Assessing algorithmic thinking skills in early primary school amid environmental studies

Abstract

This proposal introduces part of a wider project aiming for the development and the assessment of fundamental computational thinking skills, such as algorithmic thinking and abstraction, in early childhood education. More precisely, the part of the project that is presented refers to an assessment tool constructed by the authors, which focuses on evaluating algorithmic thinking skills of first and second grade primary school students. It employs data collection instruments and analysis techniques of mixed method research methodology and it is proposed to be applied in the classroom within the context of an environmental studies course. A relevant research conducted is also discussed, which focused on establishing validity and reliability of the results provided by the proposed assessment tool, evaluating students' algorithmic thinking skills and testing the relationship between algorithmic thinking skills and the levels of the content understanding of the environmental studies course.

Subject of interest

Nowadays, the cultivation of computational thinking is considered an essential objective at all educational stages worldwide (Barr et al., 2011; Barr & Stephenson, 2011; Grover, 2015), since it is expected that, by the second half of the 21st century, it will be recognized as a fundamental skill, just like reading, writing and arithmetic are at present (Wing, 2006). The international literature highlights as structural elements of computational thinking various skills that form the basis of policies aiming at its cultivation and the evaluation of its development (Barr & Stephenson, 2011; Brackmann et al., 2017; Fessakis et al., 2018; Grover & Pea, 2013; Selby & Woollard, 2014; Wing, 2006; Yadav et al., 2014). An issue that arises is the variety of opinions about what the basic aspects of computational thinking are. Nonetheless, convergence of opinion occurs about the fact that algorithmic thinking is a basic pillar of computational thinking.

By exploring the literature to define what an algorithm is, many relevant definitions can be found. A sufficient definition that serves the purposes of the presented research is: "An algorithm is a method to solve a problem that consists of exactly defined instructions" (Futschek, 2006, pp. 160). Additionally, these steps must be finite and implementable in finite time.

In recent years, several countries have established contests on informatics and computer literacy, which emphasize the development and the evaluation of algorithmic thinking skills of students in compulsory education. An example of such an international contest is Bebras (Dagienė & Futschek, 2008). Towards the same goal, several tools have been proposed, which involve the use of programming environments, such as the Fairy Assessment (Werner et al., 2015) and the FACT (Grover, 2017). For the students in the early stages of primary education, it is suggested that they run the algorithms themselves, just as a processor would do (Futschek & Moschitz, 2010). They can also take part in learning scenarios that involve tangible objects (Futschek & Moschitz, 2011).

The research approach presented in this proposal, regarding the evaluation of algorithmic thinking skills, is based on the fact that, for hundreds of years, people find the reconstruction of an image from its pieces amusing (Gallagher, 2012). However, besides its enjoyable aspect, solving puzzles also touches on issues related to everyday life and can be applied in various scientific fields and professional activities, such as biology, archeology, image processing, solving voice communication security issues, e.g., in the military and enterprises, through coding-decoding applications (Paikin & Tal, 2015; Pomeranz et al., 2011; Zhao et al., 2007). In the educational area, solving puzzles broaden the students' horizon, allowing them to form an idea of algorithms at a more abstract level and assist them to comprehend the exploration of possible paths to the solutions (Levitin & Levitin, 2011). The multidisciplinary character of solving puzzles impelled researchers to construct algorithms for solving jigsaw puzzles (Gallagher, 2012; Paikin & Tal, 2015; Pomeranz et al., 2011; Wolfson et al., 1988; Zhao et al., 2007). According to the above, the correlation between the ability to solve puzzles and the algorithmic thinking skills is by far established.

The research questions of the presented investigation focus on the examination of the validity and the reliability of the results provided by the proposed assessment tool, the evaluation of students' algorithmic thinking skills and the exploration of the correlation between students' algorithmic thinking skills and the levels of the content understanding of the environmental studies course.

Educational design and Research procedure

The proposed assessment tool employs quantitative and qualitative techniques for data gathering. The combination of qualitative and quantitative methodology works in a complementary way, offering researchers the opportunity to combine different methods in order to arrive at a more complete research approach when collecting and analyzing their data (Creswell, 2014).

