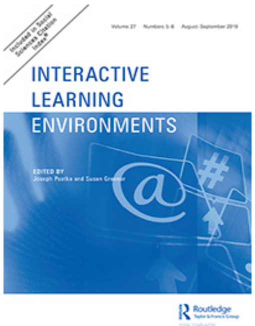

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Creativity in the acquisition of computational thinking

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ABSTRACT
Many worldwide initiatives consider both creativity and computational thinking as crucial skills for future citizens, making them a priority for today's learners. We studied the associations between these two constructs among middle school students ($N = 57$), considering two types of creativity: a general creative thinking, and a specific computational creativity. We did so using learning analytics, specifically, by operationalizing a log-based assessment of computational creativity. We find some evidence for an association between Computational Creativity and Computational Thinking: Demonstrating originality in an early stage of the game is associated with succeeding in this stage relatively easily, however negatively associated with progressing farther in the game. We also find that Computational Creativity is better explained by a state- rather than a trait-model. No associations were found between Creative Thinking and Computational Thinking. Furthermore, we find some striking associations between the two measures of creativity.

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Creativity; computational thinking; computer-aided instruction; game-based learning; learning analytics; log analysis; middle school

> Think left and think right and think low and think high. Oh, the thinks you can think up if only you try. (Dr. Seuss)

1. Introduction

Computational Thinking (CT) is one of the key literacies of the twenty-first century. CT is understood to assist in developing knowledge and understanding concepts in various domains, with great potential for developing problem-solving skills (Grover & Pea, 2013; Wing, 2006). With the recognition of its importance, CT has been integrated into school curricula around the world, and many online platforms, especially game-based learning environments, now promote its development (Eguiluz, Guenaga, Garaizar, & Olivares-Rodriguez, 2018). Despite their popularity, research on these latter environments is meagre; it is mainly qualitative and based on limited data.

Creativity is another well-studied, key component of learning (Donovan, Green, & Mason, 2014). Creativity and computational thinking have some complex relationship (as will be reviewed below), which leads us to deepen our knowledge regarding these associations by using empirical, objective measures for both constructs. However, in most cases, creativity is considered as a static, aggregated construct, ignoring the ways it may be affected by social, contextual variables (Kupers, Lehmann-Wermser, McPherson, & van Geert, 2018). This may pose a problem when studying the role of creativity in the context of interactive learning environments for

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computational thinking. Hence, we would need a measure of creativity which is based on moment-to-moment interactions with the learning environment. Therefore, we cannot ignore the question of associations between the aggregated and the momentarily conceptualizations of creativity. The current study is a first step towards studying these two questions. Despite the extensive research on creativity in computer science, few studies have used automated tools to quantitatively analyze the characteristics of creativity along learning paths, making this study foundational for future work in the area.

1.1. Computational thinking

Computational Thinking (CT), previously considered to be related only to STEM (Science, Technology, Engineering and Mathematics), is now seen an imperative skill in many areas (Kalelioğlu, Gülbahar, & Kukul, 2016). As Janette Wing puts it in the subtitle of an article that ignited recent discussions, CT "represents a universally applicable attitude and skill set everyone, not just computer scientists, would be eager to learn and use" (Wing, 2006, p. 33). Many years ago, Papert coined the concept of CT, arguing that children should learn programming so they could express ideas in other content areas such as mathematics and science. Papert also predicted that computational ideas could change the way children think in any field (Papert, 1980). In more recent work, Wing defined CT as a vital skill which should be an integral part of every child's education (Wing, 2006). Indeed, critical thinking and problem-solving skills are now considered by major organizations – like the World Economic Forum and the United Nations Educational, Scientific, and Cultural Organization – as new literacies that will be required by tomorrow's citizens (Scott, 2015; World Economic Forum, 2015).

There is no single definition of CT, however, and definitions often include concepts like data handling, problem solving, algorithmic thinking, understanding of automation, and simulations (Barr & Stephenson, 2011; Brennan & Resnick, 2012; Grover & Pea, 2013; ISTE & CSTA, 2011; Lye & Koh, 2014; NRC, 2012). We refer to Brennan and Resnick's framework of CT (2012), specifically to the dimension of CT concepts; therefore, we explored CT acquisition with a game-based learning environment, the main purpose of which is to teach basic CT concepts, like sequencing, loops, and conditions. In this environment (Kodetu; more details below), students need to (block)-program to solve challenges. Programming and CT have been shown to be inter-connected, and programming is considered fertile ground for teaching and studying CT (Buitrago Flórez et al., 2017; Lye & Koh, 2014; Tsarava et al., 2017).

CT has been recognized for its importance in developing knowledge and understanding concepts in computer science and for its potential to develop more general-purpose problem-solving skills (Ruan, Patton, & Tissenbaum, 2017). Various scholars have highlighted the importance for students to acquire CT skills in elementary school before they actually start learning programming (Qualls & Sherrell, 2010). The Royal Society argues that children should develop digital literacy, at least to the level of their ability to read and write. It also says every elementary school student should learn computing concepts and principles and have the opportunity to explore the creativity of computing through computer-friendly environments, such as platforms for block-programming (The Royal Society, 2012). The National Research Council (NRC) defines CT as one of the eight practices that should be incorporated into scientific education in K-12 (NRC, 2012). With this type of encouragement, educational institutions worldwide have begun to establish national K-12 curricula, academic standards and instructional activities focused on teaching CT skills (Kafai & Burke, 2013).

