

## Article

# Development of Computational Thinking through STEM Activities for the Promotion of Gender Equality

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**Abstract:** In the article, the authors evaluate the computational thinking skills according to gender of a group of male and female students of industrial engineering and systems engineering from universities located in the Andean region of Peru; the five key skills were evaluated: abstraction, decomposition, generalization, algorithmic design, and evaluation. To strengthen computational thinking, activities related to agriculture, livestock, the environment, safety, and education were proposed, which are of interest to the community where the students live. The research methodology followed is quasi-experimental of the post-test type with intentional non-probabilistic sampling. During the development of the activities, the students used microcontrollers, sensors, and actuators; thus, they also used block-based programming to implement hardware and software prototypes. The results have shown, according to the inferential analysis, that there are no significant differences between male and female students in any of the computational thinking skills. These results were due to the educational strategy applied in the development of STEM activities, which focused on solving real problems in the student community and generated the same enthusiasm in female and male students compared to other activities that only generated motivation in male students.

**Keywords:** computational thinking; gender; STEM activities; electronic devices



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## 1. Introduction

Various organizations, such as UNESCO, BID, etc., state that the practice of STEM disciplines (science, technology, engineering, and mathematics) contributed to the development and progress of different sectors, such as education, health, livestock, the environment, agriculture, renewable energy, etc. [1]. The practice of STEM disciplines in education is also key to teaching different skills and abilities to students at an early age, not only for the local context but also for the world, either in the labor or academic fields. In this way, it generates or instills the desire to pursue careers in the different STEM disciplines that are in high demand today and in the future [2]. However, one of the problems that exists worldwide and mostly in Latin American countries is the low participation of women in STEM disciplines; only 13% of graduates in ICT and 18% in engineering are women, due to different reasons. Factors such as prejudices and stereotypes that limit pursuing careers in engineering, science, etc. [3]. In a study carried out by the Inter-American Development Bank, he points out that in the world, only 10% of women choose to study a career in STEM

areas, while in Peru, only 29% of those who are inclined towards a career in science and technology are women due to gender barriers [4].

Regarding the choice of scientific and technological careers of PRONABEC scholarship holders [5] in Peru until the 2015-II semester, they have found that 88% of graduates register studies in the area of engineering and technology, of which 73% are male and 27% are female. The growing number of female graduates has produced greater participation in careers related to the areas of: Art and Architecture (78%), Economics and related (57%), Basic Sciences (57%), and Agriculture and related (56%); while, in the Huancavelica region, through Scholarships, 18 young people have been able to pursue higher education 2655 young people between 2012 and 2015. Fifty-five percent of the scholarships awarded went to men, while the remaining 45% went to women. Likewise, 69% of the scholarships were given for studies in careers linked to engineering and technology and 25% in business careers, among others; most of the engineering and technology careers were assigned to males; it is also added, that the level of achievement in mathematics is located in the last 3 levels and in reading comprehension in the penultimate place of the total of regions [6].

Added to this, countries worldwide share the same characteristics with respect to the gender gap that exists in the choice of technical and scientific careers by women. This fact implies that women do not feel that they participate in the solution of problems within their context, and this is more marked in rural areas since there are no greater opportunities for women. However, at the same time, various studies show that there are worldwide efforts to improve education and seek equality in different sectors [7]. In this regard, various authors point out that it is necessary to instill and generate interest from an early age to reduce or eliminate stereotypes; thus, also train classroom teachers with innovative pedagogical methods to encourage girls to pursue careers related to mathematics, engineering, physics, etc.; also, update study plans that are appropriate to gender and that contribute to the orientation and change of preconceived ideas by girls. Therefore, another of the factors considered relevant in this research is the gender variable and to what extent it influences the choice of university degrees related to STEM disciplines by young Peruvians.

In the academic field, to instill more women in the choice of STEM disciplines, computational thinking has been used as an educational strategy in the classroom through activities that are related to STEM disciplines, such as the use of technological resources (microcontrollers, sensors, actuators, etc.) in combination with problem solving methods [8,9]; in addition, STEM disciplines and computational thinking share common characteristics by proposing activities that involve tasks, such as algorithm development, coding, use of technological resources, and teamwork [10]; all these activities must be in the curriculum together with the pedagogical approaches and assessment instruments [11–14].

The objective of this article is to evaluate the abstraction, decomposition, generalization, algorithmic design, and evaluation of computational thinking skills according to gender in a group of male and female students recently enrolled in the career of industrial and systems engineering in the academic periods 2020, 2021, and 2022. To strengthen the computational thinking skills of the students, STEM activities were proposed to solve problems related to agriculture, livestock, the environment, safety, and education, which are real problems in the community where the students live.

## 2. Literature Review

### 2.1. Benefits of Computational Thinking

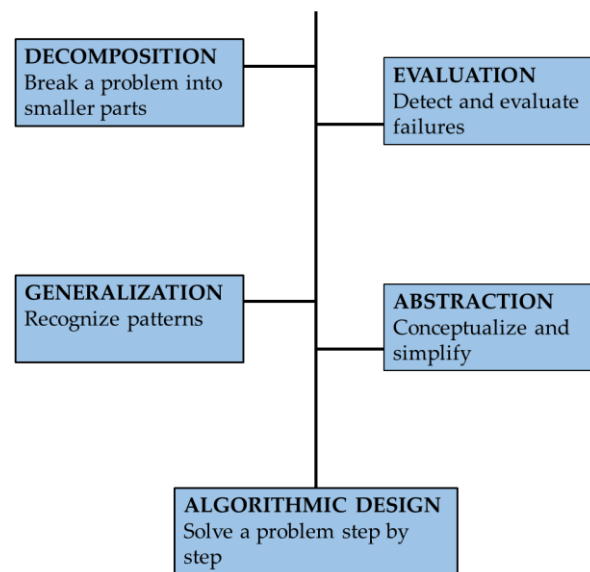
Today, the importance and use of technology in various sectors (health, livestock, education, agriculture, etc.) is evident, as is the training of more people in STEM activities. As Oppenheimer [15] points out, “the risk of doing nothing will be enormous and will condemn the region to permanent backwardness because, in the coming years, there will be an extraordinary acceleration of scientific and technological advances that will further separate advanced countries from developing countries”. Therefore, today we need educated citizens who participate and contribute to technology-based innovation, including literacy and digital transformation using computer and mathematical skills [16].

