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Research article

Study to find out the perception that first year students in engineering have about the Computational Thinking skills, and to identify possible factors related to the ability of Abstraction

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ABSTRACT

Since the end of the 20th century, the digitalization of society, including the educational systems, has been growing exponentially. At the same time, education systems have been evolving towards competency-based assessment. Likewise, at the beginning of this century, the idea of Computational Thinking was resurrected by J. Wing, for solving problems and designing systems using concepts of computer science. Today, we can see how all these questions are taking shape in a new competence, called Computational Thinking, related to others that already exist. In this paper, we have studied the skills of Computational Thinking in university students, focusing on abstraction and its possible relationship with other factors. Results conclude that the students fail in relation to abstraction and in algorithmic thinking. Although the ability of abstraction is not easy to measure, a linear regression analysis has been carried out in order to determine its possible study.

1. Introduction

Computational Thinking is a competition that is coming to light in recent years due, among other factors, to the rapid implementation of digital technologies, not only in the education system, but also in industry, in the tertiary sector and in the administrative and management system.

According to different authors, Computational Thinking can be included in different fields of knowledge and real life, being related to other skills and abilities such as the problem solving [dataset] (Wing, 2010; Grover and Pea, 2013; Bilbao et al., 2017). Little by little, it has gained ground in the academic plans in different countries and has been integrated into their educational systems [dataset] (Dagienė and Stupuriene, 2016; Varela et al., 2019; Angeli and Giannakos, 2020). Originally, Computational Thinking was linked to the concept of Informatics, even as part of that field of Science. Thus, there are numerous authors who directly relate this new competence to skills such as programming, coding, etc (Mannila et al., 2014; Swaid, 2015; Román-González et al., 2017; Shute et al., 2017). However, other authors defend a more global vision of this competence that can be applied to different fields and areas, beyond Computer Science, such as the STEAM subjects [dataset] (Kim and Kim, 2018; Park and Green, 2019; Conde et al., 2020). This controversy sometimes depends on the field of research or work of the authors and scientists, since already in 2006 Jannette Wing mentioned that Computational Thinking represents a universal applicable attitude and skill set everyone, not just computer scientists, would be eager to learn and use [dataset] (Wing, 2006).

Initially, for [dataset] Wing (2006; 2010), computational thinking involved problem solving, system design, and understanding human behavior in different situations, making use of several of the fundamental concepts associated with computing. Computational thinking included a number of mental tools that reflect the breadth of the field of Computer Science. On the other hand, according to [dataset] Grover and Pea (2013), there is a lot of literature related to computational thinking, but there is little related to experiences with students, referring exclusively to pre-university students.

As far as any other subject, "far away" from Computer Science, the possible improvement that the learning of computational thinking can bring is not sufficiently described. According to [dataset] Hemmendinger (2010), most of the definitions of computational thinking offered lack precision and do not provide enough examples, although most definitions of any kind do not usually include any example.

In 2011, the International Society for Technology in Education (ISTE) and the Computer Science Teachers Association (CSTA) worked

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alongside leaders in education, centered in higher education, industry and schools (K-12) in order to develop an operating definition of Computational Thinking (CT) [dataset] (ISTE & CSTA, 2011). In those years, this definition provided a first wide framework and terminology that teachers could use in the process of developing CT at schools. The competences of the CT that were applied are the following [dataset] (ISTE, CSTA & NSF, 2011):

- Formulating problems in a way that it is possible to use a computer and other tools in their resolution.
- Organizing data logically and analyzing them.
- Representing data through abstractions.
- Automating solutions.
- Identifying, analyzing and implementing possible solutions in order to obtain the most effective combination.
- Generalizing and transferring this process to a wide variety of solutions.

Subsequently, the concept of Computational Thinking has been worked on by different authors, with different results, although always with the aim of providing an intangible asset to society in which the digital aspect is becoming increasingly important. This paper presents a study based on a questionnaire consisting of 27 items, applied to university students, which is in itself a novelty, since the vast majority of previous studies that have been generated with results on the application of CT have been in pre-university studies.