1.2. Creativity

Creativity plays a key role in human inventive potential in all disciplines, and its influence dominates many spheres of life (Navarrete, 2013). There is increasing consensus that creativity is an essential skill for the twenty-first century, and, as such, it should be included in the curriculum from an early age (Beghetto, 2010; Vygotsky, 2004). Supplying students with opportunities to engage in creative ways may promote not only their academic achievement, but also the ways they manage their learning, the affective aspects of their learning, and their attitudes towards learning (Davies et al., 2013).

It is difficult to pin down what "creativity" is, however, and there are a great many conceptualizations. One of the most commonly used frame was proposed by Elis Paul Torrance over 50 years ago; he defined creativity as the process of becoming sensitive to problems, deficiencies, missing elements and gaps in knowledge, identifying problems, seeking solutions, formulating hypotheses, examining the hypotheses and rephrasing them, and then communicating the results (Torrance, 1965). According to Torrance – and to many who have followed him – creativity covers four areas: (1) fluency, or the ability to generate a large number of ideas and directions of thought for a particular problem; (2) flexibility, or the ability to think about as many uses and classifications as possible for a particular item or subject; (3) originality, or the ability to think of ideas that are not self-evident or banal or statistically ordinary, but unusual and sometimes even refuted; and (4) elaboration, or the ability to expand an existing idea, to develop and improve it by integrating existing schemes with new ideas. We used this framework (albeit omitting the elaboration dimension), as will be explained later, in our study.

Is there a single creativity, or are there multiple creativities? It has already been shown that there are multiple intelligences and multiple literacies, and this understanding has major implications on the ways students learn and teachers teach, but we have yet to answer this question in the context of creativity. Over a decade ago, Sternberg (2005) suggested creativity should not be treated as a single attribute but as a set of attributes; hence, there may be multiple creativities. Asking whether creativity is domain-specific is one way of asking about its multiplicity; however, the answer is not necessarily "yes" or "no". It is more likely to be a model that includes both domain-general and domain-specific elements (Baer, 2010; Plucker & Beghetto, 2004). Creativity may also be dependent on the context of the learning and on the measuring tool (Reiter-Palmon, Illies, Kobe Cross, Buboltz, & Nimps, 2009).

Overall, the diversity of creativity demonstrations encourages us to study creative solutions along the learning process, to explore the associations between different measures of creativity, and to look for linkages between types of creativity and knowledge acquisition.

1.3. Creativity and computational thinking

Creativity is closely related to computer science and has a central role in fostering motivation and interest in this field of study. Studies have found a bi-directional connection between creativity and computer science. On the one hand, creativity may serve as a catalyst to solving algorithmic problems, creating computational artifacts, and developing new knowledge. As was previously shown, scores from a standardized creativity test (the one that we used in the current study) predicted creativity in problem solving in computer programming, among undergraduate students (Liu & Lu, 2002). On the other hand, practicing the skills required for computer science – e.g. observation, imagination, visualization, abstraction, and creation and identification of patterns – can support the development of creative thinking (Clements & Gullo, 1984; Seo & Kim, 2016; Yadav & Cooper, 2017). Indeed, engaging with rich digital environments was shown to promote creativity (Lau & Lee, 2015; Psotka, 2013). It is not surprising, then, that software engineering – in which CT inherently, conveniently resides – has been identified as a field that can benefit from creativity (Díaz, Aedo, & Cubas, 2014; Zhou, 2016).

Research on creativity in CT (or programming) usually employs one of two possible types of exploration. The first type focuses on *creativity within the scope of CT*, that is, on creative artifacts, which are products of the CT learning process (usually programmes written by learners). Yadav and Cooper say platforms like Alice or Scratch provide opportunities for students "to extend their creative expression to solve problems, create computational artifacts" (Yadav & Cooper, 2017, p. 31). Such studies argue that creativity enabled by programming environments may act as a driving force for learning (Knobelsdorf & Romeike, 2008; Romeike, 2007; Roque, Rusk, & Resnick, 2016). In this category, we can also include studies looking for associations between creativity and other variables that refer to constructs out of the learning environment. For example, Doleck, Bazelais, Lemay, Saxena, and Basnet (2017) examined associations between creativity as an inherent component of computational thinking and academic achievement. It is important to note that some studies have used an automatic method for detecting creativity in programming (Bennett, Koh, & Repenning, 2010; Manske & Hoppe, 2014). We took a similar approach.

The second type of study explores the relationship between measures of *creativity outside the scope of CT* and variables associated with the acquisition of CT. The main questions raised are whether creativity supports the acquisition of CT (Pérez Poch, Olmedo Torre, Sánchez Carracedo, Salán Ballesteros, & López Álvarez, 2016), and whether teaching CT can improve creativity (Chao, Liu, & Chen, 2014; Seo & Kim, 2016). For example, Knochel and Patton (2015) argue that presenting creativity in programming to design students promotes better creative design.

Therefore, associations between CT and creativity – either within or outside the scope of CT – have been recently studied, and preliminary evidence suggest some interesting links between these constructs. Still, a gap exist, as only little has been studied regarding the relationship between the two types of creativity. Also, most of the relevant studies have only focused on aggregated measures of creativity. We aim at bridging this gap by operationalizing a "continuous" (rather than aggregated) measure of CT-related creativity, and to test for its associations with a standard, aggregated, non-CT-related measure of creativity.