From the experience of developed countries, such as Europe, it is necessary to generate computational thinking and problem-solving skills and abilities in students of all ages using computer tools and unplugged in the classroom [17]. Academic research has revealed that the activities carried out to strengthen computational thinking contributed to the understanding of the problem, planning, coding, and feedback that improved the daily activities of each student. As you know, nowadays the skills of algorithmic design, coding, programming, and problem solving acquire pre-eminence and are constantly changing according to the rapid advance of science and technology. In this context, computational thinking helps or contributes to a significant improvement in the generation of student competencies to be part of future jobs and be active citizens in proposing solutions for the benefit of society [18]. According to Puhlmann [19], the benefits that computational thinking brings are diverse and depend largely on what skills and competencies will be strengthened in students. In most of the studies reviewed, the competencies are related to employment, understanding of the functioning of the digital world, application in different areas, digital education, productivity, strengthening of computer programming, development of computer algorithms, gender equality, and work. team up; additionally, computational thinking is considered a tool for strengthening skills for the PISA exam in early-age students.

## 2.2. Computational Thinking in Higher Education

According to the literature reviewed, computational thinking originated with the development of skills in regular elementary school students; however, today there are successful interventions in university education, basically in the first years of college. Good practices suggest starting the strengthening of computational thinking in first-cycle students in ICT or computer science courses; moreover, applying computational thinking in courses that are not related to computer science [20,21]. In this way, by creating a referential framework for computational thinking that teachers could use to apply in their different courses, most authors agree in pointing out that “one has to go beyond training students to solve problems using a programming language” but should focus on awakening and strengthening their skills and motivations, which are considered fundamental aspects for the improvement of student performance. Terreni [22] states that computational thinking is characterized by a set of ordered skills that increase the cognitive capacity of students compared to computer programming. Moreover, he emphasizes that computational thinking is made up of various processes that lead to solving a problem, starting with understanding and problem statement, followed by the identification of alternatives to possible solutions, argumentation, use of technological resources, execution of activities and performance tests, and feedback. These processes can be applied in different disciplines according to the proposed curriculum.

Regarding the use of computer tools, there are several tools; the most common are: programming languages and environments or IDE, the Python language that is normally used in the first years of computer science or engineering careers in general; with this type of languages, students are inserted into the world of programming, interacting with computational concepts, developing applications to their needs; moreover, there are experiences of gamification before programming; thus, also, the teaching of algorithms, programming structures and programming variables through Lighthbot, mBlock and educational robots, where they focus on the fundamentals of programming and development of competences proper of computational thinking [23–25]. Since computational thinking is considered a cognitive process in problem solving, it involves the following skills: thinking algorithmically, thinking in decomposition, recognizing patterns, abstracting and presenting in a simplified way, and evaluating for decision-making [26–28]. Figure 1 shows the five key skills of computational thinking.



**Figure 1.** Key computational thinking skills.

### 2.3. STEM Activities and Gender

STEM disciplines are usually classified into two major parts: “applied” sciences (computer science, engineering, and engineering technologies) and “pure” sciences (biology, chemistry, physics, environmental sciences, mathematics, and statistics); therefore, people must follow these disciplines to be considered STEM people; in addition, the countries that have more STEM professionals are the ones that lead the world market and are considered first world countries [29].

Various organizations worldwide have the purpose of increasing the participation of more women in STEM disciplines; in this way, they mitigate the gender gap. In order to reduce the gender gap, they depend on many factors, not only the cultural and socio-economic context but also factors such as self-efficacy, self-perception, and the educational experiences received from the school stage or regular basic education [30]. Six factors are indicated as a result of research carried out by various authors that cause the underrepresentation of women in STEM disciplines; these factors are: “(1) cognitive ability”, “(2) relative cognitive strengths”, “(3) professional preferences”, “(4) lifestyle and values”, “(5) field-specific ability beliefs”, and “(6) stereotypes and biases related to gender”. Factors 1 and 2 are related to mathematical and verbal reasoning, while factors 3, 4, and 5 are related to motivation that has an impact on personal and group interests, positive mentalities, positive goals, and positive personal values; finally, factor 6 is related to the sociocultural aspects that mainly affect the cognitive and motivational parts [31–34].

In most of the women who became interested in STEM careers, it was from personal experiences; for example, participating in extracurricular activities, seeking family support, contacting and interacting with stakeholders, and seeking appropriate information; meanwhile, those students who chose a STEM career based on self-efficacy performance from their personal experience of success in the classroom; finally, already being in the race, there are external factors that are related, such as infrastructure, technology, teachers, etc., that contribute to the validation of their objectives or otherwise lead to failure, such as student desertion. Ortiz-Martínez [35] proposes developing activities to maintain students’ interest in STEM careers; thus, continuously monitor until you achieve your goals, mainly in the first year of your professional career. In order to have concrete results, she recommends carrying out activities in a controlled context where feedback can be given and actions can be taken instantly. Regarding men, research indicates that for them there is greater dissemination to inculcate them in STEM careers; moreover, there are more funds or financing for technological activities than their female counterparts [32,36].

According to the scientific literature, there are eight effective pedagogical methods or techniques for girls to awaken their inclinations toward STEM careers: involvement and empowerment; diversification of culture; immersion in other languages; guidance; practice and iteration; synthesis; collaboration and communication; and reflection. These principles are made effective through practices or activities that use technological resources to solve problems that motivate girls to solve real-world problems that are of direct interest because they are related to the needs of their context, such as protection and community service [37]; developing these experiences from an early age in girls are of vital importance to instill in STEM disciplines, as professional women scientists point out, indicating that 66% of women generated interests in science and technology before starting secondary education [38,39].

#### 2.4. Computational Thinking and Gender

In the educational field, the most common factor to deal with is gender, which is related to the performance and attitudes of girls and boys; they even differ in common reading and writing activities. Regarding the development of computational thinking skills through the proposal of educational robotics activities in school education according to gender, it is scarce [40]. In the fields of computing or electronics, social stereotypes also negatively affect girls' motivation [41].

