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Investigating the Association between Algorithmic Thinking and Performance in Environmental Study

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Abstract: Presently, computational thinking (CT) is considered necessary for adapting to the future. Concurrently, the COVID-19 pandemic has accentuated the demand for strengthening Environmental Education as a means to improve sustainability and stimulate environmental protection and public health. Having in mind that CT does not concern only technocrats but also applies in solving everyday problems, we introduce the novel idea of the synergistic learning of CT and Environmental Study. Thus, our research aim is to explore the correlation between algorithmic thinking (AT), as a fundamental CT competency, and educational achievements in the Environmental Study course during the early primary school years. Towards this end, we implemented a quantitative research study, employing an innovative assessment framework we propose. The adoption of cluster sampling eventuated in a sample of 435 students. The exploitation of ordinal logistic regression analysis and machine learning method validated the correlation of the two fields and pointed out that AT levels constitute a predictive factor for performance in the Environmental Study course and vice versa. These results support the novel idea of concurrently cultivating environmental consciousness and CT and build a robust base for future studies that will focus on providing an ecological reflection on CT activities.

Keywords: computational thinking; STEM; educational methodologies; educational apps; teaching programming; gamification

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1. Introduction

Nowadays, the increasing attention to incorporating CT in education has provoked the concomitant emergence of need and interest in exploring its cultivation and assessment [1,2]. At the same time, while humankind is rocked with unrepresented magnitude by a pandemic originated from the mismanagement of natural habitats and wildlife, the importance of environmental awareness and sustainability is more relevant than ever [3]. Advocating for the multi-faceted nature of CT, which is not only to create future scientists or engineers, but also to enhance many cognitive and intellectual skills, facilitating people to solve everyday problems [4], we introduce the innovative idea of the synergistic learning of CT and Environmental Study.

In a classification scheme of science fields and subfields, Environmental Science and Technology is under the branch of Agriculture and Environment [5]. Furthermore, although Environmental Science does not belong to the group of the so-called core sciences (e.g., mathematics and physics), Next Generation Science Standards (NGSS) [6] set out several environmental issues, such as the role of water in Earth's surface processes, human impacts on earth systems and global climate change, as disciplinary core ideas of science. NGSS also include the influence of engineering, technology and science on society and the natural world in the list of the proposed crosscutting concepts. Consequently, NGSS accept that Environmental Science is under the broad umbrella of STEM (Science, Technology, Engineering, and Mathematics).

Until now, several educational approaches have been proposed regarding the synergistic learning of CT and other STEM fields, such as physics [7], chemistry [8], and mathematics [9]. Nevertheless, as far as we know, no study has been conducted yet examining the potential educational synergy between CT and Environmental Study. Motivated by this research opportunity and in light of the imperative need of: (a) creating environmental literal citizens well-trained to establish environmental and resource sustainability [10] and (b) cultivating CT as necessary equipment in the contemporary digital era, we focus on investigating the relationship between CT and performance in the Environmental Study course. This article provides evidence of a relevant research study we conducted, focusing on assessing AT as a fundamental CT competency.

Indeed, although pertinent studies expound on different skills as fundamental CT elements [1], there is a convergence of opinions that AT is one of its fundamental components [11,12]. Exercising AT turns out to be one of the major CT competencies, facilitating our understanding of existing problems and empowering us to provide solutions in order to deal with them [13], while it creates a fertile ground for sensitizing the ethical concerns that algorithms introduce [14].

This article discusses part of a wider research study we carried out exploiting a novel assessment framework, with the objective of investigating age [15], gender [16], and learning achievements in the Environmental Study course as predictive factors of core CT competencies, namely AT and abstraction [17]. The proposed assessment framework, which is of a constructivist, multidisciplinary and game-based structure, was applied to 435 primary first and second graders. We directed our attention to the early ages, following the recent international trend of developing CT as soon as possible in compulsory education [18,19]. The primary motivation of cultivating CT even from kindergarten derives from the demand to equip future generations to respond to real-life challenges [19]. Having in mind that learning CT can be approached through digital game mediums [20] such as jigsaw puzzles [21] and being aware that game-design requires CT [2], we constructed the research study discussed in this article around the assumption that solving jigsaw puzzles could estimate students' CT skills, such as AT.

The discussed research study was implemented in the framework of quantitative methodology, aiming to answer the research question: "Is there an association between AT skills and educational achievements in the Environmental Study course during the early years of primary school?" Thus, we set the hypothesis that: "There is no association between AT skills and educational achievements in the Environmental Study course during the early years of primary school." In order to test the hypothesis set, we performed chi-square statistic, calculated *p*-value, determined odds ratio, conducted ordinal logistic regression analysis and employed the machine learning method. The research results confirmed the association between AT skills and educational achievements in the Environmental Study course, supporting the innovative idea of cultivating environmental consciousness together with CT, and laying the foundations of future studies regarding the provision of ecological reflection on CT activities.