2. Research questions

Following the literature review, the main goal of this study was to explore the role of creativities – both inside and outside the learning process – in the acquisition of computational thinking (CT). To avoid confusion, we used Creative Thinking to refer to the "outside" creativity and Computational Creativity to refer to the "inside" creativity (detailed in section 3.5). To meet our research goal, we formulated the following research questions:

(1) What are the associations between Creative Thinking and the acquisition of CT?
(2) What are the associations between Computational Creativity and the acquisition of CT?
(3) What are the associations between Creative Thinking and Computational Creativity?

3. Methodology

3.1. Learning environment: Kodetu

Kodetu is a web app built using Google's Blockly[1] for teaching basic programming skills ([Authors], 2017). Each of Kodetu's 15 levels presents the user with a maze in which an astronaut should get to a marked destination. Guiding the astronaut to her destination is done via a block-based code the user is editing. Moving to the next level is possible only upon completing the current level.

The level progression is as follows: Level 1 introduces a very simple forward-path coding. Levels 2–3 introduce rotations in different path points. Levels 4–6 combine more than one rotation in different combinations, and Level 7 is a long maze intended to show the hard manual work it takes to describe a path step by step. Level 8 introduces loops and limits code size (only 2 blocks) to force learners to use repetition to solve a simple maze. Code length is limited from this point on. Levels 9 (shown in Figure 1) and 10 enhance the use of loops.

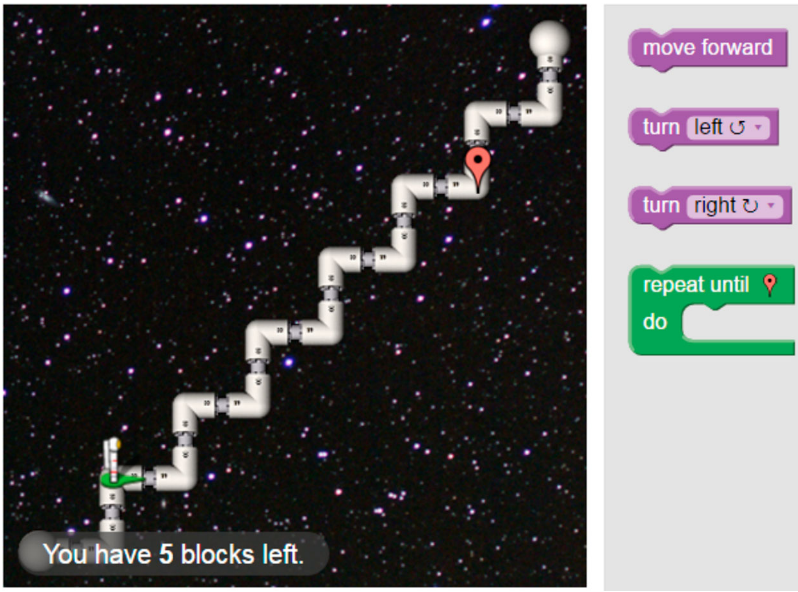

Figure 1. Sample level of Kodetu (Level 9).

Levels 11–12 present conditionals, checking lateral path existence, and Levels 13–14 introduce *If-Else* conditionals. Finally, Level 15 poses the classic problem of a general maze (difficult even for experienced coders). The system is offered in three languages: English, Spanish, and Basque. While the app is being used, the system logs any action taken by its users.

3.2. Population and research process

The data we analyzed were collected in April 2017 from a population of $N = 131$ primary school Spanish students, 10–12 years old (53% boys and 47% girls – 69 and 62, respectively). The students arrived to an outreach activity organized by the Faculty of Engineering of the University of Deusto, and participated in a workshop about technology, programming, and robotics. During this workshop, the students used Kodetu for about 50 min. For the vast majority of the students, it was their first encounter with Kodetu (82%, 108 of 132).

Participants also completed a pen-and-paper creativity task (Torrance's TTCT – Figural Test; see section 3.4). Data from Kodetu log files were connected to data obtained via the creativity task using a unique ID for each participant. This ID was produced by Kodetu and was written down on the creativity test form by the participant. Because of some typos, value matching – from the log files and from the creativity test – was done manually.

3.3. Dataset and preprocessing

The full log file included 101,728 rows, each representing an action taken by a user, including its time-stamp, the level in which it was taken [1–15], its result [Success, Failure, Timeout, Error, Unset], and the written code associated with this action.

For our analysis of creative solutions, we only referred to correct solutions (see more details in section 3.5.2), omitting all other logged solution attempts. This left us with 1332 rows from Levels 1–14 (no correct solution was logged for Level 15). As only a few students reached Levels 13 and 14, we did not consider them in our analyses.

3.4. Research tools

We used the Torrance Test for Creative Thinking (TTCT) – Figural Test (Torrance, 1974) to assess Creative Thinking in three dimensions: fluency, flexibility, and originality. TTCT – the reliability and validity of which has been repeatedly proven (Cramond, Matthews-Morgan, Bandalos, & Zuo, 2005; Kim, 2011) – offers both verbal and figural tests. As thinking about programming may involve both graphic and literal processes, the figural test was 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 with which they built their code. Second, conceptual problem-solving of that type involves more graphic thinking than literal thinking (Liu & Lu, 2002). Furthermore, a recent analysis of both figural and verbal versions of TTCT showed the scores on two versions are highly associated, but the figural version is a more comprehensive, reliable, and valid measure of creativity (Kim, 2017). TTCT – Figural Test was previously successfully used 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 presented with a sheet 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. An eligible drawing used the circle as part of the drawing. Details on scoring these sheets are in section 3.5.1.