The backbone of the assessment tool is a digital platform designed and implemented by the authors to serve the needs of their research. It is compatible with all the operating systems and it runs on smart mobile devices, aiming to exploit the benefits of mobile learning (Zhu et al., 2016). In fact, this platform is a computational environment (CE) through which students exercise their ability to assign values to entity attributes, while they work on a thematic unit of the environmental studies course. Each student selects the entities to be studied. During the preparation of the thematic unit, the teacher can embed relevant images into the CE, to facilitate the visualization of the entities under study. Alternatively, students can employ their own images. For example, in the case of outdoor learning activities students can shoot photos of entities, using their smart mobile devices. They can also create their own pictures by deploying a painting application embedded into the CE.

The thematic unit of the environmental studies course employed for the presented research was animals and, more especially, their eating habits. Although the research focused on five components of computational thinking i.e., abstraction, algorithmic thinking, selection, organization and analysis of data, this proposal discusses only the work done regarding the assessment of algorithmic thinking skills. Thus, only the relevant parts of the CE will be presented.

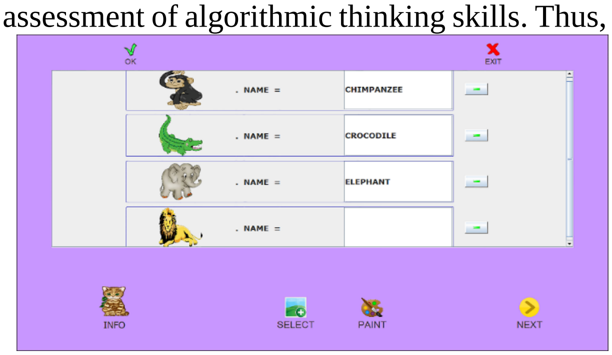

Figure 1. Assigning values to the attribute "NAME"

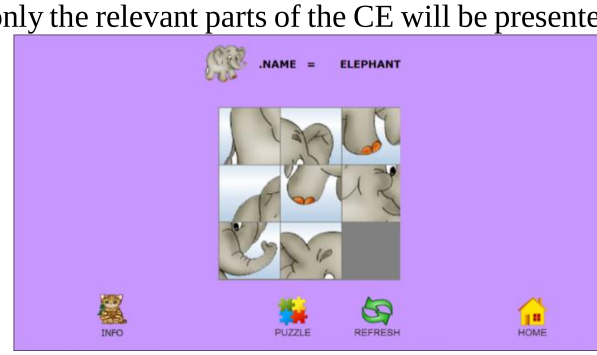

Figure 2. A 9-piece elephant puzzle

Primarily, the student chooses and/or paints the pictures of the animals. For each one of these images, a command line shows up on the screen (Figure 1). The following step is to specify each animal's name, by assigning the value to the relevant attribute (Figure 1). As shown in Figure 1, the authors propose a hybrid schema of visual and text-based programming techniques, emphasizing object-orientation (Hillar, 2015). However, there is no direct reference to programming concepts and practices.

After determining the animals' names, the CE automatically creates puzzles for each image selected or painted (Figure 2). These puzzles are unique, just like the students' paintings and photographs, as well as the entities each student decides to study. The user can select the picture of the puzzle and the number of its pieces: 4, 6, 9 or 12.

Each puzzle is a grid that contains mixed pieces of an animal's image. A part of the picture is missing, i.e., a cell of the grid is empty. Each piece can be moved horizontally, vertically or diagonally, if one of the neighboring cells is empty. The piece to be moved will be placed in the empty cell and the cell that was previously occupied by the piece moved will be empty. The user must keep on repositioning the pieces of the image until the puzzle is solved. The more pieces the puzzle has, the harder is to solve.

At a quantitative level, the researchers test the children’s ability to solve puzzles in relation to the kind of puzzles they solve (4, 6, 9, 12-piece puzzles), by examining the CE’s log files. Log files provide information on the number of the puzzles solved, their kind and the number of movements the students made to solve them.

