Empowering AI competences in children: A training program based on simple playful activities

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Abstract

Empowerment of AI competences (EmpAI) is a project based on the assumption that it is possible to identify basic human abilities that, once trained, may foster understanding of AI concepts and applications in children as young as fifth and sixth-graders. Main efforts have been made to design educational activities to teach children computer programming; there is now a need for research both to identify those competencies that should be included in a definition of AI literacy and to design educational experiences that foster AI literacy. We present a training program designed to enhance some abilities present in fifth and sixth-grade children and the planned experimental validation to verify its efficacy in fostering AI literacy.

Keywords

Artificial Intelligence, Learning, Training program, Children

1. Introduction

Artificial intelligence (AI) has been having a huge impact on our society, even on the youngest members. Young children have access to digital contents and services through interfaces that exploit AI methodologies and tools, which are so introduced in everyday life inconspicuously but pervasively since an early age of the users. Thanks to these advanced interfaces, devices and software platforms (e.g., for watching programs on demand or for playing) can recognize voices and faces, can communicate via spoken language, can learn users' preferences, acquire new skills over time and more. While significant efforts have been made to design educational activities to teach children computer programming (see [1] for a review); it is now time to address teaching of AI competences.

The aim of the EmpAI project is to foster AI literacy in audiences without technical backgrounds through a training program aimed at enhancing four basic abilities that, in turn, may improve learning of AI concepts. We defined these abilities 'basic' in that they are at play since the early stages of development, as explained below. We assume that the success of the process relies on the exploitation of these abilities already possessed by children. To make children practice these abilities through pleasant and informal activities, which can be easily implemented in the school settings, is a precondition for favoring their understanding of AI (i.e., how computers reason, act, learn and make

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decisions). This approach is supported by several empirical studies that have found that involving children in pleasant activities may result beneficial for learning (e.g., [2] [3]).

2. Background

The development of AI systems relies on theories and practices of computer science. Computer science is no longer an area cultivated only by academics and professionals, but is important to every citizen. There is a general agreement on the fact that computer science should be part of general education from the earliest stages in order to develop computational and critical thinking skills [4]. There are many resources that can be used to teach Italian students computer science and coding (e.g., CS Unplugged [5], Programma il Futuro [6] [7]). Programming events are held to teach young people how computers work, to introduce them to computer science and to increase computational thinking skills. However, although there are many resources that can be used by parents, teachers and educators to teach the basic principles of computer science to young people ([8] [9] [10]: they all have an Italian version) there are no similar resources for specific AI topics. Despite the many worldwide efforts to address the need for AI curriculum resources [11], to date there exist few attempts to develop methods to teach young children AI concepts (see, e.g., [12]) and no specific syllabus nor any resources are available to the Italian teachers and educators (for other countries see e.g. [13] [14]).

The assumption underlying the present project is that it is possible to enhance children's understanding of AI concepts by making them exercise some basic abilities they already possess. With the aim to test the implied prediction, the children participants in the present investigation will attend a course on coding and AI (hereafter, Coding&AI curriculum) and will be assigned to one of two conditions depending on whether, along with the curriculum, they will undergo a training activities to enhance four basic abilities (training group) or control activities (control group).

The results of the studies concerned with methods for teaching programming languages to children from an early age have revealed the importance of simplifying the process to meet children's level of comprehension and need for motivational engagement. For example, Papert [15] designed for use by children Logo, a LISP-like language. But since the strict syntax of text-based computer language can be unintuitive or frustrating for novice programmers (see [16]), several projects developed graphical programming environments with the aim to simplify syntax difficulties (see, e.g., Scratch by Resnick [17]). The children in the present investigation will undergo a Coding&AI curriculum in which they will learn to program Codey Rocky robot with mBlock5, based on Scratch 3.0[2] (see Figure 1). The robot is equipped with a range of sensors. Namely infrared distance sensor, color sensor, gyroscope, accelerometer, sound and light sensors. It moves on wheels and can produce output through RGB lights, speakers and a LED screen. Codey Rocky exploits mBlock software which supports both blocked-based and Python programming. Programs are loaded into the robot through a Bluetooth connection. There are several computational kits for young children, which use blocks or puzzle-pieces to represent code that controls robots or virtual sprites (for a review, see [18]). We choose to use Codey Rocky robot because it combines, on the one hand, a certain degree of simplicity in the approach to programming based on a Block-based coding approach and, on the other, it provides a wide range of sensors of the physical environment and of the user, and of actuators, part of which is devoted to roving and part to convey information and content that can also be given emotional interpretation. Within the Coding&AI curriculum, children will learn to program Codey Rocky Robot for obstacle avoidance, lines following, vocal commands and soft biometric (age, sex, etc.) and emotion recognition.

