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Relationship between the Learning of Computational thinking and the Development of Reasoning

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Abstract— *This work describes a quasi-experimental study which aims to investigate the relationship between the contruction of Computational Thinking and the reasoning development of students of the last years of Elementary School. The research was carried out using a 10-hour course in Games Development, offered in two private schools with 50 participant students, in two consecutive years, with four different classes. The proposed teaching-learning practice was built on theoretical assumptions of meaningful learning and experiential learning. Computational Thinking and students' reasoning were evaluated before and after the course, using the Computational Thinking Test and the tests that compose the BPR-5 Testing Battery. The statistical analysis of the data showed an increase in Computational Thinking, as well as in Verbal Reasoning, Abstract Reasoning and Mechanical Reasoning of the students who took part in the experiment. A positive correlation between Computational Thinking and the five types of reasoning evaluated was also documented.*
Keywords— ***Computational Thinking, Intelligence, Cognitive Assessment.***

I. INTRODUCTION

It can be said that many young people have vast experience and familiarity in interacting with new technologies, but at the same time have little experience in creating and expressing themselves with new technologies. An extended view of digital fluency assumes that students go beyond the simple domains of Information and Communication Technologies (ICT), requiring an understanding of how computers work and learning to formulate problems and expressing their solution so that either a computer or human beings can carry out.

This way of thinking of Computer Science itself was named Computational Thinking, a term that became popular from the article entitled "Computational Thinking" published in 2006 by Jeannette M. Wing. It should be noted that some of Wing's ideas were already present in Papert's experiments on the LOGO programming language, as well as the idea that the skills developed when learning to program would be transposed into other spheres of life. (PAPERT, 1980)

Although not scientifically proven, it is assumed that the problem-solving process used in Computer Science can be generalized and transferred to a wide variety of problems in everyday life. Thus, the Computational Thinking would not be a skill related exclusively to the Computer Science graduation course.

It is relevant to elucidate the effects of Computational Thinking learning under cognition. If the influence in the development of reasoning is identified, the importance of this discipline in basic education will surpass a mere market demand.

In scientific literature, there are few studies that evaluate Computational Thinking with objective instruments, and there is practically no research on the impacts of this learning in cognition. Therefore, the main objective of this work is to investigate the relationship between the construction of Computational Thinking and the development of reasoning. The present article was organized in this article is composed of seven sections that follow this Introduction, Computational Thinking, Differential Intelligence Paradigms, Meaningful Learning And Experiential Learning, Methodology, Results and Discussion, Conclusion and References.

II. COMPUTATIONAL THINKING

In the book "Mindstorms: children, computers, and powerful ideas", researcher Papert (1980) discusses the

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impact of computers on people's lives and how their use influences the way people think. He noted that children, when learning to program with LOGO, use computer models to organize thinking as they "program the computer to make more complex decisions and find themselves engaged in reflecting on more complex aspects of their own thinking" (PAPERT, 1980, p. 28).

In several sections of the work, Papert presents themes related to what is now called Computational Thinking (CT), however there is no concern from the author in defining this concept. It should be noted that the term "Computational Thinking" is mentioned only once, referring to the insertion of the computer in society and the difficulty of creating an engaging experience with the technologies used in programming clubs. Still, in the work of Papert (1980), Computational Thinking is understood as a way to structure thinking. The author relates CT to logical reasoning, problem solving and debugging. "Learning to be a master of programming is learning to become highly skilled at isolating and correcting bugs" (PAPERT, 1980, p. 23).

The concept of Computational Thinking was popularized through an article by Wing (2006), in which the author states that "Computational Thinking involves solving problems, designing systems and understanding human behavior, by drawing on the concepts fundamental to Computer Science" (WING, 2006, p. 33).

In Computational Thinking: What and Why? Wing (2010, p. 1) describes the mental activity in solving a problem that admits a computational solution and defines Computational Thinking as the "thought processes involved in formulating problems and their solutions, so that solutions are represented in a form that can be effectively carried out by an information-processing agent".

