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The effects of mental rotation on computational thinking

Giuseppe Città[a], Manuel Gentile[a,*], Mario Allegra[a], Marco Arrigo[a], Daniela Conti[b], Simona Ottaviano[a], Francesco Reale[a], Marinella Sciortino[b]

[a] *Institute for Educational Technology, National Research Council of Italy, Palermo, Italy*
[b] *Department of Mathematics and Computer Science, University of Palermo, Italy*

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ABSTRACT

Although several investigations of spatial reasoning and mental rotation skills have been conducted in research areas linked to STEM education, to the best of our knowledge, few of these studies have examined the relationship between spatial reasoning and computational thinking. Given this gap in the literature, the present study investigates the role and action of spatial reasoning, and specifically the effects of mental rotation on computational thinking within an embodied and enacted perspective. To achieve this, we carried out a study involving 92 students in five primary-school classes (1st grade - 5th grade). The findings reveal a positive correlation between computational thinking skill and mental rotation ability.

1. Introduction

A growing number of research studies have shown that human ideas are grounded in sensorimotor experience (Bishop & Martin, 2014; Degenaar & O'Regan, 2017; Di Paolo & Thompson, 2014; Gallagher, 2017). Within an Enactivist framework (Di Paolo, Buhrmann, & Barandiaran, 2017), increased and deeper consideration of the embodied features of cognition has strengthened the conception of mental activity, emergent from concrete, situated, and action-based practices. In this context, the body is described as a dynamic knowing system (Merleau-Ponty & Landes, 2013), which knows and learns during a flow of effective actions (Maturana & Varela, 2013, p. 2877). Consequently, knowledge emerges from different kinds of experience, all of which arise from a body that acts in the world and is equipped with various sensorimotor capacities, embedded and mutually linked within a biological, psychological, and cultural context (Durt, Tewes, & Fuchs, 2017; Varela, Thompson, & Rosch, 1991). Viewed from an Enactivist perspective, the highest-level cognitive processes and the acquisition of the most abstract knowledge are constantly and closely linked to the environment. These elements (cognition, knowledge acquisition, and environment) can be conceived of as systems that mutually act and change through "learning processes" (Cox, 2018; Li, Clark, & Winchester, 2010). This paper aims to contextualize Computational Thinking (CT) and programming concepts in the field of Enactivism. These forms of reasoning are generally described as a set of abstract mental activities and a symbolic manipulation of codes, respectively (Francis, Khan, & Davis, 2016). We argue that CT reasoning processes (e.g. abstraction, decomposition, pattern mapping, pattern recognition, algorithmic thinking, automation, modeling, simulation, assessment, testing, debugging, and generalization) should be seen as events during which cognizers are adapted to entrench computational concepts (mathematical and logical concepts) within real physical contexts. Approaching the study of CT as an embodied and enacted problem-solving process highlights the fact that space perception, space conceptualization, and general spatial abilities play an essential role within this process. Through a deep characterization of spatial reasoning and the specific expression of mental rotation, in particular, this paper clearly states its core hypothesis: the idea that spatial skills (in general)

* Corresponding author.
E-mail address: manuel.gentile@itd.cnr.it (M. Gentile).

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and mental rotation ability (in particular) are essential variables to explore when studying student CT and programming performances (Altun & Mazman, 2015; Jones & Burnett, 2008). With this in mind, we have selected and elaborated various unplugged learning activities, in which the physical aspect is essential and students' bodies are the core of the learning process. The main characteristic of these activities is the extent to which they are embodied and enacted. On the basis of this theoretical framework, the present study seeks to answer the following questions:

1. What relationship exists between mental rotation skills and student computational work? Is mental rotation ability correlated with coding performance?
2. Is this relationship influenced by factors such as gender and age?