[2] https://www.makeblock.com/steam-kits/codey-rocky

Figure 1: Codey Rocky robot programmed with mBlock5.

Recent approaches to teach programming acknowledge the importance of training the ability to formulate informal programs (see code.org unplugged activities). Informal programs are descriptions of the steps needed to transform an input into an output; hence they occur often in everyday life. Informal programs are preparatory to the specification of formal programs, thus, empowering the individuals' ability to deal with them can be a way to foster learning of computer programming [19] [20]. Likewise, studies have shown that the acquisition of self-efficacy is helpful in learning such programming [21]. On the same line of reasoning, we believe in the importance of developing simple methods to train the basic abilities that are relevant to the acquisition of AI concepts in children. Although mastering AI involves skills and exploits advanced resources, these skills may rely on basic abilities that can be involved in informal activities and games. These basic abilities, that do not need to be learned through formal education or instruction, but that can be further trained and, then, improved, should support understanding and interaction with intelligent systems.

3. Empowerment of AI competences through training of natural basic abilities

We identified four basic abilities, we devised a training program based on such abilities and we conceived an experiment to test the effectiveness of the training in promoting children's learning to program intelligent behaviors in Codey Rocky robot.

The experiment will test two further predictions. First, our training program should improve how children approach the study of AI. The motivational aspects of learning are important components able to stimulate and support the efforts necessary to strategically approach the study; these aspects are strictly interrelated with learners' implicit beliefs about the malleability of their intelligence and capacities. In turn, these implicit beliefs affect learners' self-regulation during the learning processes [22]. The training program consists of simple and playful activities to approach; therefore, it should result in a growth "mindset" in computer science achievement for both male and female students (see [23]. Second, our training should improve the awareness about what a robot is and is not. Studies have revealed that some aspects of robotic actions lead individuals to believe that the actions imply mental states (for a review see [24]) and children's attribution of mental states to robots have recently received great attention [25] [26]. Given that the training program makes it simple to understand basic principles of AI, it should increase children's awareness about differences between human minds and artificial minds.

To sum up, pre- and post-training evaluations will prove its effectiveness along the three dimensions:

1) improved ability to program the robot;

2) a growth “mindset” in computer science achievement, hopefully even regardless of gender;
3) increased awareness about the robot’s mental qualities.

The relevance of each basic ability to the acquisition of AI concepts was assessed based on relevant literature in philosophy of mind, developmental psychology, and Artificial Intelligence, as detailed below. We introduce the abilities along with the activities to train them. None of the activities requires previous knowledge about AI concepts or approaches, and none of them involves computers or other technical equipment.

Ability to differentiate between syntax and semantics

Studies on infants and preschoolers have revealed that they behave differently with humans and non-human artifacts thus suggesting that they have a sense of the person. For example, a seminal study by Meltzoff [27] investigated in a group of 18-month-old infants the reenactment of intended acts, performed by human beings versus robot-like devices. As the results have revealed, infants did not re-enact the action performed by the robot-like device, probably because they did not recognize its intentions and goals. Hence, also infants distinguish humans from robot, with the proviso that the robot has not a human-like appearance: as the results of a study on 6.5-month-old infants have revealed, they exhibited the ability to attribute agency to human and humanoid-robot motions, but not to a robot without a human-like appearance [28]. Further, studies on preschoolers have shown that they attribute different states to being human and robot, although they typically exhibit similar behaviour towards both [29]. Based on this evidence, we argue that early in the development children can grasp a crucial difference between human minds and artificial minds: the latter manipulate symbols but do not understand meaning.