In the studies carried out on the development of computational thinking skills, they state that gender took on greater importance in the field of regular basic education [42]; moreover, it is stated that computational thinking seems to have a moderate gender bias, since the activities are mostly more oriented to children [43]; moreover, it is evident that the proposals of activities or projects are preferred by children because they are of an implementation or construction and programming nature that is reflected in the computational thinking score than that of women; this shows us that there are gender differences due to the type of project proposal; therefore, the type of activity or project presumably influences the increase in the gender gap between boys and girls [44].

In the activities developed to strengthen computational thinking, there are representative differences in the use of strategies and approaches for boys and girls that are appropriate to them; the results indicate that the gender gap in the computational thinking competence is almost non-existent, because the proposal of the pedagogical techniques used in the process of teaching computational thinking skills inspired boys and girls to continue exploring; regarding the instructional design, they state that it must be adapted to the nature of the boy and girl; for example, the planning and implementation of prototypes and coding, since girls and boys have different strategies in the development of their activities; in this way, personalized tasks are provided according to gender in the execution of computational thinking activities [42,45,46]; additionally, tools such as educational interactive games, block-based programming, educational robotics, etc. are added. Together with an adequate strategy based on gender, significant improvements are achieved in the mitigation of the gender gap [47,48]. Another important aspect to consider is collaboration and teamwork between genders, where forming teams made up of both sexes benefited both men and women from teamwork when solving problems of the proposed activities, participating equally [49]. These demonstrated experiences are the basis for proposing innovative pedagogies in the development of computational thinking with a gender approach appropriate for the age at the school stage and the first years of higher education [50].

It is evident that in the scientific literature there are many initiatives in the concept, technological tools, evaluation instruments, and skills in relation to computational thinking, to a lesser extent with respect to gender in the achievement of computational thinking skills; however, this topic has been gaining more interest, especially in regular basic education, where it is desired to inculcate with educational activities or strategies so that more women bet on areas related to technology in the profession they wish to follow; in this scenario, computational thinking plays an important role in mitigating the gender gap.



### 2.5. Evaluation of Computational Thinking

To date, there are various instruments for the evaluation of computational thinking, both in the field of regular basic education and higher education; these instruments differ mainly in the complexity that is related to the ages of the students.

In the field of regular basic education, there is the proposal of Román-Gonzalez [51] that proposes the Computational Thinking Test (TPC) made up of 28 questions with programming characteristics based on blocks; Zhong [52] proposes the three-dimensional integrated assessment framework based on the work of Brennan [53], which contains six types of tasks based on three dimensions: directionality (forward task and reverse task), openness (open task, semi-open task, and open task). closed) and process (self-report or reflection report); with this type of task, computational concepts, computational practices, and computational perspectives are evaluated; Sáez-López's [54] proposal is based on the evaluation of block-based programming syntaxes and also on the dimensions of computational concepts and computational practices; moreover, computational thinking skills have been evaluated using the Dr. Scratch software [55–57]. This tool evaluates programming logic, data structure, abstraction, modularity, parallelism, etc., basically the content of the program developed in the Scratch environment.

In the field of higher education, various researchers used the Román-González Computational Thinking Test (CTt) [51], an instrument validated in criteria and convergence by international experts [58,59]. It was used in basic education by regular students with ages ranging from 10 to 16 years in the European educational context [19]; it has also been used in research in the university environment, focused on university students who are starting their careers [25,60,61].

In a recent investigation, Román-González [62] points out that the construct of computational thinking has reached a state of maturity, concluding that to date, computational thinking is a type of cognition with a high level of abstraction that serves both to solve problems and to create and express ideas, and that for this purpose, it can rely on both traditional computer programming and model building. of “machine learning”; regarding the computational thinking assessment instruments, he points out that there are instruments for the different educational stages, the most representative being the “Beginners Computational Thinking Test” (5–10 years) [63], the “Computational Thinking Test” (10–16 years) [58], and the “Algorithmic Thinking Test for Adults” (>16 years) [64]. This last proposal, due to the age range, could be used in the university environment; however, only the test of algorithmic thinking would be evaluated.

In recent years, in the university environment, various instruments have emerged to assess computational thinking in university students, which involves the assessment of computational thinking skills and attitudes [65–67]. In this proposal, the skills of “abstraction, decomposition, generalization, algorithmic thinking, and evaluation” were evaluated, as were the attitudes of “problem solving, teamwork, communication, and spiritual intelligence.”

### 3. Methodology

The present investigation follows the quasi-experimental design of the post-test type with intentional non-probabilistic sampling proportional to the number of students; two groups were carried out by gender, and the scores of the five computational thinking skills were recorded for three academic periods: 2020, 2021, and 2022. The students come from the universities of the Huancavelica region, located in the city of Pampas in the province of Tayacaja. For the sample, first year students of industrial engineering and systems engineering professional careers were considered entrants in the study periods 2020, 2021, and 2022. The ages of the students range from 17 to 20. Table 1 shows the participants that form the sample of the population of men and women students.

**Table 1.** Sample of students.

Population/Sample	Men	Women	Total
Industrial Engineering 2020	21	15	36
Industrial Engineering 2021	24	13	37
Systems Engineering 2022	40	09	49
TOTAL	85	37	122

In the three periods of the execution of the investigation, STEM activities have been carried out through the use of Arduino boards, a distance sensor (HC-SR04), a temperature and humidity sensor (DHT11), an infrared sensor (HC-SR501), a sensor light-dependent resistor (LDR), and a multicolor LED. The activities consisted of solving problems related to the province of Tayacaja, where the typical problems of the area are related to agriculture, livestock, security, and education.

The instrument used to assess computational thinking consists of 28 questions [51]. This instrument is perfectly adapted to students with recent entrance to the university; furthermore, most of the students come from rural schools with limited skills in mathematical reasoning, logic, etc.; therefore, the instrument is perfectly adapted to the cognitive level of students with ages ranging between 17 and 20 years of age. Table 2 shows the test items related to abstraction, decomposition, generalization, algorithmic design, and evaluation skills [19,60].