2. Computational thinking as a problem-solving process

The notion of Computational Thinking (CT) is controversial, since there is no agreed or universal definition of this term in the literature (Lockwood & Mooney, 2017; Moreno-León, Román-González, & Robles, 2018). The expression was used for the first time by Papert within the context of mathematics education (Papert, 1996); it referred to the implementation of children's procedural thinking through computer programming (Papert, 1980). In 2006, Jeanette Wing, building on Papert's work, argued that computational thinking should be considered a core skill, not just in computer programming processes, but in every action involving human analytical ability (Wing, 2006). Wing's paper suggests that CT involves the use of abstraction and decomposition at the following times: during complex task resolutions, when choosing an appropriate representation of a problem, and when modeling relevant aspects of a problem to make it tractable. She describes it as a form of heuristic reasoning used to discover solutions, and a multilevel abstraction through which humans think. Using Wing's definition as a starting point, other academics have proposed various views and proposals relating to CT (Barr & Stephenson, 2011; Brennan & Resnick, 2012; Wing, 2008), as well as strategies and tools for evaluating it (Yadav, Good, Voogt, & Fisser, 2017; Council, 2011; Román-González, Pérez-González, & Jiménez-Fernández, 2017; Rojas-López & García-Peñalvo, 2018). The remarkable number of recent works on this topic suggest that this research field is in its early, embryonic phase. Taking this context into account, the present study avoids presenting generic arguments about CT and refers to key points revealed by two recent research reviews (Kalelioğlu, Gülbahar, & Kukul, 2016; Lockwood & Mooney, 2017). These analyses of the literature in this new field reveal that key elements, generally associated with mathematics and logic, are essential connected features of CT. Kalelioğlu et al. (2016) have proposed an open (not yet finalized) framework, within which CT is defined as a problem-solving process with the following stages: problem identification; data gathering/representation/analysis; solution generation/selection/planning; solution implementation; and solution assessment/improvement. These stages are categories of actions consistent with Wing's perspective; each category involves some cognitive acts. Problem identification implies abstraction and decomposition. Abstraction represents a critical element of CT (Wing, 2008) and allows cognizers to remove irrelevant aspects of a problem so as to focus on crucial components. This ability is closely connected to decomposition, which allows cognizers to divide complex problems into smaller ones to propose suitable solutions (Council, 2011). Data gathering, representation, and analysis allow cognizers to deeply comprehend the problem through pattern mapping, pattern recognition, and conceptualization. Solution generation, selection, and planning require algorithmic thinking. More specifically, algorithmic thinking allows cognizers to focus on the structure of problems and problem solutions, and to order them in a series of logical steps. It is strictly connected to the concept of “algorithm,” which is usually described as the “natural output” of CT (Aho, 2012). Thinking algorithmically produces output algorithms which must be clear, unambiguous, and replicable (Kalelioğlu et al., 2016). During solution implementation, the operations of automation, modeling, and simulation can be carried out; during the assessment and improvement stages, a solution can be assessed, tested, debugged, and generalized (applied) to different problems.

3. Spatial reasoning and mental rotation ability

As no definition of the term, “spatial reasoning,” is unanimously shared among researchers, it has generated significant debate (Davis, Group, & Others, 2015). It is often considered analogous to terms such as “visualization” and “visual-space reasoning;” however, the differences, analogies, and specific relationships between these concepts have generated much argument (Gutiérrez, 1996). Taking into account the absence of a shared definition (Uttal & Cohen, 2012), as well as various debates, spatial reasoning is either a single or multilayered emergent skill (Gersmehl & Gersmehl, 2007). It is fruitful to define this term as a complex system of cognitive components, involving the core ability to connect a perceived and constructive 3D world (Nagy-Kondor, 2017). Seen from this perspective, spatial reasoning is closely related to skills, such as generating, representing, transforming and recalling nonlinguistic information (Linn & Petersen, 1985), which are fully involved in the processes of object representation, usage, and relationships occurring in actual contexts (Williams, Gero, Lee, & Paretti, 2010). Thus, spatial reasoning can be characterized as a knowledge of space coordinates at the core of every action. Such a description suggests a broad definition of “spatial reasoning” (Augello et al., 2018) as a set of linked skills that include abilities e.g., symmetrizing, locating, orienting, balancing, decomposing/recomposing, transforming, scaling, comparing, and navigating (Bruce et al., 2013) – based on assumptions that it is “an ever-evolving potential that arises from the complex interplay of many aspects” (Davis et al., 2015) of given processes. The complexity of spatial reasoning emerges from the relationship among co-evolved and complementary mental and physical actions and various spatial skills (Francis et al., 2016).

One focus of the present investigation is “mental rotation,” a specific ability through which various skills involved in spatial reasoning connect in specific mutual relationships. The term “mental rotation” was coined by Shepard and Metzler (1971) to describe a process based on a particular visuospatial ability, in which a cognizer is able to represent how 2D or 3D objects look when they are rotated. Visuospatial ability, engaged in mental-rotation tasks, has been described as the capacity to conceive a rotation of objects in a 2D/3D space (Burnett & Lane, 1980) through a mental or actual manipulation of these objects piece by piece (as elements of a particular object) or in a holistic fashion (Clements & Battista, 1992; Olkun, 2003). Mental rotation is usually described as a shape-matching activity, in which an agent must decide whether two elements (e.g., two objects or pictures), simultaneously or consecutively exhibited from various angular orientations, are equivalent or different (Shepard & Metzler, 1971). In mental rotation tasks that aim to simulate mental rotation processes, objects are usually exactly alike or mirror images. They are sometimes presented with disparities in orientation that vary the degree of rotation. Within these tasks, the various spatial skills mentioned above (symmetrizing, locating, orienting, balancing, decomposing/recomposing, transforming, scaling, comparing, and navigating) emerge as mutually connected and reveal each process of mental rotation to be a complex phenomenon, nested in a joint activity that involves bodily actions, cognitive processes, and a given environment.