The activity relative to the ability to differentiate between syntax and semantics is called “The Egyptians school desk” and it is inspired by the Chinese room experiment by Searle [30], where a computer executes a program, but it is shown that it has not a mind, consciousness, or understanding. The broader conclusion of the argument is that minds must result from biological processes; computers can at best simulate these biological processes.

We provide a brief description of the activity: the children are divided into two groups. The participants in the “interpreter” group must associate a string of hieroglyphic symbols (input) to another string of hieroglyphs (output), following matching rules. The task of the participants in the “translator” group is to decipher and then translate the association of symbols identified by fellow interpreters. Children will be stimulated to think about the fact that interpreter children can manage to accomplish the task without knowing the language of the ancient Egyptians, and thus they have performed like a computer.

Ability to classify data

Infants form categories in the first year of life on the basis of external, perceptual features such as shape, color, and parts, and on the basis of prototypes, or averages, that are extracted from the structural regularities of the input (for a review, see [31]). Labels may be “invitations to form categories” for infants as young as 9 months of age [32]. Further, evidence suggests that function is a potentially important cue for categorization in infancy and beyond. For example, 10-, 14- and 18-month-olds in a study were familiarized with objects that possessed correlated forms and function properties (e.g., rolling, shaking) [33]. They were then tested with a new object that did not embody the properties of the training examples (e.g., a violation of the form-function correlation). The pattern of behaviour revealed that 10-month-olds learned the form of the objects, 14-month-olds learned the form and the function but as independent properties, and 18-month-olds learned the correlation between the object’s form and its function. By at least 4 years of age children’s artifact categories are based on beliefs about the function of objects [34]. Moreover, the ability to form categories and to flexibly shift from a category to another one is an important measure of cognitive flexibility (or set-shifting), and it is a key developmental achievement (see e.g., [35]).

Based on this evidence, we argue that infants already grasp the notion of data classification and we devise an activity involving such ability .

We provide a brief description of the activity: the children are required to build their own boat by assembling some different pieces represented on some cards. The children are then invited to divide themselves into groups on the basis of the features of their boats without any instruction about the criteria to follow. Thus the children freely observe their boats and try to organize them into categories on the basis of the visible features (e.g., color, shape) or functions they prefer. The children are then invited by the examiner to progressively form other categories following different features (e.g. “Can you create a group of boats based on the color of sails?”), and functions (e.g.“Can you create a group of boats that can be good for fishing?). The children will then be stimulated to think about the fact that the same data can be classified following different criteria and that it is possible to form categories also in other different domains.

Ability to plan

Studies in the psychological literature have revealed that very primitive problem solving begins early, before one year of age. By 8 to 9 months of age, infants pull a cloth or a string to retrieve an object. More complex motor acts like grasping a spoon to self-feed take several weeks to become skillful, and this learning does not readily transfer to other tools [36]. As for more complex forms of problem solving, we know that even 5-years old children can follow and to create an ordered set of instructions when, for example, they construct a safe place for a little dog to play [37].

The activity devised to train children’s ability to plan is inspired by the Automated Planning task [38], one of the first areas where AI researchers have focused their efforts. Automated planning aims at finding a sequence of actions that, starting from an initial state of the world under consideration, brings the world into a state where a desired goal is satisfied.

We provide a brief description of the activity: the children will build sequences of steps that lead to a desired state and will identify some target and reason about its achievement. Particularly, the children are required to help Little Red Riding Hood cross the woods to buy a cake for her granny. Little Red Riding Hood moves on a simple map of a fantasy world, where she can choose many paths that lead from one location to another (e.g., from home to lake, from home to hill, and so forth). She needs to cross the woods, along the shortest way, while avoiding meeting the wolf. The children are then invited to reason about some key concepts of problem solving: the notion of state (place, with properties), the notion of instruction (going from one place to a next one), the notion of goal (reaching the bakery), the notion of solution (a course of operations), and of optimal solution (the best way for doing something).