2. Theoretical Framework

Aiming to establish the conceptual framework of our research approach, we are going to shortly discuss its fundamental axes i.e., early childhood education, CT, AT, Environmental Study and game-based learning.

2.1. Early Childhood Education

Early childhood education concerns young children from birth through age eight [22], and it is of great importance as it boosts a variety of early-life competencies and later-life attainments. During the sensitive early years, children rapidly mature linguistically, cognitively, socially and emotionally, in a way that will determine their future functioning in many fields [23,24]. Children who benefit from high-quality early learning, from kindergarten to the first primary school grades, develop considerably more appropriate behavior, socially interact significantly better and show much more emotional maturity than peers that do not participate in early learning settings [23].

Research has revealed that children's development of socio-emotional skills during the early years of education is crucial for long-term school and life achievements [25]. Furthermore, competencies cultivated in early childhood education, such as language, literacy and math cognitive skills, as well as self-regulation, motivation, engagement and persistence in learning, are precursors of children's future academic performance [26].

2.2. Computational Thinking

Contemporary educational and social demands lead to cultivating CT even within the context of early learning settings [15–17]. Indeed, in the modern digital era, CT is seen as a set of competencies that are essential for the productive citizenry [27], as it is estimated that by the end of the century it will have evolved into a fundamental set of skills, such as reading, writing and arithmetic [28]. It is inextricably linked to Computer Science, and, in addition, its development is related to the study of a wide range of STEAM (Science, Technology, Engineering, Arts and Mathematics) fields [29]. The range of its effects covers every kind of thinking. For example, it has a long tradition of influencing the law [30] and especially the prospect of providing a set of logical rules that can automate the legal decision process [31].

The growing interest in integrating CT into the learning process has led researchers, educators, and education policymakers to engage conscientiously in the cultivation and evaluation of students' CT skills. Thus, a great deal of research has been conducted regarding: (a) the development of curricula that include CT [32,33], (b) the implementation of instructional tools aiming at enhancing CT [34,35], (c) the design and implementation of educational environments that promote CT [36] and (d) the development of tools for assessing basic CT skills [37,38].

As far as the evaluation of CT is concerned, recent studies show that the relevant subject remains open, as a research challenge [1,39]. This is an extremely urgent issue that needs to be tackled, because without valid and reliable assessment tools, it is very difficult for CT to be successfully integrated into the educational system, running a serious risk of disappearing as a structure, although it deserves very serious consideration [40].

2.3. Algorithmic Thinking

One of the core components of CT is AT, which pertains to the ability to develop skills or rules that can formulate solutions to problems by indicating the exact steps needed [41]. Although these solutions can take various forms, such as flowcharts and pseudocode, the most common is that of converting an algorithm into a computer program [42].

AT is closely related to fundamental skills, such as abstraction, logic, structured thinking, problem-solving skills, creativity [43], ability to locate the structural elements of a problem, top-down design, iteration, identifying optimal solutions, data organization, generalization and configuration ability [44]. Based on the above, it is anticipated that, in many cases, students consider learning algorithms a laborious and unattractive process. Its complexity makes AT a skill that is difficult to cultivate and imposes the need to build effective teaching approaches to enhance it [43].

Especially at the beginning of cultivating AT, the simplest possible methods should be sought, aiming at achieving a natural learning process. More specifically, when it comes to beginners, there is a need for: (a) tasks related to the daily life of the trainees, (b) dealing with problems that do not necessitate antecedent programming knowledge, (c) using language that will provide the ability to represent algorithms in a natural way, (d) systems that will allow the learner to experiment with algorithms, offer instant learning experiences, be flexible to run numerous algorithms and provide feedback [43].

It is worth mentioning that AT does not have exclusive tendency towards technological solutionism, treating major social and environmental problems in a simplistic way of proposing new technological solutions without exploring environmental consequences [45].

On the contrary, it is strongly related to environmental issues, supporting environmental awareness and sustainability [46,47].

2.4. Environmental Study

Systematic engagement with the sciences inspires children to observe, pose questions, form hypotheses, design and perform experiments, make measurements, process and explain data, and substantiate theories and models [48]. The science activities introduced in preschool and elementary school classes have the privilege of fitting effortlessly into the natural way children process their experiences. Furthermore, they support their innate curiosity about the way the world around them functions. Typical examples of such activities are: mixing basic colors [49], creating shadows [50,51], observing the movement of a worm [52], recording the seasonal changes of a tree, observing water—how it flows and how its path could be controlled [53].