Cooper and Shepard (1973) describe this complexity using the following four sub-processes of mental rotation tasks:

- realizing a visual encoding of the stimuli;
- rotating an object (referring to another);
- comparing two objects (similar or different);
- responding (Wright, Thompson, Ganis, Newcombe, & Kosslyn, 2008).

Describing mental rotation processes as joint actions involving these elements emphasizes the key role of perception and motor processes (Smith, 2005). The actions and perceptions of a body within a specific physical context are crucial elements of the knowledge construction involved in each activity, since they are organs for experiencing the world (Augello et al., 2018; Città et al., 2018; Määttänen, 2015). From this perspective, mental rotation can be described as a process that directly involves the elements of perception, proprioception,[1] executive control, and working memory[2] (Berneiser, Jahn, Grothe, & Lotze, 2018; Città et al., 2018). Presenting mental rotation within specific contexts (within specific tasks) shows how various spatial skills become connected (Kozhevnikov, Kosslyn, & Shephard, 2005).

4. Spatial reasoning and computational thinking

Several investigations of spatial reasoning skills and mental rotation have been carried out within various research areas. Among these, one robust set of studies has demonstrated that spatial reasoning and its implementation in specific processes of mental rotation (Kozhevnikov et al., 2005) are closely linked both to mathematical skills and to achievements in mathematics (Cheng & Mix, 2014; Holmes, Adams, & Hamilton, 2008; Verdine et al., 2014). Cheng and Mix (2014), having observed mental rotation in 6-8-year-old children, argue that training children through mental rotation tasks improves their performance on calculation problems. Thompson, Nuerk, Moeller, and Cohen Kadosh (2013) have shown that mental rotation abilities are connected, not only to numerical abilities, but also to the way in which humans organize number representations, confirming research indicating that numerical cognition and high-level numerical skills involve a robust activation of spatial understanding (Dumontheil & Klingberg, 2012). Various studies have suggested that developing spatial reasoning within the elementary mathematics curriculum could help children master STEM disciplines (Science, Technology, Engineering, and Mathematics) (Buckley, Seery, & Canty, 2018; Mulligan, Woolcott, Mitchelmore, & Davis, 2018; Uttal & Cohen, 2012; Wai, Lubinski, & Benbow, 2009). The positive effects of not-strictly-mathematical components on mathematical abilities and the role of Computational Thinking have been investigated (Orton et al., 2016; Sengupta, Kinnebrew, Basu, Biswas, & Clark, 2013; Swanson, 2017). Some studies argue that improving spatial reasoning and mental rotation can strengthen mathematical skills; others that mathematical skills can only be enhanced by improving computational thinking. To the best of our knowledge, few studies have investigated the relationship between spatial reasoning and computational thinking; research on a possible connection appears to be at an early stage. Only one or two studies have explicitly suggested that spatial reasoning and computational thinking are mutually connected, suggesting that some spatial abilities are core cognitive skills of computational thinking (Ambrosio, Almeida, Macedo, & Franco, 2014; Román-González et al., 2017). Against this backdrop, the present study aims to contextualize the role and action of spatial reasoning, specifically mental rotation, within an embodied and enacted approach to computational thinking.

5. Method

5.1. Participants

This trial involved five classes of an Italian primary school of Palermo, from 1st grade to 5th grade. Ninety-two students were involved within an age range from 6 to 10 years. In Table 1, the distribution of student gender across the sampled classes was as follows:

[1] The term “proprioception” refers to sensory information that reveals the position and movements of the self.

[2] Specifically, the modalities people use to manage information from the environment to achieve some goals in specific tasks within an action.