**Table 2.** Test items for assessing computational thinking skills.

Computational Thinking Skills	Number of Items	Marcos Román-González Test Items
Abstraction	16	1–3, 7, 11–15, 21–23, 25–28
Decomposition	16	4–7, 10–13, 15, 21–23, 25–28
Generalization	19	4–6, 8–12, 14, 15, 17, 18, 20, 22, 23, 25–28
Algorithmic design	28	1–28
Evaluation	14	3, 7, 10, 11, 15, 16, 19, 20, 23–28

The test is composed of 28 items; each correct answer has a score of one point, while an incorrect answer has zero points; therefore, for abstraction ability, there is a maximum of 16 points; for decomposition, 16 points; for generalization, 19 points; for algorithmic design, 28 points; and for evaluation, 14 points. The test was applied during the three academic periods 2020, 2021, and 2022, at the end of each academic period.

## 4. Results

### 4.1. Distribution of Students in STEM Careers

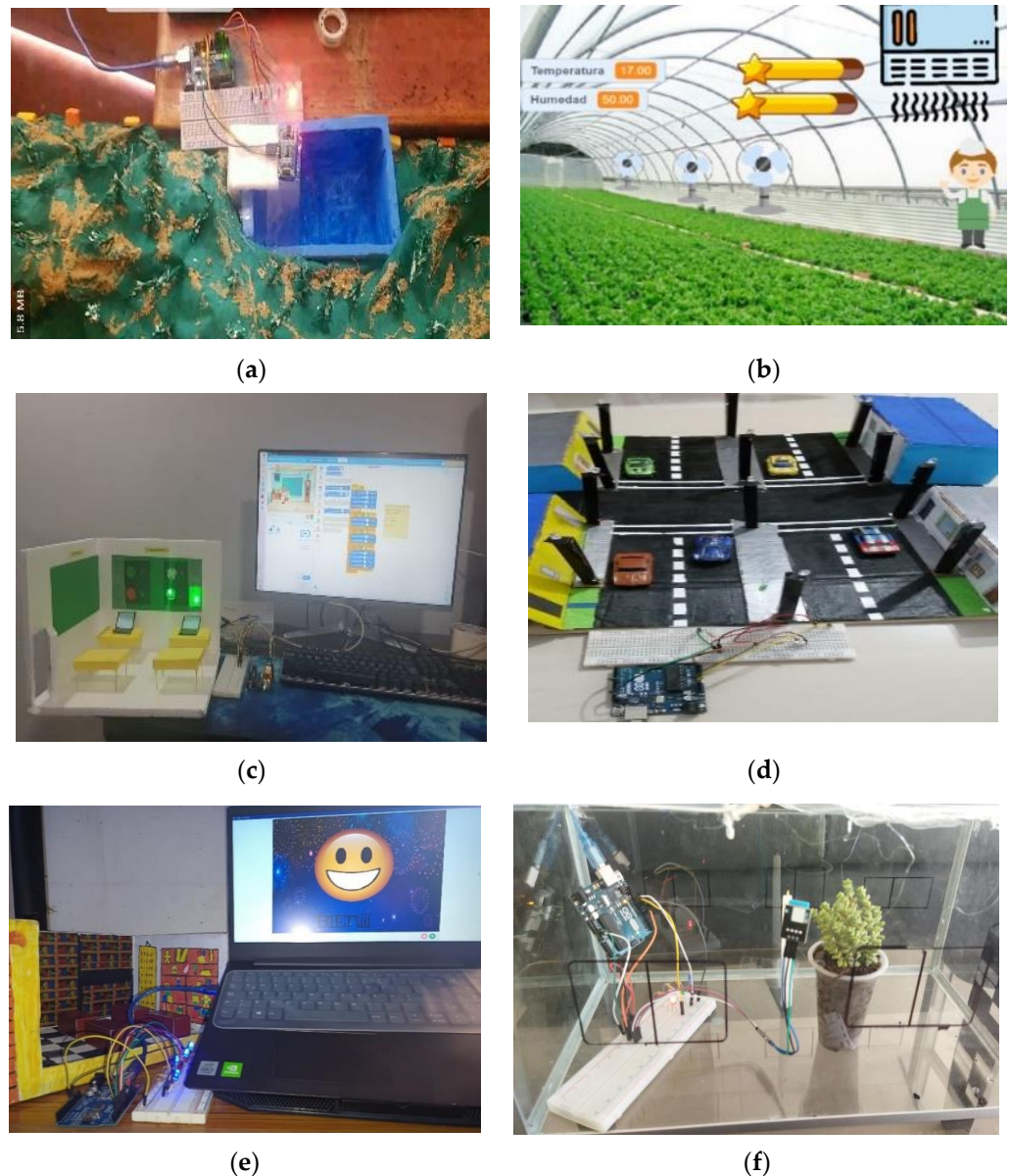
Table 3 shows the percentage of students enrolled according to gender in industrial and systems engineering careers. The industrial engineering career in both academic periods 2020 and 2021 has a higher percentage of participation of women compared to the period 2022; the students who studied in the period 2022 correspond to the systems engineering career, and it can be identified that more women prefer the industrial engineering career because it is less technical than the systems engineering career.

**Table 3.** Percentage of students enrolled by gender.

Professional Careers	Percentage of Students Enrolled	
	Men	Women
Industrial engineering: 2020	58%	42%
Industrial engineering: 2021	65%	35%
System engineering: 2022	82%	18%

#### 4.2. Execution of STEM Activities

For the execution of the STEM activities, groups of five people were formed, made up of women and men; the activities were programmed to strengthen computational thinking skills during 16 weeks in the classroom; the proposed activities were characterized to solve the problems of the regional and rural context of the students, for example, livestock, environment, agriculture, security, and education. The development of the skills was distributed as follows: the abstraction skill was distributed in 5 weeks; the decomposition and generalization skill had a duration of 3 weeks; the algorithm design skill had a duration of 6 weeks; and the evaluation skill had a duration of 2 weeks. During the execution of the technological projects, microcontrollers, sensors, and actuators were used; for example, Arduino boards, a distance sensor (HC-SR04), a temperature and humidity sensor (DHT11), an infrared sensor (HC-SR501), a light-dependent resistor sensor (LDR), and a multicolor LED were used. The results were software- and hardware-based technology products or prototypes. Figure 2 shows the prototypes implemented.



