Article

Journal of Educational Computing Research
0(0) 1–33

DOI: 10.1177/0735633120940954
journals.sagepub.com/home/jec
SAGE

The Associations Between Computational Thinking and Creativity: The Role of Personal Characteristics

Rotem Israel-Fishelson[1], Arnon Hershkovitz[1], Andoni Eguíluz[2], Pablo Garaizar[2], and Mariluz Guenaga[2]

Abstract

Computational Thinking (CT) and creativity are considered two vital skills for the 21st century that should be incorporated into future curricula around the world. We studied the relationship between these two constructs while focusing on learners' personal characteristics. Two types of creativity were examined: creative thinking and computational creativity. The research was conducted among 174 middle school students from Spain. Data collected using a standardized creativity test (Torrance's TTCT) were triangulated with data drawn from students' log files that documented their activity in a game-based learning environment for CT (Kodetu). We found some interesting associations between CT and the two constructs of creativity. These associations shed light on positive associations between each of the two creativity constructs and CT acquisition, as well as between the two creativity constructs themselves. Additionally, we highlight differences between boys and girls, as girls were found to be more creative on both creativity measures. Other differences

[1]School of Education, Tel Aviv University, Israel
[2]Faculty of Engineering, University of Deusto, Spain

Corresponding Author:
Arnon Hershkovitz, School of Education, Tel Aviv University, P.O. Box 39040, Tel-Aviv 6997801, Israel.
Email: arnonhe@tauex.tau.ac.il

associated with school affiliation, prior coding knowledge, and technology affinity are also discussed.

Keywords

computational thinking, creativity, game-based learning, learning analytics, log analysis

The accelerated development of science and technology and the exponential growth of data underscore the need to encourage innovative thinking and to impart skills to address challenges we have not yet envisioned. Computational thinking and creativity are two skills that have been recognized as essential for digital age citizens (Deschryver & Yadav, 2015; Kalelioğlu et al., 2016). Furthermore, it is generally acknowledged that these skills must be instilled from an early age and should be incorporated into the school curriculum (Anthony & Frazier, 2009), as they are of crucial importance for any field of expertise (Hambrusch et al., 2009).

Computational Thinking (CT) is defined as the conceptual foundation required to define and solve real-world problems using algorithmic methods to reach solutions that are transferable and necessary to various contexts and disciplines (Shute et al., 2017). CT is understood to assist in developing problem-solving skills (Grover & Pea, 2013; Wing, 2006) and improving thinking abilities and techniques to extract knowledge hidden in data (Buitrago Flórez et al., 2017). The global recognition of CT's significance has led to the establishment of national K-12 curricula, standards, and computer-based and unplugged activities worldwide (ISTE, 2017; World Economic Forum, 2015). Many computer-based learning platforms support the development of CT skills (Kim & Ko, 2017), but despite the contribution of these platforms, research has so far focused mainly on qualitative approaches and limited data volumes (Brennan & Resnick,2012; Tang et al., 2020).

Creativity is a thinking ability that enables people to solve problems in an innovative manner and to produce original and valuable products (Torrance, 1974). For many years, creativity was taught mainly in the context of art and design, but today its contribution to various spheres of life has also been recognized (Donovan et al., 2014; Navarrete, 2013). Moreover, the importance of exploring the relationship between creativity and technology is emphasized, especially in the educational context (Mishra, 2012).

Because of the great importance of these two constructs, and due to lack of sufficient research about their interconnections, we are motivated to look deeper into the association between creativity and computational thinking. Having such an understanding may benefit various education stakeholders and enable them to design better teaching and learning experiences to promote either CT or creativity, and hopefully both. This paper expands the knowledge base on the relationship between these two constructs (Hershkovitz et al., 2019) and focuses on differences stemming from personal characteristics.

Computational Thinking

Computational Thinking (CT), once considered to be related primarily to the STEM field (Science, Technology, Engineering, and Mathematics), is now seen as a vital skill that applies to a wide range of areas, including social studies, humanities and the arts (Kalelioğlu et al., 2016; Tang et al., 2020). Seymour Papert, who was the first to coin the concept of CT, predicted that computational ideas can change the way children think in any domain (Papert, 1980). Indeed, his prediction has materialized, and today it is clear that CT is a universal competence that every child should acquire (Barr & Stephenson, 2011; Voogt et al., 2015).

CT has been acknowledged both for its importance in developing knowledge and understanding of concepts in computer science and for its potential for developing more general-purpose problem-solving skills (Ruan et al., 2017). CT has been proven to influence all three skills—mathematics, literacy, and computational problem-solving (Barr & Stephenson, 2011)—which the Organisation for Economic Co-operation and Development (OECD) has identified as crucial for workforce development (OECD, 2015). Moreover, major organizations such as the World Economic Forum and the United Nations Educational, Scientific, and Cultural Organization (UNESCO) consider CT to be part of the new literacies necessary for tomorrow's citizens (Scott, 2015; World Economic Forum, 2015). The National Research Council (NRC) defined CT as one of eight practices that should be incorporated into science education (NRC, 2012). To achieve these goals, educational institutions and organizations worldwide have begun to establish national K-12 curricula, academic standards, and instructional activities to instill CT skills (Guenaga et al., 2017; Kafai & Burke, 2013; Seow et al., 2019).

In line with these trends, various learning platforms have been developed to facilitate and foster the acquisition of CT concepts, as proposed by Brennan and Resnick (2012). Among these platforms are many computer-based, user-friendly, game-based platforms designed for children and teens (Kim & Ko, 2017). These platforms are usually built around linearly progressing challenges that facilitate knowledge construction by breaking down the concepts into incremental learning components. They also support trial and error behavior for improving knowledge acquisition (Wang & Chen, 2010). Such platforms allow a targeted, automatic, big-data analysis of the processes involved in the acquisition of CT concepts (Israel-Fishelson & Hershkovitz, 2019).

We do not yet have a satisfactory understanding of how CT is acquired. It is thus necessary to understand and promote CT acquisition already from an early age while taking personal characteristics into consideration.

Creativity

In recent years, creativity has been recognized as a necessary skill for the 21st century (Said-Metwaly et al., 2017) that can be nurtured and that needs to be embedded in the curriculum from an early age (Beghetto, 2010; Vygotsky, 2004). Multiple studies have highlighted that creative experience within classroom activities not only can promote academic achievements but also can encourage innovative thinking, motivate students and increase their engagement in learning (Anthony & Frazier, 2009; Davies et al., 2013). Creativity has been studied extensively over the years from various perspectives (Kaufman & Beghetto, 2009; Runco & Jaeger, 2012). Some have treated creativity as a process (e.g., Guilford, 1950; Torrance, 1965), others have explored creativity as a personal trait (e.g., Parsons, 1971), and still others have examined the creative product itself (e.g., Martindale, 1989).

Despite the many conceptualizations of the term "creativity", the consensus is that creativity is a multi-dimensional variable comprised of four characteristics: (1) Fluency – the ability to generate a large number of ideas and directions of thought for a particular problem; (2) Flexibility – the ability to think about as many uses and classifications as possible for a particular item or subject; (3) Originality – the ability to think of ideas that are not self-evident or banal or statistically ordinary, but rather those that are unusual and even refuted, and (4) Elaboration – the ability to expand an existing idea and to develop and improve it by integrating existing schemes with new ideas (Guilford, 1950; Torrance, 1965).

Creativity has been examined from various perspectives, among them the thinking processes involved, the qualities of the creative person, and the creative product itself. Many scholars have concluded that creativity is not a fixed trait but rather a skill that can be imparted, practiced, and enhanced (Amabile & Pillemer,2012; Hsiao et al., 2014). Furthermore, creativity may also be dependent on the context of the learning and on the measuring tool (Reiter-Palmon et al., 2009). The question of whether creativity is transferable, i.e., whether it is domain-general or domain-specific, has been the topic of extensive discussion (Plucker & Beghetto, 2002). The answer to this question is still open and unresolved, with some scholars suggesting that creativity is both domain-general and domain-specific (J. Baer, 2010; Hong & Milgram, 2010).

These questions encourage us to explore the ways in which creativity is expressed throughout the learning process, to investigate the associations between the various measures of creativity, and to examine relationships between different types of creativity and knowledge acquisition.

Creativity and Computational Thinking

Already 40 years ago, Papert (1980) claimed that creativity could be developed using computers, but only in recent years has creativity been recognized as directly related to computer science, and its importance and contribution to inspiring motivation in every field of study have been acknowledged (Romeike, 2007). Various researchers have demonstrated the bi-directional connection between creativity—and CT in particular—and computer science. On the one hand, computerized platforms and programming activities have been shown to inspire creativity in the production of artifacts in areas such as art, graphic design, and music (Clements, 1995; Lau & Lee, 2015; Mishra & Yadav, 2013; Seo & Kim, 2016). On the other hand, creativity was found to serve as a catalyst to solving algorithmic problems, creating computational artifacts, and developing new knowledge (S. Kong, 2019; Pérez Poch et al., 2016). As was previously shown, results of standardized creativity tests predicted creativity in problem-solving on computerized programming platforms (Liu & Lu, 2002). Digital learning platforms that promote programming or CT often offer opportunities to expand creative expression and support the development of creative thinking. This is because creativity involves a set of thinking tools that overlap with the fundamentals of CT, among them observation, imagination and visualization, abstraction, and creation and identification of patterns (Yadav & Cooper, 2017).