Table 1
Distribution of student gender across the sampled classes.

grades	1st	2nd	3rd	4th	5th	Total
female	10	9	12	8	6	45
male	12	10	9	7	9	47
Total	22	19	21	15	15	92

5.2. Preliminary activities

The trial took place over two 90-min sessions in each class. The first session consisted of preliminary activities (the same for all classes) aimed to introduce the different concepts of coding and to lead them back to elementary operations carried out every day in coherence with the paradigm of situated learning. Students were introduced to the algorithm thinking and coding (e.g., sequencing and executing an instruction) by examples with LEGO constructions and sequences of instructions for dressing or cooking recipes. This introduction was followed by a brief debate, designed to assess whether every student understood the explained concepts and could come up with examples. During the second part of the activity (second session), students engaged in game-based tasks, structured to incorporate the "My Robotic Friends"[3] and "Graph Paper Programming"[4] lessons from code.org,[5] as well as "CS Unplugged free activities for classroom or home" (Bell, Rosamond, & Casey, 2012). Through these practical activities, students were stimulated to actively use the concepts they had previously learned according to a well-defined symbolic code.

Given the substantial differences in development related to the different ages of the students involved, we introduced abstract coding patterns at different levels of complexity within the classes. Students of the 1st and 2nd grades (6–7 years old) have been involved in algorithm elaboration tasks aimed at comparing different resolution strategies and using the FOR cycle and simple cyclic constructs. Students aged between 8 and 10 years (3rd, 4th, 5th grades) were involved in tasks aimed to an elaboration of an algorithm for the reproduction of a drawing on a two-dimensional grid using selection cycles and nested coding patterns. These tasks introduced students to the challenge of thinking of problem solutions as sequences of instruction code and clarified the importance of unambiguous instructions.

5.2.1. Example of an activity

This section describes a specific unplugged task that was carried out in the classroom as an example of coding. The main topics involved in the "Robot-Tino Walk" activity are an algorithm, coding, and debugging; it uses a large chessboard of 24 tiles (6 × 4). The chessboard (Fig. 1) is composed of path tiles, target tiles (bearing the image of a flower or a honeypot) and obstacle tiles (featuring the image of a frog or a rain cloud). A child plays the role of a robot, Robot-Tino (Fig. 2). Moving across the chessboard, the child physically executes a sequence of simple instructions, which are written on sheets depicting the chessboard. The aim is to enable other students to direct Robot-Tino (the child-robot) to a goal, using a logical sequence of instructions (the script). The activity is implemented in three steps: "Elaboration," "Execution/Error Detection," and "Bug Fixing."

During the "Elaboration" phase, students, divided into small groups (2–4 children each), must guide a child-robot to a goal within the chessboard. Each group guides Robot-Tino using a logical sequence of instructions (the script) written in a specific set of symbols. Each student in the group is actively involved and collaborates in writing the script. In other words, the groups define algorithms and translate them into specific symbols.

In the "Execution/Error Detection" phase, the groups focus on physically executing the scripts they have created. They can see that, when the instructions are ambiguous or unclear, Robot-Tino does not know what to do and cannot reach the goal. During this step, children learn that every instruction must be clear and unambiguously interpretable, as a small mistake can cause many problems. Thanks to the execution step, any errors become visible. Finally, in the "Bug Fixing" phase, students in each group must precisely identify the errors that are preventing Robot-Tino from reaching the goal. With the help of a teacher, they discuss how to fix those errors. Each group explores and evaluates the program, formulates a hypothesis about each error and attempts to repair it. The corrected code is implemented again by Robot-Tino. An embodied and enacted code execution profoundly engages students and enables them to experience the accuracy of a path, both physically and in real time (Fadjo, 2012; Khan, Francis, & Davis, 2015). In other words, through this approach to implementation, students perceptively experiment and share mistakes and work together on various possible corrections.

5.3. Evaluation session

During the last session, the students took a mental rotation test and coding tests.

5.3.1. Mental rotation test

In the Mental Rotation Test (Vandenberg & Kuse, 1978), each participant was asked to determine whether one image of an object

[3] https://curriculum.code.org/csf-1718/courseb/6/.
[4] https://code.org/curriculum/course2/1/Teacher.
[5] https://code.org/.

Fig. 1. The 6 × 4 tiles chessboard.

Fig. 2. Robot-Tino in action.

in a pair of images was same as the other or mirrored it. This test was administered using a mobile device (tablet) in accordance with both (a) the findings of Shepard and Metzler and (b) the first step (pre-test) of Wiedenbauer and Jansen-Osmann's mental rotation assessment in children (Wiedenbauer & Jansen-Osmann, 2008). The experimental stimuli were colored illustrations of six animals: an elephant, fox, alligator, cow, leopard, and horse, presented on a black background. The pictures were drawn from the Snodgrass and Vanderwart standardized set of 260 pictures (Snodgrass & Vanderwart, 1980).