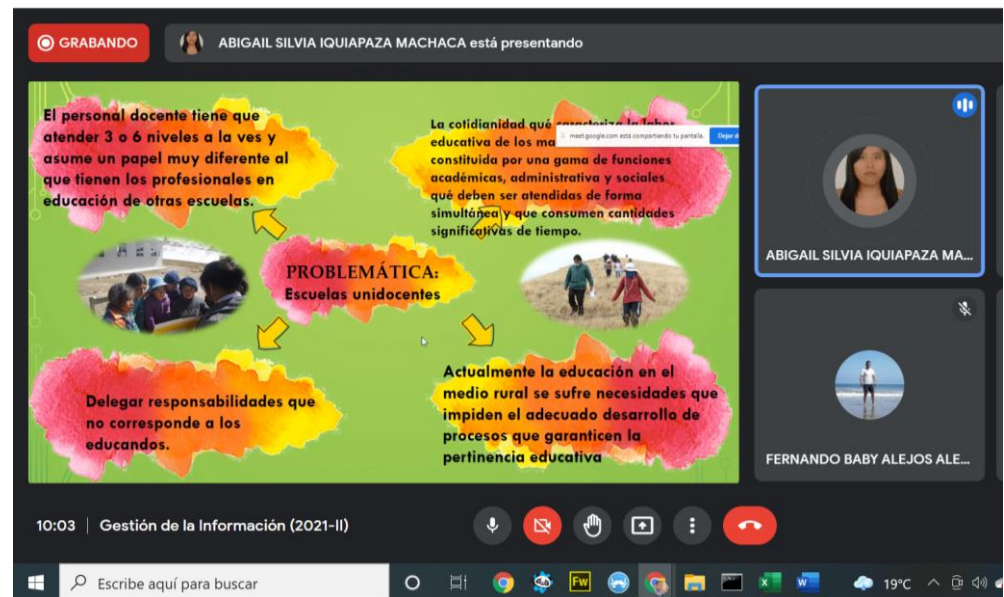
**Figure 2.** Results of STEM activities: (a) Vinas lagoon level monitoring prototype; (b) greenhouse environmental parameter monitoring prototype; (c) basic operations teaching prototype; (d) parking lot safety; (e) animal monitoring prototype; and (f) soil parameter monitoring prototype.



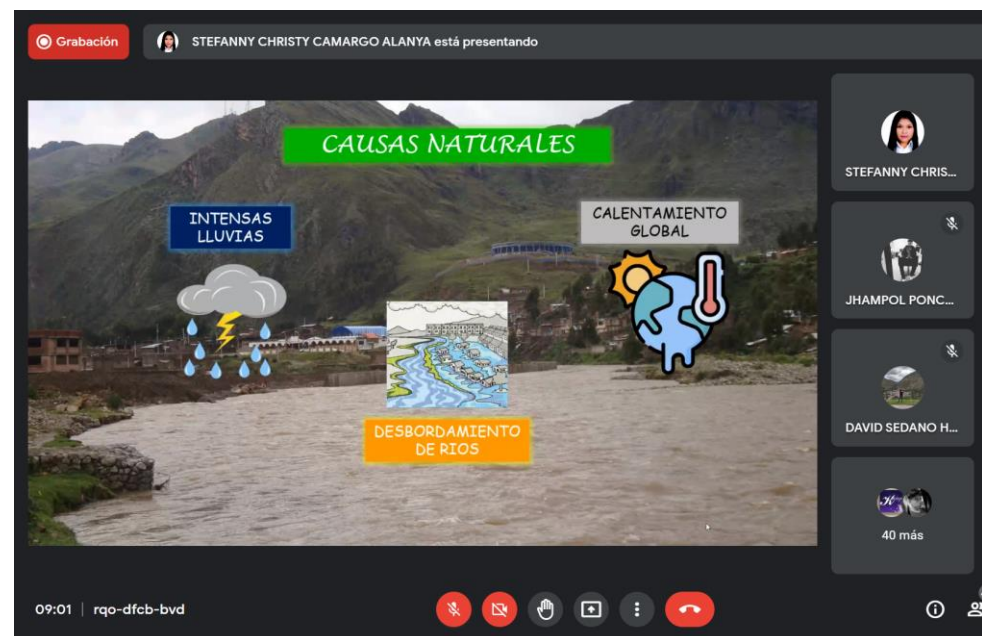
### 4.3. Strengthening Computational Thinking Skills

#### 4.3.1. Abstraction

Exercises on the ability to abstract from computational thinking were developed [26]. The students identified the problematic situation of the project, managing to abstract the most important parts of the problem of the project in a mental map; they also exposed the mental map to the other teams, receiving feedback from the teacher to continue improving in the abstraction of the problem. Figure 3 shows the activities developed to strengthen the abstraction ability.



(a)

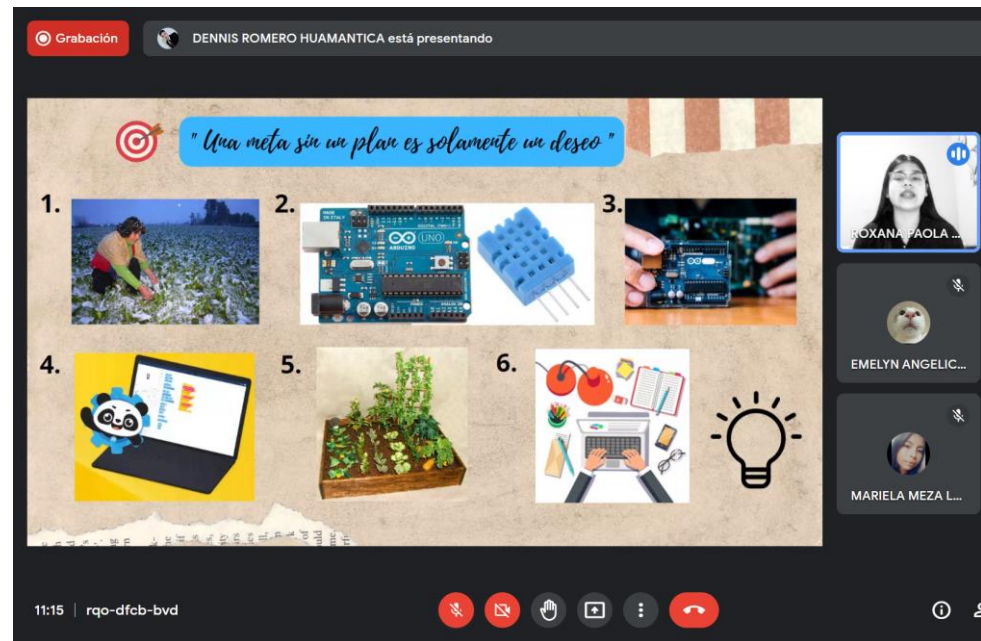


(b)

**Figure 3.** Activities related to abstraction: (a) Representation in mental maps; (b) Cause and effect of the problem.

### 4.3.2. Decomposition

Exercises on the decomposition ability of computational thinking were developed [26]. The professor explained the steps to search for information related to the solution of the problem; he also detailed the technological resources to be used in solving the problem. The students investigated information from bibliographical sources to propose the solution. They raised the possible solutions, dividing them into several activities; then they presented the proposed activities to the other teams, where they received feedback from the teacher to continue improving. Figure 4 shows the activities developed to strengthen the decomposition ability.