In this way, the foundations are laid for a deeper understanding of concepts related to Environmental Sciences, while giving impetus to the growth of critical thinking and the development of problem-solving skills through trial and error [53]. Let us consider a group of young children who are planting a community or school garden. Through this activity, they begin to grasp fundamental scientific concepts and learn about the natural world around them—how much water each plant needs, what the roots are for, how the growth of a plant depends on the seasons of the year, and so on.

In the context of environmental education, students acquire knowledge about the environment and environmental problems, become aware of them and develop their problem-solving skills [54]. They learn about the geographical characteristics of their region and become acquainted with natural phenomena and disasters they may face. Thus, future citizens are formed, who have demythologized the fear of natural phenomena, such as earthquakes and tsunamis, and are prepared to confront them calmly and effectively, both in a collective and a personal way [55].

The orientation of education towards environmental awareness and sustainability is of particular importance, aiming at the cultivation of individual and collective consciousness to address contemporary environmental and health challenges [3]. Coherently organized contact with environmental education can bring about a general change in the attitude of modern people, preventing them from distinguishing themselves from nature. Furthermore, studying sustainability science provides students with a unique lens through which they can engage present events and envision a sustainable future that may arise from current and prospective hardships [56]. For example, students who study sustainability science are equipped with a remarkable set of tools to analyze the crisis that entailed from the COVID-19 global pandemic and conceptualize a more sustainable future [56].

2.5. Game-Based Learning

A way to foster Environmental Study is by employing game-based learning activities. Play instinctively constitutes a part of people's lives [57] and stimulates feelings of pleasure and excitement, regardless of age [58]. However, the value of games is not limited to their entertaining character. Mammals—including humans—are biologically prepared to use play as a learning tool [59]. The dynamics of utilizing games to achieve learning goals had already been recognized in ancient Greece. According to Plato, toys should be faced as a means of guiding preferences and predisposing children to the role they will play as adults. For example, if a child is to become a farmer or a builder, they should play with toys related to agricultural activities or house-building, respectively, and their teacher should provide them with tools modeled accordingly [60].

Within the context of game-based educational environments, students' learning motivation is improved, their exploratory mood is developed, their interest in learning is strengthened and their active participation in the educational process is encouraged [61]. Game-based learning approaches offer interactive learning experiences that are more engaging than traditional techniques and add to the acquisition and retention of knowledge [61,62]. Moreover, they guide even preschoolers in learning computational logic [63] and have a positive effect on students' problem-posing and problem-solving abilities [62]. In addition, the atmosphere in the classroom becomes conducive to learning and enhances students' interest in computer programming and STEM activities [59].

Jigsaw Puzzles

For hundreds of years, people have been pleasantly entertained by assembling an image from its pieces [64,65]. However, solving puzzles related to assembling an image is not limited to its fun aspect, but also touches on issues related to everyday life [65,66]. In addition, it finds application in various scientific domains and professional fields, such as biology, archeology, image processing [67,68] and voice communication security [69].

Several research efforts focus on studying jigsaw puzzles and exploring their algorithmic solutions [64,67]. Actually, this study is a demanding mathematical and engineering problem, which has aroused the interest of mathematicians, engineers, and computer scientists [65]. The fact that scientists and researchers are looking for algorithms to solve puzzles creates the basis for claiming that solving puzzles requires AT. Therefore, an individual's ability to solve puzzles could constitute the touchstone for assessing their AT skills.

3. Materials and Methods

In this study, the control variables under investigation are first and second graders' AT skills and performance in the Environmental Study course. Both these variables are categorical. The assessment of AT skills is implemented through solving jigsaw puzzles of graded difficulty, while the assessment of performance in the Environmental Study course is accomplished employing a pertinent worksheet. For analyzing the data gathered, we exploited RStudio, an integrated development environment (IDE) for the programming language R, which is suitable for statistical computing and graphics [70,71]. In the following sections, we thoroughly discuss issues regarding the materials and methods employed.

3.1. Research Context and Sample

The research took place under the umbrella of a robust ethical framework, with the permission of the Greek Ministry of Education, in the school year 2018–2019 on the island of Crete and, more specifically, in Heraklion city, which is the fourth largest city in Greece. The first and the third author committed to conducting the relevant interventions. Aiming at the transparency of what was happening in the classroom during the research process, the teacher of each class was present, but not actively involved.

In order to draw conclusions for the wider population of first and second-graders of Heraklion city, we adopted the cluster sampling method [72] and estimated the sample size by employing the Cochran formula [73]. Thus, we ended up with a sample of 435 primary school students in first and second grade. The sample was both gender-balanced (48.28% girls and 51.72% boys i.e., 210 girls and 225 boys) and grade-balanced (50.11% first-graders and 49.89% second-graders i.e., 218 first-graders and 217 second-graders).

