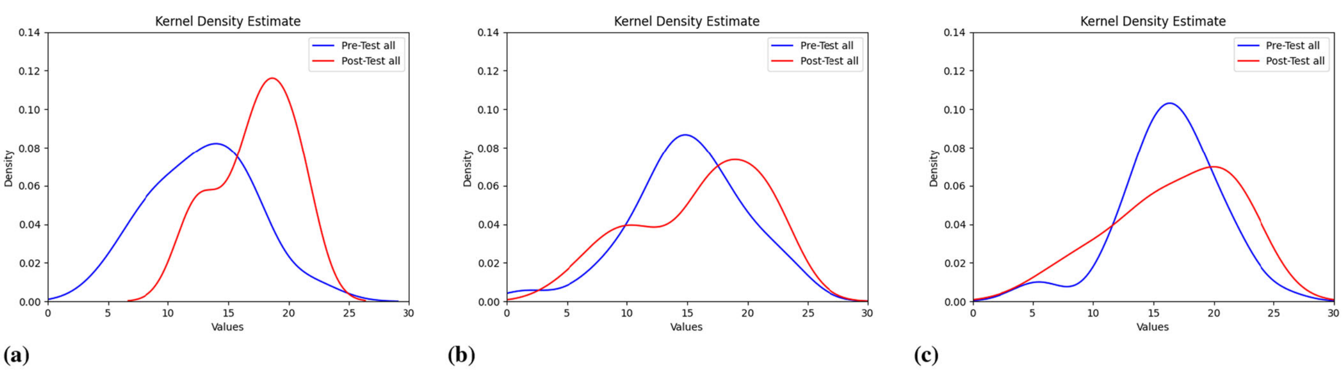

FIGURE 4 | Pre and posttest differences in different courses. The values on the x-axis are the number of correct answers to the test (out of 30). (a) 1st grade, (b) 2nd grade, and (c) 3th grade.

If we focus on the analysis of these curves we can see that the maximum of the curve shifts slightly to the right each year (12 right answers in the first year, 15 in the second year and 17 in the third year), indicating that the average starting level of the students is slightly higher each year. In addition, there is a slight shift of the total curve to the right. These qualitative observations indicate that the initial level of students is slightly higher in each grade.

5.1.2 | Posttest Analysis

If we analyse the results of the students in the post-intervention test, we can see that the maximums of the distributions of results hardly vary between grades (20 for first and second year and 22 for third).

Based on statistical evidence, we can state that students improve their scores in the computational thinking test after working sessions with the Kibotics simulator. Therefore the answer to RQ1 is affirmative, the use of the 3D robotics simulator in the classroom does help students to improve their CT skills. This improvement before and after the intervention is significant in the first year. In the following 2 years, this improvement is slightly visible in the graphs. Therefore the answer to RQ2 is that there are appreciable differences in the effects of the intervention between courses in terms of the improvement of TC skills among students.

In the first year, many students are facing a programming class for the very first time, so it seems reasonable that their improvements are more noticeable than for those in the second or third year who have already had one or two compulsory subjects where they have worked on programming. Based on the graphs of the posttest results for the three grades, in Figure 4a–c, and the small difference between the maximum values achieved in the three curves, the question arises as to whether the test is poorly adapted for the two upper grades. If this is the case, it is possible that the second and third year students "saturate" the score and the posttest scores are not really reflecting the level of the students. It may also be the case that the selected teaching units were too easy for the second and third year students and they are "learning almost nothing new." Choosing more demanding robotics units in higher courses (they are already available at Kibotics web platform) would be sensible then. It should also be noted that in the third year more than half of the students who answered the pre-test did not answer the posttest. This may be a source of uncertainty in the obtained results too.

5.2 | Comparison Between Male and Female Students

In this section, we analyse the results obtained in the computational thinking tests separated by gender to try to answer the research question RQ3: Are there differences in the acquisition of TC skills by gender? For this purpose, we have plotted the pretest and posttest results segregated by group and gender in Figures 5a,b, 6a,b, 7a,b. We have analyzed for girls and for boys both the increment of CT skills between before and post the intervention at the three courses, and the final absolute level of CT skills after the intervention.

5.2.1 | Pretest Analysis

In the results of the pre-intervention CT test we can observe the starting situation in each grade of male and female. In the graphs for each year it can be seen that the maximum of the distribution is higher for male than for female (15 vs. 10 in the first year, 15 vs. 12 in the second year and 17 vs. 15 in the third year). This indicates a previous difference in CT skills, placing the male students at a slightly higher level than female at the beginning, before working in class with the robotics simulator.