Google for Education describes Computational Thinking as a process that includes four computational thinking techniques: decomposition, pattern recognition, generalization and abstraction, and algorithm design. In this sense, Computational Thinking is understood as:

> a set of skills and problem-solving techniques used by software engineers to create programs for the applications you use, such as search, email, and maps. Computational thinking includes the skills and ways of thinking that are used when writing computer programs, but go beyond the use of computers (GOOGLE, 2015).

Royal Society (2012, p. 29) states that "Computational Thinking is the process of recognizing aspects of computation in the world that surrounds us and applying tools and techniques from Computer Science to understand and reason about both natural and artificial systems and processes".

Publications and researches led by Code.Org (CODE.ORG, 2015), Liukas (2015) and BBC Learning (2015) merged the elements cited by Grover and Pea (2013) summarizing the so-called "Four Pillars of Computational Thinking" (or dimensions) for a problem solving approach: Decomposition, Pattern Recognition, Abstraction, and Algorithms:

- Decomposition – breaking down a complex problem or system into smaller, more manageable parts;
- Pattern Recognition – looking for similarities among and within problems;
- Abstraction – focusing on important information only, ignoring irrelevant details;
- Algorithms – developing a step-by-step solution to the problem, or the rules to follow to solve the problem.

Considering the different definitions for Computational Thinking presented in this paper, it is understood that there is no consensus, for they are associated with the grouping, under the same term, of different impacts of computer usage in our society. Computational Thinking covers processes of three distinct categories: Cognitive Processes, Behavioral Processes, and Social Processes.

- Cognitive processes: related to the impact of computer usage in human cognition. They involve abstraction, logical reasoning, decomposition, algorithm, error debugging, and pattern recognition.
- Behavioral Processes: involve the demands and modifications of behaviors and attitudes: collaboration, perseverance, and sharing experiences.
- Social Processes: refer to the impacts of the computer on society, such as: automation, simulation, the use of social networks, changes in work organization and its influence in other branches of knowledge.

Therefore, Computational Thinking may be considered a set of transformations noted in the way of thinking, acting, and behaving socially due to the use of computers. With this proposal of categorization, it becomes easier to delimit the field of study of new researches which deal with Computational Thinking. The scope of this research, for example, is limited to analyzing Computational Thinking with regards to the cognitive processes involved.

III. DIFFERENTIAL INTELLIGENCE PARADIGMS

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Primi (2003) states that psychology has been seeking for decades to answer the question about the nature of intelligence, which is the central theme of many researches. To ease the understanding of theories about human intelligence, Afonso (2007) suggests classifying the different theories into four paradigms:

- Biological paradigm: refers to the understanding of intelligence as a phenomenon resulting from biological factors, from neuronal level – anatomy, physiology, and functioning of the nervous system, to the most elementary levels, both genetic and biochemical, or more macroscopic, developmental and evolutionary.
- Constructivist or Psychogenetic Paradigm: considers intelligence as a way of adapting to the environment, in which knowledge is constructed by the individual, through the two complementary processes of assimilation and accommodation.
- Informational Paradigm: takes the computerized processing of data as a metaphor and seeks to understand the intelligence in terms of mental processes of information handling.
- Differential Paradigm: emerges from the indication of individual differences in cognitive functioning, as noted through evidence and use of psychological tools.

The present study, proposed to measure the effects of the teaching of Computational Thinking on aspects of intelligence, will be grounded on the Differential Intelligence Paradigm.

According to Primi (2003), the psychometric approach uses a concept of intelligence based on factorial analysis, which is based on the individual differences revealed through hundreds of tests designed to assess cognitive abilities.

For Almeida (2000), the BPR-5 – Battery of Reasoning Tests is the most complete test available in Brazil. This test is based on the most recent factorial conceptions of intelligence, allowing the evaluation of general intelligence: Sperman's[1] G-Factor, as well as more specific intelligence factors. Due to these characteristics this was the instrument used to evaluate the reasoning in this work.