3.2. Instruments Used and Data Analysis

The pillar of our research is the digital platform PhysGramming (an acronym derived from Physical Science Programming) [74], which we designed and implemented from scratch to serve the needs of our work, aligning with good methods that enhance the usability of young children's applications [75].

PhysGramming is developmentally appropriate for kindergarteners and first and second-graders, and provides them with the opportunity to construct and play with their own digital games. For constructing the games, young students must first define the attributes of the entities they are dealing with (either orally or in writing), using command lines, the syntax of which deploys a novel text-based and visual programming schema we introduce (Figure 1). While assigning the values of the attributes, students experience their first contact with basic object-oriented programming concepts, even though there is no explicit reference to them.

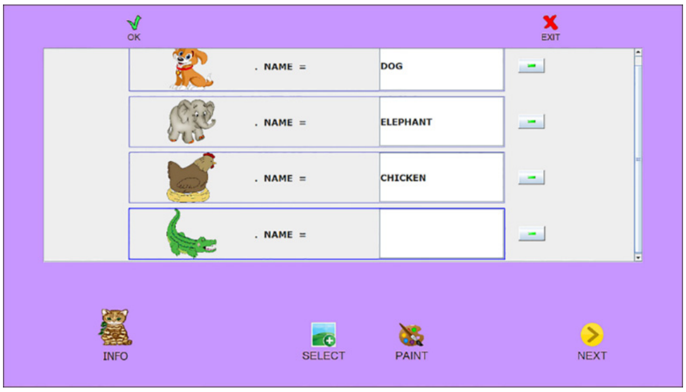

Figure 1. Assigning values to the attribute "name".

Users of PhysGramming can create puzzles, among other games, by employing pictures they have painted or shot themselves, or just retrieved from the ones embedded in PhysGramming. Since students select the pictures of the entities they study and assign their names, PhysGramming automatically creates puzzles of graduated difficulty (Figure 2).

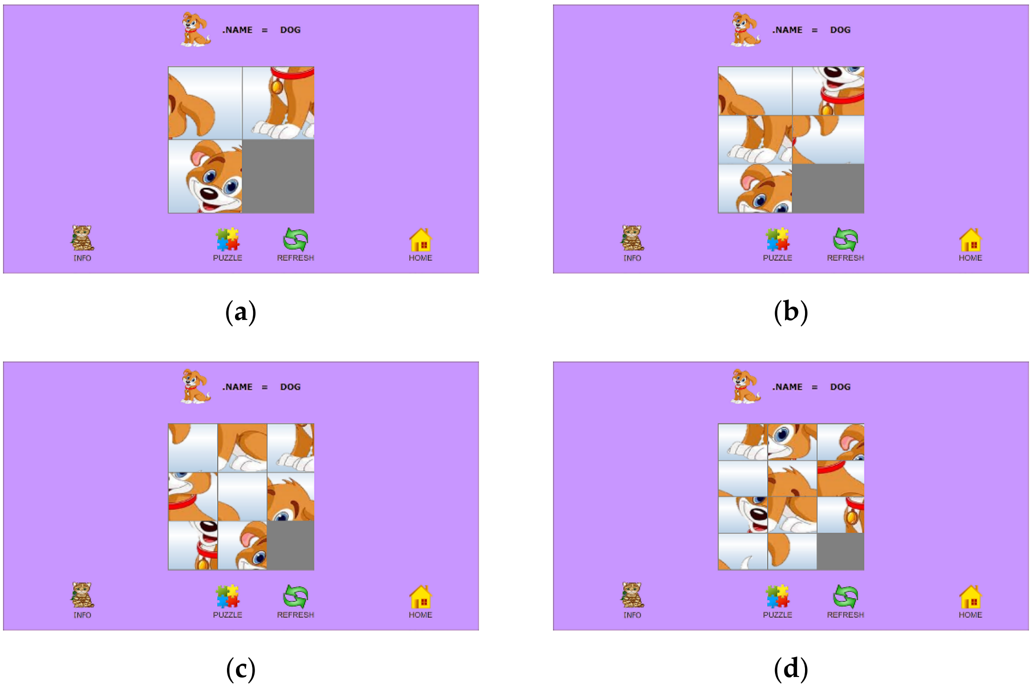

Figure 2. (**a**) Four-piece puzzle; (**b**) Six-piece puzzle; (**c**) Nine-piece puzzle; (**d**) Twelve-piece puzzle.