5.2.2 | Increments in CT Skills Per Course

Looking at the increment in CT skills between before and post the intervention, Table 3 shows the p-values for each grade and

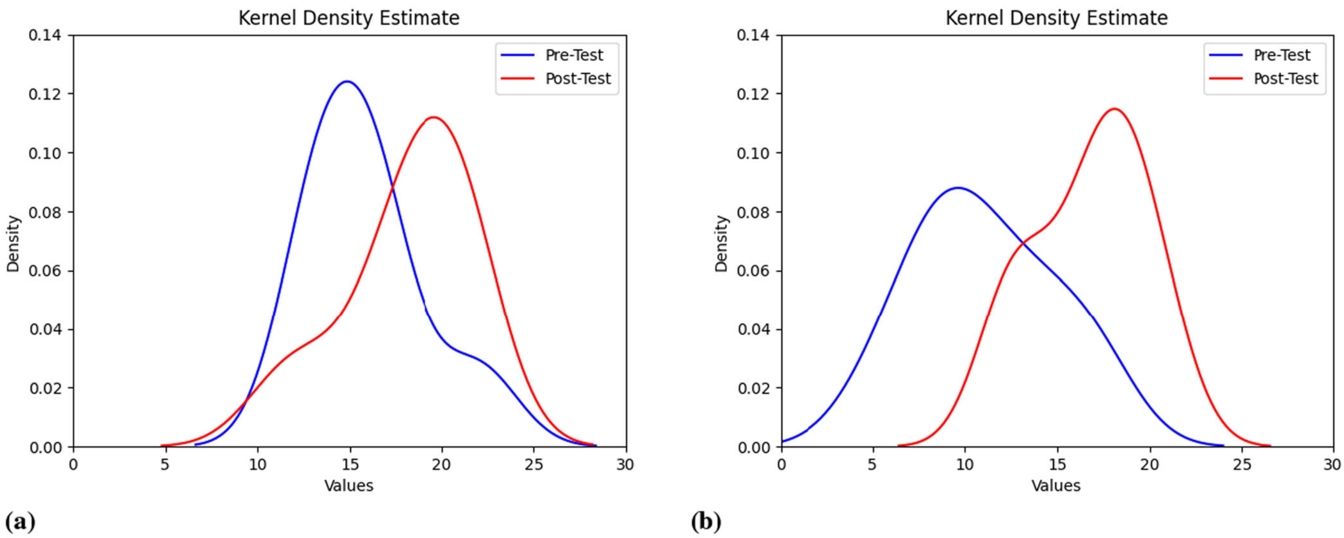

FIGURE 5 | Difference between pre and post CT test. 1st year. (a) Male students and (b) female students.