This paper continues with a brief definition and characterization of Computational Thinking; the description of the methodology in the third section; following the analysis and results, including a regression analysis; and finally, the conclusions.

2. Computer Thinking skills

Although the very name of the competition leads one to believe that Computational Thinking may be exclusively linked to the fields of computer science or robotics, there are several authors who argue that CT may be applicable and helpful in other fields, from Engineering to the Arts (Liang et al., 2013; García-Peñalvo and Mendes, 2018; Rojas-López & García-Peñalvo, 2018, 2019; Zapata-Ros, 2019). In order to measure the perception that first-year engineering students have about Computer Thinking skills, and to identify possible factors related to the ability of Abstraction, we have used the following TC concepts:

- Abstraction,
- Modeling,
- Decomposition,
- Algorithmic Thinking,
- Representation,
- Generalization
- Evaluation and Adjustment

Among them, we want to study especially Abstraction, since we understand that one of the first phases of learning and thinking, either in a computational way or in a classic way, is abstraction and its use in reasoning, working as a key piece in that process.

3. Method

3.1. Sample

The study involved 38 first-year students of the UPV/EHU of three different Bachelor degrees that are giving in the university: Bachelor Degrees in Environmental Engineering, in Industrial Technology Engineering, and in Industrial Organization Engineering. Gathering of the information has been carried out during the first academic week of the course 2019/20. The distribution by gender, and the degree to which the participants have registered, is shown in Table 1 and Table 3.

A student is a repeater if it is not the first year of the course, that is, in our classes we have beginner students, who are learning from the first time, and experimented students, who attended classes during the previous academic year or years but failed the examinations.

3.2. Description of the questionnaire

When a questionnaire is used as an instrument for the statistical exploitation of data, it must be well designed according to the standard quality criteria. For the generation of this questionnaire, and according to the ability of CT to be measured, we have used different instruments with acceptable psychometric qualities. Briefly, the questionnaire is designed to measure the seven skills of Computational Thinking. The questionnaire was revised by experts and 27 questions or items were finally selected to validate the Computational Thinking [dataset] (Korkmaz et al., 2017) of the students distributed as follows: the first three items are gender, age and if it is the first year of college, and the remaining 24 are questions related to the Computer Thinking skills we have defined:

- four for Abstraction (Q1-Q4),
- four for Modeling (Q5-Q8),
- four for Decomposition (Q9-Q12),
- three for Algorithmic Thinking (Q13-Q15),
- three for Representation (Q16-Q18),
- two for Generalization (Q19-Q20) and,
- four for Evaluation and Adjustment (Q21-Q24).

Each item has 5 possible ratings according to a Likert scale: “(1) strongly disagree”, “(2) disagree”, “(3) neither agree nor disagree”, “(4) agree”, and “(5) strongly agree”.

The evaluation of the reliability of the questionnaire was carried out using the Cronbach's alpha coefficient. This reliability is very high as shown by the statistician's value of 0.9, as it is shown in Table 2.

4. Analysis and results

This pilot study involved 38 students who are taking subjects that are common, and therefore taught at the same time, to three different engineering degrees: Bachelor Degrees in Environmental Engineering, in Industrial Technology Engineering, and in Industrial Organization

Table 1. Distribution according to the gender and experience.

	Gender		First year
Female	44.7%	Yes (no repeater)	85%
Male	55.3%	No (repeater)	15%

Table 2. *Reliability statistics.*

Cronbach's alpha	N of elements
.900	24

Table 3. Distribution according to the degrees.

	Percentage	Valid Percentage	Cumulative Percentage
Environmental	18.4	18.4	18.4
Industrial	63.2	63.2	81.6
Organization	18.4	18.4	100
Total	100	100	

Engineering. The distribution in the different engineering bachelors is shown in Table 3.

The descriptive statistics of the 24 initial questions are shown in Table 4, where it can be seen that the average of most of the questions is around 3, where the values respond to the following scale:

- (1) strongly disagree
- (2) disagree
- (3) neither agree nor disagree
- (4) agree
- (5) strongly agree

Since the value of the deviation depends on the magnitude of the variable and there is no reference value, the coefficient of variation (CV) (also known as relative standard deviation (RSD)) has been added to refer to the relationship between the size of the mean and the variability of the variable. This coefficient expresses the standard deviation as a percentage of the arithmetic mean, showing a relative interpretation of the degree of variability, independent of the scale of the variable (Figure 1).