In the Wiedenbauer and Jansen-Osmann (2008) model, a single trial consisted of a pair of drawings: one upright standard animal picture presented on the left side of the screen and a comparison illustration of the same animal on the right, rotated in the picture plane and either identical or a mirror image (see Fig. 3). Half of the pictures faced left, and the other half faced right. Between the two illustrations of each animal, the angular disparity was 22.5°, 67.5°, 112.5°, or 157.5°clockwise and counter-clockwise (i.e., 202.5°, 247.5°, 292.5°, or 337.5°). In each of the eight angular disparities, each pair of drawings was presented twice (once in an "identical" and once in a "mirror image" version), resulting in a total of 96 trials. For each trial, an initial grey 5 mm fixation square was presented for 500 ms, followed by two stimuli that prompted the child to respond by touching either a green button on the left ("same") or a red button on the right ("different/mirror image"). For each answer, the software stored the characteristics of the figure, the response time, and the correctness of the response.

5.3.2. A multidimensional test to measure Computational Skill

Each student's coding ability was evaluated using a paper-and-pencil test, administered in two versions, one for 1st and 2nd grades, and the other for 3rd, 4th, and 5th grades. The data were collected into two different datasets (*dataset 1* for 1st and 2nd grades and *dataset 2* for 3rd, 4th, and 5th grades). All of the problems shared the same idea: testing the students' ability to write and interpret an algorithm on paper in a closed environment represented by a chessboard. The instructions were limited to the following possibilities: forward displacement, left rotation, right rotation, and moving to a specific color (only in certain trials). Although there were some minor variations involving the goals and difficulties appropriate for each class, all of the tasks required the children to:

Fig. 3. Two children engaged in the mental rotation test.

- create an algorithm to define a path from a starting point to an endpoint on the chessboard, in the presence or absence of obstacles;
- design an algorithm to define a path that reproduced a specific chessboard configuration involving colored or uncolored squares;
- color the chessboard, starting from a sequence of instructions;
- determine the point of arrival on the chessboard from the starting point and a given sequence of instructions.

The evaluation analyzed various *features* of each question, such as text comprehension, answer correctness, the extent to which a solution was optimal, exercise completeness, and the degree of abstraction used by the student to arrive at a solution. For each dimension, the assessor used a dichotomous evaluation (1 if positive, 0 if negative). The evaluations were then analyzed using the Rasch model to measure the coding ability of individual students on a continuous scale. The application of Item Response Theory (IRT) techniques accounted for varying levels of difficulty among individual items and the ability of individual students.

6. Results

6.1. A descriptive statistical analysis of the mental rotation test

According to Wiedenbauer and Jansen-Osmann (2008), in the present study, no limit to the response times for questions of the mental rotation test was set. Anyway, we removed all responses where the response time (RT) was greater than 10 s, to eliminate observations resulting from a moment of distraction that could otherwise affect the analysis of results. The exclusion criterion was chosen to obtain a set of data that could be generalized for every dataset, independently by sample, on the contrary of the experiment of Wiedenbauer and Jansen-Osmann (2008), in which they eliminated responses where the response time significantly deviated from the mean. According to the 10 s criteria, from a starting sample of 8832 answers, we eliminated 440 observations, obtaining a final sample of 8392 answers (RT $M = 3.05s$, $sd = 1.85s$).

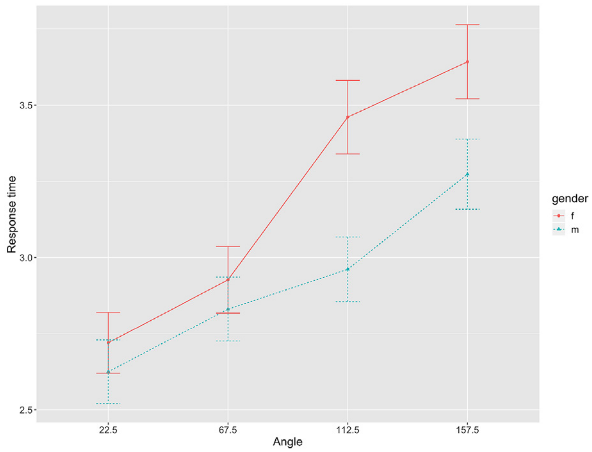

Fig. 4. Mean RT as a function of angular disparities and gender.