3.5. Research variables

3.5.1. Creative thinking

To score the creativity task, we used eligible drawings only, that is, drawings in which the circle was considered an important part of the drawing. Figure 2 gives examples of eligible and non-eligible drawings.

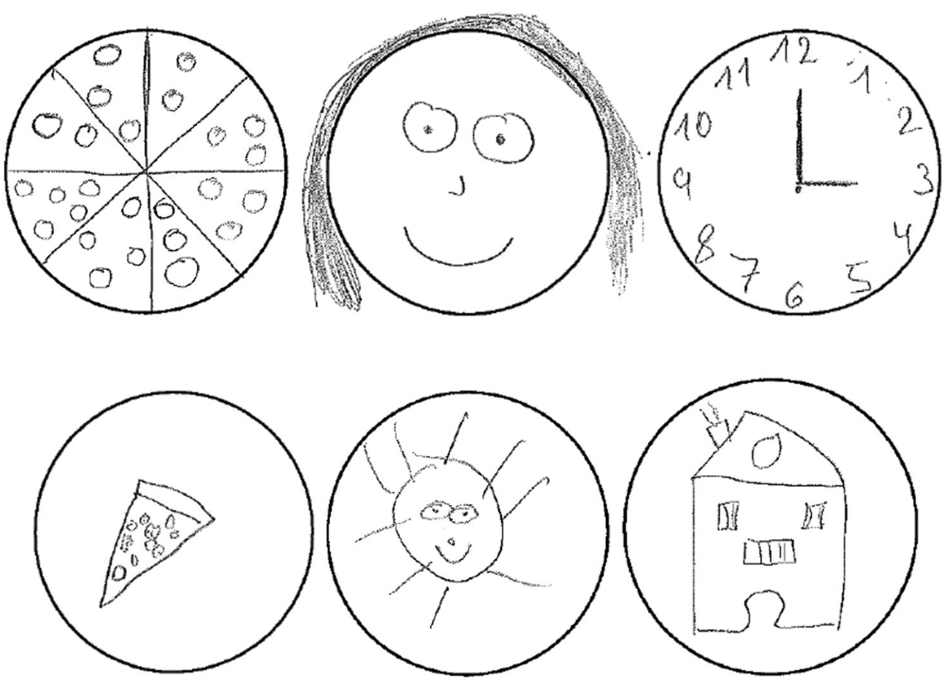

Figure 2. Examples of eligible (top row) and non-eligible (bottom row) drawings from TTCT – figural test.

We defined a set of categories to describe the drawings, based on all eligible drawings of all participants. At the end of an iterative process of merging and splitting categories, the final list consisted of 27 categories, e.g. “Face”, “Food”, “Clock”, “Symbol”, “Outside-the-Line Balloon”. This process of determining eligibility and defining categories was done jointly by the first and second authors; these authors discussed borderline cases and settled disagreements until full agreement was achieved.

Following the process described above, we defined the following four variables (for each participant):

- *Fluency*: number of eligible drawings;
- *Flexibility*: number of drawing categories;
- *Originality*: based on the set of all eligible drawings in the research population, we calculated the frequency of each drawing category; following that, this variable measures the average of drawing categories’ frequencies across the participant’s eligible drawings. As frequency and originality are inversely associated, we took the inverse of that average, to make this variable more interpretable.
- *Credibility Index*: average of standardized fluency, flexibility, and originality.

3.5.2. Computational creativity

As mentioned in the literature review, creativity is commonly treated as a four-multidimensional construct, comprised of originality, flexibility, fluency, and elaboration. However, in our learning environment – as in many similar platforms – the system does not explicitly encourage multiple solutions; once a level is solved, participants are immediately encouraged to move to the next level. Therefore, fluency and flexibility are not relevant in our analysis. Finally, as the solution to each level is composed of existing blocks, elaboration could hardly be demonstrated. Hence, we focus our current analysis on originality alone.

We kept *Computational Creativity* measures for each level separately, as we could not assume coherency across levels (actually, we tested for it). Generally, *Computational Creativity* of a correct solution in a given level was calculated as the complementary to 100% of the frequency of this solution among all the correct solutions for this level. Complementary to 100% was used for purposes of clarity and easy interpretability. When there were multiple correct solutions for an individual participant, we calculated the average across her or his correct solutions.

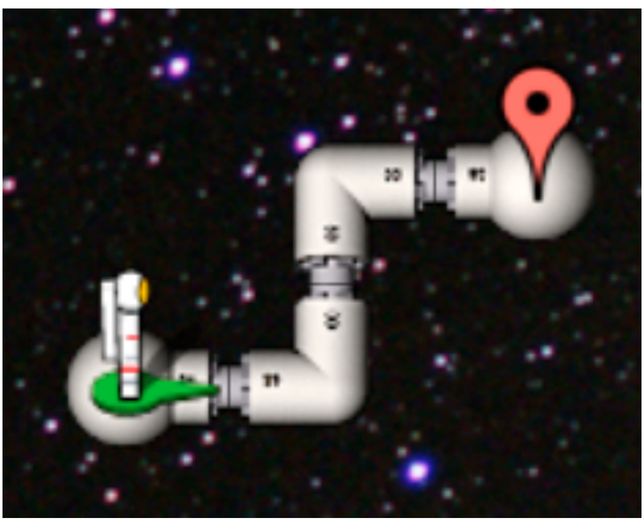

Figure 3. Initial setting in Level 5.