With respect to the symmetry or asymmetry of the distribution and flattening or not of the same, the asymmetry statistics are presented, being able to have the cases of symmetric distribution, with the index equal to 0, asymmetric to the right, when the index is positive, and asymmetric to the left, when it is negative; and of kurtosis, which measures the greater or lesser concentration of data around the mean. Analyzing their values, and as seen in their graphic representation in Figure 2, on the one hand, we can say that approximately half of the items are symmetrical; and on the other hand, we see that more than half of the items are mesokurtic. However, we can only consider that 9 of the items follow a normal distribution, since both statistics are in the interval [-0.5, +0.5].

Analyzing each question, it can be seen that the vast majority of students do not have a very clear opinion about it. As an example, and as it is shown in Figure 3, the percentages of questions 1 and 12, related to Abstraction and Decomposition respectively, are given:

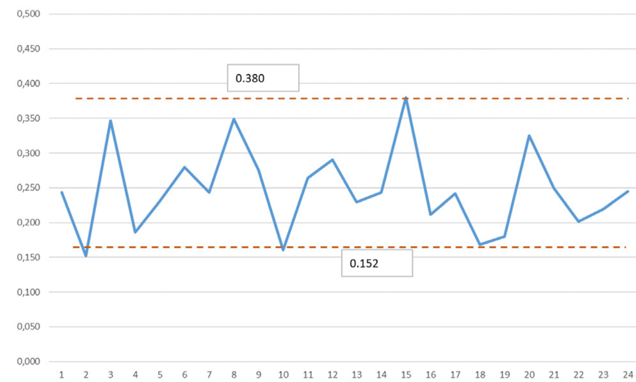

Figure 1. Coefficient of variation.

Q1: I can immediately identify the main ideas or objectives of a problem.

Q12: I can think of different alternatives to decompose the problem.

This attitude may be due both to an educational gap in the Computational Thinking competency, a competency that has not been worked on in our educational system in previous years, and to a lack of knowledge of how to measure a generalist issue and the need for students to specify it with specific examples.

A different and contrary behavior can be seen in questions 3 and 19 and 20. Question 3 refers to the difficulty students have in synthesizing the information given in a problem, in which 71% agree or totally agree with the statement (they correspond to values 1, 2 and 3). And questions 19 and 20, related to the ability of Generalization, refer to the reflection before and after the resolution of a problem in which more than 50% of the students agree or totally agree with it, and correspond to values 3, 4 and 5.

Table 4. Descriptive statistics.

	Mean	Deviation	CV	Asymmetry	Kurtosis
Q1	3.26	0.795	0.244	-0.520	0.704
Q2	3.71	0.565	0.152	-0.920	1.122
Q3	2.21	0.577	0.347	-0.020	-0.172
Q4	3.47	0.647	0.186	0.419	-0.037
Q5	3.21	0.741	0.231	-0.364	-1.057
Q6	3.13	0.875	0.279	-0.522	0.452
Q7	3.37	0.819	0.243	0.448	-0.133
Q8	3.18	1.111	0.349	-0.509	-0.350
Q9	3.55	0.978	0.275	0.119	-0.968
Q10	4.26	0.685	0.161	-0.391	-0.773
Q11	2.89	0.764	0.264	0.183	-1.225
Q12	3.16	0.916	0.290	0.339	0.421
Q13	3.47	0.797	0.229	0.260	-0.277
Q14	3.37	0.819	0.243	0.137	-0.356
Q15	3.03	1.150	0.380	0.059	-0.856
Q16	3.32	0.702	0.212	0.954	0.958
Q17	3.42	0.826	0.242	-0.341	1.057
Q18	4.03	0.677	0.168	-0.031	-0.697
Q19	4.34	0.781	0.180	-1.059	0.746
Q20	3.39	1.104	0.325	-0.737	-0.117
Q21	4.05	1.012	0.250	-1.101	1.037
Q22	3.58	0.722	0.202	0.393	-0.325
Q23	3.21	0.704	0.219	-0.813	1.334
Q24	3.97	0.972	0.245	-1.063	1.268