Research on CT and creativity has been conducted from different perspectives: examining the mutual impact of these two constructs (Miller et al., 2013; Seo & Kim, 2016) as well as examining creativity within the scope of CT. For example, Doleck et al. (2017) studied the associations between creativity as an inherent element of CT and academic achievement. Other studies used automatic methods to explore the expression of creativity within programming activities, which are perceived to be a representation of CT (Bennett et al., 2010; Manske & Hoppe, 2014). Yet only a few studies, including our study (Hershkovitz et al., 2019), focused on the association between these two perspectives.

Early results highlighted an interesting association between creativity and CT either within or outside the scope of CT (Hershkovitz et al., 2019). The current study builds on and expands our previous study in order to enhance our understanding of the role of creativity in CT acquisition. Hence, this study aims to shed light on the associations between creativity and CT, while further examining the role that personal characteristics play as reflected in an online game-based learning platform. The study refers to two types of creativity: creative thinking, defined as creativity as reflected by traditional measures of creativity, and computational creativity, a measure of how creativity is manifested in solutions within the learning platform.

Both CT and creativity have been found to be associated with some personal characteristics. Some studies have already suggested gender differences in

CT acquisition. While there is no evidence for a gender bias in knowledge acquisition through CT-related activities, gender-related differences have been found in the ways this goal is achieved. Girls feel less confident than boys prior to learning, need more training time, benefit from different types of scaffolding, and feel more confident about their achievements (Angeli & Valanides, 2020; Atmatzidou & Demetriadis, 2016; Hutchins et al., 2017; Jenson & Black, 2017). Moreover, a great deal of research has explored the associations between creativity and gender. A recent meta-analysis of 271 empirical studies—with 480 independent effect sizes for over 137,000 participants—revealed that females exhibited slightly higher creativity than males across all studies. As gender is linked with both creativity and CT, it is important to explore how it may be associated with the interconnections between these two constructs. This is a gap this research seeks to bridge. Additionally, we also examine the impact of prior programming knowledge and technological affinity on these interconnections.

Research Questions

To meet our research goal, we formulated the following research questions:

- What are the associations between CT acquisition and creative thinking, and how do personal characteristics affect these associations?
- What are the associations between CT acquisition and computational creativity, and how do personal characteristics affect these associations?
- What are the associations between computational creativity and creative thinking, and how do personal characteristics affect these associations?

Methodology

Learning Analytics

Learning analytics (LA) is "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Ferguson,2012, p. 2). LA usually uses visualization and statistical and machine learning techniques to assess and improve understanding of the learning processes and learning platforms involved (Krumm et al., 2018). Such methods are useful for predicting students' success (Emerson et al., 2019), detecting difficulties while acquiring CT concepts (Román-González et al., 2019), and evaluating the acquisition of CT concepts by aggregating students' achievements in the learning tasks (Kong, 2019).

In the context of computer science education, LA approaches have been used to study students' programming activity (Berland et al., 2013; Blikstein, 2011; Boutnaru & Hershkovitz, 2015; Eguíluz et al., 2018; Gal et al., 2017; Grover et al., 2017; Hershkovitz et al., 2019; Lu et al., 2017; Nutbrown & Higgins, 2016). The current study follows this line of research by applying LA methods to measure computational thinking and computational creativity.

The Learning Environment: Kodetu

Kodetu is an online learning environment built using Google's Blockly.[1] It is used to teach basic concepts related to CT and is aimed primarily at children in elementary and middle school (Eguíluz et al., 2018). The environment has three pre-designed games, and it also allows users to create their own games. Each game entails several levels. At each level, the user is presented with the challenge of moving an astronaut from its initial position to a marked destination. The user has to define the astronaut's movements using coding blocks available in the workspace. Moving to the next level is possible only upon successful completion of the current level. Note that the user can reset the level and solve it again. The system is available in three languages: English, Spanish, and Basque. During use, the system logs the users' actions within it. These actions, primarily code building (i.e., dragging blocks from the blocks area to the editing area) and solution submission, are documented along with the learner id, the relevant code (both in Java code and in terms of the blocks used), solution correctness, and the action timestamp.

The Kodetu platform has already been used in several CT-related studies (Eguíluz et al., 2018, 2020; Saavedra-Sánchez et al., 2019). It offers three main advantages that make it suitable for our purposes. First, it is based on block-based programming and is therefore suitable for younger students with no prior experience in programming. Moreover, because the software leads learners on a path along which they are gradually introduced to new concepts, it serves as a good platform for assessing CT while learning it. Second, it can be easily customized to fit various research goals and questions. For example, we can control the number of challenges given to students, the nature of the challenges and their order, as well as the feedback messages they receive. Indeed, we did so, as we describe subsequently. Finally, this platform offers easy access to the system log files, as the software was developed for research purposes by some of the authors (third, fourth, and fifth). Platforms such as Kodetu allow for a portfolio-driven approach to assess CT that allows for measuring its acquisition at multiple points in time throughout the learning process (Tang et al., 2020).

For the current study, a dedicated game was created in the Kodetu platform. The game comprises ten levels that were built in increasing order of difficulty and that covered several CT concepts (e.g., *sequences, loops*). In this paper, we only analyze data from levels 1-9. The first four levels are designed to enable users to practice the concept of sequences. Level 1 is a trivial level to show how the system works. Levels 2 and 3 involve turns and perspective. Level 4 presents a large maze in which a long sequence of actions, including more than one rotation, is needed to reach the goal. Level 5 limits the number of blocks that can be used (i.e., code length) to prevent participants from using long sequences and to encourage them to take advantage of new code structures of loops. Level 6 presents a trivial challenge that deals with *sequences* and *loops*. Level 7 (shown in Figure 1) also works on sequences and loops with limitation on block usage. Level 8 limits the number of blocks that can be used (i.e., code length) to prevent participants from using long sequences and to encourage them to take advantage of new code structures for conditionals. Level 9 introduces if-else conditionals and requires nested structures and a limited number of blocks. Solving the entire set of levels is intended to take 30 to 60 minutes.

Population

The data we analyzed were collected in June 2019 from 174 Spanish students attending middle school and ranging in age from 11-12 years old. Of them, 55% are boys (95 of 174) and 45% are girls (78 of 174).

Procedure

The participating students came to an outreach activity organized by the Faculty of Engineering at the University of Deusto and participated in a workshop on technology, programming, and robotics. During this workshop, the students played the designated Kodetu game for about 60 minutes. For the vast majority of the students, this was their first encounter with programming (78%, 136 of 174). In addition, 60% of the students (105 of 174) reported having a high affinity for technology.

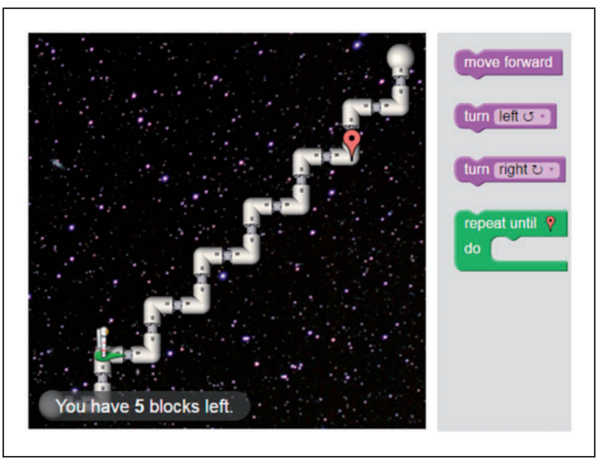

Figure 1. A Sample Level of the Kodetu Game Used in This Study (Level 7).

Prior to the Kodetu session, all participants completed a pen-and-paper creativity task (Torrance's TTCT – Figural Test) and a short questionnaire that included some background information. Data from the Kodetu log files were triangulated with the data obtained via the creativity task by means of a unique ID assigned to each participant. The participants wrote down their Kodetu-generated ID on the creativity test form. In addition, participants were asked to answer a short background questionnaire that was implemented within the Kodetu platform and that provided demographic data (age, gender), previous programming experience [yes/no], and affinity for technology [1-10 Likert scale].

Dataset and Preprocessing

The full log file contained 163,137 rows, each representing an action taken by a user, including the action's timestamp, the level at which it was taken, its result [Success, Failure, Timeout, Error], and the code associated with this action. Note that this log file extends the scope of the log file used in our previous analysis (Hershkovitz et al., 2019), in which only correct solutions were logged. The extended log file facilitates more valid computation of the CT-related research variables.

Creative Thinking Test

We used the Torrance Test for Creative Thinking (TTCT) – Figural Test (Torrance, 1974) to assess creative thinking along four dimensions: fluency, flexibility, originality, and elaboration. Note that compared with our similar prior research (Hershkovitz et al., 2019), we now add the measure of elaboration to provide a more multi-dimensional assessment of creativity. The TTCT, which has repeatedly been shown to be reliable and valid (Cramond et al., 2005; K. H. Kim, 2011), offers both verbal and figural tests. Because thinking about programming may involve both graphic and literal processes, the figural test was deemed more suitable for this study. First, the tasks involved in the studied system were mostly visual, both in terms of the puzzle presented to students and in terms of the blocks they used to build their code. Second, conceptual problem-solving of this type involves more graphic thinking than literal thinking (Liu & Lu, 2002). Furthermore, a recent analysis of both figural and verbal versions of the TTCT showed that while the scores on the two versions are highly associated, the figural version is a more comprehensive, reliable, and valid measure of creativity (K. H. Kim, 2017). The TTCT – Figural Test has been previously used successfully for studying associations with creativity in the context of programming or CT (Liu & Lu, 2002; Seo & Kim, 2016).

In this pen-and-paper test, each participant was shown a sheet of paper on which 12 identical, empty circles were printed. Participants were asked to make as many drawings as possible using the circles as part of the drawings. Hence, drawings that did not use a circle as an integral part of the drawing were not considered eligible and were omitted from our analyses. See examples in Figure 2.