At a qualitative level, the authors conducted personal interviews, recording the students’ work plan. In particular, the researchers showed each student a 6-piece dog puzzle and asked: "Where would you start to solve this puzzle?" Mainly, the students pointed to a specific part of the picture, e.g., the dog’s head. In some cases, students went a step further, describing the sequence of their actions, e.g., "I'll start from the head and I’ll continue with the body." In the cases that some students attempted to solve the puzzle, the researchers stopped them and prompted them to explain in words the way they would solve it. Checking the existence of a work plan is of great significance. The students’ ability to demonstrate their work plan proves that they did indeed exercise their algorithmic thinking skills and did not solve the puzzles coincidentally.

In order to identify and assess the content understanding of the selected thematic unit of the environmental studies course i.e., the comprehension of the animals’ nutrition habits, a relevant worksheet was constructed. The students had to declare the nutrition habits of 12 animals found in Greece. While students were working on worksheet answers, the researchers paid extra attention to prevent copying. Even if there is the possibility of a few students escaping the researchers’ attention, the chance that someone could copy all 12 answers of the worksheet is out of the question. However, the accuracy of the results would be harmed if some students were able to copy even one answer. In addition, giving random answers would also harm the accuracy of the results. Aiming to eliminate such factors, the researchers prepared one more worksheet with close-ended questions, which contained statements regarding the nutrition habits of the animals of the first worksheet. The students had to accept or reject these statements. The examination of the combination of the results of the two worksheets empowers the adequacy and the accuracy of the results concerning the students’ content understanding.

The combination of the results of the two worksheets entails a considerably large amount of different possible answers. Thus, the data are grouped and a representative value for each group is proposed. The representative values originated from the grading scale of the fifth and sixth grade of primary school, as set out in the latest relevant Ministerial Decision (Greek Ministry of Education, 2017). According to this decision, in the fifth and sixth grades of primary school, descriptive assessment is suggested in conjunction with a grading scale that is verbal and numerical, as follows: Excellent (9-10), Very Good (7-8), Good (5-6), Approximately Good (<5). The authors employ this grading scale, because for the first two grades the same Ministerial Decision proposes just descriptive evaluation.

The results provided by the assessment tool were thoroughly tested for internal consistency reliability, test/retest reliability and interrater reliability (Cohen et al., 2013; Kimberlin & Winterstein, 2008). As far as the validity is concerned, the results were tested for construct validity, criterion-related validity, internal validity, external validity, consequential validity and content validity (Cohen et al., 2013; Feldt & Magazinius, 2010). However, due to space limitations, relevant information will be not be provided in this proposal and will be presented during the conference.

The research was conducted by the authors in 2019, in the city of Heraklion, Crete, Greece. The participants (N = 435, 48.5% female) were primary school students in first grade (50.1%) and second grade (49.9%). The assessment tool was applied in the Information Technology laboratory of the schools that participated in the research. Before using the CE, the researchers gave the students clear instructions about its functionality. In all stages of the research, a well-defined and robust ethical framework was followed (Cohen et al., 2013).

Findings and Analysis

All the variables were measured at the nominal level and, thus, Latent Class Analysis (LCA) was employed (Clogg, 1995; Stamovlasis et al., 2018). LCA trace back heterogeneity in a population to several existing but unobserved subgroups of individuals, which are referred to as latent classes. The analyses are based on a set of observed variables that can be categorical and/or continuous. The classes are formed such that there is as much similarity within a class while at the same time as many differences between the classes as possible (Lanza & Cooper, 2016). The identification of these latent classes can be useful for characterizing qualitative differences between learners, which may be missed with traditional analytic approaches (Hickendorff et al., 2017). In the presented research, LCA was applied with the scores (success/fail) of solving 4, 6, 9 and 12-piece puzzles (Pz4, Pz6, Pz9 and Pz12, respectively) as input.