Consider the following example of a level with multiple correct solutions. In Level 5, the astronaut should take a path to her destination; the path first goes straight ahead, then takes a turn to the left, followed by a step forward; the path then takes a turn to the right and another step forward (see Figure 3). The most common solution directly matched the description of the path. We used F (Forward), L (Left), and R (right) to describe the corresponding commands. So the most common solution, given in 94 of 121 cases (78%), was FLFRF. However, there were other possible correct solutions, for example, FRRRFRF or FRLLFLLLF (each given in only one case). The following solution is also correct: the astronaut gets to her destination, but then falls into the eternal space, FLFRFF (given in 4 of 121 cases, 3%).

3.5.3. Computational thinking

We focused on two variables to measure the acquisition of computational thinking:

- Max Level: maximum level reached (not necessarily completed successfully).
- [Level/Average] Solution Attempts: number and average of attempts to solve each of Levels 1–12; the higher this number was, the more difficult the level was to be successfully solved.

4. Findings

To capture the acquisition of computational thinking as validly as possible, we included only participants with no previous experience in programming or in using Kodetu (based on their self-reports), *N* = 57. All statistical analyses used IBM SPSS version 24.

4.1. Exploring research variables

4.1.1. Computational thinking

On average, participants in our population completed 10.8 levels (SD = 1.97, median = 12), as determined by Max Level; this variable had a kurtosis of 2.12 (SE = 0.62) and a skewness of −1.46 (SE = 0.32). Average Solution Attempts (across levels 1–12) was 5.60 (SD = 3.40, median = 5.25), with a

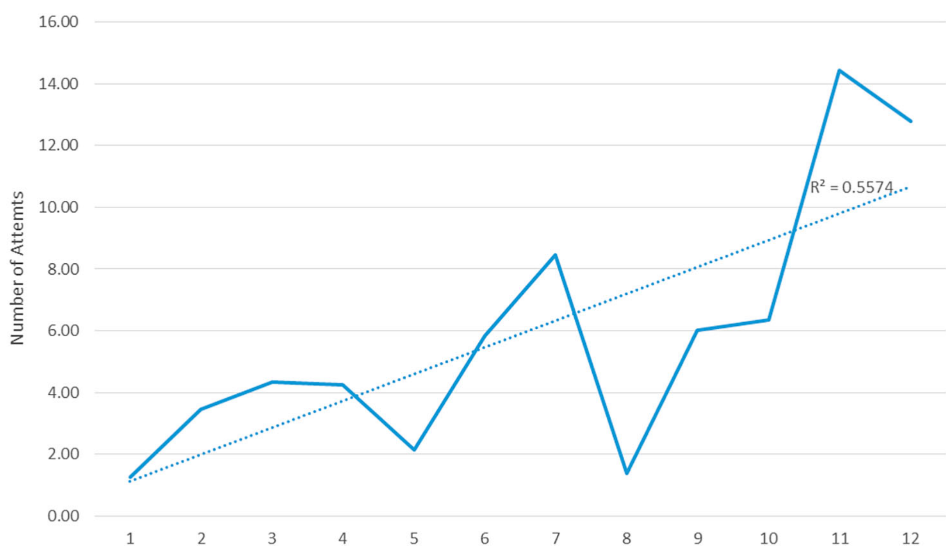

Figure 4. Level solution attempts for each level.

kurtosis of 0.70 (SE = 0.62) and skewness of 0.89 (SE = 0.32). Max Level rejected the normality hypothesis, but Average Solution Attempts did not.

Overall, there was an increasing trend in Level Solution Attempts, with $R^2 = 0.56$ for the graph trend line (see Figure 4), indicating the increasing difficulty of the game. The dramatic decrease in Level Solution Attempts in Level 8 can be explained by the design of this level: Its purpose is to introduce the concept of loops for the first time, hence the actual challenge is quite easy.

4.1.2. Creative thinking

As indicated above, Creative Thinking consisted of three dimensions (fluency, flexibility, and originality) and an overall creativity index (the average of the standardized dimensions). Based on normality tests (Kim, 2013), we assumed normality for all dimensions of Creative Thinking. A summary of the statistics is presented in Table 1.

We should comment on the relatively high mean value of originality ($M = 0.75$, SD = 0.09, $N = 51$). Recall that we defined 27 categories of drawings for TCTT – Figural Test. The distribution of the categories was in a "long tail" shape; that is, many categories had very low frequency (i.e. were highly original), and only a few had relatively high frequency (i.e. were not original). Recall also that we inversed the frequencies (by complementing to 100%), so many (24 of 27) had frequencies higher than 90%. The least original category ("Face") had a frequency of 60%.

4.1.3. Computational creativity

Since no participant successfully completed Level 15 and only a few successfully completed Levels 13 and 14, we only analyzed up to Level 12. As Level 8 had no variance in the correct solutions (i.e. all participants gave the same solution), we omitted this level from our analyses. In about half of the cases, we could not assume normality (Kim, 2013), so for simplicity, we used non-parametric tests for statistical analyses involving any level-related Computational Creativity variable. A summary of the statistics appears in Table 2. It is important to note that there was no clear trend in the average values of Computational Creativity throughout the game. We refer to this in a later section, when we discuss the associations between Computational Creativity and Computational Thinking.

When we examined Computational Creativity across different levels of the game, we discovered something very interesting. We ran 55 pair-wise between-level correlations, correcting for multiple comparisons using the post-hoc False Discovery Rate (FDR) method; this method produces a q-value which is interpreted as a *p*-value (Storey, Taylor, & Siegmund, 2004). We found significant, positive, moderate to strong correlations between the pairs of almost all consecutive levels; exceptions were the pairs of Levels 2–3 and 10–11; we also found significant, positive, moderate to strong relations between the non-consecutive pairs of Levels 3–5, 4–6, 4–7, 5–7. Significant ρ values ranged between 0.32 and 0.66. Findings are summarized in Table 3.