The 5 subtests that make up the BPR-5: AR – Abstract Reasoning, VR – Verbal Reasoning, NR – Numerical Reasoning, SR – Spatial Reasoning, and MR – Mechanical Reasoning, relate to specific intelligence factors:

- The AR subtest is mainly associated with fluid intelligence (Gf) defined as the ability to reason in new situations, to create concepts and to understand implications.
- The VR subtest is associated with fluid and crystalized intelligence (Gc), defined as the extent and depth of vocabulary verbal knowledge, and the ability to reason using previously learned concepts.
- The NR subtest is associated with fluid intelligence and partly with the quantitative skill (Gq) defined as the understanding of basic quantitative concepts such as addition, subtraction, multiplication, division, and manipulation of numerical symbols.
- The ER subtest is partly associated with fluid intelligence, but mainly with visual processing capacity (Gv) defined as the ability to represent and manipulate mental images.
- The MR subtest is partly associated with fluid intelligence, and practical mechanical knowledge.

Almeida (2000) emphasizes that all subtests are associated, to a greater or lesser extent, with fluid intelligence, an ability that is more similar to Sperman's G-factor.

IV. MEANINGFUL LEARNING AND EXPERIENTIAL LEARNING

For Ausubel, Novak & Hanesia (1980), "the most important single factor influencing learning is what the learner already knows. Ascertain this and teach him accordingly". The emphasis of this theory lies in the organization of knowledge in structures and in the restructurings that occur in the subject with the acquisition of new information.

Meaningful learning takes place when new information relates to some relevant aspect of the individual's knowledge structure; new ideas can be learned to the extent that relevant and inclusive concepts are clear and available in the individual's cognitive structure, also called concept anchoring.

According to Ausubel's theory (1980), learning can occur through reception, process by which knowledge is presented in its final form to the learner or through discovery. It is important to point out that "both receptive

[1] Sperman (1904, 1927) found in his experiments that the test scores of different intellectual activities had a correlation between the remaining ones that were still constant. For the author, all branches of intellectual activity would have a common fundamental function, which he named as General Factor, or G Factor.

and discovery learning can be developed in a meaningful or mechanical, depending on the conditions under which the learning occurs" (AUSUBEL et al, 1980, p. 23).

Learning is meaningful if the content is linked to relevant concepts and subsumptions existing in the cognitive structure, therefore the concept of advance organizers is of particular importance. The advance organizers are a knowledge that has the function of facilitating learning on a domain that may be completely unknown, working as a causeway between what the learner already knows and what he should know, these organizers function as a cognitive bridge.

For Ausubel (1980), true advance organizers are those intended to facilitate the meaningful learning of specific topics or closely related ideas. In the meantime, the introductory materials used to facilitate the learning of various topics would be called pseudo advance-organizers.

As a practical example we can mention the teaching code for the movement of sprites in Scratch[2]. In order to learn to move the characters, it is necessary to know the Cartesian plane, as well as the screen resolution used in Scratch (subsumptions).

The Experiential Learning theory highlights the central role that experience plays in the learning process, the process in which knowledge is created through the transformation of experience Kolb (1984). Another reason why the theory is called "experiential" refers to its intellectual origins in the experimental works of Lewin, Piaget, Dewey, Freire and James, constituting a unique perspective on learning and development.

For Kolb (1984), knowledge is created by the transformation of experience, resulting from the combination of understanding and transformation of experience,

> mere perception of experience itself is not enough for learning; something must be done with it. Likewise, transformation alone cannot represent learning, for there must be something to be transformed, some state or experience that is being put into practice. (KOLB, 1984, p.42).

Following Dewey, Kolb's Theory of Experiential Learning (1984) describes how experience is transformed into learning through a cycle involving experiencing, reflecting, thinking, and acting.

The model proposed by the Experiential Learning Theory portrays two opposing ways of consolidating experience: Concrete Experience (CE) and Abstract Conceptualization (AC), as well as two opposite ways of transforming it: Reflective Observation (RO) and Active Experimentation (AE).

Learning from experience is a process of building knowledge that involves a creative tension between these four ways of learning. This process is portrayed as an idealized or spiral learning cycle in which the student goes through the four fases:

- Concrete Experience: related to personal experiences and feelings involved in the learning situation;
- Reflective Observation: implies on problem solving by reviewing and reflecting on the experience;
- Abstract Concept: the understanding is based on the intellectual understanding of a situation, that is, on the conclusions constructed based on the experience, in which the level of abstraction quite high;
- Active Experimentation: involves active learning in which students plan new experiences, modify variables and influence situations, experience what they have learned and formulate hypothesis.