Research Variables

Personal Characteristics. The participants self-reported their personal characteristics at the beginning of the session, using a short online questionnaire that includes the following variables:

- Gender [M/F]
- Previous Programming Background [Yes/No]
- Affinity for Technology [1-10 Likert scale, with 1 being "Low", and 10 being "High"]

Creative Thinking. To score the creativity task, we used eligible drawings only, that is, only drawings in which a circle was considered an integral part of the drawing. In order to ensure the reliability of the eligibility determination, each of the first two authors separately coded 20 sheets for eligibility. We then ran an inter-rater reliability assessment using Cronbach's alpha, which yielded a

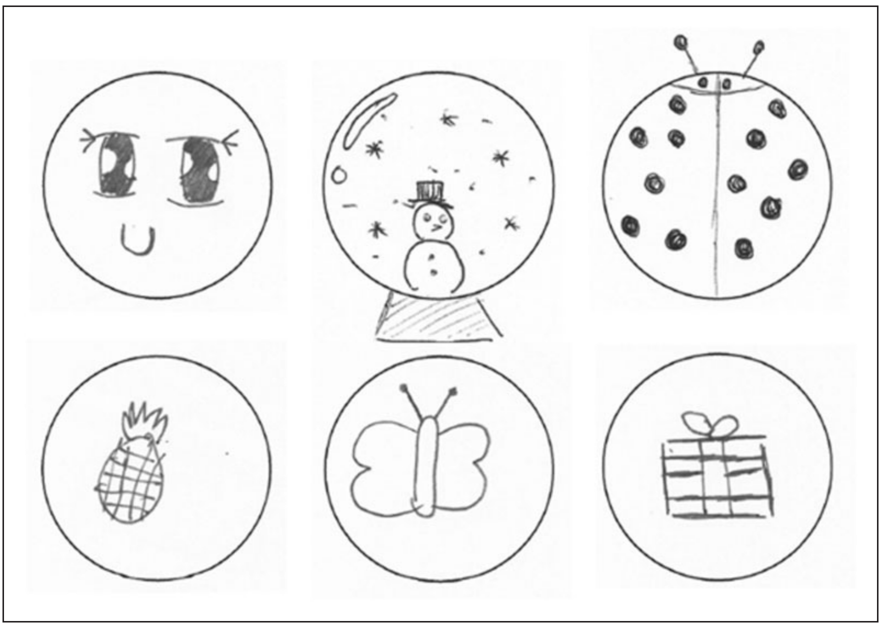

Figure 2. Example of Eligible (top row) and Non-eligible (bottom row) Drawings from TTCT – Figural Test.

satisfactory coefficient of 0.81. The authors then discussed borderline cases and agreed on guidelines for the rest of the coding, which was done by the first author. After ineligible and blank drawings were filtered out, 54% of the drawings (1199 out of 2088) remained eligible.

Originality and flexibility were based on drawing categories. To this end, we needed to classify the full pool of drawings into categories. Each of the first two authors separately coded 20 sheets for categories and then discussed their coding until they achieved full agreement. The rest of the coding was done by the first author, with frequent discussions throughout about the definitions and about splitting and merging categories. At the end of this iterative process, the final list consisted of 59 categories (e.g., Emoji, Sun, Flower, Signpost, Animal). Figure 3 shows an example of various eligible drawings in the categories of Animals (top), Planet (middle), and Signpost (bottom).

Using a process similar to the one used in determining the categories, the researchers rated each of the eligible drawings for its elaboration on a scale of 1–6, with 1 representing low elaboration and 6 representing high elaboration, depending on the level of detail in the drawing. The example above (Figure 4)

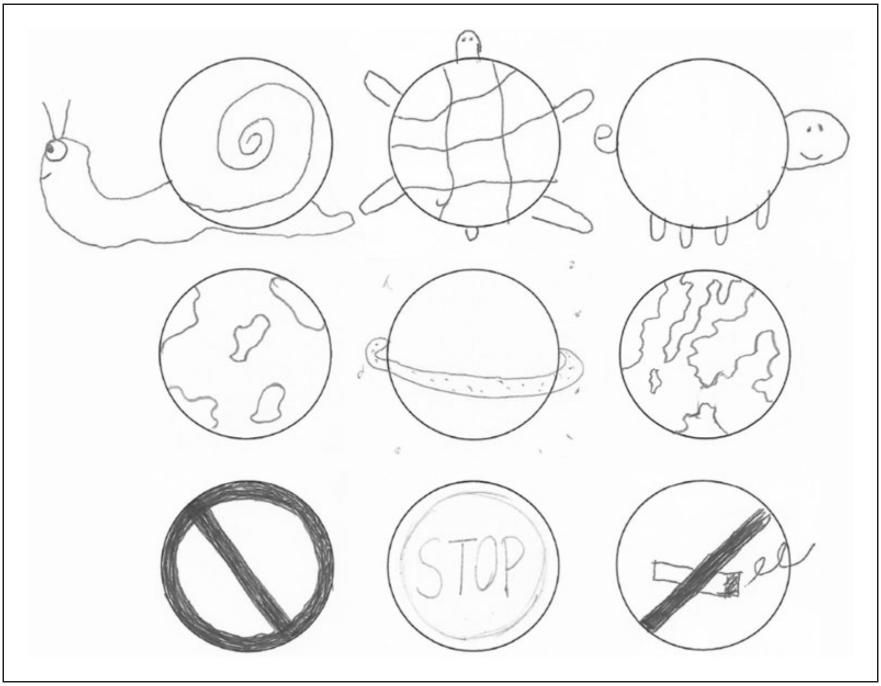

Figure 3. Examples for Drawings in Categories of Animals (top), Planet (middle), and Signpost (bottom).

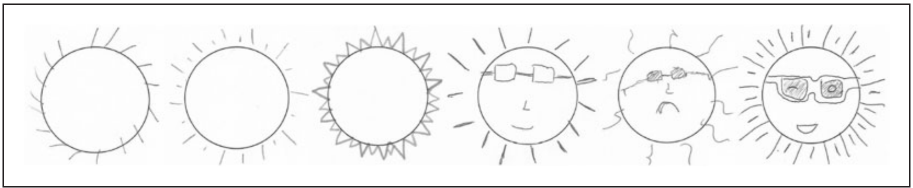

Figure 4. Examples of Six Levels of Elaboration as Evident in the Sun Category, from Low (Left) to High (Right).

shows an example of coding elaboration in six different drawings from the Sun category, with the drawing on the left rated as 1, i.e., low elaboration, and the drawing on the right rated as 6, i.e., high elaboration.

Finally, we computed the following four variables for each student:

- *Fluency*: number of eligible drawings;
- *Flexibility*: number of different drawing categories;
- *Originality*: average frequency of drawing categories, averaged across all drawings;
- *Elaboration*: number of ideas/details used in each eligible drawing.

Computational Creativity. In our analysis of creative solutions, we only referred to correct solutions, omitting all other logged solution attempts. This left us with 1591 rows.

Our analysis of computational creativity focuses on the originality of a correct solution as a proxy for creativity. This is because the Kodetu platform, like many other platforms, does not explicitly encourage multiple solutions, such that once a level is solved participants are immediately encouraged to move to the next level. Therefore, fluency, flexibility, and elaboration are not applicable in this analysis.

Originality is represented as the frequency of a particular solution among all the correct solutions, assessed on a scale of 0-1. When there were multiple correct solutions for an individual participant, we calculated the average across the correct solutions. Originality was calculated for each level separately and also aggregated for all levels.

We demonstrate this process for level 3 (see Figure 5). The path through which the astronaut should be led (by the student's code) involves two turns, first a left turn and then a right turn, with additional parts in which the astronaut walks straight ahead. Denoting "F" for going forward, "L" for turning left, and "R" for turning right, the simplest solution would be: FLFRF. Indeed, this was the most common solution, submitted in 164 of 174 cases (94%). Yet other correct solutions were also submitted, for example, FLFRFL (given in only one

Figure 5. Initial setting in Level 3.

case) or FLFRFF (given in 8 of 174 cases, 4.6%), where despite the correct solution, the astronaut falls into outer space right after arriving at its destination.

Computational Thinking. We focused on three variables to measure the acquisition of computational thinking, each computed for all levels as well as for each level separately:

- Solution Attempts.
- Correct Solution Attempts.
- Time spent on the level [min].

Findings

Exploring the Research Variables

In order to better understand the associations among *computational thinking, creative thinking* and *computational creativity*, we first report on the descriptive statistics for each of the variables. We then report on the associations among the different variables. All statistical analyses were conducted using IBM SPSS version 25.

Computational Thinking. We found that among all participants and across all levels, the average number of solution attempts was 6.16 (SD = 3.08), and the average number of correct solution attempts was 1.06 (SD = 0.19). The average time it took to solve each level was 5.13 minutes (SD = 11.99).

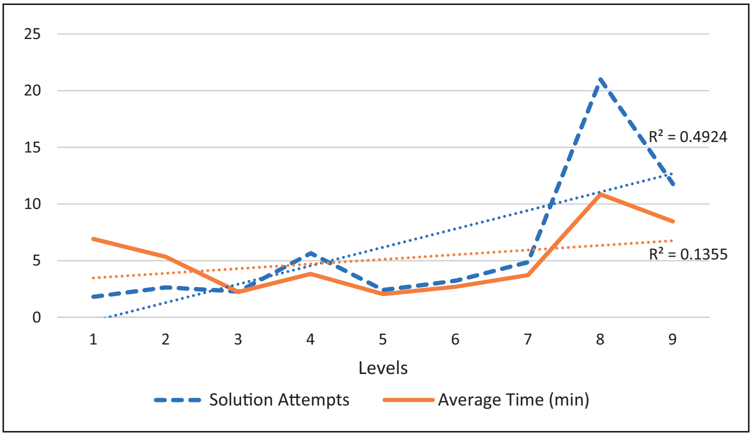

Figure 6. Solution Attempts and Average Time by Level.