To better understand the way Computational Creativity was manifested, we asked the trait-or-state question. That is, we asked whether Computational Creativity was more associated with user characteristics (trait) or with contextual variables (state). To do so, we set up two linear regression models to predict creativity for the full dataset of 418 user-level pairs.

The first model predicted creativity by level. Twelve variables denoting the game levels were set as follows: for each row in the data, the variable that corresponded to the level documented in this row was set to 1, and the others were set to 0. We called this the State Model. Similarly, following Baker (2007), we set up a Trait Model to predict creativity by session; this model used 38 variables that denoted the users.

Table 1. Descriptive statistics for creative thinking.

Variable	Average (SD)	Median	Skewness (SE)	Kurtosis (SE)
Fluency ($N = 56$)	6.12 (3.85)	6	−0.02 (0.32)	−1.14 (0.63)
Flexibility ($N = 56$)	2.75 (2.08)	2.5	1.05 (0.32)	1.44 (0.63)
Originality ($N = 51$)	0.75 (0.09)	0.73	0.48 (0.33)	−0.04 (0.47)
Creativity Index ($N = 51$)	0.14 (0.82)	0.05	0.79 (0.33)	0.47 (0.66)

Table 2. Descriptive statistics for computational creativity.

Level	N	Average (SD)	Median	Skewness (SE)	Kurtosis (SE)
1	57	0.72 (0.28)	0.16	−1.95 (0.32)	1.91 (0.62)
2	57	0.82 (0.26)	0.09	−2.65 (0.32)	5.2 (0.62)
3	57	0.68 (0.23)	0.47	0.19 (0.32)	−1.94 (0.62)
4	57	0.25 (0.14)	0.28	−0.92 (0.32)	−0.92 (0.62)
5	56	0.63 (0.3)	0.78	−1.57 (0.32)	0.5 (0.63)
6	56	0.53 (0.32)	0.73	−0.98 (0.32)	−1.07 (0.63)
7	54	0.56 (0.32)	0.75	−1.13 (0.32)	−0.74 (0.64)
8†	53		–	–	–
9	49	0.88 (0.19)	0.93	−3.92 (0.34)	14.97 (0.67)
10	46	0.91 (0.09)	0.92	−6.78 (0.35)	46 (0.69)
11	40	0.41 (0.24)	0.59	−0.68 (0.37)	−1.58 (0.73)
12	29	0.32 (0.17)	0.46	−0.47 (0.43)	−1.58 (0.85)

†As explained above, originality score in this level is not applicable.

Table 3. Correlations of computational creativity between pairs of levels (significant values are marked with grey background).

Level	2	3	4	5	6	7	8†	9	10	11	12
1	0.33* $q = 0.04$	0.14 $q = 0.07$	0.05 $q = 0.48$	0.02 $q = 0.50$	0.14 $q = 0.34$	−0.14 $q = 0.34$	–	0.04 $q = 0.48$	−0.07 $q = 0.48$	−0.15 $q = 0.35$	−0.20 $q = 0.34$
2		0.10 $q = 0.39$	0.03 $q = 0.48$	−0.02 $q = 0.50$	0.14 $q = 0.34$	0.24 $q = 0.14$	–	−0.08 $q = 0.48$	−0.04 $q = 0.48$	0.27 $q = 0.16$	–†
3			0.37* $q = 0.02$	0.32* $q = 0.04$	0.30* $q = 0.06$	0.03 $q = 0.49$	–	−0.06 $q = 0.48$	0.05 $q = 0.48$	0.07 $q = 0.48$	0.18 $q = 0.35$
4				0.55** $q = 0.001$	0.55*** $q < 0.001$	0.34* $q = 0.04$	–	0.19 $q = 0.26$	0.24 $q = 0.16$	0.07 $q = 0.48$	0.16 $q = 0.36$
5					0.66*** $q < 0.001$	0.48*** $q < 0.001$	–	0.02 $q = 0.50$	0.28 $q = 0.12$	0.15 $q = 0.35$	−0.06 $q = 0.48$
6						0.45** $q = 0.004$	–	−0.004 $q = 0.53$	0.29 $q = 0.11$	0.09 $q = 0.48$	−0.05 $q = 0.48$
7							–	0.05 $q = 0.48$	0.32* $q = 0.07$	0.26 $q = 0.16$	−0.06 $q = 0.48$
8†								–	–	–	–
9									0.59*** $q < 0.001$	0.14 $q = 0.36$	0.34 $q = 0.14$
10										0.14 $q = 0.36$	–†
11											0.60** $q = 0.004$

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

The models were built with M5' feature selection, and their goodness of fit was measured using squared correlation. To validate the generalizability of the models, we calculated their fitness using two-fold cross-validation; that is, each detector was trained on half of the data and tested on the other half; then the training/testing groups were switched; finally, fitness measures were averaged across these two cycles. To compare the two models, we adjusted R^2 to control for the number of parameters ($Adj.R^2 = 1 - (1 - R^2)((N - 1)/(N - k - 1))$). The models were built using RapidMiner Studio Version 9.0.003.

The State Model had an adjusted R-squared of 0.71; the Trait Model had an adjusted R-squared of −0.09. Therefore, we concluded state explanations were better predictors of Computational Creativity than trait explanations.

