Does Any AI-Based Activity Contribute to Develop AI Conception? A Case Study with Italian Fifth and Sixth Grade Classes

Matteo Baldoni[1], Cristina Baroglio[1], Monica Bucciarelli[2, 3], Sara Capecchi[1, 4], Elena Gandolfi[2], Cristina Gena[1], Francesco Ianì[2, 3], Elisa Marengo[1], Roberto Micalizio[1], Amon Rapp[1], Ivan Nabil Ras[2]

[1]Universit di Torino, Dipartimento di Informatica
[2]Universit di Torino, Dipartimento di Psicologia
[3]Center for Logic, Language and Cognition
[4]Laboratorio Informatica e Scuola CINI
matteo.baldoni@unito.it, cristina.baroglio@unito.it, monica.bucciarelli@unito.it,
sara.capecchi@unito.it, elena.gandolfi@unito.it, cristina.gena@unito.it, francesco.iani@unito.it,
elisa.marengo@unito.it, roberto.micalizio@unito.it, amon.rapp@unito.it, i.ras@unito.it

Abstract

Artificial Intelligence is undoubtedly becoming pervasive in everyday life of everyone. In this setting, developing correct AI conception since childhood is not only a need to be addressed in educational curricula, but is also a children right.

Accordingly, several initiatives at national and international levels aim at promoting AI and emerging technology literacy, supported also by a proliferation in the literature of learning courses covering a variety of topics, learning objectives and targeted ages. Schools are therefore pushed to introduce innovative activities for children in their curricula.

In this paper, we report the results of a case study where we tested the contribution of an AI block-based course in developing computational thinking, and human and AI minds understanding in fifth and sixth grade children.

Introduction

AI is significantly affecting adults', as well as, children's lives due to its pervasive nature. Especially for children, growing up in environments involving intelligent machines (e.g., home assistants and smart toys), AI may represent an opportunity, but also a threat. Young children can be too trusting on smart toys, and can even be influenced by them (Williams et al. 2018; Belpaeme et al. 2018). Promoting AI literacy since early childhood, thus, is critical for enabling future generations to thrive in an AI-pervaded society, and not being controlled by it.

The challenge is to support children in developing the correct attitudes and mindset that allow them to fluently use AI as a tool but, at the same time, being able to critically evaluate AI answers (Long and Magerko 2020). As pointed out in (Yang 2022), showing to children that AI may be affected by prejudices and errors is an essential learning goal of an AI curriculum, and it is also a children right (UNICEF 2019). AI correct attitudes and mindset, thus, should ensure that students perceive AI without any misconception (Wong et al. 2020).

At international and national levels, institutions and governments have set up plans and initiatives to promote digitalization, emerging technologies, computational thinking and innovation in schools. Some examples are the *Digital Education Action Plan* (European Commission 2021-2027), *Informatics for All* (Informatics for All 2023), the National Artificial Intelligence Initiative in US (United States Government 2023), and the National Plan for a Digital School in Italy (MIM). Other proposals can be found in (Van Mechelen et al. 2023; Yang 2022; Song et al. 2022; Touretzky et al. 2019). These initiatives are frequently supported by public funds, through which schools can buy technologies, such as tablets or educational robots, and adapt classes to become laboratories (MIM). Additionally, many block-based courses, tools and software for teaching and practicing programming&AI are freely available (see e.g. (Van Mechelen et al. 2023; Sabuncuoglu 2020)). The combination of public support and the availability of teaching material seems, at first sight, ideal for reaching the goal of increasing the level of digitalization, and increasing technologies comprehension, computational thinking and AI conception in children. However, it is reasonable to ask whether this is really the case: are available AI teaching courses, complementing regular schools curricula, effective in reaching the ambitious goal of developing an appropriate AI conception in children?

In this paper we focus on a case study involving twelve fifth and sixth grade classes, where we delivered an AI course and assessed how the course affected the children along the three following aspects:

1) *Computational thinking*: the standard curriculum proposed by the Italian Ministry of Education already includes a number of activities concerning logic reasoning and problem solving, which are structured according to the computational thinking main principles (even though computer science is not a subject taught in primary and middle schools, but only in high schools). Our interest is to assess whether a block-based programming and AI course, complementing regular schools curricula promoted by the Italian Ministry of Education, can improve these capabilities in children.