Overall, there was an increasing trend in solution attempts per level (see Figure 6), indicating the growing difficulty of the game. A similar trend was found for the average time per level, with the exception of a decrease from Level 1 to Level 3, which may be related to the participants' adaptation to the interface at these initial levels. In addition, there was a decrease from Level 8 to Level 9 that may be associated with the introduction of the concept of conditionals in Level 8.

An examination of performance by gender indicates no significant differences between girls and boys. Moreover, no significant differences were found when comparing performance according to previous programming background or affinity for technology. The results are summarized in Table 1.

Creative Thinking. As indicated above, creative thinking consisted of four dimensions (fluency, flexibility, originality, and elaboration). Based on normality tests (H.-Y. Kim, 2013), we assumed normality (Skewness < 0.5 in absolute value) for all dimensions of creative thinking, except for originality. Table 2 summarizes the statistics.

Note that the mean value of originality was relatively high ($M = 0.89$, $SD = 0.16$, $N = 174$). Recall that we defined 59 categories of drawings from the TCTT – Figural Test. The distribution of the categories took the shape of a "long tail"; that is, many categories had a very low frequency (i.e., were highly original), and only a few had a relatively high frequency (i.e., were not original). The most common (i.e., least original) category (Emoji) had a frequency of 75%. As for the other dimensions of creativity, the results show that the students were able to submit about seven eligible drawings on average (i.e., more

Table 1. Computational Thinking by Personal Characteristics (SD).

	Solution attempts		Correct solution attempt		Average time	
	Average (SD)	T-Test	Average (SD)	T-Test	Average (SD)	T-Test
Gender						
Girls	6.48 (3.5)	t(163) = 1.11	1.03 (0.15)	t(163) = 1.54	3.17 (0.92)	t(163) = 1.6
Boys	5.94 (2.79)		1.06 (0.21)		2.87 (1.4)	
Previous Coding Knowledge						
No	6.11 (3.2)	t(164) = −0.5	1.02 (0.06)	t(164) = 0.92	3.01 (1.16)	t(164) = 0.253
Yes	6.41 (2.92)		1.01 (0.04)		2.95 (1.4)	
Affinity for Technology						
Low	5.73 (3.14)	t(164) = −1.52	1.02 (0.06)	t(164) = 0.54	2.91 (1.00)	t(164) = −0.79
High	6.48 (3.11)		1.02 (0.06)		3.06 (1.35)	

Table 2. Descriptive Statistics for Creative Thinking.

Variable	Average (SD)	Median	Skewness (SE)
Fluency	6.96 (3.65)	7	−0.23 (0.18)
Flexibility	4.25 (2.94)	4	0.48 (0.18)
Originality	0.89 (0.16)	0.94	−4.43 (0.18)
Elaboration	2.88 (0.89)	2.83	−0.12 (0.18)

than half of the drawings required in the test), with an average of four different categories per student.

When comparing performance by gender, we found that the girls' originality was significantly higher than that of the boys, with $t(163) = 2.15$, $p < 0.05$. When comparing performance according to previous programming background, we found that flexibility was significantly higher for students with no previous programming knowledge than among students with a prior background in programming, with $t(164) = 2.02$, $p < 0.05$. Additionally, for students with a low affinity for technology, the score for elaboration was significantly higher than for those with a high affinity for technology, with $t(164) = 2.4$, $p < 0.05$. The results are summarized in Table 3.

Computational Creativity. Among all the participants, the computational creativity score was low (on a scale of 0-1), as indicated by an average value of 0.24 (SD = 0.24). No clear trend was observed throughout the game (see Table 4). In more than half the cases, we could not assume normality (H.-Y. Kim, 2013), as can be seen from the high levels of the skewness coefficients (that is, higher than 1). At most levels, one dominant solution was observed despite the existence of several others, as solved by a minority of students. Exceptions were

Table 3. Creative Thinking by Personal Characteristics (SD).

	Fluency		Flexibility		Originality		Elaboration	
	Average (SD)	T-Test	Average (SD)	T-Test	Average (SD)	T-Test	Average (SD)	T-Test
Gender								
Girls	7.38 (3.33)	$t(163) = 1.46$	4.61 (2.65)	$t(163) = 1.68$	0.92 (0.07)	$t(163) = 2.15$*	2.9 (0.65)	$t(163) = -0.04$
Boys	6.55 (3.86)		3.84 (3.09)		0.87 (0.21)		2.9 (1.07)	
Previous Coding Knowledge								
No	7.03 (3.49)	$t(164) = 0.45$	4.47 (2.93)	$t(164) = 2.02$*	0.9 (0.16)	$t(164) = 0.7$	2.91 (0.89)	$t(164) = 0.09$
Yes	6.72 (4.27)		3.36 (2.86)		0.87 (0.17)		2.89 (0.94)	
Affinity for Technology								
Low	6.9 (3.69)	$t(164) = -0. 2$	4.43 (3.05)	$t(164) = 0.72$	0.91 (0.13)	$t(164) = 1.03$	3.11 (0.88)	$t(164) = 2.4$*
High	7.01 (3.66)		4.09 (2.87)		0.88 (0.18)		2.77 (0.89)	

*$p < 0.05$.

Table 4. Descriptive Statistics for Computational Creativity.

Level	Average (SD)	Median	Skewness (SE)
1	0.17 (0.25)	0.9	2.91 (0.18)
2	0.21 (0.27)	0.11	2.35 (0.19)
3	0.1 (0.2)	0.05	3.96 (0.18)
4	0.67 (0.19)	0.7	0.49 (0.19)
5	0.03 (0.13)	0.02	7.48 (0.18)
6	0.63 (0.17)	0.67	0.67 (0.19)
7	0.02 (0.72)	–	–
8	0.02 (0.09)	–	–
9	0.45 (0.15)	0.42	−1.78 (0.2)

Levels 7 and 8, in each of which a single solution was submitted by the entire population, probably because of the design of these levels and their block limits. Levels 4 and 6 exhibited the highest variability among participants.

A comparison of the computational creativity scores by personal characteristics revealed significant differences between girls and boys. The average computational creativity was greater for girls than for boys, with $t(163) = 2.25$, $p < 0.05$. No other differences were found. The results are summarized in Table 5.

In order to examine computational creativity across different levels of the game, we ran 36 pair-wise between-level correlations. We used the post-hoc False Discovery Rate (FDR) method for correcting the multiple comparisons; this method produces a q-value, which is interpreted as a p-value (Storey et al., 2004). We did not find any significant positive correlations between pairs of levels, with the exception of Levels 2 and 3, implying that each level promotes creativity differently on a varying scale. Table 6 summarizes the findings. Note that Levels 7 and 8 were removed from the table as only one solution was possible, and therefore creativity could not be coded at these levels.

Creative Thinking and Acquisition of Computational Thinking. We tested for correlations between the computational thinking variables and the creative thinking variables. The findings indicate that flexibility and originality were significantly and negatively correlated with average time, with Spearman's ρ taking values of -0.16 and -0.18, respectively, at $p < 0.05$. Likewise, we found a significant negative correlation between flexibility and solution attempts, with $\rho = -0.17$, at $p < 0.05$. When we examined the correlation between the two variables by level, we found five cases—Levels 1, 3, 5, 6, and 7—that demonstrated significant correlations. Note that except for one case (Level 1), all correlations were negative (findings are summarized in Table 7). These significant correlations by

Table 5. Computational Creativity by Personal Characteristics (SD).

	Average (SD)	T-Test
Gender		
Girls	0.26 (0.08)	t(163) = 2.25*
Boys	0.24 (0.06)	
Previous Coding Knowledge		
No	0.26 (0.08)	t(164) = 1.24
Yes	0.24 (0.06)	
Affinity for Technology		
Low	0.26 (0.07)	t(164) = 1.61
High	0.24 (0.07)	

*p < 0.05.

Table 6. Correlations of Computational Creativity Between Pairs of Levels.

Level	2	3	4	5	6	7†	8†	9
1	0.13 q = 0.23	0.18 q = 0.09	−0.09 q = 0.54	−0.02 q = 0.86	0.08 q = 0.63	–	–	−0.011 q = 0.93
2		0.28*** q = 0.00	0.18 q = 0.09	−0.05 q = 0.8	−0.06 q = 0.8	–	–	−0.22 q = 0.07
3			0.16* q = 0.16	0.13 q = 0.23	0.02 q = 0.86	–	–	−0.04 q = 0.86
4				0.05 q = 0.8	−0.01 q = 0.93	–	–	−0.03 q = 0.86
5					0.14 q = 0.23	–	–	0.02 q = 0.86
6						–	–	−0.09 q = 0.63

*q < 0.05, **q < 0.01, ***q < 0.001.
†In this case, there was no variance in Computational Creativity in at least one variable.

level, which differ from those emerging on the game level, indicate that different levels promote varying degrees of the four constructs of creative thinking.