For this author, learning will be effective when the student makes progress through an environment made up of stages of concrete experience, reflective observation, conceptualization and practical activity.

Kolb and Fry (1975) argue that the learning cycle can begin at any of the four points, and that these steps should be approached as a continuous spiral. However, they suggest that teaching material should be planned to respect the entire learning process, taking into account the sequence of the experiential learning cycle, in order to offer each learner the opportunity to develop skills at each stage of the experiential learning cycle. The Games Development course used in this research, when searching for subsumptions to support the new knowledge, started learning from the Concrete Experience.

V. METHODOLOGY

The experiment was carried out through an course in Games Development, with duration of 10 hours, offered as an extra class activity in the inverse shift of classes for students enrolled in grades 6 to 9 of Elementary School in two private schools in the city of Porto Alegre, in the State of Rio Grande do Sul, Brazil. To verify the effect of the proposed pedagogical intervention, two evaluations of the 50 participant students were carried out. The first

[2] https://scratch.mit.edu/

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evaluation was done before the course and the second after the end of the course.

The nature of this study did not allow the random selection of the sample and the control group was not used, because it is a course offered extra class, for this reason, this research is characterized as a quasi-experimental study. However, as the experiment occurred in 7 weeks, this interval reduced the possibility of school learning being responsible for the observed increase.

In the quasi experiment, since no random distribution of units is made under conditions, other principles are used to show that alternative explanations are not plausible. To verify the effect of the proposed pedagogical intervention, two evaluations of the 50 students who participated in the experiment were carried out. The first one before the Games Development Course and the second after the pedagogical intervention, later the average of the groups was compared based on statistical tests.

In order to ensure that the results achieved were related to the research and not to external variables, the Games Development course was offered in four editions. The data collected in this study had the objective of testing two hypothesis which were formulated at the beginning:

- The teaching of Computational Thinking improves students' reasoning ability;
- There is a correlation between Computational Thinking and reasoning ability.

For this purpose, it was foreseen in the research design to analyze the relation of the score achieved in the Computational Thinking Test and the BPR-5 tests, as shown in Fig. 1.

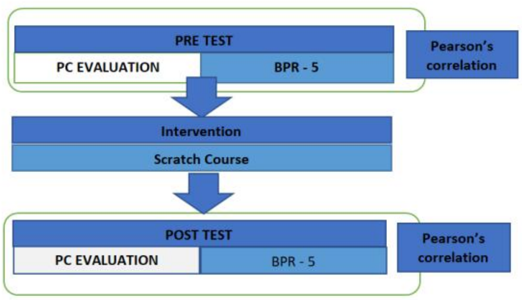

Fig. 1: analysis of the relationship between variables

The first two classes of this experiment happened between October and November 2016 and the others between April and May 2017. The experiment lasted 7 weeks, with weekly meetings with the participant students. The first and the last week were dedicated to evaluation with BPR-5, five weeks were used to carry out the Games Development course.

All of the lessons of the course proposed by this project were planned to start seeking to rescue past experiences of the students, to find subsumptions and to generate discussions about experiences outside the computational context. Next, the students interacted with code snippets. At the later time they were asked about the operation of the code and tested modifications in the programming. Finally, each lesson ended with challenges on the topic covered in Scratch.

VI. RESULTS AND DISCUSSION

6.1 Evaluation of Computational Thinking and Validation of the Teaching Methodology

To meet the specific goal of evaluating students' Computational Thinking, we used the Computational Thinking Test prior to the start of the Games Development course (pre test) and after the course (post test). The test used to evaluate the students was developed by (Román-González, 2015, 2016; Román-Gonzáles, Pérez-González, et al., 2017), it is a multiple choice test in which there are 28 items with four answer options (only one correct), with a maximum time of 45 minutes to complete the task. This test is intended for children of school age between 12 and 13 years old and aims to measure the level of their Computational Thinking development.

Table 1: Student's mean

School/Class	Students	Pre test	Post test	Difference
School A – 2016	16	17,43	19,69	2,26
School B – 2016	11	14,82	16,09	2,03
School A – 2017	16	14,06	16,69	2,63
School B – 2017	7	15,14	17,29	2,15
Total	50	15,46	17,60	2,14

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Considering the difference between means, it can be stated that in all classes of the Games Development Course, there was an increase in students' Computational Thinking. However, further testing is required to determine its statistical relevance.