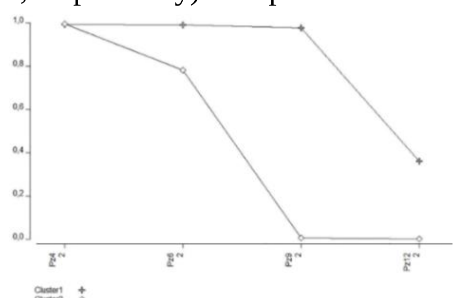

Figure 3. Conditional probabilities of the two clusters/latent classes representing the levels of algorithmic thinking skills

LCA leads to a two-cluster solution (df = 6, classification-error = 0.0109, BIC = 1250.75, AIC = 1213.04, Npar = 9, entropy R2 = 0.92, $G^2(2) = 14.02$, $\chi^2(2) = 157.31$) as the best parsimonious model with the lowest BIC values. Cluster 1 (51.49%) includes students having high probability of success in solving 4, 6 and 9-piece puzzles, and with a low probability of success in solving 12-piece puzzles. Cluster 2 (48.51%) includes students having high probability of success in solving 4 and 6-piece puzzles, which however fail in solving 9 and 12-piece puzzles (Figure 3).

The effect of covariates is depicted in Table 1. Gender is related to students' achievement in the algorithmic thinking tasks. Cluster 1, which includes students with the highest algorithmic thinking skills, is positively associated with boys (b = 0.094, $p < 0.05$, one tail) and negatively associated with girls (b = - 0.094, $p < 0.05$, one tail). The statistical association, however, is marginal.

There is also an effect of grade. Cluster 1, students with the highest algorithmic thinking skills, is positively associated with the second grade (b = 0.118, $p < 0.05$) i.e., the high achievers are most probably belonging to the second grade.

Students were allocated into two groups. The first included those students that did not follow any plan and the second included those students that followed a plan.

Table 1. The association of cluster membership with the covariates. Coefficients, standard deviation, z-values, Wald and p-values.

	Cluster1	SD	z-value	Cluster2	SD	z-value	Wald
Gender							
Boy	0.094	0.052	1.79	-0.094	0.052	-1.79	3.20*
Girl	-0.094	0.052	-1.79	0.094	0.052	1.79	
Grade							
First	-0.118	0.053	-22.15	0.118	0.053	22.15	4.91**
Second	0.118	0.053	22.15	-0.118	0.053	-22.15	
Content understanding							
Aprox. Good	-0.248	0.095	-26.07	0.248	0.095	26.07	13.69***
Good	-0.139	0.093	-14.93	0.139	0.093	14.93	
Very Good	0.160	0.086	1.87	-0.160	0.086	-1.87	
Excellent	0.227	0.093	24.48	-0.227	0.093	-24.45	
Plan							
without plan	-0.627	0.199	-31.53	0.627	0.199	31.53	9.94***
with plan	0.627	0.199	31.53	-0.627	0.199	-31.53	

* $p < 0.05$ (one tail), ** $p < 0.05$, *** $p < 0.01$

Cluster 1 is positively associated with the second group (b = 0.627, p < 0.01) and negatively associated with the first group (b = -0.627, p < 0.01). That is, students with the highest algorithmic thinking skills most probably followed some kind of plan. On the contrary, Cluster 2 is negatively associated with the second group (b = -0.627, p < 0.01) and positively associated with the first group (b = +0.627, p < 0.01). Students with low algorithmic thinking skills most probably are those who followed no plan.

Finally, Cluster 1 is positively associated with the excellent level of content understanding (b = 0.227, p < 0.01) and negatively associated with the approximately good level (b = -0.248, p < 0.01). The opposite holds for Cluster 2. Conclusively, the algorithmic thinking skills are statistically associated with students' performance in the environmental studies course.

Contribution to the teaching and learning of science and to the interest of NARST members

In the modern digital era, the demand of societies to develop students' computational thinking skills at all stages of compulsory education has attracted the attention of researchers, educators and policy makers all over the world and provoked relevant inquiries. Responding to this request, the authors attempt a novel contribution to the relevant research area, reemphasizing that an essential requirement for the effective development of computational thinking skills, such as algorithmic thinking, is a coherent theoretical framework providing clear definitions along with the construction of assessment tools developmentally appropriate for the target groups. When completed, the tools will be freely distributed to the academic and educational community.

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