3.2.1. Assessing Algorithmic Thinking

In order to assess AT competencies, we focus on the most difficult puzzle (based on the number of its pieces) each student manages to solve, exploiting the information provided by the log files of PhysGramming. The scale we propose has four levels: Basic (four-piece puzzle), Medium (six-piece puzzle), Satisfactory (nine-piece puzzle) and Excellent (twelve-piece puzzle), adopting the viewpoint of relevant research studies that also propose four levels for evaluating CT skills [76].

PhysGramming is programmed so that the lower right cell of each puzzle is initially empty. The student can move the pieces adjacent to the empty cell, in horizontal, vertical, or diagonal direction. Thus, in four-piece puzzles, all the pieces can be moved, making the solving process quite easy. However, in all other cases, the pieces that are not adjacent to an empty cell cannot change position, until an adjoining cell becomes empty. Actually, the more pieces the puzzle contains, the more the pieces cannot change position until a neighboring cell becomes empty, raising the difficulty level of the puzzle reconstruction and requiring higher levels of AT.

Taking into account relevant research studies that propose solving jigsaw puzzles in early childhood education [77] and the special characteristics of our research, we decided to stick to four types of puzzles with graded levels of difficulty and twelve to be the maximum number of puzzle pieces. Two factors contributed to forming this decision. Firstly, unlike the puzzles of PhysGramming, the typical jigsaw puzzles comprise of interlocking pieces that can only connect to the appropriate adjacent piece, facilitating the solving effort. Secondly, PhysGramming was shortly presented the same day the assessment tool was applied in the classroom, and, thus, students lacked familiarity with its functionality, which they had to explore while being assessed.

3.2.2. Assessing Content Understanding

The unit of the Environmental Study course, in the framework of which we chose to conduct our research, was the eating habits of animals. We selected the particular thematic unit based on children's special relationship with animals, which explains why animals hold children's attention even when tempting toys are available [78]. As a means of assessing students' content understanding, we created a worksheet in which students were asked to record the eating habits of 10 animals (Figure 3).

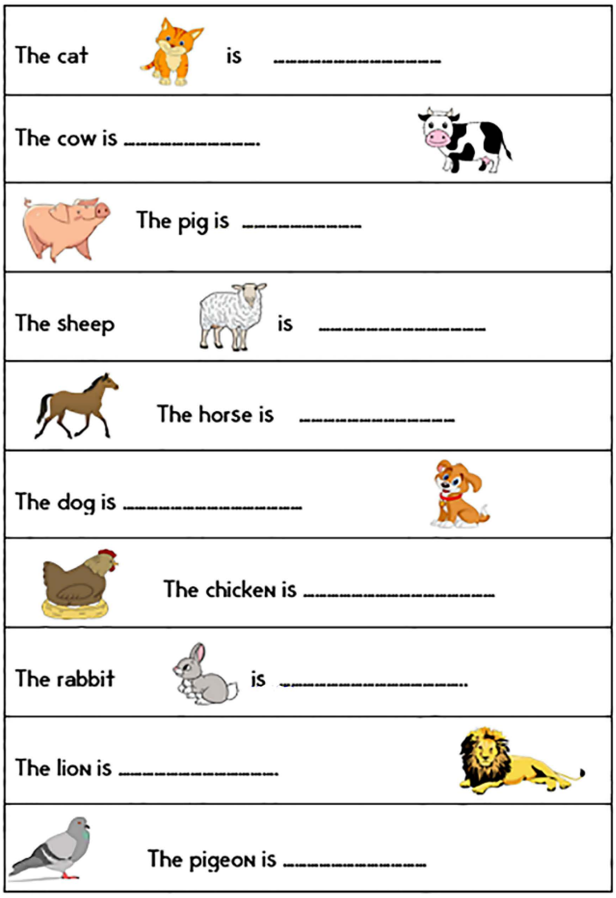

Figure 3. Assessment worksheet about animals' eating habits.

The choice of the topic was indicative. We could choose any other topic, such as, for example, the body covering of animals, the type of a plant depending on whether it sheds its leaves or keeps them all year round, the materials' shape, etc. In case of choosing another topic, the content of the worksheet should be formatted appropriately, in order to examine the relevant content. Nevertheless, regardless of its subject, the selected topic must have been taught before assessing the comprehension of its content.

When applying the proposed assessment tool, special care must be taken to avoid cheating. Aiming to eliminate the effect of factors such as cheating and giving random answers that would damage the accuracy of our research results, we created a second worksheet identical to the abovementioned one. Nevertheless, the students were not asked to fill it in since the teacher had filled it in before handing it out to the students. This time, students were asked to identify the wrong answers that the teacher deliberately gave.