Ability to behave based on test-operate-test-exit units

This human ability is central to the ability to plan introduced above. Plans can only be executed successfully under the joint control of the environment and some stored or inherited information about how the environment is organized. The execution of a plan implies the control of a sequence of operations. The starting point is to ask whether the state of affairs under consideration is optimal. If the answer to the question is negative, namely if the situation is not the desired one, the organism performs an action aimed at diminishing the discrepancy between the actual state and the goal state, until when the desired state is obtained, and hence the answer is positive and allows one to exit, namely to stop the cycle test-operate-test.

This ability is inspired by Miller, Galanter and Pribram [39] who theorized that an organism’s behaviour is based on test-operate-test-exit units which they called TOTEs.

We provide a brief description of the activity: the young participants are required to test for incongruencies in the actual state-goal state and consider whether a set of data are present on which they could operate to reduce the distance between the actual state and the goal state. Exiting would consist in deciding on some resolution to the incongruence to which one has to respond.

We are refining the four training activities following a co-design methodology already tested in our past research [40] [41]. The methodology exploits cooperative and participatory design in which learners involved may become a member of the design team and collaborate actively in the design process. The co-design methodology includes brainstorming, storyboarding, pencil and paper exercises. The collected data are usually analyzed following qualitative and inductive approaches [42]. The activities are tangible, kinesthetic and engaging and follow the methodological approach of the Italian Inter-universities Consortium for Informatics (CINI: [7], but see also [43]). In the first stage participants are encouraged to ask questions and explore their everyday life to find some basic ideas of AI; in the second stage they are encouraged in their autonomy and are offered opportunities to develop abstract thinking and to acquire new specific as well as cross-disciplinary skills.

The activities to train the basic abilities, once refined, will form the critical training. With the aim to test its effectiveness in fostering Coding&AI abilities, the participants will undergo a Coding&AI curriculum, but only half of them will undergo the training. The Coding&AI will be inspired by the code.org program (https://code.org/), in particular the course E, but they will be revisited in order to be successfully performed and executed with an educational robot. They will be oriented to program four intelligent behaviours of Codey Roby robot: obstacle avoidance, line following, vocal command, emotion reacting/age recognition. The experiment will test the prediction that the training should favour learning from the Coding&AI lessons.

3.1 Method

3.1.1. Participants

Classes of children attending the fifth and the sixth grades of public schools in Turin will be recruited. The classes will be randomly assigned to two groups to have a similar sample size; in particular, both the experimental and the control groups will be composed by students of 6 classes, respectively (3 fifth grade classes, 3 sixth grade classes).

Using an a priori power analysis, we estimated that at least 200 participants are required to obtain a suitable statistical power level of .80 to detect a significant within-between interaction, assuming a small effect size (f=.1) and α=.05.

3.1.2 Materials

The experimental material for the Coding&AI curriculum will comprise 12 tablets and 12 Codey Rocky robots. The experimental material for the training and control activities is in the process to be defined.

The material for the pre-test and the post-test assessment will comprise 1) Bebras tasks [44] to assess children's ability to program Codey Rocky robot, 2) the Questionnaire about beliefs in AMOS 8-15 [45] to assess their "mindset" in computer science achievement, and the ASM scale [46] to assess children's perception of the robot's mental qualities.

Bebras is an international initiative whose goal is to promote computational thinking among teachers and pupils of all ages. The Bebras tasks consist of a set of multiple-choice questions, as well as interactive tasks related to problem-solving that do not strictly depend on programming. The tasks do not require prior computer programming abilities, but all questions are related to computational thinking concepts.

The AMOS 8-15 beliefs questionnaires include ratings of theory of intelligence, self-confidence, mastery goals and effort attributions. These questionnaires consist of 20 items, including questions, situations and pairs of alternatives. They are concerned with students' theory and beliefs on intelligence and allow us to detect, for example, to what extent the student perceives her/his intelligence as modifiable and therefore able to profit substantially from learning situations. Particularly, in the current project we use questionnaires on theory and beliefs of intelligence and questionnaire on mastery goals. The former consists of seven items measuring incremental intelligence (e.g., "Learning new things improves intelligence"), entity intelligence (e.g., "My intelligence is something about me I cannot change"), confidence in our own intelligence ("I usually think I'm intelligent"); the latter consists of five items measuring mastery goals orientation (e.g., "I study because I like learning new things") and performance goal orientation (e.g., "I study because I would be proud of getting good grades"). The ratings are given on a Likert scale from 1 (“totally disagree”) to 4 (“totally agree”). The scores are calculated by summing the ratings attributed to each item (score range = 0-16 for the theory of intelligence questionnaire, 0-6 for the beliefs of intelligence questionnaire, 0-20 for the mastery goals questionnaire).