When examining the correlations by personal characteristics (see Table 8), we found some interesting results. A significant negative correlation emerged between flexibility and average time for boys, with $\rho = -0.29$, at $p < 0.01$. No correlations were found among the girls. Furthermore, among students with low affinity for technology, we found a negative correlation between flexibility and

Table 7 Correlations between Computational Thinking and Creative Thinking by Levels; only significant correlations are shown (N=174)

	Solution Attempts	Correct Solution Attempts	Average Time
Fluency			
Level 1	$\rho=-0.04$ p=0.62	$\rho=0.04$ p=0.65	**$\rho=-0.16^{*}$**
Flexibility			
Level 1	$\rho=-0.04$ p=0.58	$\rho=-0.01$ p=0.94	**$\rho=0.15^{*}$**
Level 7	**$\rho=-0.18^{*}$**	$\rho=0.00$ p=0.96	$\rho=-0.14$ p=0.07
Originality			
Level 5	**$\rho=-0.15^{*}$**	$\rho=-0.06$ p=0.42	$\rho=-0.04$ p=0.62
Elaboration			
Level 1	$\rho=0.1$ p=0.19	$\rho=-0.15$ p=0.05	**$\rho=-0.27^{**}$**
Level 3	$\rho=0.11$ p=0.14	$\rho=-0.15$ p=0.05	**$\rho=-0.19^{**}$**
Level 6	**$\rho=-0.2^{**}$**	**$\rho=-0.16^{*}$**	**$\rho=-0.21^{**}$**

* $p<0.05$, $^{**}p<0.01$

Table 8 Correlations between Computational Thinking and Creative Thinking by Personal Characteristics; only significant correlations are shown

	Solution Attempts	Correct Solution Attempts	Average Time
Flexibility			
Boys (N=95)	ρ=-0.11 p=0.26	ρ=-0.09 p=0.41	**ρ=-0.29****
Low Affinity for Technology (N=69)	**ρ=-0.24***	ρ=-0.04 p=0.72	ρ=-0.23 p=0.06

* $p<0.05$, $^{**}p<0.01$

total attempts, with $\rho=-0.24$ at $p<0.05$, while no correlations were found for students with high affinity for technology.

The above results indicate that **the more creative the students were** (as measured by a standardized creativity test), **the less time and effort it took them to solve the levels in the game**. These findings were expressed on the game level, in the analysis of each level separately, and in the analysis according to personal characteristics.

Table 9 Correlations between Computational Thinking and Computational Creativity by Levels; only significant correlations are shown (N=174)

	Solution Attempts	Correct Solution Attempts	Average Time
Level 3	ρ=0.14 p=0.08	ρ=0.05 p=0.53	**ρ=0.27****
Level 4	ρ=0.14 p=0.06	ρ=-0.02 p=0.78	**ρ=0.25****
Level 6	**ρ=0.17***	ρ-0.08 p=0.28	ρ=0.11 p=0.16
Level 9	**ρ=0.18***	ρ=0.1 p=0.27	**ρ=0.33****

* p<0.05, ** p<0.01

Computational Creativity and Acquisition of Computational Thinking

Next, we tested the associations between computational thinking and computational creativity, with computational creativity reflected by the originality of a correct solution at a given level compared with all other correct solutions. We did so for the aggregated measures as well as for each level of the game separately. We found that on the whole, computational creativity exhibited a negative correlation with solution attempts, with $\rho = -0.17$, at $p < 0.05$, and with average time, with $\rho = 0.2$, at $p < 0.01$. We also found four cases—Levels 3, 4, 6, and 9—which demonstrated significant positive correlations, as reported in Table 9. These results indicate that the more creative the students were in producing a solution, the more time and effort it took them to solve certain levels in the game.

When examining the correlations by personal characteristics (see Table 10), we found that for girls, computational creativity is negatively correlated with solution attempts and average time, with $\rho = -0.23$ and $\rho = -0.25$, respectively, both at $p < 0.05$. For boys, a negative correlation emerged between computational creativity and average time, with $\rho = -0.22$, at $p < 0.05$. Moreover, for students with no previous coding knowledge, computational creativity was negatively correlated with solution attempts and average time, with $\rho = -0.27$ and $\rho = -0.25$, at $p < 0.01$, respectively. For students with previous coding knowledge, a negative correlation emerged between computational creativity and correct solution attempts, with $\rho = -0.33$, at $p < 0.05$. Moreover, we found that for students with low affinity for technology, computational creativity showed a negative correlation with solution attempts and average time, with $\rho = -0.3$ and $\rho = -0.26$, at $p < 0.05$, respectively.

Table 10 Correlations between Computational Thinking and Computational Creativity and correlations between Creative Thinking and Computational Creativity by Personal Characteristics

		Computational Thinking			Creative Thinking			
Personal Characteristics		Solution Attempts	Correct Solution Attempts	Average Time	Fluency	Flexibility	Originality	Elaboration
Gender	**Girls (N=78)**	**ρ=-0.23***	ρ=-0.18 p=0.12	**ρ=-0.25***	ρ=-0.08 p=0.51	ρ=-0.01 p=0.91	ρ=0.15 p=0.18	ρ=-0.08 p=0.49
	Boys (N=95)	ρ=-0.13 p=0.22	ρ=-0.07 p=0.52	**ρ=-0.22***	ρ=-0.12 p=0.25	ρ=0.1 p=0.33	**ρ=0.23***	ρ=-0.06 p=0.6
Previous Coding Knowledge	**No (N=136)**	**ρ=-0.27****	ρ=-0.05 p=0.53	**ρ=-0.25****	ρ=-0.01 p=0.85	ρ=0.07 p=0.41	ρ=0.17 p=0.05	ρ=-0.01 p=0.95
	Yes (N=38)	ρ=-0.06 p=0.72	**ρ=-0.33***	ρ=-0.06 p=0.7	ρ=-0.29 p=0.08	ρ=0.08 p=0.65	**ρ=0.32***	ρ=0.08 p=0.65
Affinity for Technology	**Low (N=69)**	**ρ=-0.3***	ρ=-0.14 p=0.25	**ρ=-0.26***	**ρ=-0.29***	ρ=0.1 p=0.43	**ρ=0.25***	ρ=-0.01 p=0.97
	High (N=105)	ρ=-0.08 p=0.44	ρ=-0.08 p=0.4	ρ=-0.17 p=0.09	ρ=0.07 p=0.49	ρ=0.04 p=0.68	ρ=0.13 p=0.19	ρ=-0.03 p=0.74

* $p<0.05$, **$p<0.01$

Creative Thinking and Computational Creativity

Finally, we examined the associations between the measures related to creativity: computational creativity and creative thinking. We found a **significant positive correlation between originality and the aggregated variable of computational creativity**, with $\rho = 0.2$, at $p < 0.01$. These results indicate that **students who created more original drawings in the TTCT task were more creative in the game**.

The following results emerged from examining the correlations by demographic variables (see Table 10). For boys, we found a significant positive correlation between originality and computational creativity, with $\rho = 0.23$, at $p < 0.05$. No correlations emerged between these variables among the girls. When examining students with previous coding knowledge ($N = 136$), we found that their originality was positively correlated with computational creativity, with $\rho = 0.32$, at $p < 0.05$. No correlations emerged for students with no previous coding knowledge. In contrast, for students with low affinity for technology, fluency exhibited a negative correlation with computational creativity, while originality exhibited a positive correlation with computational creativity. These results indicate that among this group, **students who produced a higher number of drawings in the TTCT task were less creative in the game, but those who created more original drawings in the TTCT task were more creative in the game**.

Discussion

In this study, we explored the associations between computational thinking (CT) and two types of creativity—computational creativity and creative thinking—as reflected in the solutions generated by middle school students within a game-based learning platform and on a standardized creativity test. In addition, we examined the role played by personal characteristics in these associations.

In the analysis of CT among all the participants, our findings indicate that, in general and as expected, the level of difficulty increased throughout the game, as reflected by the number of solution attempts and the average time. Creative thinking was relatively high, mainly because of the multitude of categories. Computational creativity, on the other hand, did not exhibit a clear trend. At some of the levels, one solution was dominant, and at others, only a single solution was possible. One interesting finding is that no significant differences emerged between the CT variables based on personal characteristics. Nevertheless, previous studies have found gender differences (Eguíluz et al., 2018). In-depth investigation and understanding of these differences are crucial to promoting the acquisition of CT. We indeed intend to continue exploring these aspects. In the context of gender differences, we found significant differences between boys and girls for both creativity constructs. Girls were significantly more creative than boys in terms of both creative thinking and computational creativity. While the literature on gender-based differences in relation to creativity has been inconclusive (Abraham, 2016), the current study is in line with previous studies demonstrating that girls score higher than boys when tested for creativity (J. Baer & Kaufman, 2008; Cheung & Lau, 2010; Kousoulas & Mega, 2009; Lee et al., 2017; Matud et al., 2007). A recent comprehensive meta-analysis of the associations between gender and creativity analyzed 271 studies, 480 independent effect sizes, and a total of N = 137,247 participants. The analysis found a significant relationship between gender and creativity, with females showing slightly higher levels of creativity than males (Thompson, 2016).

In our study, associations emerged between CT, creative thinking, and computational creativity. CT exhibited significant negative correlations with two of the dimensions of creative thinking—flexibility, and originality. The more creative students were on the standardized creativity test, the less time and effort they required to solve the levels in the game. This finding corresponds to that of an earlier study indicating a positive association between standardized creativity tests and secondary school students' academic achievements (Anwar et al., 2012). A more recent study found similar associations among students in computer science education (Whalley & Ogier, 2020). Moreover, these findings support the notion that creativity may contribute to computer science and to computational thinking in particular (S. Kong, 2019; Miller et al., 2013). When examining these associations by personal characteristics, we found that similar relationships—i.e., higher levels of creativity yield less efforts in acquiring CT—held for some sub-populations but not for others (in particular, for boys but not for girls, and for students with low but not with high affinity for technology). In our future research we will continue studying these relationships.