4.2. Creative thinking and acquisition of computational thinking

We tested for correlations between the Creative Thinking variables and both Max Level and Average Solution Attempts, and found no significant correlations. There was, however, a marginally significant

Table 4. Correlations between creativity thinking (columns) and computational thinking (rows).

	Fluency ($N = 56$)	Flexibility ($N = 56$)	Originality ($N = 51$)	Creativity Index ($N = 51$)
Max Level	$\rho = -0.0$ $p = 0.95$	$\rho = 0.22$ $p = 0.11$	$\rho = 0.27$ $p = 0.052$	$\rho = 0.10$ $p = 0.50$
Average Solutions Attempts	$r = -0.07$ $p = 0.62$	$r = -0.03$ $p = 0.84$	$r = -0.06$ $p = 0.68$	$r = 0.03$ $p = 0.84$

*$p < 0.05$.

positive correlation between originality and Max Level, with $\rho = 0.27$, at $p = 0.052$ ($N = 51$). Findings are presented in Table 4.

4.3. Computational creativity and acquisition of computational thinking

Next, we tested for associations between Computational Creativity – the originality of a student's correct solution in a given level compared with other students who completed this level successfully – and acquisition of computational thinking.

We found no associations between Computational Creativity and Level Solution Attempts (with one data point for each variable at each level except Level 8), with $\rho = 0.18$, at $p = 0.60$. That is, overall, Computational Creativity was not linearly associated with level difficulty. We continued this analysis by testing correlations of these two variables in each level separately. We found only one case with a significant correlation: in Level 2, Computational Creativity was significantly negatively correlated with Level Solution Attempts, with $\rho = -0.28$, at $p < 0.05$ ($N = 57$). Recall that we reversed originality values so that a high score meant high originality. Therefore, the more original a participant's solution was in level 2, the fewer attempts she or he needed to complete this level.

Taking a more aggregated view of the data, we tested for correlations between Computational Creativity in each level and both Max Level and Average Solution Attempts. In this case, we found a significant negative correlation between level 2 Computational Creativity and Max Level, with $\rho = -0.37$, at $p < 0.01$ ($N = 57$). That is, providing an original solution in an early stage of the game was negatively associated with progressing farther in the game. We found no further significant correlations between originality and Max Level in other levels; nor did we find correlations between any of the level-based originality and Average Solution Attempts.

4.4. Creative thinking and computational creativity

In the next step, we tested for associations between the creativity-related measures outside and inside the learning environment. As we were not assuming dependence within the level-based originality measures, we correlated each of the Creative Thinking measures with each of the level-based originality variables. In four cases – levels 4, 9, 11, and 12 – we found significant correlations between the two types of creativity measures, with Spearman's ρ taking values between 0.30–0.55 (findings are summarized in Table 5). In these levels, Creative Thinking's fluency, flexibility, and creativity index were positively correlated with the level-based originality. These findings suggest that in some cases, creativity in programming is positively associated with the broad construct of creativity.

5. Discussion

In this study, we explored associations between the acquisition of computational thinking (CT) by middle-school students who used a game-based learning environment, referring to two types of creativity. The first was defined by the originality of correct solutions within the learning environment, the second by a traditional creativity test, not related to computational thinking. Overall, we found no correlations between the solution-based originality (measured by Computational Creativity) and task difficulty (measured by Level Solution Attempts). Other recent studies argue for a direct, positive

Table 5. Correlations between creative thinking and computational creativity.

Level	Fluency	Flexibility	Originality	Creativity index
1	0.09 $p = 0.53$ $N = 56$	0.09 $p = 0.50$ $N = 56$	0.01 $p = 0.97$ $N = 51$	0.11 $p = 0.43$ $N = 51$
2	−0.05 $p = 0.74$ $N = 55$	−0.10 $p = 0.48$ $N = 55$	−0.27 $p = 0.06$ $N = 50$	−0.14 $p = 0.33$ $N = 50$
3	0.11 $p = 0.41$ $N = 56$	0.18 $p = 0.19$ $N = 56$	0.09 $p = 0.51$ $N = 51$	0.10 $p = 0.50$ $N = 51$
4	0.40** $N = 56$	0.32* $N = 56$	0.07 $p = 0.64$ $N = 51$	0.30* $N = 51$
5	0.15 $p = 0.28$ $N = 55$	0.06 $p = 0.65$ $N = 55$	−0.11 $p = 0.45$ $N = 51$	0.01 $p = 0.92$ $N = 51$
6	0.10 $p = 0.49$ $N = 55$	0.11 $p = 0.42$ $N = 55$	−0.03 $p = 0.81$ $N = 51$	−0.01 $p = 0.97$ $N = 51$
7	0.06 $p = 0.66$ $N = 53$	0.004 $p = 0.98$ $N = 53$	0.02 $p = 0.90$ $N = 49$	0.05 $p = 0.74$ $N = 49$
8†	–	–	–	–
9	0.34* $N = 48$	0.37** $N = 48$	0.25 $p = 0.10$ $N = 45$	0.39** $N = 45$
10	0.17 $p = 0.27$ $N = 45$	0.24 $p = 0.11$ $N = 45$	0.23 $p = 0.15$ $N = 42$	0.25 $p = 0.11$ $N = 42$
11	0.44** $N = 39$	0.46** $N = 39$	0.23 $p = 0.18$ $N = 37$	0.48** $N = 37$
12	0.55** $N = 28$	0.49** $N = 28$	−0.02 $p = 0.91$ $N = 26$	0.40* $N = 26$

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.
†As explained above, originality score in this level is not applicable.

relationship between difficulty and creativity (Chae & Seo, 2015; Espedido & Searle, 2018). However, note that we measured task difficulty individually not globally: that is, the same task may have been difficult for one student and easy for another. Therefore, the finding should be phrased as follows: there was no correlation between solution-based originality and acquisition of CT. This may be explained by the tension between knowledge and time constraints, as discussed in the next paragraph.