The evaluation of the content understanding is based on studying the union of the sets of wrong answers in both worksheets. The proposed grading scale is based on the relevant and most recent Ministerial Decision [79] and is constituted of four levels: Excellent (Zero or one mistake), Very Good (Two or three mistakes), Good (Four or five mistakes), Almost Good (More than five mistakes).

3.2.3. Validation

The results of our research would be of no value if the assessment tool we propose had not been tested for the validity and reliability of the results it provides. Thus, both validity and reliability were thoroughly examined, based on methods proposed in the international literature [72]. Since the subject of this article does not include the abovementioned issue, we indicatively report that Pearson's r (Pearson correlation coefficient)—which is commonly used to quantify the strength of the relationship between test/retest scores [80]—was measured to be 0.81. This result demonstrates very good test/retest reliability. In other words, it indicates very good stability of measurements acquired from a sample at different times [80,81].

4. Results

We are going to test the hypothesis set, i.e., the lack of association between AT skills and the content understanding of the Environmental Study course, at a 5% level of significance, and, thus, with the alpha level of 0.05.

Based on the contingency tables of observed (Table 1) and expected frequencies, chi-square is calculated to be 36.434, degrees of freedom are 9 (df = 9) and the p-value is 3.32×10^{-5}. Since $p < 0.05$, we reject the hypothesis set and accept its alternative. Thus, we accept that there is association between AT and content understanding.

Table 1. Contingency table of observed frequencies.

AT \ CU [1]	Excellent	Very Good	Good	Almost Good	Sum
Excellent	32	26	15	9	82
Satisfactory	35	52	28	27	142
Medium	36	45	40	44	165
Basic	4	7	16	19	46
Sum	107	130	99	99	435

[1] CU stands for content understanding.

Next, we examine the association of each one of the AT levels with each one of the content understanding levels and we calculate the odds ratio (Table 2). Results indicate that students that have been placed in one of the two higher levels of AT are more likely to be placed in one of the two higher levels of content understanding as well. On the contrary, students that have been grouped into one of the lower levels of AT are more likely to be grouped into one of the lower levels of content understanding.

Table 2. The ratio of the odds of CU levels in the presence of AT levels.

AT \ CU	Excellent	Very Good	Good	Almost Good
Excellent	2.37	1.11	0.72	0.36
Satisfactory	1.01	1.59	0.77	0.72
Medium	0.78	0.82	1.15	1.42
Basic	0.26	0.39	1.97	2.71

Next, we apply the ordinal logistic regression method [82] in order to investigate if AT levels constitute a predictive factor for the content understanding of the Environmental Study course and vice versa. Our first step is to explore the odds for students with excellent content understanding to have excellent AT versus basic, medium or satisfactory AT. Using R's polr function, we obtain the regression output coefficient table that includes the values of coefficient, standard errors, and t-value. In addition, we calculate the p-values (Table 3). The first line of Table 3 presents the values of coefficient, standard errors, t-value and p-value. The three lines that follow present the estimates of the three intercepts, which show where the latent variable is cut to make the four groups we observe in our data. Table 3 indicates that for students that have excellently understood the content of the Environmental Study course, the log odds of having basic AT (versus all the other levels of AT) is 0.02 points lower than students who have not excellently understood the content.

Table 3. Ordinal logistic regression model for excellent content understanding.

	Value	Std Error	t-Value	p-Value
excellentContUnder	32	26	15	9
basic | excellent	35	52	28	27
excellent | medium	36	45	40	44
medium | satisfactory	4	7	16	19

We also calculate odds ratio, confidence intervals and predicted probabilities. Indicatively, the results reveal that the predicted probability for a student with excellent content understanding to have excellent AT is 1.01 times greater than not.

Finally, we apply the machine learning method, seeking to predict the possibility of new data being classified into the AT levels, with dependence on the content understanding. In order to construct the prediction equations, we employed 80% of the research data, while the remaining 20% was exploited for testing [83].

In Chart 1, the independent variable is the content understanding of the Environmental Study course and the dependent variable is AT (probabilities). We see that the higher the level of the content understanding, the higher the probability of being placed at the higher levels of AT (satisfactory and excellent). On the contrary, the probability of being placed at the lower levels of AT (basic and medium) decreases as the level of the content understanding increases.

Analogous results are obtained if we apply the ordinal logistic regression model considering that the content understanding of the Environmental Study course (probabilities) is the dependent variable and AT is the independent variable. The relevant diagram (Chart 2) indicates that the higher the AT level, the higher the probability of students to be classified at the higher levels of content understanding. In a like manner, the lower the AT levels, the higher the probability of students to be classified at the lower levels of content understanding.