The normality of the sample made the use of parametric tests possible. The paired T-test was performed, resulting in a one-tailed P (T <= t) of 0.000025. Thus, it has been proven that there is evidence of a 5% increase in the average score of the Computational Thinking Test after students attend Games

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Development classes. Considering the Confidence Interval, the averages increased between 1.17 and 3.11 points. The results can be seen in Table 2.

Table 2: Paired t-test

	Pre test	*Post test*
Mean	15,46	17,6
Difference	24,29429	17,46939
Observations	50	50
Mean difference	2,14	
Pearson correlation	0,732276	
Hypothesis of the mean difference	0	
gl	49	
T statistic	-4,44442	
P(T<=t) one-tailed	0,000025	
One-tailed t critical value	1,676551	
P(T<=t) two-tailed	0,000050	
Two-tailed t critical value	2,009575	

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The difference in means through the statistical tests presented corroborates the validation of the teaching-learning methodology used in this study, showing its efficiency to promote Computational Thinking.

6.2 Computational Thinking and Students' Reasoning Ability

In order to verify the effect of the learning of Computational Thinking on the students' reasoning ability, we performed the analysis of the means of the gross results of the tests: VR – Verbal Reasoning, AR – Abstract Reasoning, MR – Mechanical Reasoning, SR – Spatial Reasoning and NR – Numerical Reasoning, which showed that there was an increase of the mean in all tests.

Considering the decision rule of the Shapiro-Wilk test, it was identified that, in this case, it is not possible to use the paired t-test to compare the means of the pre test and post test, since the sample achieved in the pre tests RV, RA and BPN5, does not follow a normal distribution. Analyzing the results of the post test, it was verified that in the RA and RV tests, it was not possible to reject the null hypothesis. For this reason, to standardize the statistical analysis of the means obtained in the reasoning tests, the Wilcoxon test was used to compare the difference of means.

Comparing the means obtained in the Verbal Reasoning test, the Wilcoxon test showed a statistically significant increase in the mean, with a significance level of 5%. The students who attended the course have increased the score of this test between 0.5 and 2.5 points higher than the score of the first evaluation. These results are presented in Table 3.

Table 3: Verbal Reasoning Analysis

Information	***Values***
Statistic	806
P-value	0,0036
Null hypothesis	0
Lower limit	0,499974285
Pseudo-median	1,499974734
Upper limit	2,499952547
Trust level	0,95

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Regarding the difference of means of the Abstract Reasoning test, the Wilcoxon test proved that the increase in mean is statistically relevant, with a significance level of 5%. In this test the students obtained a growth of around 1.5 points compared to the first test performed, as shown in Table 4:

Table 4: Abstract Reasoning Analysis

Information	***Values***
Statistic	814
P-value	0,0027
Null hypothesis	0
Lower limit	0,500039073
Pseudo-median	1,999999486
Upper limit	2,500061646
Trust level	0,95

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The mean increase in the Mechanical Reasoning test was also verified using the Wilcoxon test with a significance level of 5%. For this test a score difference of 1.5 points with a margin of error of 1 point is expected, that is, the students who attended the course obtained an increase in the score of this test between 0.5 and 2.5 points higher than the result of the first evaluation. These results are presented in Table 5:

Table 5: Mechanical Reasoning Analysis

Information	***Values***
Statistic	726,5
P-value	0,0068
Null hypothesis	0
Lower limit	0,499976114
Pseudo-median	1,500079589
Upper limit	2,500008729
Trust level	0,95

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The Wilcoxon test did not confirm the existence of score difference regarding the first and second evaluations of the Spatial Reasoning test since the p-value is higher than 0.05. The results of this test are shown in Table 6.