Computational creativity—a manifestation of original solutions within the learning environment—for the most part exhibited negative correlations with solution attempts and average time, which constitute measures of CT. That is, the more efforts students invested in achieving a correct solution, the less creative their solutions were. These associations were evident for both genders, as well as among those students with no previous coding experience and among those with low affinity for technology. Additionally, we found that among students with previous coding experience, the higher their success rate, the less creative their solutions were. Various studies have indicated a relationship between prior programming experience and performance (Berland et al., 2013; Soares et al., 2015). Hence, we may be observing a negative impact on creativity at both ends of content-related competency: While novice students did not have the knowledge structures required to provide creative solutions, experienced students were focused on completing the tasks properly and did not attempt to be creative. To examine these differences thoroughly, students must be explicitly encouraged to submit as many different solutions as possible, which we intend to do in our future research.

It is also worth noting that at some levels of the game, a positive correlation emerged between computational creativity and measures of CT acquisition. That is, students who provided more original and unique solutions needed more time and attempts to solve these levels. This is not surprising, as producing a creative solution may take more time than producing a "standard" solution (Akinboye, 1982; M. Baer & Oldham, 2006), and indeed was observed in our previous study (Hershkovitz et al., 2019). A possible explanation may also be related to the characteristics of the levels themselves as stimulating or suppressing creativity. This highlights the importance of the learning environment design in supporting and even promoting creativity. Indeed, different studies emphasize the influence of the learning environment design on the expression of creativity (Doering & Henrickson, 2015; Roque et al., 2016).

We also found some intriguing associations between the two types of creativity. Computational creativity exhibited a positive correlation with the originality dimensions of creative thinking. These results may imply a "transfer of creativity" from one domain to another. Yet taken together with the finding that such associations were observed only for a few levels of the game, they may also imply that creativity is context-dependent. This supports the hierarchical model of creativity, integrating both domain-general and domain-specific types of creativity (Baer, 2010; Hong & Milgram, 2010). It also reflects earlier findings linking standardized creativity scores to creativity in problem-solving on programming platforms, also supporting the hierarchical model (Liu & Lu, 2002).

This study contributes to the growing body of literature on CT and creativity, and more importantly, to the still very limited knowledge base on computational creativity. Our findings show that creativity can contribute to the acquisition of computational thinking and also can be transferable across domains, underscoring the importance of nurturing creativity while promoting CT. Many learning environments seek efficiency and penalize original solutions as they are often considered longer than the desired solution. This feature can impair learners' motivation and hinder learning. Indeed, in the context of task completion, longer solutions are not necessarily less effective than shorter solutions (Chao et al., 2014). Therefore, instructional designers should adapt their perception and incorporate creative tasks as an inherent part of learning environments. Educators who want to better promote the acquisition of computational thinking should encourage student creativity, whether by using dedicated learning environments or by fostering this skill in classroom activities.

While our results and insights contribute to understanding the associations among CT, creative thinking, and computational creativity, some limitations are worth noting. First, because we analyzed data from a single learning platform (Kodetu), it is possible that our findings were a result of some unique characteristics of this platform (Saito et al., 2017). Specifically, the studied platform does not encourage multiple correct solutions and in some cases limits the free use of coding blocks, which may affect and limit creative solutions. Furthermore, the analysis is based on students from a single country (Spain). Personal and cultural characteristics may affect how creativity is exhibited (Deng et al., 2016; Runco & Johnson, 2002; Zhou et al., 2013). Therefore, we recommend replicating this study in other countries to offer a more international and multicultural view. Indeed, this is our plan. In addition, we plan to broaden our perspective by examining similar platforms under different conditions and using a more multicultural approach.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

Note

1. See https://developers.google.com/blockly.

ORCID iDs

Rotem Israel-Fishelson https://orcid.org/0000-0002-5650-4561
Arnon Hershkovitz https://orcid.org/0000-0003-1568-2238

References

Abraham, A. (2016). Gender and creativity: An overview of psychological and neuroscientific literature. *Brain Imaging and Behavior*, *10*(2), 609–618. https://doi.org/10.1007/s11682-015-9410-8

Akinboye, J. O. (1982). Correlates of testing time, age and sex in the Nigerians' performance on the Torrance test of creativity. *Journal of Psychological Researches*, *26*(1), 1–5.

Amabile, T. M., & Pillemer, J. (2012). Perspectives on the social psychology of creativity. *The Journal of Creative Behavior*, *46*(1), 3–15. https://doi.org/10.1002/jocb.001

Angeli, C., & Valanides, N. (2020). Developing young children's computational thinking with educational robotics: An interaction effect between gender and scaffolding strategy. *Computers in Human Behavior*, *105*, 105954. https://doi.org/10.1016/j.chb.2019.03.018

Anthony, K., & Frazier, W. (2009). Teaching students to create indiscovered ideas. *Science Scope*, *33*(3), 20–27.

Anwar, M. N., Aness, M., Khizar, A., Naseer, M., & Muhammad, G. (2012). Relationship of creative thinking with the academic achievements of secondary school students. *International Interdisciplinary Journal of Education*, *1*(3), 1–4.

Atmatzidou, S., & Demetriadis, S. (2016). Advancing students' computational thinking skills through educational robotics: A study on age and gender relevant differences. *Robotics and Autonomous Systems*, *75*, 661–670. https://doi.org/10.1016/j.robot.2015.10.008

Baer, J. (2010). Is creativity domain specific? In J. C. Kaufman & R. J. Sternberg (Eds.), *The Cambridge handbook of creativity* (pp. 321–341). Cambridge University Press.

Baer, J., & Kaufman, J. C. (2008). Gender differences in creativity. *The Journal of Creative Behavior*, *42*(2), 75–105. https://doi.org/10.1002/j.2162-6057.2008.tb01289.x

Baer, M., & Oldham, G. R. (2006). The curvilinear relation between experienced creative time pressure and creativity: Moderating effects of openness to experience and support for creativity. *The Journal of Applied Psychology*, *91*(4), 963–970. https://doi.org/10.1037/0021-9010.91.4.963

Barr, V., & Stephenson, C. (2011). Bringing computational thinking to K-12: What is involved and what is the role of the computer science education community? *ACM Inroads*, *2*(1), 48–54.

Beghetto, R. A. (2010). Creativity in the classroom. In J. C. Kaufman & R. J. Sternberg (Eds.), *The Cambridge handbook of creativity* (pp. 447–463). Cambridge University Press.

Bennett, V. E., Koh, K. H., & Repenning, A. (2010). *Computing creativity. Divergence in computational thinking* [Symposium]. Proceedings of the 44th ACM Technical Symposium on Computer Science Education. ACM. https://doi.org/10.1145/2445196.2445302

Berland, M., Martin, T., Benton, T., Petrick Smith, C., & Davis, D. (2013). Using learning analytics to understand the learning pathways of novice programmers. *Journal of the Learning Sciences*, *22*(4), 564–599.

Blikstein, P. (2011). *Using learning analytics to assess students' behavior in open-ended programming tasks* [Conference session]. Proceedings of the 1st International Conference on Learning Analytics and Knowledge – LAK '11. ACM Press.

Boutnaru, S., & Hershkovitz, A. (2015). Software quality and security in teachers' and students' codes when learning a new programming language. *Interdisciplinary Journal of E-Skills and Lifelong Learning*, *11*, 123–148.

Brennan, K., & Resnick, M. (2012). *New frameworks for studying and assessing the development of computational thinking* [Presentation paper]. Proceedings of the 2012 Annual Meeting of the American Educational Research Association. American Educational Research Association.

Buitrago Flórez, F., Casallas, R., Hernández, M., Reyes, A., Restrepo, S., & Danies, G. (2017). Changing a generation's way of thinking: Teaching computational thinking through programming. *Review of Educational Research*, *87*(4), 834–860.

Chao, J.-Y., Liu, C.-H., & Chen, J.-Y. (2014). The influence of courses integrating Atayal culture and LEGO Dacta on the programming ability and creativity of Aboriginal children. *Global Journal of Computers & Technology*, *1*(2), 34–43.

Cheung, P. C., & Lau, S. (2010). Gender differences in the creativity of Hong Kong school children: Comparison by using the new electronic Wallach-Kogan creativity tests. *Creativity Research Journal*, *22*(2), 194–199. https://doi.org/10.1080/10400419.2010.481522

Clements, D. H. (1995). Teaching creativity with computers. *Educational Psychology Review*, *7*(2), 141–161. https://doi.org/10.1007/BF02212491

Cramond, B., Matthews-Morgan, J., Bandalos, D., & Zuo, L. (2005). A report on the 40-year follow-up of the torrance tests of creative thinking: Alive and well in the new millennium. *Gifted Child Quarterly*, *49*(4), 283–291. https://doi.org/10.1177/001698620504900402

Davies, D., Jindal-Snape, D., Collier, C., Digby, R., Hay, P., & Howe, A. (2013). Creative learning environments in education—A systematic literature review. *Thinking Skills and Creativity*, *8*, 80–91. https://doi.org/10.1016/J.TSC.2012.07.004

Deng, L., Wang, L., & Zhao, Y. (2016). How creativity was affected by environmental factors and individual characteristics: A cross-cultural comparison perspective. *Creativity Research Journal*, *28*(3), 357–366. https://doi.org/10.1080/10400419.2016.1195615

Deschryver, M. D., & Yadav, A. (2015). Creative and computational thinking in the context of new literacies: Working with teachers to scaffold complex technology-mediated approaches to teaching and learning. *Journal of Technology and Teacher Education*, *23*(3), 411–431.