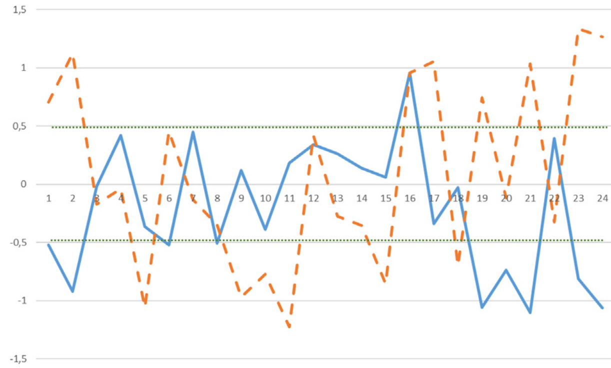

Figure 2. Asymmetry and kurtosis.

4.1. Bivariate correlation

In order to find one or more factors that are related to the Abstraction skill, a bivariate correlation analysis is performed within each of the skills. In principle, the value of 0.05 has been chosen as a significant correlation. Correlation is the most used technique to measure linear association in all sciences. Correlation indicates a possible association or relationship between two variables, and it is important to emphasize that it does not imply causality. Many authors, such as [dataset] Xu et al. (2012), consider that Pearson's correlation coefficient, Spearman's and Kendall's tau are the most widely used to study the degree of association of two variables (simple correlation) through different correlation techniques.

Pearson's correlation is a parametric method, which assumes a normal distribution of the data and a linear association between variables X and Y. For [dataset] Kreinovich et al. (2013), the Pearson correlation coefficient provides a global description of the relationship between random variables. In some practical situations, there is a strong correlation for some of the X and/or Y values and a weak correlation for other X and/or Y values. The final result in our study is shown in Table 5, where the analyzed items are Q10, Q13, Q14, Q17, Q20 and Q23, which have been renamed with the identifiers: I1 to I6, respectively.

Q10/I1: A complex problem is easier to solve by dividing it into smaller or more manageable parts.

Q13/I2: I am able to establish the steps I have to take when I perform a task.

Q14/I3: I am able to effectively sort out the steps I take when solving a task.

Q17/I4: I can accurately interpret evidence, statements, graphs, questions, data.

Q20/I5: After solving a problem, I consider whether the procedure followed is applicable to other problems.

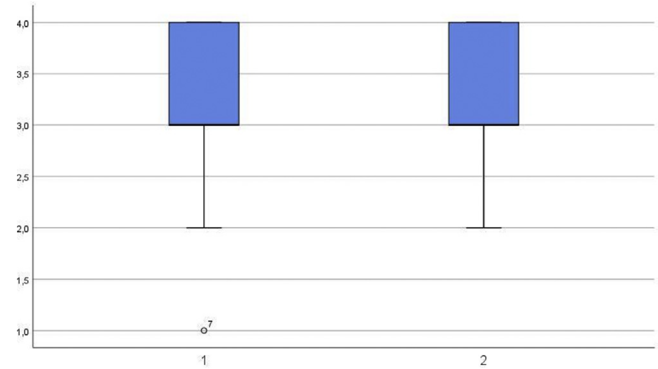

Figure 4. Box diagram for one question of evaluation (Q23/I6). 1 = Female, 2 = Male.

Q23/I6: I reach justified, sensible, and unbiased conclusions.

When the value of the coefficient approaches 1 it means that the variables are highly related and when it is in the opposite direction (close to zero), it is established that their relationship is low; therefore, when the correlation coefficient is zero it indicates a null relationship. Normally, the interpretations shown in Table 6 are accepted.

On the other hand, the correlation does not depend on the direction, either positive or negative; that is, a positive result indicates a direct or positive association between variables, while a negative result indicates an inverse or negative association between the variables.