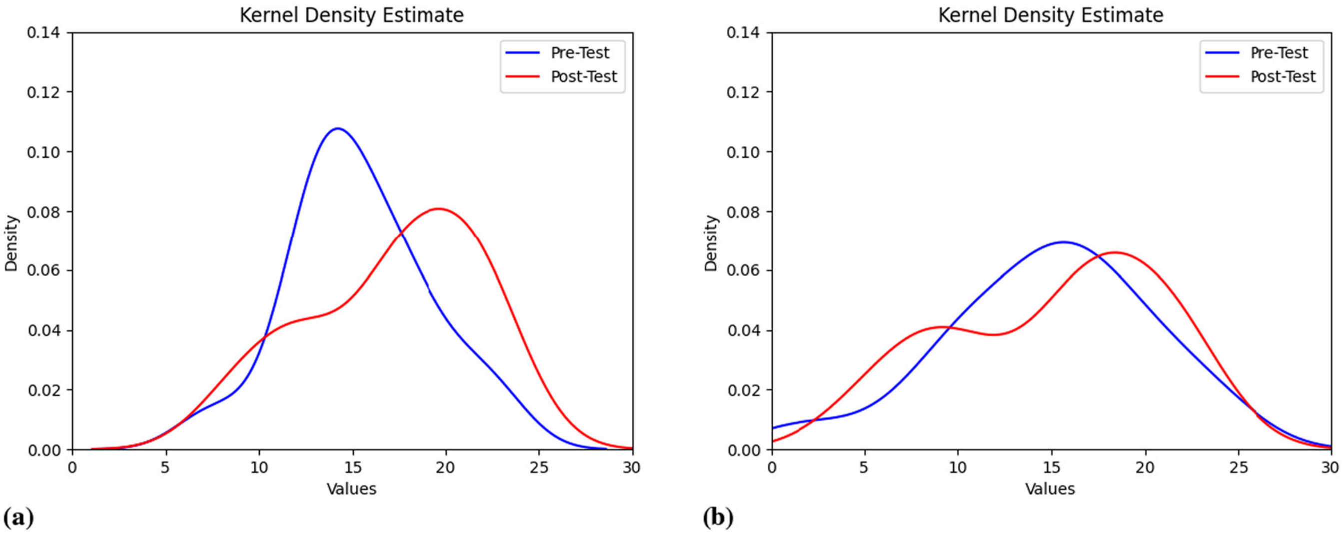

FIGURE 6 | Difference between pre and post computational thinking (CT) test. Second year. (a) Male students and (b) female students.

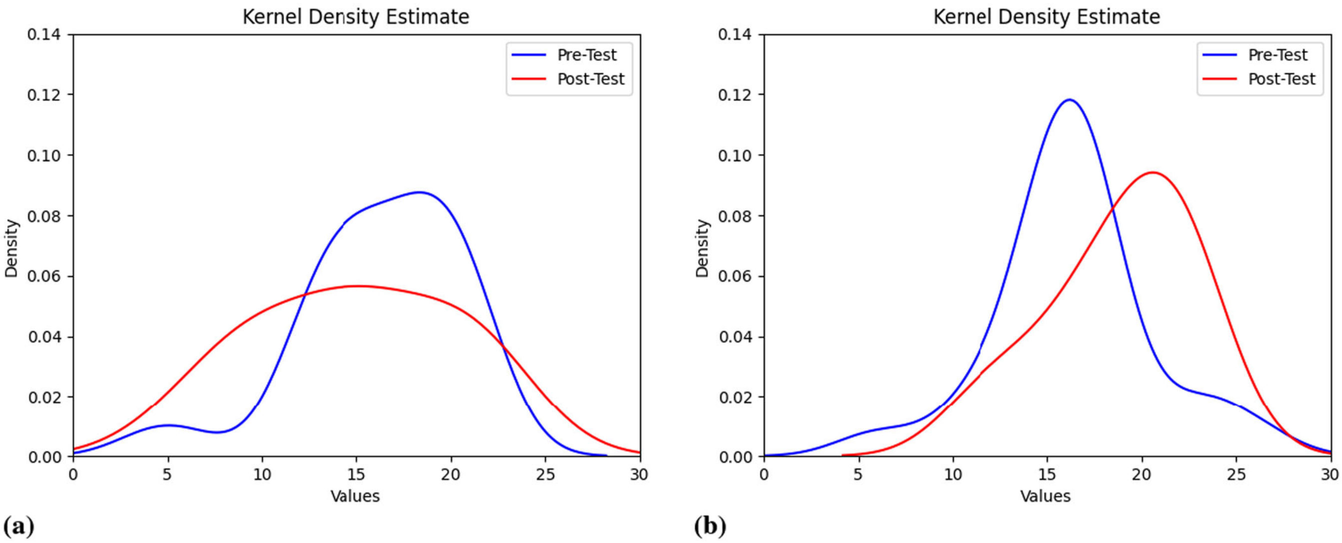

FIGURE 7 | Difference between pre and post computational thinking (CT) test. Third year. (a) Male students and (b) female students.

TABLE 3 | Difference between pre and post computational thinking (CT) test.

	Male		Female	
Grade	***p* value**		***p* value**	
First	0.25	No statistical difference	0.0001	Statistical difference
Second	0.01	Statistical difference	0.32	No statistical difference
Third	0.40	No statistical difference	0.15	No statistical difference

gender. It can be observed that there is no statistically valid change between the results before and after the test in the first year for the male students but there already is in the second year (0.01) (Table 3). With female students the results are the opposite, there is a significant difference in the first year (0.0001) but no huge difference in the two upper years.

These observations could be consistent with students' prior knowledge about programming. Male students, who typically come to the first year of secondary school with programming knowledge acquired in extracurricular activities, do show an improvement in their computational thinking skills after the intervention, but shorter than female students. However, this is no longer the case in subsequent grades, where the prior levels of boys and girls are more similar after the robot programming sessions of the first year. In the case of girls a large improvement is observed in the first year, perhaps as a consequence of not having previous programming knowledge. However, in the following years, no large improvement in the acquisition of computational thinking skills is observed.

5.2.3 | Posttest Analysis

Looking at the final CT level after each course, we studied the responses of students grouped by gender to the extended computational thinking test after the intervention. The results are presented in the Table 4.