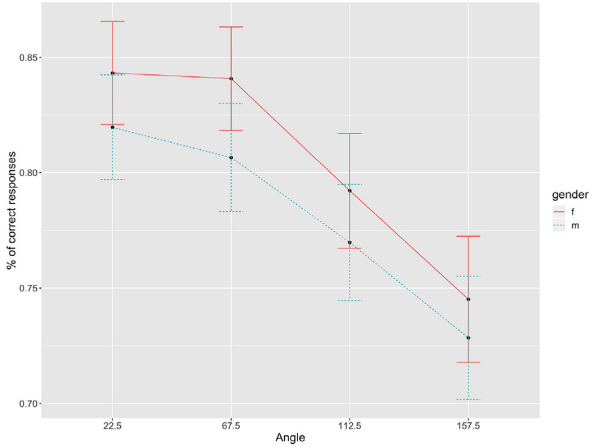

Fig. 5. Percentage of correct responses as a function of angular disparities and gender.

Figs. 4 and 5 illustrate the results of a mental rotation test respectively for the response times and the correct responses for the four angular disparities (from 22.5° to 157.5°). The results show that there is a significant difference in response times between the four angular disparities, with larger RT for higher angular (Fig. 4); when the angular disparity increases the percentage of correct responses decreases (Fig. 5). These results are in line with previous studies (Meneghetti, Toffalini, Carretti, & Lanfranchi, 2018; Moè, 2009; Wiedenbauer & Jansen-Osmann, 2008).

Referring to the gender difference the present study highlights a result that is not in line with the literature. In our study, females gave more correct responses than males for each angular disparity; they were slower but more accurate than males in responding to the items.

In literature, males show to be more accurate than females (Goldstein, Haldane, & Mitchell, 1990). Anyway, in most of the experiments, however, the subjects were adults between 18 and 40 years old. The mental rotation has been measured rarely on young children. Males, in general, begin to achieve better mental rotation performances when they reach puberty (Brandner & Devaud, 2013; Quaiser-Pohl, Geiser, & Lehmann, 2006; Titze, Jansen, & Heil, 2010; Wiedenbauer & Jansen-Osmann, 2008).

Fig. 6 presents a histogram of RT after outliers were eliminated. As expected, this figure shows a non-normal distribution. The results follow a Gamma distribution, with most observations concentrated in a short period of time (between 2 and 3 s), followed by fewer and fewer observations as the time increases. In common with other experiments and studies (Meneghetti et al., 2018; Voyer & Bryden, 1990; Wiedenbauer & Jansen-Osmann, 2008), children in the present study took more time to answer some questions, independent of difficulty, because they were tired.

6.2. A descriptive statistical analysis of Computational Skill

This section discusses the Rasch model analysis, which was used to measure variable coding ability, starting by evaluating the exercises carried out by students. The latent regression Rasch model (Adams, Wilson, & Wang, 1997; De Boeck & Wilson, 2004; Zwinderman, 1991, 1997) includes personal attributes to account for individual differences; this method allows covariates to be

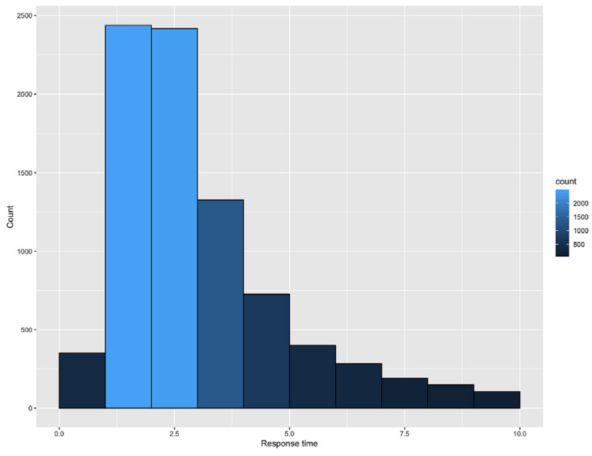

Fig. 6. Distribution of RT.

added to IRT models. The latent regression Rasch model is a type of multilevel IRT model that is useful for analyzing item response data in studies with an interest in explaining individual differences (Cheong & Raudenbush, 2000; Pastor, 2003). The power of the latent regression Rasch model lies in its added predictors, which allow individual differences to be explored flexibly in relation to the (latent) ability measured by standardized tests. Like most latent trait models, the Rasch model assumes that items can be accounted for using only one latent trait or psychological function (Slinde & Linn, 1979). The latent regression Rasch model is an extension of the standard Rasch model (Rasch, 1961), adding linear predictors for the persons' latent trait. The Rasch model uses response difficulty to compare students' ability, assessing the probability of responding correctly to a particular item, starting at a given level of ability. In the present study, the latent Rasch model was used to consider both the difficulty of items and the ability of the children, dividing the sample in two groups (children from 1st grade to 2nd grade and children from 3rd grade to 5th grade). A parametric bootstrap was used to evaluate whether the Rasch model was a good fit and the goodness of fit. The *Gof.rasch* function on R was used to perform a parametric bootstrap goodness-of-fit test using Pearson's χ^2 statistic; the null hypothesis states that the observed data have been generated under the Rasch model with parameter values as the maximum likelihood estimates ($\hat{\theta}$). To check the null hypothesis, we generated B samples under the Rasch model and computed the Pearson's χ^2 statistics $T_b(b = 1, ..., B)$ for each dataset. We used a parametric bootstrap (Rizopoulos, 2006) to verify that the model had a good fit; in fact, the p-value approximated by the number of times $T_b > T_{obs}$ (the value of the statistics in the original data set) plus one divided by B + 1, had a value of 0.37 (far over the limit of 0.05). The Rasch model for dataset 2 also had a good fit, resulting in a p-value of 0.57.