(a)



(b)

Figure 4. Activities related to decomposition: (a) Decomposed activities; (b) Activity planning.

### 4.3.3. Generalization

Exercises on the ability to generalize computational thinking were developed [26]. From the information collected from other projects, the students identified patterns or similarities regarding activities that they would reuse to solve the problem; then they exposed the activities that they identified in other projects and that would be reused during the execution of the project. Figure 5 shows the activities developed to strengthen the generalization ability.



(a)



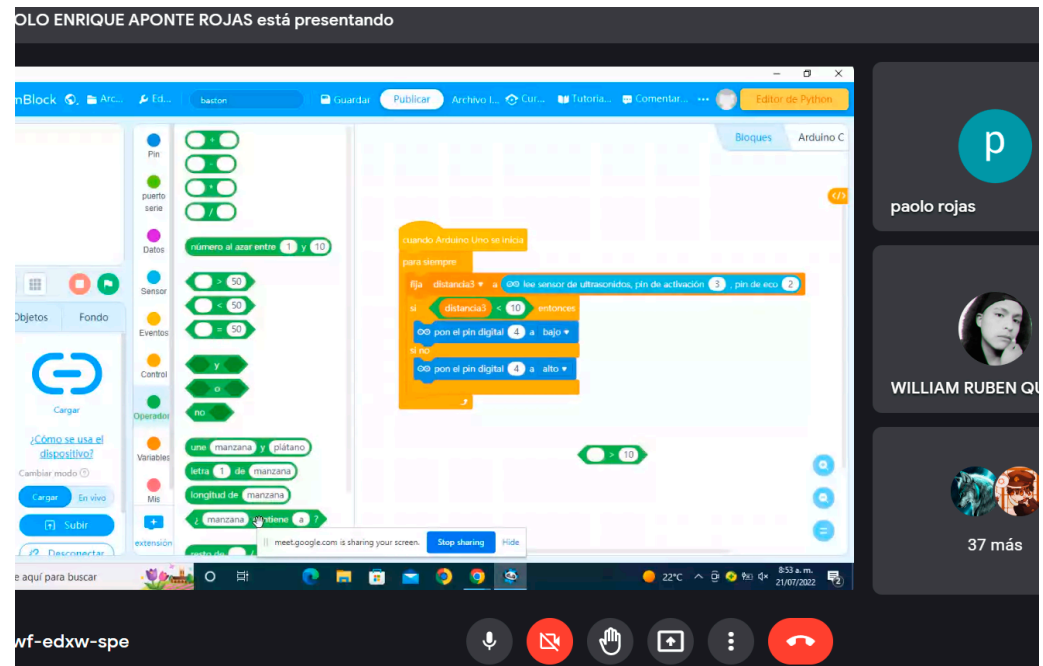
(b)

**Figure 5.** Activities related to generalization: (a) Reuse of activities from other projects; (b) Identification of activities from other projects.

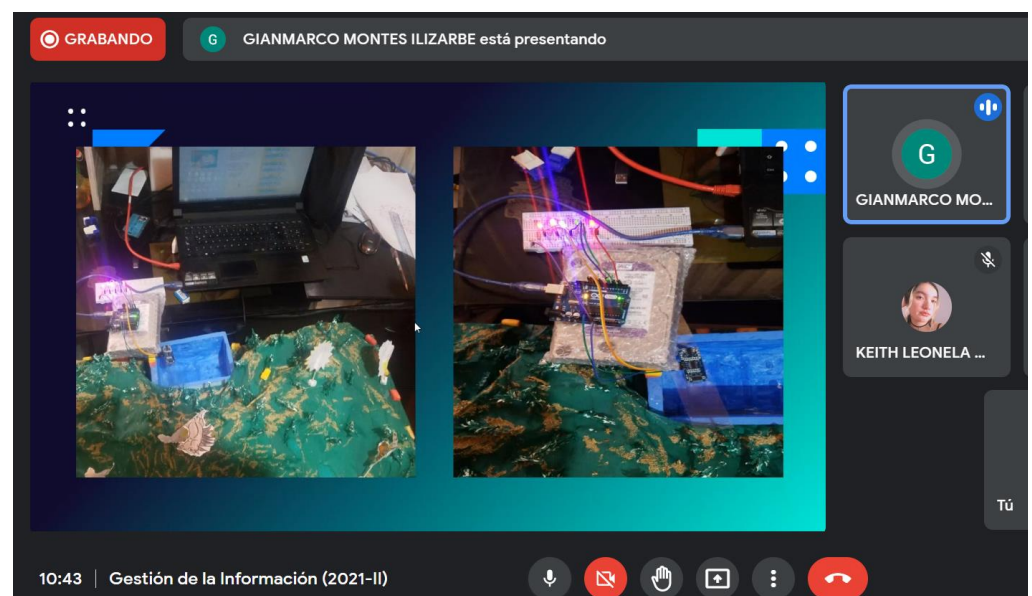


#### 4.3.4. Algorithmic Thinking

Exercises on computational thinking and algorithmic design skills were developed [26]. The students executed the activities step by step until solving the problem; within the activities, they implemented circuits using Arduino boards, sensors, and electronic actuators; thus, they also developed programs using mBlock, where they used computational concepts and computational practices, and finally debugged the program until obtaining the expected results. Figure 6 shows the activities developed to strengthen the abilities of algorithmic design.