In this case we see disparate results. There is no statistical difference in the first year, showing that boys and girls finish the first year with similar CT levels (0.09). But there are differences in the second (0.04) and third year (0.03). As can be seen in Figure 8a,b, girls score worse in the posttest after the-second year of secondary education, but they score better in the third year. It can also be seen that the graph of girls' scores is shifted to the right, indicating that girls as a whole have better scores than boys, which is more to the left.

The analysis of the posttest results presents difficulties because the results are disparate. In the first year, the results in the posttest are similar between male and female, there is no statistical difference between the two. Looking at the graph in Figure 4a, although the distribution of the female's scores peaks at a value of 18, slightly below the 20 (peak of male's distribution), but female's distribution is more compressed around the peak than male's. In second and third year *p*-value indicates that there is statistical difference between male and female posttest responses. In second grade male students score slightly over female. Peaks in both distributions are very close (20 in male vs. 17 in female), Figure 8a, but male distribution indicates that more male students score higher than female. In third grade the situation is the opposite, peak of female distribution is higher and distribution is more tighter than male's, Figure 8b.

5.3 | Previous Exposure to Programming

The answers to one of the self-assessment questions, that of "Have you ever had a computer programming class?" give us important information to understand some results in the previous section. The first thing we can observe from the data is that in the lower grade (first year of secondary education), the percentage of male students who claim to have prior knowledge of computer programming (answering yes to the corresponding question in the questionnaire about it) is higher than that of girls. 10% of girls versus 43% of boys have answered yes to the question *Have you ever had a computer programming class?*, Table 5.

This inequality should not appear in higher grades because the subject is compulsory for all in upper secondary education. By contrast during primary education, students may have acquired knowledge of computer programming either because their school offered it as an option or because they participated in extracurricular activities. However, in the second year, this inequality continues to appear in the results. Only 16% of girls and 32% of boys answer affirmatively to the question on

TABLE 4 | Difference between male and female in post computational thinking (CT) test.

Grade	*p* value	
First	0.09	No statistical difference
Second	0.04	Statistical difference
Third	0.03	Statistical difference

TABLE 5 | Have you ever had a computer programming class? (yes/no).

Grade	Female	Male
First	1/9	3/4
Second	33/6	25/12
Third	14/10	15/17

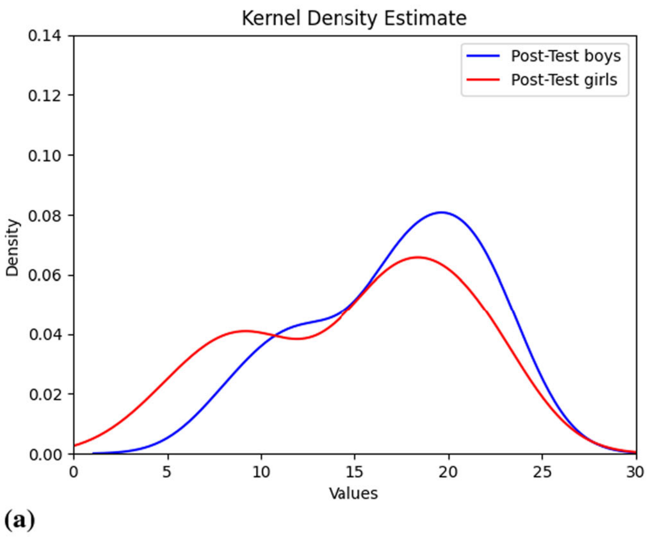

FIGURE 8 | Difference between male and female in post computational thinking (CT) test. (a) 2nd year and (b) 3th year.

whether they have had programming classes before. This may be because they have not considered programming content as part of the compulsory subject in the first year. Another important aspect that may have an influence and that has been reported in the literature [20] is the fact that girls in this age group have a poorer self-perception of their performance in programming tasks.

In any case, by having a compulsory subject of technology, robotics and programming during secondary education, the gap between boys and girls with prior knowledge should be reduced. Everyone should receive this knowledge in high school.

6 | Discussion

In our study, we acknowledge that more than half of the students who took the pre-test in the third year did not complete the posttest. This substantial attrition rate could potentially introduce a bias in the results, as the sample size for the posttest was significantly smaller, which might affect the generalizability of the findings. Additionally, the lack of posttest data from these students means that we could not assess any possible changes in their computational thinking skills, thus limiting our ability to draw firm conclusions about the overall effectiveness of the intervention. Future studies could consider implementing strategies to improve response rates, such as offering incentives or reducing the burden on participants, to minimize potential biases and better understand the long-term impact of the intervention on students' computational thinking development.