6.3. Mental rotation Ability and Computational Skill

Starting from the obtained measurements of mental rotation skill and coding ability, we verified the correlation between abilities. For the first group of 41 subjects, mental rotation and Rasch coding ability had a correlation of $0.33(p = 0.035)$, while for the second group of 51 subjects, they had a correlation of $0.27(p = 0.058)$. These results underlined the existence of a positive correlation between the two abilities in both groups (although the second group was close to the limit of 0.05, this may reflect the small size of the sample). To quantify the relationship between mental rotation and coding ability and to strengthen the results obtained using correlation measures, a different approach was used to evaluate whether gender and/or age influenced the relationship between *MentalRotation Ability* and *Computational Skill*.

The observations of outcome variables considered in this analysis were not independent because we repeated measurements of the same subject; moreover, the users were not independent because, theoretically, there could have been a class effect leading to the application of a nested model. We therefore relied on mixed linear models, which allowed us to reproduce the nested model and to define a specific variance term for the intra-subject analysis. The following analyses were all carried out using the lmer package (version 1.1.18.1) (Bates, Mächler, Bolker, & Walker, 2015). Let CT_{cs}, the dichotomous response variable, correspond to the evaluation of computational thinking ability for the student *s* of the *c* class (0 for a low level of a specific coding ability, 1 for a high level of that ability). First, it is important to determine the model that best describes the hierarchical nature of the collected data. We have therefore compared the following two models for dataset 1 and dataset 2.

$$CT_{cs} = \beta_0 + \beta_{0(s)} + \varepsilon_s \tag{1}$$

$$CT_{cs} = \beta_0 + \beta_{0(cs)} + \beta_{0(s)} + \varepsilon_{cs} + \varepsilon_s \tag{2}$$

For both datasets, an Anova comparison proved that Model (1) was the best choice. Starting from the Model (1), we progressively added the fixed effects for *item*, feature (Model 3), *MentalRotation ability* (Model 4), *class* (Model 5), and *gender* (Model 6). The following models were compared:

$$CT_{cs} = \beta_0 + \beta_1{*}item + \beta_2{*}feature + \beta_{0(s)} + \varepsilon_s \tag{3}$$

$$CT_{cs} = \beta_0 + \beta_1{*}item + \beta_2{*}feature + \beta_3{*}MentalRotation + \beta_{0(s)} + \varepsilon_s \tag{4}$$

$$CT_{cs} = \beta_0 + \beta_1{*}item + \beta_2{*}feature + \beta_3{*}MentalRotation + \beta_4{*}Class + \beta_{0(s)} + \varepsilon_s \tag{5}$$

$$CT_{cs} = \beta_0 + \beta_1{*}item + \beta_2{*}feature + \beta_3{*}MentalRotation + \beta_4{*}Class + \beta_5{*}Gender + \beta_{0(s)} + \varepsilon_s \tag{6}$$

The tables below show the Anova comparison of these models and both datasets. Table 2 shows that Model (5) was preferred for the first dataset. There were significant effects for item, feature, *MentalRotation*, and *class* fixed effects. *Gender* did not provide a

Table 2
Anova comparison of the models with fixed and random effects for dataset 1.

	Df	AIC	BIC	logLik	deviance	Chisq	Chi Df	Pr (> Chisq)
Model1	2	1068.33	1077.75	−532.17	1064.33			
Model3	9	906.34	948.72	−444.17	888.34	175.99	7	0.0000***
Model4	10	903.42	950.51	−441.71	883.42	4.92	1	0.0266*
Model5	11	901.26	953.06	−439.63	879.26	4.16	1	0.0414*
Model6	12	902.76	959.27	−439.38	878.76	0.50	1	0.4808

Table 3
Anova comparison of the models with fixed and random effects for dataset 2.