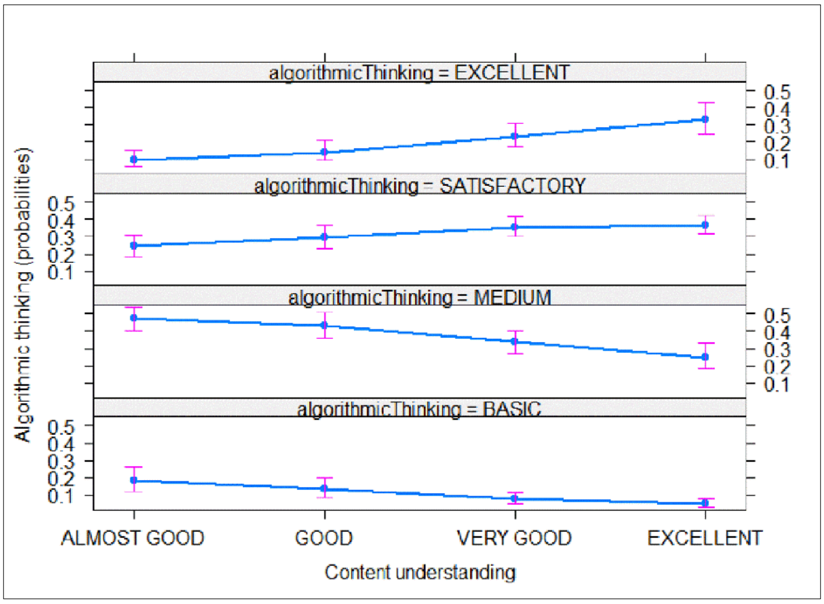

Chart 1. AT levels in relation to content understanding.

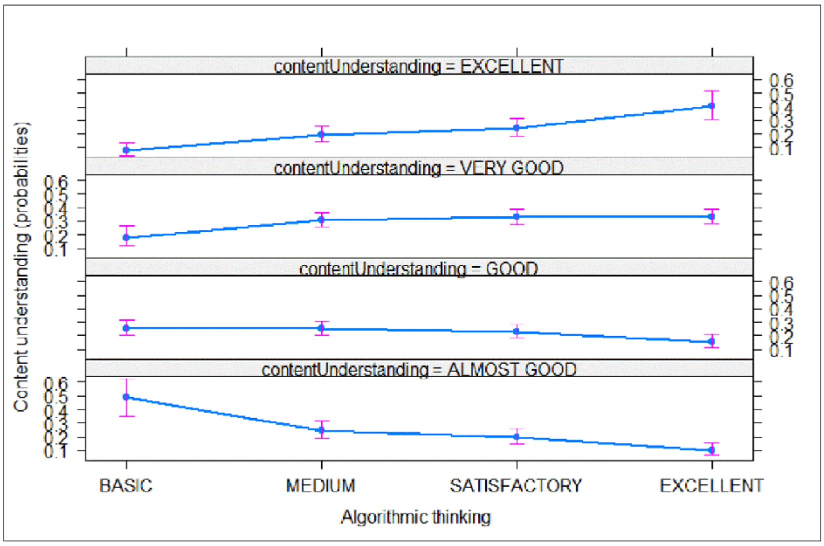

Chart 2. Content understanding levels in relation to AT.

5. Discussion

If CT is to become viable in the educational systems around the globe, its assessment will need to play a prominent role. This assumption is echoed in the academic discourse on CT, in which the crucial role of CT assessment is emphasized and the construction of developmentally appropriate assessment tools figures prominently [15–17,38,39]. At the same time, the demand for establishing a truly ethical and honest relationship between people and the planet that we inhabit so carelessly, and the need to guarantee a sustainable future for posterity, demands nothing less than introducing Environmental Science even from kindergarten [84,85]. Reflecting on a multidisciplinary collaboration, we support the synergistic cultivation of CT competencies and environmental awareness from the first grades of compulsory education. Towards this aim, we propose a relevant assessment framework, which we have employed in order to investigate the association between fundamental CT skills and several factors, such as age, gender and performance in the Environmental Study course [15–17].

The results of the research study discussed in this article confirm the association between AT skills of first and second-graders with the content understanding of the Environmental Study course. The odds ratio calculation for each one of the AT levels in relation to each one of the content understanding levels brings out the way they are correlated to each other. For example, the presence of excellent AT raises the odds of the presence of excellent content understanding by 2.372. On the contrary, the presence of excellent content understanding reduces the odds of the presence of medium AT (odds ratio = 0.782) and even more the presence of basic AT (0.264).

Applying ordinal logistic regression analysis, we come to the same, but more detailed, information regarding the association we investigate. For example, the predicted probability for a student with excellent content understanding to have excellent AT is 1.01 times greater than not. This probability is considerably high if we take into account that excellent AT level is checked against all the remaining AT levels.