The information of existence of relationship, strength and direction, appears synthesized in a correlation coefficient and a significance level (sig.). We have used Pearson's correlation coefficient, following the following directions:

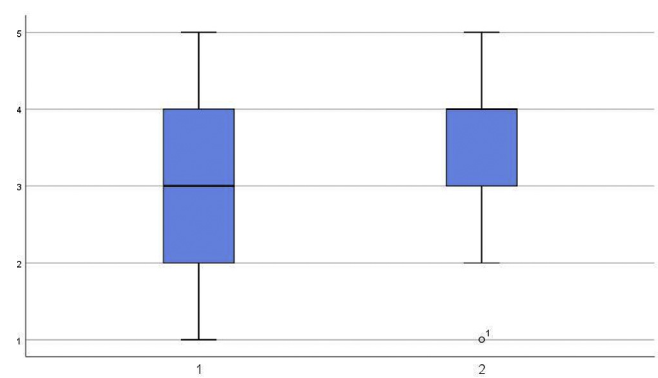

Figure 5. Box diagram for one question of generalization (Q20/I5). 1 = Female, 2 = Male.

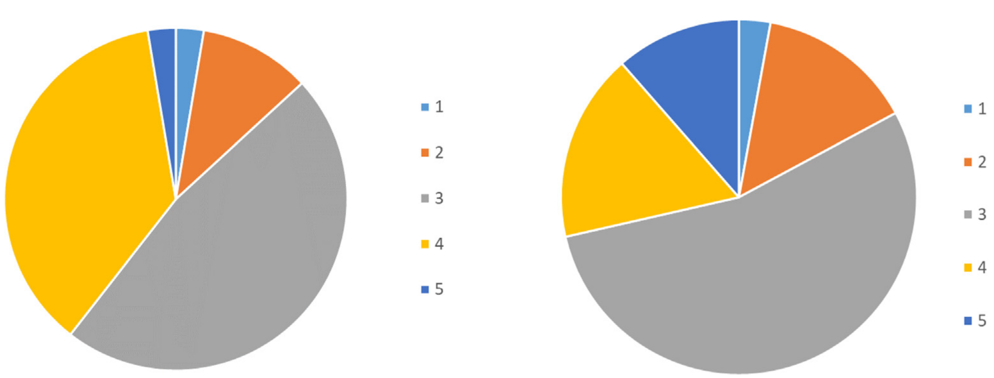

Figure 3. Circular histograms of Q1 and Q12.

Table 5. Item-factor scores correlation analysis.

	I1	I2	I3	I4	I5	I6
Correlación de Pearson	1	0.31	0.304	-0.201	0.145	-0.118
Sig. (bilateral)		0.058	0.063	0.226	0.386	0.48
Correlación de Pearson		1	0.181	0.182	.427**	0.3
Sig. (bilateral)			0.277	0.275	0.007	0.068
Correlación de Pearson			1	-0.036	0.164	0.143
Sig. (bilateral)				0.831	0.326	0.391
Correlación de Pearson				1	0.257	0.215
Sig. (bilateral)					0.119	0.194
Correlación de Pearson					1	.377*
Sig. (bilateral)						0.02
Correlación de Pearson						1

** Correlation is significant at level 0.01 (bilateral).
* Correlation is significant at level 0.05 (bilateral).

1. The level of significance: indicates whether or not there is a relationship between two variables. When the significance is less than 0.05 there is a significant correlation. The statistical treatment of the data has been done with the SPSS software, where it is said that we will reject the null hypothesis of independence (and we will conclude that a significant linear relationship exists) when the critical level is lower than the established significance level (generally, 0.05) [dataset] (IBM Corp, 2016).
2. The correlation coefficient (r). This coefficient can range from -1 to +1. The further away from 0, the stronger the relationship between the two variables. The sign (positive or negative) of the correlation indicates the direction of the relationship.

In statistics, a result is called statistically significant when it is not likely to have been due to chance. A statistically significant difference only means that there is statistical evidence that there is a difference between the variables studied. It does not mean that the difference is large, important, or significant in the strict sense of the word, it only indicates that there are differences. However, there is no scientific reason that indicates that the values of 0.05 and 0.01 are necessarily the most adequate [dataset] (Mark et al., 2016; Molina Arias, 2017).