	Df	AIC	BIC	logLik	deviance	Chisq	Chi Df	Pr (> Chisq)
Model1	2	686.65	695.12	−341.33	682.65			
Model3	7	510.83	540.47	−248.41	496.83	185.83	5	0.0000***
Model4	8	508.28	542.15	−246.14	492.28	4.55	1	0.0330*
Model5	10	511.21	553.56	−245.61	491.21	1.06	2	0.5875
Model6	11	512.51	559.08	−245.25	490.51	0.71	1	0.3996

significative improvement. Table 3 shows that Model (4) was preferred for the second dataset. As in the previous case, the class fixed effect did not provide an improvement.

For the first dataset, Model (5) showed a fixed effect $\beta_3 = 2.13(p = 0.02)$ for *MentalRotation*; for the second dataset, Model (4) showed a fixed effect $\beta_3 = 2.37(p < 0.0001)$ for *MentalRotation*. The marginal R^2 for Model (5) in the first dataset (Nakagawa & Schielzeth, 2013) is 0.289, while the conditional R^2 is 0.417, showing a fairly good fit and a significant improvement due to the *MentalRotation ability* random effect. According to Barry, Brooks, Catchpole, and Morgan (2003), the model shows a good level of dispersion (1.00). For Model (4) in the second dataset, the marginal (0.46) and conditional R^2 (0.577) show a good fit and significant improvement, due to the MentalRotation random effect. The model also shows a good level of dispersion (0.938).

7. Conclusion

From a theoretical point of view, the present study has used an unplugged approach to coding to show how a high-level cognitive process is closely connected to sensorimotor factors. From an Enactivist perspective, the highest-level cognitive processes and the acquisition of the most abstract knowledge are constantly and closely linked to the environment. Specifically, we have placed embodied features of cognition at the center of these research activities to show how the complex processes underlying computational thinking emerge from concrete, situated, and action-based practices. An analysis of the results allows us to conclude that mental rotation is correlated with the response variable; having good mental rotation increases an individual's likelihood of giving correct responses in the coding test. Gender does not influence the relationship between coding ability and mental rotation skills. In addition, the relationship between coding and mental rotation ability is quite stable among the different school grades, with only a slight effect of age for 1st and 2nd grades.

These results represent a first step in exploring the relationship between spatial abilities and computational thinking. A clarification is necessary concerning the type of exercises used in this study to evaluate the computational thinking ability of the children. As described in section 5.2.1 we used exercises in which the coding primitives are movement actions; it may suggest that it is quite natural to find a correlation between the spatial abilities of the child with the computational thinking calculated as described. The literature shows that especially for children in the first classes of primary school it is necessary to anchor the coding concepts to real and situated experiences. In fact, during the introduction session, the algorithm concept was presented to children referring to real-life examples such as the sequence of instructions for dressing, the recipes for cooking and the construction of buildings with LEGO bricks. Moreover, the movement primitives have been used to facilitate the introduction of abstract concepts typical of computational thinking such as cycles, nesting, and conditional structures. Consequently, computational thinking exercises explicitly asked the children to use such constructs, therefore, using high-level cognitive functions which are fundamental parts of what is commonly recognized as computational abilities. Finally, as described in paragraph 5.3.2, the evaluation mechanism of the exercises explicitly refers to dimensions such as the degree of abstraction and the optimization of the solution that serves to bring out the computational thinking ability of the child as a whole. For these reasons, we argued that the link highlighted can also be found in coding tasks not expressly physical; anyway, further studies are still necessary to confirm this hypothesis.

It is clear that the limited numbers of participants in this study require further validation on a larger scale. It will also be important to assess whether or not spatial skills are pre-ordered in the area of computational thinking, and whether (and how) a training intervention to improve these skills is reflected in the students' computational achievements. As previously noted, studies that suggest possible connections between spatial and computational thinking skills present the former as core skills.

Through this research, we have contextualized these studies within a cognitive perspective to explain why spatial skills have been called the core of computational thinking. We have also proposed a vision of computational thinking as anchored to a specific spatial ability, mental rotation. Our overall goal is to substantiate the parallelism often used implicitly to resolve computational problems. In other words, we understand the resolution of a problem as the search for a path. Thus, what has often been seen as a simple metaphor may hide a cognitive explanation of what we call computational thinking.

8. Ethics statement

This study was carried out in accordance with the recommendations of Comitato Bioetico A.O.U.P. P. Giaccone. The protocol was approved by the Comitato Bioetico A.O.U.P. P. Giaccone. All subjects gave written informed consent in accordance with the Declaration of Helsinki.

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