(a)

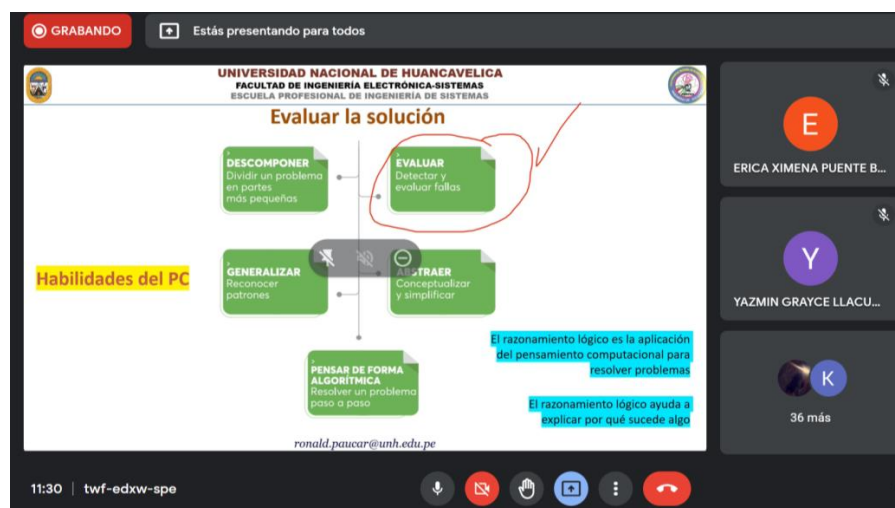


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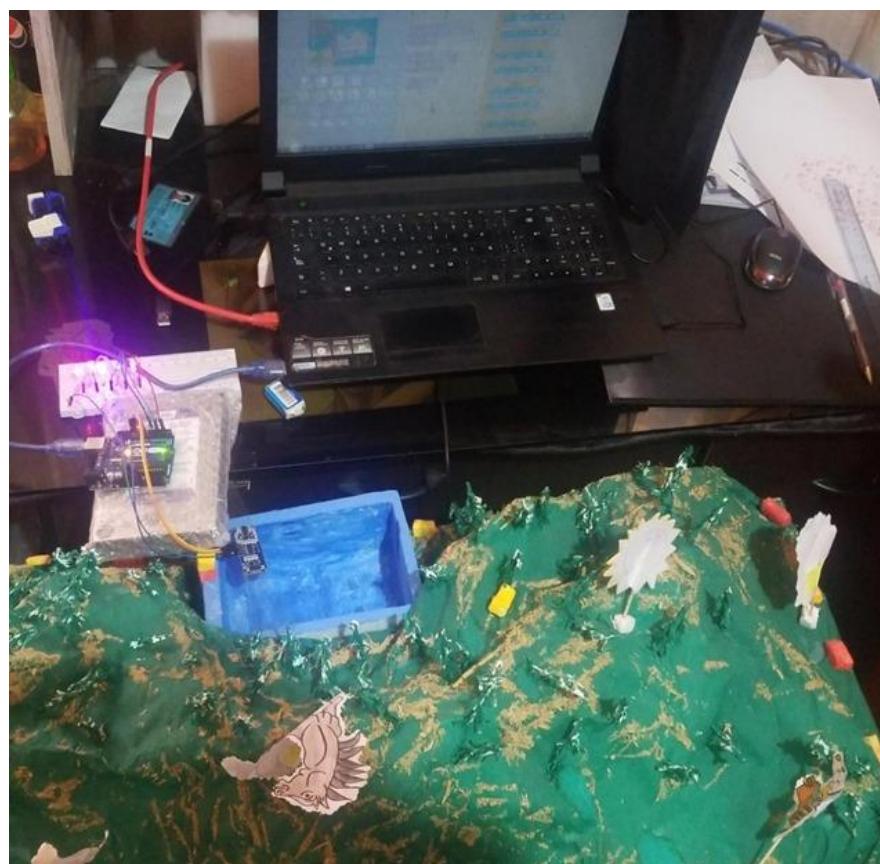
**Figure 6.** Activities related to algorithmic design: (a) Implementation of circuits using sensors and actuators; (b) Development of programs in mBlock step by step.

#### 4.3.5. Evaluation

Exercises on computational thinking and assessment skills were developed [26]. The students evaluated the product or prototype (hardware/software, website, social network applications, etc.), reviewed the operation of its components, and provided feedback to correct errors; they also analyzed the possible use of the product in other projects; then the students demonstrated how the prototypes work, describing the software and hardware components. Figure 7 shows the activities developed to strengthen the evaluation ability.



(a)



(b)

**Figure 7.** Activities related to evaluation: (a) Feedback for prototype evaluation; (b) Demonstration of the operation of the implemented prototype.



#### 4.4. Assessment of Computational Thinking Skills by Gender

An inferential analysis of the data are carried out using the Shapiro Wilk test, in which it is determined that the data of all the subgroups follow a normal distribution ( $p$  value  $> 0.05$ ), which leads us to develop the parametric test of  $t$ -Student for independent samples for each academic period. Tables 4–6 show the inferential analyzes of computational thinking skills for the three academic periods: 2020, 2021, and 2022.

**Table 4.** Inferential analysis of computational thinking skills in 2020.

Computational Thinking Skills	Sample Mean		F-Test $p$ Value Variance	$t$ -Student	$p$ Value Mean
	Men	Women			
Abstraction	8.7143	8.8667	0.2121	0.018	0.9861
Decomposition	8.4762	8.9333	0.2407	−0.468	0.6430
Generalization	9.9048	10.1333	0.3736	−0.185	0.8546
Algorithmic design	15.6190	15.7333	0.1282	0.160	0.8741
Evaluation	7.1905	7.4000	0.2170	−0.220	0.8275

**Table 5.** Inferential analysis of computational thinking skills in 2021.

Computational Thinking Skills	Sample Mean		F-Test $p$ Value Variance	$t$ -Student	$p$ Value Mean
	Men	Women			
Abstraction	8.4583	8.0000	0.6518	−0.425	0.6738
Decomposition	8.0000	7.8462	0.5434	−0.139	0.8903
Generalization	9.7500	9.2308	0.6303	−0.389	0.6994
Algorithmic design	14.5000	14.3077	0.6935	−0.105	0.9172 *
Evaluation	6.5833	7.0000	0.5486	0.428	0.6713

**Table 6.** Inferential analysis of computational thinking skills in 2022.

Computational Thinking Skills	Sample Mean		F-Test $p$ Value Variance	$t$ -Student	$p$ Value Mean
	Men	Women			
Abstraction	9.6000	11.0000	0.1342	1.311	0.1961
Decomposition	9.5500	10.5556	0.0738	0.996	0.3245
Generalization	12.0000	12.5556	0.0289 *	0.346	0.7375
Algorithmic design	18.5250	19.3333	0.0516	0.462	0.6460
Evaluation	8.7250	9.4444	0.5606	0.762	0.4501

The variance test (F-test) is analyzed to determine the pertinent statistic, observing in all cases that there are no significant differences ( $p$  value  $> 0.05$ ), for which reason  $t$ -Student is applied for variances of similar populations [68].