It is appreciated that there are highly correlated items, but it has been decided to leave all of them for study purposes (so that all the defined CT skills are represented).

The descriptive statistics of the 6 selected items appear in Table 7.

The asymmetry statistics indicate that the items we are analyzing are not distributed following a normal distribution, a hypothesis that is demonstrated in Table 8 where the statistics for the test of normality have a significance lower than 0.05, thus rejecting the hypothesis of normality in all items. The hypothesis of normality has been made taking into account also the gender.

The following (Table 9) shows the percentages of each item in each of the values of the scale: 1 = totally disagree; 2 = disagree; 3 = neither agree nor disagree; 4 = agree; 5 = totally agree.

Table 6. Degree of association of variables according to Pearson's correlation coefficient, r.

Coefficient	Interpretation
r = 1	Perfect correlation
>0.80	Very hard
0.60 < r < 0.80	Hard
0.40 < r < 0.60	Moderate
0.20 < r < 0.40	Low
0.00 < r < 0.20	Very low
r = 0	Null

Items in which students have no opinion are shown in bold. Specifically, items I2 and I3 related to Algorithmic Thinking, in which they are asked about their ability and facility to order and establish steps in a task, item I4 related to the interpretation of evidence..., and item I6 related to their appreciation of the conclusions they reach when solving a problem. Here it should be noted that 10.5% of respondents do not analyze the results they obtain, and therefore may obtain erroneous results.

In addition, there is a failure of the students in algorithmic thinking, which is 52.6% below 4.

4.2. Analysis by gender

With respect to the behavior of the gender variable in the selected items, it is noted that there are no differences, as the Figures 4 and 5 show.Where there is evidence of differences is in item I5 where men reflect on the procedure followed in solving a problem.

4.3. Regression analysis

To identify possible factors related to the ability of Abstraction is another of the purposes of the study, that is, to identify, if possible, those factors that are more related to abstraction, understanding this as the ability to identify the main ideas and synthesize the information that there is in the problem posed. It is interesting to know the effect that one or more variables can cause on another, and even predict to a greater or lesser extent values in a variable from another.

Regression methods study the construction of models to explain or represent the dependence between a response or dependent variable (Y) and the explanatory or independent variable, X. To do this, a linear regression analysis is proposed in which the dependent variable is called ABS (which will be the abstraction), and the independent variables are the 6 items that we have defined previously in Table 5. The variable ABS is the mean of the questions Q1 and Q3 of the initial questionnaire.

The structure of a typical linear regression model, considering the simplest case of a line, is the following:

Table 7. *Statistics of the 6 items.*

	I1	I2	I3	I4	I5	I6
Mean	4.26	3.47	3.37	3.42	3.39	3.21
Deviation	.685	.797	.819	.826	1.104	.704
Asymmetry	-.391	.260	.137	-.341	-.737	-.813
Standard error of asymmetry	.383	.383	.383	.383	.383	.383
Kurtosis	-.773	-.277	-.356	1.057	-.117	1.334
Standard error of kurtosis	.750	.750	.750	.750	.750	.750

Table 8. Tests of normality.

	Gender	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	gl	Sig.	Statistic	gl	Sig.
I1	1	.315	17	.000	.785	17	.001
	2	.296	21	.000	.774	21	.000
I2	1	.295	17	.000	.859	17	.015
	2	.255	21	.001	.861	21	.007
I3	1	.234	17	.014	.889	17	.044
	2	.261	21	.001	.865	21	.008
I4	1	.280	17	.001	.864	17	.017
	2	.254	21	.001	.853	21	.005
I5	1	.255	17	.005	.887	17	.041
	2	.302	21	.000	.843	21	.003
I6	1	.269	17	.002	.825	17	.004
	2	.362	21	.000	.727	21	.000

[a] Correction of significance of Lilliefors.

Table 9. Percentages.