Doering, A., & Henrickson, J. (2015). Fostering creativity through inquiry and adventure in informal learning environment design. *Journal of Technology and Teacher Education*, *23*(3), 387–410.

Doleck, T., Bazelais, P., Lemay, D. J., Saxena, A., & Basnet, R. B. (2017). Algorithmic thinking, cooperativity, creativity, critical thinking, and problem solving: Exploring the relationship between computational thinking skills and academic performance. *Journal of Computers in Education*, *4*(4), 355–369. https://doi.org/10.1007/s40692-017-0090-9

Donovan, L., Green, T. D., & Mason, C. (2014). Examining the 21st century classroom: Developing an innovation configuration map. *Journal of Educational Computing Research*, *50*(2), 161–178. https://doi.org/10.2190/EC.50.2.a

Eguíluz, A., Garaizar, P., & Guenaga, M. (2018). An evaluation of open digital gaming platforms for developing computational thinking skills. In D. Cvetković (Ed.), *Simulation and gaming*. InTech. https://doi.org/10.5772/intechopen.71339

Eguíluz, A., Guenaga, M., Garaizar, P., & Olivares-Rodríguez, C. (2020). Exploring the progression of early programmers in a set of computational thinking challenges via clickstream analysis. *IEEE Transactions on Emerging Topics in Computing*, *8*(1), 256–261. https://doi.org/10.1109/TETC.2017.2768550

Emerson, A., Smith, A., Smith, C., Rodríguez, F., Wiebe, E., Mott, B., Boyer, K., & Lester, J. (2019). *Predicting early and often: Predictive student modeling for blockbased programming environments* [Conference session]. Proceedings of the 12th International Conference on Educational Data Mining.

Ferguson, R. (2012). Learning analytics: Drivers, developments and challenges. *International Journal of Technology Enhanced Learning*, *4*(5/6), 304–317. https://doi.org/10.1504/IJTEL.2012.051816

Gal, L., Hershkovitz, A., Morán, A. E., Guenaga, M., & Garaizar, P. (2017). *Suggesting a log-based creativity measurement for online programming learning environment*

[Conference session]. Proceedings of the Fourth (2017) ACM Conference on Learning @ Scale—L@S '17. ACM Press. https://doi.org/10.1145/3051457.3054003

Grover, S., & Pea, R. (2013). Computational thinking in k–12. *Educational Researcher*, *42*(1), 38–43. https://doi.org/10.3102/0013189X12463051

Grover, S., Basu, S., Bienkowski, M., Eagle, M., Diana, N., & Stamper, J. (2017). A framework for using hypothesis-driven approaches to support data-driven learning analytics in measuring computational thinking in block-based programming environments. *ACM Transactions on Computing Education*, *17*(3), 1–25.

Guenaga, M., Mentxaka, I., Garaizar, P., Eguiluz, A., Villagrasa, S., & Navarro, I. (2017). *Make world, a collaborative platform to develop computational thinking and STEAM* [Conference session]. International Conference on Learning and Collaboration Technologies. Springer, Cham.

Guilford, J. P. (1950). Creativity. *The American Psychologist*, *5*(9), 444–454. https://doi.org/10.1037/h0063487

Hambrusch, S., Hoffmann, C., Korb, J. T., Haugan, M., & Hosking, A. L. (2009). A multidisciplinary approach towards computational thinking for science majors. *ACM SIGCSE Bulletin*, *41*(1), 183–187. https://doi.org/10.1145/1539024.1508931

Hershkovitz, A., Sitman, R., Israel-Fishelson, R., Eguíluz, A., Garaizar, P., & Guenaga, M. (2019). Creativity in the acquisition of computational thinking. *Interactive Learning Environments*, *27*(5–6), 628–644. https://doi.org/10.1080/10494820.2019.1610451

Hong, E., & Milgram, R. M. (2010). Creative thinking ability: Domain generality and specificity. *Creativity Research Journal*, *22*(3), 272–287. https://doi.org/10.1080/10400419.2010.503535

Hsiao, H. S., Chang, C. S., Lin, C. Y., & Hu, P. M. (2014). Development of children's creativity and manual skills within digital game-based learning environment. *Journal of Computer Assisted Learning*, *30*(4), 377–395. https://doi.org/10.1111/jcal.12057

Hutchins, N. M., Zhang, N., & Biswas, G. (2017). *The role gender differences in computational thinking confidence levels plays in STEM applications* [Conference Session]. Proceedings of International Conference on Computational Thinking Education. The Education University of Hong Kong.

Israel-Fishelson, R., & Hershkovitz, A. (2019). Persistence in a game-based learning environment: The case of elementary school students learning computational thinking. *Journal of Educational Computing Research*, 1–28. https://doi.org/10.1177/0735633119887187

ISTE. (2017). *Turn coders into computational thinkers*. https://www.iste.org/explore/articleDetail?articleid = 936&category = Innovator-solutions&article = Turn + coders + into + computational + thinkers

Jenson, J., & Black, K. (2017, July 4–6). *Gender and game making: Attitudes, competencies and computational thinking* [Conference Session]. DiGRA 2017: The 10th Digital Games Research Association Conference. Melbourne, VIC, Australia.

Kafai, Y. B., & Burke, Q. (2013). Computer programming goes back to school. *Phi Delta Kappan*, *95*(1), 61–65.

Kalelioğlu, F., Gülbahar, Y., & Kukul, V. (2016). A Framework for computational thinking based on a systematic research review. *Baltic Journal of Modern Computing*, *4*(3), 583–596.

Kaufman, J. C., & Beghetto, R. A. (2009). Beyond big and little: The four C model of creativity. *Review of General Psychology*, *13*(1), 1–12. https://doi.org/10.1037/a0013688

Kim, A. S., & Ko, A. J. (2017). *A pedagogical analysis of online coding tutorials* [Symposium]. Proceedings of the 2017 ACM SIGCSE Technical Symposium on Computer Science Education – SIGCSE '17. ACM.

Kim, H.-Y. (2013). Statistical notes for clinical researchers: Assessing normal distribution (2) using skewness and kurtosis. *Restorative Dentistry & Endodontics*, *38*(1), 52–54. https://doi.org/10.5395/rde.2013.38.1.52

Kim, K. H. (2011). Proven reliability and validity of the Torrance Tests of Creative Thinking (TTCT). *Psychology of Aesthetics, Creativity, and the Arts*, *5*(4), 314–315. https://doi.org/10.1037/a0021916

Kim, K. H. (2017). The Torrance tests of creative thinking—Figural or verbal: Which one should we use? *Creativity. Theories—Research—Applications*, *4*(2), 302–321. https://doi.org/10.1515/ctra-2017-0015

Kong, S. (2019). Components and methods of evaluating computational thinking for fostering creative problem-solvers in senior primary school education. In S. Kong & H. Abelson (Eds.), *Computational thinking education* (pp. 119–142). Springer.

Kousoulas, F., & Mega, G. (2009). Students' divergent thinking and teachers' ratings of creativity: Does gender play a role? *The Journal of Creative Behavior*, *43*(3), 209–222. https://doi.org/10.1002/j.2162-6057.2009.tb01315.x

Krumm, A., Means, B., & Bienkowski, M. (2018). *Learning analytics goes to school: A collaborative approach to improving education*. Routledge.

Lau, K. W., & Lee, P. Y. (2015). The use of virtual reality for creating unusual environmental stimulation to motivate students to explore creative ideas. *Interactive Learning Environments*, *23*(1), 3–18. https://doi.org/10.1080/10494820.2012.745426

Lee, J., Jung, Y., & Park, H. (2017). Gender differences in computational thinking, creativity, and academic interest on elementary SW education. *Korean Association of Information Education*, *21*(4), 381–391. https://doi.org/10.14352/jkaie.2017.21.4.381

Liu, M.-C., & Lu, H.-F. (2002, August 18-21). *A study on the creative problem-solving process in computer programming* [Conference session]. Proceedings of the International Conference on Engineering Education, Manchester, UK. ICEE.

Lu, O. H. T., Huang, J. C. H., Huang, A. Y. Q., & Yang, S. J. H. (2017). Applying learning analytics for improving students engagement and learning outcomes in an MOOCs enabled collaborative programming course. *Interactive Learning Environments*, *25*(2), 220–234.

Manske, S., & Hoppe, H. U. (2014). *Automated indicators to assess the creativity of solutions to programming exercises* [Conference session]. 2014 IEEE 14th International Conference on Advanced Learning Technologies. IEEE. https://doi.org/10.1109/ICALT.2014.147

Martindale, C. (1989). Personality, situation, and creativity. In *Handbook of creativity* (pp. 211–232). Springer.

Matud, M. P., Rodríguez, C., & Grande, J. (2007). Gender differences in creative thinking. *Personality and Individual Differences*, *43*(5), 1137–1147. https://doi.org/10.1016/j.paid.2007.03.006

Miller, L. D., Soh, L. K., Chiriacescu, V., Ingraham, E., Shell, D. F., Ramsay, S., & Hazley, M. P. (2013). *Improving learning of computational thinking using creative thinking exercises in CS-1 computer science courses* [Conference session]. Proceedings—Frontiers in Education Conference, FIE. IEEE. https://doi.org/10.1109/FIE.2013.6685067

Mishra, P. (2012). Rethinking technology & creativity in the 21st century: Crayons are the future. *TechTrends*, *56*(5), 13–16.

Mishra, P., & Yadav, A. (2013). Of art and algorithm: Rethinking technology & creativity in the 21st century. *TechTrends*, *57*(3), 10–14.

National Research Council. (2012). *A framework for K-12 science education: Practices, crosscutting concepts, and core ideas*. The National Academies Press.