Interestingly, we found that demonstrating originality in an early stage of the game was associated with succeeding in this stage relatively easily, but not with overall progress in the game. The first part of the finding is in line with the idea that creativity builds on prior knowledge in the relevant subject matter (Feldhusen, 2002; Kousoulas, 2010; Weisberg, 1998); therefore, those participants who demonstrated originality early in the game may have been those with prior knowledge in problem solving or knowledge in other relevant fields, and this explained their relatively ease in succeeding. As for the second part of the finding, a creative solution may take more time to produce than a "standard" solution (Akinboye, 1982; Baer & Oldham, 2006), thus slowing down the participants who were more original earlier in the game. As participation in this study was limited in time, this delay may have not allowed the students who gave an original answer to get as far in the game as their non-creative peers. Note that we are not suggesting that creativity hinders learning; rather, this creativity-progression relationship should be examined in learning environments that are less constrained by time, and we plan to do so.

We also found some striking associations between the two measures of creativity. In four out of 11 levels, level-based Computational Creativity was positively associated with two dimensions of Creative Thinking – fluency and flexibility – and with the overall creative index. This finding supports the hierarchical model of creativity, which integrates both domain-general and domain-specific types of creativity (Baer, 2010). It also resonates previous findings of associations between TTCT score and creativity in problem-solving in programming (Liu & Lu, 2002). Somewhat surprisingly, the dimension of originality was not associated with Computational Creativity in these cases (or any other), even though they are conceptually and computationally quite similar. That is, in some cases, Creative Thinking is associated with Computational Creativity, however it is not necessarily originality that expresses itself similarly in the case of acquiring CT. Creativity may be task-specific (Baer, 2012), that is, originality (and fluency and flexibility) may have different meanings when students are asked to make a sketch using a circle and when they are asked to provide a solution to a programming challenge. Recall that there was a crucial difference between the two contexts of measuring creativity. In the standard creativity test, students were asked to provide multiple solutions, but they were not asked to do so in the learning environment. Thus, an interesting future research direction that we are planning to take involves explicitly asking for multiple solutions in the programming game; a similar approach has been already taken in mathematics education – not only to study creativity, but also to promote it (Levav-Waynberg & Leikin, 2012),

The lack of associations between Computational Creativity and CT acquisition (measured by data-driven difficulty measures), and the associations between pairs of Computational Creativity in consecutive levels may, at first glance, direct us to suggest a trait- rather than state-related model of this type of creativity. However, an explicit examination of the state-or-trait question (for Computational Creativity) results in the opposite conclusion. These are not necessarily contradictory findings. Rather, they suggest that a state-model of creativity within a CT learning environment may be suitable; it is not the difficulty that matters, but features of the task yet to be uncovered. This understanding resonates with previous studies suggesting that the nature of the state may affect creativity (Gu, Zhang, Chen, Hao, & Wnag, 2013; Ye, Ngan, & Hui, 2013). Accordingly, in future work, we plan to consider more characteristics of the tasks involved and to examine whether creativity may be promoted by manipulating the characteristics of the task.

This study contributes to the growing body of literature on creativity, and more importantly, to the still very scarce knowledge base on creativity in programming. Taking a log-based approach would allow us to study this phenomenon on a larger scale, and we plan to do so. The study has some other important implications. First, if creativity in acquiring CT is better explained as a personal trait than as contextually dependent, and if creativity is reflected in the ways CT is acquired, then developers of relevant learning environments, along with teachers who wish to promote this important skill, should personalize learning experiences through creativity. Many learning environments seek efficiency and penalize original solutions (which are often longer than the desired solution); this behaviour may demotivate learners and hinder learning. Clearly, when referring to the task completion, longer solutions are not necessarily less effective than shorter solutions (Chao, 2016). Second, educators should understand that even if creativity is better explained as a trait than a state, this explanation is not necessarily "stable" along the whole learning experience and may not be applicable across domains; this insight has implications for curriculum developers and policy makers. Overall, this research raises many questions that we hope will ignite many more studies in the field.

Admittedly, this study had some limitations. First, we analyzed data from a single learning environment (Kodetu), and it is possible that our findings were a result of some unique characteristics of this platform (Saito, Sasaki, Washizaki, Fukazawa, & Muto, 2017). Specifically, the studied platform does not encourage multiple correct solutions and penalize for non-standard solutions, which may affect creative submission. Indeed, we plan to studying creativity in similar platforms in less restrictive ways of use. Moreover, the analysis was based on students from a single country (Spain); as creativity is a personal behaviour, socio-cultural and educational factors may affect the way creativity is exhibited (Deng, Wang, & Zhao, 2016; Runco & Johnson, 2002; Zhou, Shen, Wang, Neber, & Johji, 2013). Therefore, it is advisable to replicate this study in other countries to offer a more international, multi-cultural view (we plan to do so). Second, we used a single measuring tool for creativity (TTCT), and as different tools may grasp different aspects of creativity, they should also be used; this is another direction we are planning to take.

Note

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

Disclosure statement

No potential conflict of interest was reported by the authors.

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