It is inferred about the population means by observing in Table 4 that there are no significant differences between men and women in any of the skills measured ( $p$  value  $> 0.05$ ).

The variance test (F-test) is analyzed to determine the pertinent statistic, observing in all cases that there are no significant differences ( $p$  value  $> 0.05$ ), for which reason  $t$ -Student is applied for variances of similar populations.

It is inferred about the population means by observing in Table 5 that there are no significant differences between men and women in any of the skills measured ( $p$  value  $> 0.05$ ).

The variance test (F-test) is analyzed to determine the pertinent statistic, observing that in all cases there are no significant differences ( $p$  value  $> 0.05$ ), for which  $t$ -Student is applied for variances of similar populations, with the exception of the generalization group ( $p$  value  $< 0.05$ ), for which the other statistic is developed.

It is inferred about the population means by observing in Table 6 that there are no significant differences between men and women in any of the skills measured ( $p$  value  $> 0.05$ ).

## 5. Discussion

According to the results obtained in the previous section, they argue for each result obtained in relation to the preference of the career of industrial engineering and systems engineering according to gender; they also argue regarding the evaluation of computational thinking skills according to gender.

Regarding the preference of STEM-related careers, it is observed that for the periods 2020 and 2021, the percentage of preference of women for the industrial engineering career is very similar, while for the period 2022, the preference for the systems engineering career is 18% and 82% for women and men, respectively. Half of the women went for careers related to management, such as industrial engineering, while only 18% went for more technical careers, such as systems engineering. Various researchers point out that the choice of career is due to several factors, such as cognitive level, professional tastes, relative cognitive strengths, lifestyles, specific skills in the field, values, and gender stereotypes [31–34]. Moreover, it involves the geographical space where the students are located, such as the Huancavelica region, which is located in an Andean zone of Peru. In this place, there is a greater diffusion of STEM careers for men; studies show that men receive more funds for training and research in STEM disciplines than their female counterparts, which has the effect that more men prefer STEM careers [32,36].

Regarding computational thinking skills, according to an inferential analysis in which it was determined that there are no significant differences between male and female students in any of the computational thinking skills measured during the 3 academic periods 2020, 2021, and 2022 [69,70], both male and female students developed computational thinking skills; these results were due to the educational method or strategy applied in the development of STEM activities, which focused on solving real-world problems that have direct relevance to the lives of the community through community protection and service. to the community, this type of activities generated the same enthusiasm in male and female students compared to activities such as educational robotics that only generate motivation in male students [35,37]; moreover, it was evidenced in women that the use of microcontrollers, electronic sensors and actuators allowed them to develop their activities and also allowed them to enthusiastically observe the results in real time of the algorithm or program developed., generating immediate visual feedback of the programming, motivating students to check their operation and refine its functionalities [71,72], to this is added the use of programming in blocks, where it allowed female students to generate creativity in the representation or development of scenarios (landscapes, characters, houses, furniture, etc.) that motivated them to execute and strengthen their computational skills, as Sáinz [73] points out, women always look for gender-related biases to represent or develop their creativity.

During the execution of STEM activities, the existence of strong points according to gender has also been observed [74]. The strong point of the male students is that they are practical in carrying out the activities in which they propose, while the weak point highlights organization. On the other hand, the strong point of the female students is organization and teamwork; these qualities helped both male and female students to develop their activities and, as a consequence, had an impact on strengthening their computational thinking skills because all these qualities were shown in the group work made up of both genders.

## 6. Conclusions

During the execution of the STEM activities, it has been evidenced that the students, both women and men, have worked as a team, exchanged ideas, proposed alternative solutions in the best way, with feedback from the classroom teacher; as they developed their activities, they abstracted from the problematic situation by representing it in mental maps; they identified patterns in the records found, to later use them in their activities; they decomposed, proposing solutions by parts of complex activities; they elaborated algorithms, developed programs using Arduino boards, sensors, actuators and then obtained a friendly

graphical interface using mBlock; with the teacher's feedback, they refined their programs until they obtained the expected results. This set of activities carried out strengthened the computational thinking skills of the female and male students of the engineering career; in addition, they had an impact on the learning of other courses as well as on the practices and technological perspectives. The results of these STEM activities were homogeneous, both for male and female students. It has also been demonstrated through inferential analysis that there are no significant differences between male and female students in any of the computational thinking skills.

The proposal of activities related to agriculture, livestock, the environment, security, and education, which are of interest to the community where the students live, generated enthusiasm in the female and male students to solve the problem; moreover, it has been shown that female students were more motivated in some activities that allowed them to develop computational thinking skills more than male students; the skills that the female students developed the most are the ability of algorithmic design, followed by decomposition, abstraction, evaluation, and generalization.

At the university level, the proposals for activities that are related to the needs of the community, such as agriculture, livestock, the environment, security, and education, are adequate to strengthen the participation of more women in STEM disciplines in the future. It is also important to develop this type of activity in the first years of the university to inculcate technical and scientific jobs in industrial engineering and systems engineering careers. These activities are appropriate to develop in computing, programming, algorithms, information management, and ICT courses; thus, this proposal can also be developed in courses of Science, Technology, and Environment, computing, and education for work in the field of regular basic education.

The limitations of the research: the research was carried out with the participation of students who come mostly from rural areas of the Huancavelica region of Peru; thus, the observation and evaluation of the students were also conducted in virtual mode due to COVID-19.

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