Navarrete, C. C. (2013). Creative thinking in digital game design and development: A case study. *Computers & Education*, *69*, 320–331. https://doi.org/10.1016/j.compedu.2013.07.025

Nutbrown, S., & Higgins, C. (2016). Static analysis of programming exercises: Fairness, usefulness and a method for application. *Computer Science Education*, *26*(2–3), 104–128.

Organisation for Economic Co-operation and Development. (2015). *The future of productivity*. The British Council.

Papert, S. (1980). *Mindstorms: Children, computers, and powerful ideas*. Basic Books.

Parsons, M. J. (1971). White and black and creativity. *British Journal of Educational Studies*, *19*(1), 5–16. https://doi.org/10.1080/00071005.1971.9973296

Pérez Poch, A., Olmedo Torre, N., Sánchez Carracedo, F., Salán Ballesteros, M. N., & López Álvarez, D. (2016). On the influence of creativity in basic programming learning at a first-year Engineering course. *International Journal of Engineering Education*, *32*(5B), 2302–2309.

Plucker, J. A., & Beghetto, R. A. (2002). Why creativity is domain general, why it looks domain specific, and why the distinction does not matter. In *Creativity: From potential to realization* (pp. 153–167). American Psychological Association.

Reiter-Palmon, R., Illies, M. Y., Kobe Cross, L., Buboltz, C., & Nimps, T. (2009). Creativity and domain specificity: The effect of task type on multiple indexes of creative problem-solving. *Psychology of Aesthetics, Creativity, and the Arts*, *3*(2), 73–80. https://doi.org/10.1037/a0013410

Román-González, M., Moreno-León, J., & Robles, G. (2019). Combining assessment tools for a comprehensive evaluation of computational thinking interventions. In S. Kong & H. Abelson (Eds.), *Computational thinking education* (pp. 79–98). Springer.

Romeike, R. (2007). *Three drivers for creativity in computer science education* [Conference session]. IFIP-Conference on Informatics, Mathematics and ICT 2007, Boston, MA.

Roque, R., Rusk, N., & Resnick, M. (2016). Supporting diverse and creative collaboration in the scratch online community. In *Mass collaboration and education* (pp. 241–256). Springer International Publishing.

Ruan, L. L., Patton, E. W., & Tissenbaum, M. (2017). Evaluations of programming complexity in App Inventor. In S. C. Kong, J. Sheldon, & K. Y. Li (Eds.), *International Conference on Computational Thinking Education 2017*. The Education University of Hong Kong.

Runco, M. A., & Jaeger, G. J. (2012). The standard definition of creativity. *Creativity Research Journal*, *24*(1), 92–96. https://doi.org/10.1080/10400419.2012.650092

Runco, M. A., & Johnson, D. J. (2002). Parents' and teachers' implicit theories of children's creativity: A cross-cultural perspective. *Creativity Research Journal*, *14*(3–4), 427–438. https://doi.org/10.1207/S15326934CRJ1434_12

Saavedra-Sánchez, D., Vidal-Sepúlveda, M., & Olivares-Rodríguez, C. (2019). *Effort analysis of computational thinking process over a gamified and non-gamified environments* [Conference session]. The 2nd Latin American Conference on Learning Analytics.

Said-Metwaly, S., Noortgate, W. V., den., & Kyndt, E. (2017). Methodological issues in measuring creativity: A systematic literature review. *Creativity. Theories—Research—Applications*, *4*(2), 276–301. https://doi.org/10.1515/ctra-2017-0014

Saito, D., Sasaki, A., Washizaki, H., Fukazawa, Y., & Muto, Y. (2017). *Quantitative learning effect evaluation of programming learning tools* [Conference session]. 2017 IEEE 6th International Conference on Teaching, Assessment, and Learning for Engineering (TALE). IEEE. https://doi.org/10.1109/TALE.2017.8252335

Scott, C. L. (2015). *The futures of learning 2: What kind of learning for the 21st century?* UNESCO, Education Research and Foresight. [ERF Working Papers Series, No. 14].

Seo, Y.-H., & Kim, J.-H. (2016). Analyzing the effects of coding education through pair programming for the computational thinking and creativity of elementary school students. *Indian Journal of Science and Technology*, *9*(46), 1–5. https://doi.org/10.17485/ijst/2016/v9i46/107837

Seow, P., Looi, C., How, M., Wadhwa, B., & Wu, L. (2019). Educational policy and implementation of computational thinking and programming: Case study of Singapore. In S. Kong & H. Abelson (Eds.), *Computational thinking education* (pp. 345–361). Springer.

Shute, V. J., Sun, C., & Asbell-Clarke, J. (2017). Demystifying computational thinking. *Educational Research Review*, *22*, 142–158.

Soares, A., Fonseca, F., & Martin, N. L. (2015). Teaching introductory programming with game design and problem-based learning. *Issues in Information Systems*, *16*(III), 128–137.

Storey, J. D., Taylor, J. E., & Siegmund, D. (2004). Strong control, conservative point estimation and simultaneous conservative consistency of false discovery rates: A unified approach. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, *66*(1), 187–205. https://doi.org/10.1111/j.1467-9868.2004.00439.x

Tang, X., Yin, Y., Lin, Q., Hadad, R., & Zhai, X. (2020). Assessing computational thinking: A systematic review of empirical studies. *Computers & Education*, *148*, 103798. https://doi.org/10.1016/j.compedu.2019

Thompson, T. L. (2016). The mothers and fathers of invention: A meta-analysis of gender differences in creativity (unpublished dissertation). In *ProQuest Dissertations and Theses*. Florida State University.

Torrance, E. P. (1965). Scientific views of creativity and factors affecting its growth. *Daedalus*, *94*(3), 663–681. https://doi.org/10.2307/20026936

Torrance, E. P. (1974). *Torrance tests of creative thinking*. Scholastic Testing Service.

Voogt, J., Fisser, P., Good, J., Mishra, P., & Yadav, A. (2015). Computational thinking in compulsory education: Towards an agenda for research and practice. *Education and Information Technologies*, *20*(4), 715–728.

Vygotsky, L. S. (2004). Imagination and creativity in childhood. *Journal of Russian & East European Psychology*, *42*(1), 7–97.

Wang, L. C., & Chen, M. P. (2010). The effects of game strategy and preference-matching on flow experience and programming performance in game-based learning. *Innovations in Education and Teaching International*, *47*(1), 39–52.

Whalley, J., & Ogier, H. (2020). *Paperclips, circles, and six-legged spiders: An exploration of self-perceived and measured creativity among CS students* [Conference session]. Proceedings of the Twenty-Second Australasian Computing Education Conference. ACM Press. https://doi.org/10.1145/3373165.3373167

Wing, J. M. (2006). Computational thinking. *Communications of the ACM*, *49*(3), 33–35.

World Economic Forum. (2015). *New vision for education unlocking the potential of technology*.

Yadav, A., & Cooper, S. (2017). Fostering creativity through computing. *Communications of the ACM*, *60*(2), 31–33. https://doi.org/10.1145/3029595

Zhou, J., Shen, J., Wang, X., Neber, H., & Johji, I. (2013). A cross-cultural comparison: Teachers' conceptualizations of creativity. *Creativity Research Journal*, *25*(3), 239–247. https://doi.org/10.1080/10400419.2012.730006

Author Biographies

Rotem Israel-Fishelson is a PhD candidate in the Department of Mathematics, Science, and Technology Education at Tel Aviv University's School of Education. Her main research interest is the study of computational thinking and creativity using learning analytics methods. She earned her M.Sc. in Media Technology (2016) from Linnaeus University (Sweden) and her B.A. in Instructional Design (2012) from Holon Institute of Technology (Israel). In addition, Rotem is a lecturer in the Faculty of Instructional Technologies at the Holon Institute of Technology.

Arnon Hershkovitz is a Senior Lecturer in Tel Aviv University's School of Education (Israel). His research focuses on the new (or newly-shaped) skills required by learners and instructors in the cyber-learning ecosystem, specifically computational thinking, creativity, classroom management and feedback. He studies these skills using a learning analytics approach, currently in the context of STEM education. He holds a B.A. in Mathematics and Computer Science, an M.A. in Applied Mathematics (both from the Technion - Israel Institute of Technology), and a PhD in Science Education (Tel Aviv University).

Andoni Eguíluz is a researcher and lecturer in the Computer Engineering Department, University of Deusto (Spain). He is a fellow of the Advanced Study Program of the Massachusetts Institute of Technology (USA) and a member of the Deusto Learning Lab research group. His main research interests are education, games, multimedia, audiovisual and web accessibility, technology and innovation. Prior to his academic career, he was a technological entrepreneur and was director and researcher on a number of software projects involving games, serious games, accessibility, multimedia, web, 3D, user interaction, graphical interfaces, compiling environments, compiler generators, and more.

Pablo Garaizar is a professor in the Faculty of Engineering, the University of Deusto (Spain). He is a member of the Deusto Learning Lab research group. He holds a B.Sc. in Computer Engineering (University of Deusto), a B.A. in Psychology (UNED), an M.Eng. in Networks and Systems Administration (University of Deusto), and a PhD in Computer Engineering (University of Edusto). He is interested in finding new ways of using information and communication technologies to improve learning and is also interested in web programming, computer security, telematic networks and systems administration.

Mariluz Guenaga is a professor in the Faculty of Engineering, the University of Deusto (Spain), and serves as the director of the Deusto Learning Lab research group. She is the Coordinator of the Spanish Network of Learning Analytics (SNOLA) and a senior member of the IEEE. She received a PhD in Computer Engineering from the University of Deusto (Spain). Her research interests focus on the innovative use of technology in STEM education, learning analytics, and game-based learning.