2) Conception of *artificial mind*: is a block-based AI

course based on an education robot sufficient to perceive AI as a tool and not as "something magic"? To answer this question we used the AMS scale (Manzi et al. 2020), which measures what (human) mental states are attributed to a machine.

3) Conception of *human mind*: in this case we wanted to assess whether the course, which was performed in a formal context (i.e., in class) but with no mark, could promote a change in the perspective children have toward their own capacities. To answer this question we used the AMOS Italian standardized questionnaires (Cornoldi et al. 2005).

This case study represents the preliminary results of a broader project whose aim is to investigate which abilities facilitate children and young adults in understanding machines that exhibit an intelligent behavior. The results of our case study show that a block-based AI course falls short in providing a proper AI conception. Rather, the results suggest that the curriculum covered in class, promoted by the Italian Ministry of Education, provides a baseline for computational thinking abilities. Hands-on activities with educational robots, on the other side, could deliver practical competences, but do not properly convey artificial and human mind conceptions.

Related Work

The idea of teaching AI to children is not new, and date back to the seminal work by Papert and Solomon (1971). Since then, many software tools, resources, and curricula have been developed to promote Computational Thinking. These tools allow students to focus on learning core programming concepts such as sequencing, conditionals, iterations, and so on (see e.g., (Román-González, Moreno-León, and Robles 2019; code.org)).

AI education, however, goes beyond computational thinking since it explores how machines sense, think, learn, make decisions, and act (Williams et al. 2018). To fill in this gap, a number of educational AI-tools have been made available to teachers and students. For instance, Cognimates (Druga et al. 2018) is an extension of Scratch with AI-based blocks for speech recognition and generation, and object recognition; eCraft2Learn (Kahn and Winters 2017) provides analogous extensions for the Snap! language. In addition, a number of educational robots have been launched on the market with the promise to make children familiar with AI.

To foster AI literacy, however, AI tools alone are not sufficient, and structured AI curricula are instead needed. AI4K12 (Touretzky et al. 2019) is a first attempt to developing common guidelines for teaching AI to K12 students. The project identifies "five big ideas" of AI that every K12 student should know, and for each of them outlines the learning goals that students at different grades should meet.

AI4K12 represents a reference framework for the development of AI curricula, and it has been used for instance in (Kim et al. 2021), which proposes curriculum for AI education in elementary schools that relies on three main competences: AI knowledge (i.e., comprehend the core concepts of AI), AI skill (i.e., computational thinking and AI-tools usage), and AI attitude (i.e., AI in society and ethics).

Along the same line, though only focusing on machine learning (ML), (Tedre et al. 2021) identifies some elements that educators need to consider when developing a ML-based curriculum. Interestingly, among these they identify the need for children to develop an AI conception which enables them to explain how services they use daily work.

"AI for Kids" (Yang 2022) is a pedagogical model complementary to AI4K12. This model stresses the idea that AI education should be grounded on the theory of embodied learning, for which any content to be learned should be related to a particular context relevant to learners experience. That is, the curriculum must be centered on goals, actions and contexts that are meaningful for the learners. For instance, in the curriculum outlined in (Yang 2022), children learn about AI-powered technologies in humans daily life, and to use them in the context of ocean protection, which is culturally relevant to Hong Kong children, for whom the curriculum was designed.

Most of the proposal in literature, whether they refer to a general framework or not, envisage learning activities that enable the children to develop small AI-projects through block-based programming facilities enriched with dedicated AI-based blocks. For instance, PopBots (Williams et al. 2019) is another curriculum targeting children 4-7 years old that exploits a LEGO educational robot. The idea is to teach young children AI by means of hands-on activities concerning knowledge-based systems, supervised machine learning and generative music. Similarly, Song et al. (2022) outlines a course for elementary schools, inspired to the five big ideas of AI4K12 (Touretzky et al. 2019), where block-based programming represents the backbone of several teaching modules. Also the approach described in (Akram et al. 2022) uses block-based programming for explaining AI techniques and algorithms, but such a proposal adopts a multi-disciplinary perspective and AI techniques are contextualized in concrete problems. For instance, the module on knowledge-based systems is done together with a module of physical sciences so that students will have the opportunity to build models (i.e., rules) of physical aspects of the world.

Method

The study presented in this work is part of the research project EmpAI aiming at investigating efficient teaching methodology supporting students in developing a correct AI conception. In this paper, we report on the preliminary results of the study to explore whether the delivery of a programming and AI course, within the school context, including hands-on activities with an educational robot, is an effective way to increase AI conception in children, specifically targeting fifth and sixth grade classes.