5.1. Perspectives

Our research efforts aimed at the first two grades of primary school, where the foundations are built for the subsequent academic trajectory of the children, while at the same time attitudes are formed towards the learning process [16,17]. We went ahead to the assessment research area, as it is not only useful for teachers who want to monitor their students' progress, but also helps to promote learning and maintain cognitive achievement. Furthermore, without valid and reliable assessment tools, introducing CT in compulsory education could not be successful.

Going beyond the cultivation and the assessment of individual disciplines in the first school years, we investigated the synergy of CT and Environmental Study. The originality of our work relies on the fact that there is no recorded study to test the correlation between the CT skills of first-graders with the content understanding of the Environmental Study course. Furthermore, most of the relevant surveys target older children [86,87], leaving the part of preschool and early school education under-explored.

In attempting an overall evaluation of our research approach, in terms of the impact it had on the members of the educational community who participated in the research, we would say that both students and their teachers easily accepted the proposed assessment tool. Especially the piece that had to do with solving puzzles immediately became beloved by the students. The animated fireworks that appear on the screen after solving each puzzle, accompanied with a rewarding sound, turned out to be very joyful for the users. In fact, in all the classrooms in which the assessment tool was applied, a festive atmosphere emerged. Every time a student managed to solve a difficult puzzle of nine or twelve pieces, they shouted out to the first author: "Mrs., fireworks". Thus, a creative competition developed between the students, who tried their best. The first author, aiming at strengthening the positivity of the echo of the students' experience, strengthened the creative atmosphere, rewarding the students verbally and motivating them to continue the good work. The nice atmosphere developed in the classrooms eliminated the reservations of some teachers, who initially objected to the implementation of our research interventions because they were concerned about the completion of the material.

5.2. Limitations and Future Research Directions

A limitation of the work concerns the research population, which consisted of students only from the city of Heraklion. For this very reason, we plan to expand our research to a nationwide level. Another limitation of our work is conducting the research study amid one thematic unit of the Environmental Study course, i.e., animals' nutritional habits. In fact, to be more precise, the assessment tool was also applied amid studying which animals sleep in the winter season, employing a small sample of 75 students. This small-scale research study confirmed the results presented in this article. Nevertheless, our future research direction is to confirm our results by applying the assessment tool in several thematic units of the Environmental Study course, conducting a large-scale research study.

Moreover, a limitation of our study is the lack of examining potential underlying factors that might have an effect on the correlation between AT and performance in the Environmental Study course. For example, a recent meta-analysis that examined 34 studies in a wide range of ages—from first-graders to fourth-year students—confirmed the association between CT and academic achievement and revealed that their positive link is moderated by culture, grade level, achievement indicators, and gender [88]. Thus, our future research orientation includes the implementation of an experimental design with the objective of investigating such factors.

Finally, we intend to examine children's growing AT abilities by adopting a quasi-experimental design and exploiting PhysGramming's new edition, which is not limited to supporting CT assessment but also adds to the efforts of CT development in the early ages.

6. Conclusions

This study provides evidence of a multidisciplinary assessment approach of constructivist and game-based nature, designed in the interest of examining the correlation between educational achievements in the Environmental Study course and AT skills of first and second-graders.

The rationality of our research is threefold. Firstly, it relates to the impact that technology will have on the future of the next generation, arousing the interest in introducing CT as soon as possible in compulsory education in order to equip this future generation with 21st-century skills and prepare it for a new reality regarding the job market [19]. Secondly, it pertains to the fact that environmental education is experiencing dynamic growth in research and practice due to enduring environmental challenges [10]. Finally, yet importantly, a significant factor that triggered the implementation of our study was the detection of a research gap regarding the correlation between CT competencies and performance in the Environmental Study course. In order to establish the synergy of the two disciplines, we started with their joint evaluation. Thus, we propose an assessment tool that reflects on multidisciplinary collaboration, taking advantage of incorporating a diversity of scientific perspectives and considering several instructional approaches [89].

Summarizing the contribution of our work to the scientific community, we should refer to fostering CT in early primary school years, assessing AT skills of young students while solving digital puzzles, examining the correlation between AT and Environmental Study, highlighting the option of synergistically cultivating CT and environmental consciousness, and injecting object-oriented programming concepts in early childhood education. Hence, the subject of this study is of interest to educators and researchers who approve the cultivation of CT from the very first grades of elementary school, applaud the orientation of education towards environmental awareness and sustainability, and advocate the synergistic learning of CT and STEM fields. It also concerns those who support game-based learning, and adopt educational practices that face students as active creators rather than passive consumers of digital technology.

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