Table 6: Spatial Reasoning Analysis

Information	***Values***
Statistic	607
P-value	0,4683
Null hypothesis	0
Lower limit	-0,500038266
Pseudo-median	0,499933548
Upper limit	1,499944641
Trust level	0,95

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The mean difference of the Numerical Reasoning test was not statistically relevant, since with the Wilcoxon p-value test it was higher than 0.05, not allowing rejection of the null hypothesis. Table 7 shows the results of this test:

Table 7: Numerical Reasoning Analysis

Information	***Values***
Statistic	718,5
P-value	0,0508
Null hypothesis	0
Lower limit	-7,64E-05
Pseudo-median	1,000038909
Upper limit	1,99997262
Trust level	0,95

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When comparing the means of the set of reasoning tests, Wilcoxon's test showed a statistically significant increase in mean, with a significance level of 5%. Considering the margin of error, students who attended the Games Development Course obtained an increase in BPR-5 between 3.0 and 7.5 points higher than the result of the first evaluation. These results are presented in Table 8:

Table 8: BPR-5's Analysis of Means

Information	***Values***
Statistic	1015,5
P-value	1,00E-04
Null hypothesis	0
Lower limit	3,000005013
Pseudo-median	5,499951932
Upper limit	7,500006083
Trust level	0,95

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Based on the results, it is possible to observe that the proposed course has favored a growth in Computational Thinking and students' reasoning.

6.3 Relationship Between Computational Thinking and Different Types of Reasoning

In order to analyze the relationship between Computational Thinking and the different types of reasoning: Verbal Reasoning, Numerical Reasoning, Spatial Reasoning, Abstract Reasoning and Mechanical Reasoning, the Pearson correlation was used.

According to Table 9, the Computational Thinking Test showed a correlation with all reasoning tests, reaching a very high correlation with the sum of the BPR-5 scores that was 0.74. This fact demonstrates that there is a very close relationship to Computational Thinking and a general factor of intelligence.

Table 9: Pearson Correlation

CTT	VRT	ART	MRT	SRT	NRT	BPR5
Pre test	0,505	0,649	0,405	0,630	0,562	0,696
Post test	0,462	0,670	0,457	0,629	0,646	0,742

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VII. CONCLUSIONS

The use of Román's Computational Thinking Test (2015) and the BPR-5 - Battery of Reasoning Tests are considered a differential of this study, since these instruments allowed the measurement of the Computational Thinking and the reasoning of the participant students in an objective way. Since the score in the Computational Thinking Test was significantly higher after the course, the results obtained allowed us to validate the present teaching methodology and infer about the possible benefits that should be obtained with its adoption in the Elementary School classrooms.

In this study it was not possible to use a control group, which would isolate external factors that could influence the development of Computational Thinking, however, as the experiment occurred in 7 weeks, this interval reduced the possibility of school learning to be responsible for observed increase. It should be noted that the methodology was used in 4 different classes, presenting an increase in Computational Thinking and different types of reasoning in all classes. Considering that the course editions occurred in different schools and in two consecutive years, this fact reinforces the role of the Games Development Course in the measured results, avoiding the hypothesis of being due to external factors such as school learning. In the present study all the classes of the Games Development Course were given by the researcher himself, which facilitated the standardization of the classes. When replicating this experiment to the classroom it becomes relevant to pay attention to the lesson plan used and it may be necessary to have a greater detail to be replicated by a third party. The students did not receive the tests and did not have access to the results obtained until the end of the research. As the time interval used between the test and retest was 7 weeks, this time was sufficient to prevent students from remembering the questions used in the tests. It should be noted that in the precision studies of the BPR5 - Battery of Proofs of Reasoning Lemos (2006) used the interval of only 1 month between test and retest finding a correlation coefficient higher than 0.75

This work has confirmed that even brief interventions, such as the one used in this research, when prepared with an adequate methodology, can produce relevant effects for its participants. The fact that a 10-hour course produces changes in cognitive ability, which can be measured and statistically proven, confirms the importance of inserting content for the development of Computational Thinking in Brazilian schools.

Another relevant fact of this research was to demonstrate the correlation between Computational Thinking and other types of reasoning, reinforcing their importance in cognitive development. As the increase in Computational Thinking favored the development of Verbal Reasoning, Abstract Reasoning and Mechanical Reasoning, it is possible to conclude that the improvement in the cognition of the subject regarding the construction of Computational Thinking can favor the learning of other curricular components.

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