The preliminary experiment presented here, consists in two groups composed of six classes each. One group attended a programming and AI course while the other attended a subset of it, consisting of the programming part only.

Figure 1 summarises the paths attended by the two groups, where we called *programming group* the path including three initial programming activities. We call *pro-*

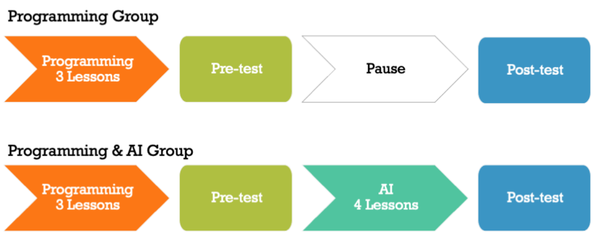

Figure 1: Summary of the activities performed to the two groups.

gramming&AI group the path including four AI-based activities in addition to the three initial programming ones. As summarized in the figure, the two paths consisted of four phases. The first shared phase aimed at providing a common background to all the children independently of their personal past experiences (even outside school). It consists of three lessons. After this phase, both groups participated to a pre-test assessment, aiming at evaluating the initial children's competences and conceptions. The third phase is where the two paths differ. Children in the *programming group* just followed the standard teaching. Children in the *programming&AI group*, instead, were additionally delivered an AI block-based course composed of four lessons, and used an educational robot. The final phase was a post-test assessment where children from both groups had to complete the same test given as pre-test.

This design allows us to analyse the two paths by comparing the performances between the two groups. If a positive statistically significant improvement for the *programming&AI group* exists w.r.t. to the *programming group*, one can reasonably ascribe the improvement to the additional activities that were performed. Otherwise, one can conclude that no significant contribution is given by those additional AI block-based activities to the measured criteria.

The experiment lasted from November 2022 to May 2023 during the school-year with roughly a lesson every two weeks. Each lesson took two hours, except pre-test and post-test lasting one hour. During the lessons, children were working in pair on a tablet, programming a robot in five out of the seven lessons. Pairs were made randomly and were changing from lesson to lesson. Test and re-test, instead, were done individually and no hint were given to children except explaining the meaning of some words if needed.

The children participating in the study were 236 (of which 52% female) attending the fifth and sixth grade class. Of these, 121 attended the *programming&AI group* course, composed of 7 lessons consisting of a block-based programming and AI activities. The remaining 115 were part of the *programming group*. The classes were selected from two schools in the municipality of Torino in Italy belonging to very different socio-cultural contexts. This design was made in order to reduce the effect of external factors impacting on the study (e.g., activities external to school time, or teaching modalities proper of the school or of the teachers). The number of classes belonging to each group was equally distributed between the two schools. Within a school, the assignment of classes to one group or the other was made random.

Before the data analyses, we excluded 44 children because of the following reasons: they missed more than 25% of the lessons, they were diagnosed with developmental disorders or disabilities, they did not participate in the pre-test or post-test evaluation, they did not have parental consent to participate. The final sample included 192 children (Mean age = 10,98 years; SD = 0.62; 54% female): 110 of the *programming&AI group* and 82 children of the *programming group*.

Implementation

We chose the mBlock 5 programming language (Makeblock 2020b) (which is based on Scratch 3.0), and the Codey rocky (Makeblock 2020a) robot. Lessons were developed based on the "Makeblock and STEAM on board" courses by Innovation for Education, within the Campustore Academy project (Innovation for Education). This project is accredited by the Italian Ministry for Education to bring innovation into schools. We defined the topics to be covered in 7 lessons of two hours each, and adapted the material, accordingly. See Table 1 for an overall view of the lessons.

Lessons were orchestrated by a computer science researcher following a predefined set of slides and replicating the same lessons for each class involved in the study. Each lesson was structured using the same general schema and using the mBlock main character ("Panda") to explain the concepts and to propose questions and exercises to the children.

Each lesson started with a summary of the needed concepts previously covered. Then, the topic of the lesson was first introduced using a metaphor (e.g., for messages we used the mail exchange; for events we used the metaphor of a ringing bell), and then tackling the programming part. For this phase, a desired target behaviour was programmed starting from a simple example and then incrementally building on it, until reaching the desired result. During this phase, children were actively involved in the choice of what blocks were needed to reach a desired result. Once agreed on a correct block, the children added it to their programs on their tablets, while the orchestrator did the same on a screen projected to the class as a guideline for children in difficulty.