The ASM scale is a measure of the mental states that participants attribute when looking at pictures depicting specific characters, in our investigation Codey Rocky robot. The scale consists of 25 questions grouped in five different state categories: Perceptive, Emotional, Desires and Intentions, Imaginative, and Epistemic. The child has to respond “Yes” or “No” to each question. If the answer is Yes, then the experimenter asks a follow-up question: “How much? A little bit or very much?”, yielding a 3-point scale. For example, in answer to the question: “Do you think that he/she/it can understand?”, the range of answers could be: No (0), Yes, a little bit (1), or Yes, very much (2). The total score is the sum of all answers (range = 0–50); the five partial scores were the sum of the answers within each category (score range = 0–10).

3.1.3 Design and Procedures

The participants in the experiment will belong to classes different from those taking part in the co-design activities and will have no previous experience in coding. The classes will be randomly assigned to two groups: the experimental group and the control group (see Figure 2). Within the regular daily school schedule, the researchers will provide to both experimental and control groups the Coding&AI curriculum (4 preliminary lessons every two weeks lasting 2 hours each) to teach to program the Codey Rocky robot. Following these preliminary lessons, which will last approximately 2 months, both the experimental and the control groups will undergo the pre-test assessment; three main dependent variables will be tested:

- the children’s ability to program the robot;
- children’s implicit theories and confidence in one’s own intelligence and learning skills (AMOS 8-15, [45]);
- the children’s perception of the robot’s mental qualities (the Attribution of Mental States questionnaire, ASM, [46]).

After the pre-test assessment, a training lasting two months (4 lessons every two weeks lasting 2 hours each) within the regular school schedule will be provided to the experimental group, whereas the control group will be engaged in control activities for a comparable amount of time. Both the training and the control lessons will be conducted by the researchers.

After the training and the control lessons, both groups of participants will undergo the Coding&AI curriculum (4 advanced lessons) for two months.

To demonstrate the efficacy of the training, once the Coding&AI curriculum will be concluded, all the children will be reassessed with the same measures used in the pre-test assessment. In both pre-post training conditions, the researchers that will test the children will be blind to the children’s group assignment.

Figure 2: Graphical summary of experimental design.

Once the training activities will be fully designed and validated, we plan to make them available through a platform collecting best practices, didactic resources, games and tests. We also plan to design an app in collaboration with Quercetti educational toy company[3] to integrate activities performed with classic toys.
Concerning educational resources, following code.org structure we plan to propose web-based tutorials composed by a variable number of stages and including many exercises. The initial exercises will be very trivial, increasing very slowly in complexity from one exercise to the next. A primary aim is to allow teachers to be able to follow their students during these tutorials with very little specific training in informatics.

4. Conclusions

EmpAI is a project whose aim is to identify and train basic abilities that may facilitate fifth-grade and sixth-grade children in learning from a Coding&AI curriculum. A main assumption of the project is that enhancement of basic critical abilities should be fostered through informal and pleasant activities that exploit abilities already at play in learners [4].

We have identified four abilities and devised activities to train them. We will carry on an experiment to verify whether fifth and sixth grade children who undergo the training will benefit from the Coding&AI curriculum.

Training programs for becoming experts in domains that are effective for children are also effective for young adults (see, e.g., [47]). If the current training program will prove effective, it has the potential to be extended to older participants. With the aim to broaden AI education, we will develop a set of standards for K-12 classrooms to determine what each grade should know about AI. Given the lack of specific syllabus and resources available for Italian teachers and educators, we will build a proposal for a core educational curriculum for AI.

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