	I1	I2	I3	I4	I5	I6
1				2.6	7.9	2.6
2		7.9	13.2	5.3	13.2	7.9
3	13.2	**47.4**	**44.7**	**47.4**	21.0	**55.3**
4	47.4	34.2	34.2	36.8	47.4	34.2
5	39.4	10.5	7.9	7.9	10.5	

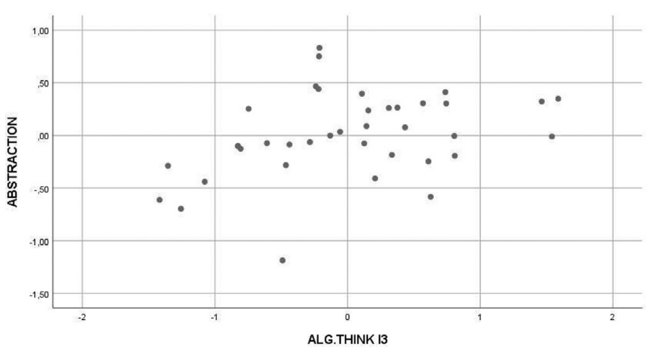

Figure 6. Regression between abstraction and I3.

$$Y = \beta_0 + \beta_1 X + \varepsilon$$

In this expression we are admitting that all the factors or causes that influence the dependent variable Y can be divided into two groups: the first one contains an explanatory variable X and the second one includes a wide set of uncontrolled factors that we will include under the name of perturbation or random error, ε, which causes that the dependence between the dependent and independent variables is not perfect, but it is subject to uncertainty.

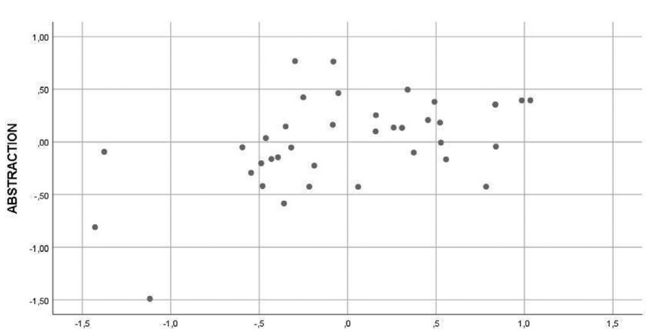

Figure 7. Regression between abstraction and I6.

Therefore, the effect that one or several variables can cause on Abstraction has been studied by means of a linear regression analysis. In our case, Abstraction has been the dependent variable.

The results have been obtained, which can be seen in Figures 6 and 7, where the other variables have been items I3 and I6, respectively. We recall that these items are related to algorithmic thinking (I3) and to evaluation and adjustment (I6), and are the following:

I3: I have the ability to effectively order the steps I take when solving a task.

I6: I reach justified, sensible and impartial conclusions.

As can be seen, there is a relationship between abstraction and algorithmic thinking, and between abstraction and evaluation and adjustment. Although there is no clear linearity between the variables, the relationship is appreciable, a question that can be reasoned by the implication and relationship of abstraction with more than one skill of Computational Thinking (and many other skills).

5. Conclusion

This study has been carried out in order to know the students' perception of the seven skills that have been used in Computational Thinking: abstraction, modeling, decomposition, algorithmic thinking, representation, generalization, and evaluation and adjustment. We used a questionnaire of 27 items, validated by experts, applied to university students. We have made a study of each skill according to the questions it has associated, and if we identify the values 4 and 5 of the scale as passed, we conclude that the students fail in relation to abstraction, since 86% are below 4. There is also a failure of the students in algorithmic thinking, which is 52.6% below 4. Although the questionnaire was designed to measure the seven skills of Computational Thinking, it is appreciated that there are highly correlated items, so we propose that the items must be dynamics by two main reasons: in order to measure more specifically the skills, and because the multiple definitions of Computational Thinking.

On the other hand, we have found that the ability of abstraction is not easy to measure. In this sense, a linear regression analysis has been carried out, verifying that this ability can be measured using two questions: one corresponding to algorithmic thinking and the other related to evaluation and adjustment.

Declarations

Author contribution statement

J. Bilbao, E. Bravo, O. García, C. Rebollar, C. Varela: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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Data availability statement

The data that has been used is confidential.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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