Considering the above paragraph, from the analysis of the experimental data we can conclude the following:

- In all the grades there is a difference in the prior knowledge of male and female students. Male score higher. This is specially notorious in first grade. This fact can be explained due to their greater exposure to previous programming-related activities.
- Despite this initial female disadvantage, there is no statistical difference in the results of the CT test measured after the intervention in the first grade. Comparing them with the pre-intervention results, it can be seen that girls improve their results and boys do not as much. This indicates that the robotics classes have contributed to equalizing the existing inequality between gender in terms of CT acquisition.
- In higher grades (second and third grade) the situation is reversed. The percentages of students who have previously received programming classes should be equal between genders, but the fact is that they don't perceive it that way. The score in the pre-test is still higher in male students but differences are reduced compared to 1st grade. Although this starting point is more balanced between genders at the end of the intervention, in the posttest there is a difference between the performance of male and female students. In second year male score better and in third year the female students score better. With the collected data we cannot conclude anything else, maybe we can ask ourselves whether the distinct attitudes are responsible for this difference, as [5] proposes, or perhaps other issues that have not been captured in the measurement tests.

Although our study does not provide direct evidence on the influence of social factors in computational thinking development, previous research suggests that access to technology at home and participation in extracurricular programming activities may significantly impact students' learning outcomes [51]. Access to technology at home, such as having a personal computer, provides opportunities for students to engage in programming and problem-solving activities, thereby enhancing their computational skills. Participation in extracurricular programming courses fosters a collaborative environment where students can share knowledge and develop critical thinking abilities. Additionally, the role of school environments, such as Innovation Classrooms, has been highlighted as a key factor in fostering computational thinking skills [52]. These factors could partly explain the differences observed in our study and should be considered in future research to better understand their impact on students' performance.

One important pedagogical implication of our findings is the need to address gender disparities in the development of computational thinking. To help mitigate these differences, it is crucial to implement teaching strategies that actively promote inclusivity and equal participation. For example, educators can use gender-neutral language in classroom activities and materials, ensuring that both male and female students feel equally encouraged to engage with computational tasks [53]. Additionally, integrating collaborative and problem-solving-based activities that highlight the value of diverse perspectives can help bridge the gender gap [54]. Offering female students strong role models in technology and computing-related fields, through guest speakers or mentorship programs, can also serve to inspire confidence and interest [55]. Furthermore, teachers can make a conscious effort to monitor and address any gender biases that may arise during interactions in the classroom, providing targeted support and feedback to students as needed [56]. These strategies, combined with an inclusive curriculum that highlights the relevance of computational thinking across all areas of life, may contribute to reducing the gender gap and promoting greater equity in the development of these essential skills.

7 | Conclusions

Despite the recognized importance of computational thinking there is still a gender gap in the acquisition of these skills that needs to be mitigated. This article explores the differences in the acquisition of CT between boys and girls in 3 years of secondary education in Spain. To do so, the skills were measured using the extended computational thinking test before and after a CT intervention using the Kibotics 3D robotics simulator.

Although the results are not conclusive, it can be observed that at all levels boys obtain higher scores in the pre-intervention test than girls. This difference is especially significant in the lower grade, reflecting the greater exposure of boys to previous extracurricular activities related to school activities. Post-intervention test shows that gender difference is reduced in the first course. In higher grades posttest results does not allow us to draw any clear conclusions, since we can find opposite scenarios in the second and third course.

We are aware that this is a preliminary study; the differences found between the different courses may be due to cyclical factors that have not been taken into account in this study.

As one future line, it would be very interesting to repeat this study with the same students over three consecutive school years, so that we could analyze more rigorously the differences in the acquisition of computational thinking as a function of the age. A longitudinal design would help address some limitations of the current study by allowing us to track the same students over time, reducing inter-cohort variability and providing a clearer picture of how CT develops with age. This approach would also help to control for individual differences and external factors, providing stronger evidence of gender-based trends. Additionally, it would enable us to examine long-term intervention effects and identify whether observed gender differences persist, diminish, or evolve as students progress through their education. Another future line is to conduct a similar study in other schools with even more students. It is also intended to analyze which methodological aspects help to reduce this gender difference to establish guidelines for working on CT in the classroom. Furthermore, incorporating an analysis of the socioeconomic background of students could provide further insight into the gender differences in computational thinking, helping to identify external factors that may influence the development of CT skills.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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