After this phase, children were asked to work pairwise to change some parts of the program to achieve a different behaviour, or to implement a completely new behaviour. During this phase, children could try the implemented programs (on "Panda" or on Codey rocky depending on the lesson), and could also implement additional behaviours of their wish.

The last fifteen minutes of the lesson were reserved for children to freely experiment (change, improve, extend) with the developed programs.

All material used for the lessons has been collected in a

Lesson	Introduction and Loops	Conditions and Variables	Event Programming	Message Exchange	Avoid Obstacles	Follow a Line	Listen and Execute
Hours	2	2	2	1	2	2	2
Classes	12	12	12	6	6	6	6

Table 1: Summary of the seven lessons and their main focus.

moodle course (EmpAI 2021) (see Appendix 2 for a short description).

Programming Lessons

The aim of the three programming lessons shared between the two courses was to provide a common basis for all children before performing the pre-test. With this aim, the topics addressed were the following.

L1- Introduction and Loops.
L2- Conditions and Variables.
L3- Event programming.

Introduction and Loops. The aim of the first lesson was to introduce the concept of "program" to children as a sequence of steps designed to achieve a goal. In this lesson, children were engaged by asking them to imagine how their favourite computer game or digital device works. During this lesson we also introduced the programming environment, explaining the mBlock application which was installed on the tablets. At this stage, we did not use or introduce the Codey rocky robot yet.

In the second half of the lesson, *forever* and *repeat* loops were explained, and some programs using these constructs were developed, both collectively and as exercises to be solved pairwise by children.

Conditions and Variables. As a second lesson we explained the conditional constructs. First, we introduced the *if then* statement and developed some program using it. Then, we explained what a *variable* is, its use, how it can be defined in mBlock, and how the variable value can be checked by means of the *if then* construct. One of the developed programs consisted in asking a user to guess a number generated randomly, not exceeding ten attempts. This also entails the explanation of how to implement a comparisons between numbers. Finally, we explained the *if then else* construct.

Event programming. In this lesson we introduced Codey rocky. The robot consists of two parts that can be physically split. One is called *Codey* and the other is called *Rocky*. This latter is equipped with rubber belts by means of which the robot can move. *Codey*, instead, is the part that can be programmed. It consists of a display and three buttons, each one identified with a different label (used to discriminate the event source). While *Codey* can work without *Rocky* the opposite does not hold, since *Rocky* cannot be programmed (Codey Rocky is visible in picture 2). For this lesson, we used *Codey* to explain event programming where events are produced by pressing the buttons on the robot. Children had to program reactions to events generated by pressing each of the three buttons. As a result of catching an event some messages or drawing had to be shown on the display, or the led

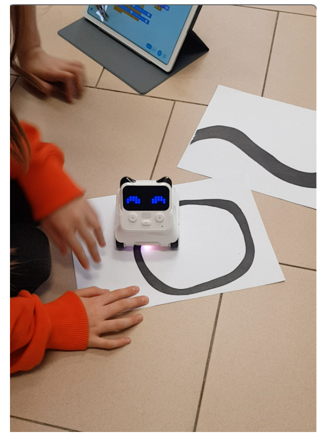

Figure 2: Use of Codey Rocky in the lesson "Follow a Path".

below the display had to blink for a certain duration setting a certain color.

AI Block-Based Lessons

After performing the pre-test, we delivered four additional lessons (AI in Figure 1) to the *programming&AI group* only. The first of these lessons was about the exchange of messages and how different behaviours could be programmed based on them. The remaining three lessons concerned the programming of "intelligent" behaviours for Codey rocky. In summary, the lessons were as follows:

L4- Message exchange.
L5- Avoiding obstacles.
L6- Follow a line.
L7- Listen and execute commands.

Message exchange. During this lesson children programmed the character "Panda" to communicate with *Codey* via message exchange. First, communication in one direction (from Panda to *Codey*) was implemented. Then, the program was extended so to achieve a bidirectional communication between the two.

Avoid obstacles. Starting from this lesson we used both *Codey* and *Rocky*. Codey rocky is equipped with a number of sensors, including an infrared one. First, we explained how the robot can be programmed to move forward and turn leftward/rightward. Then, we set the goal of making it capable of avoiding obstacles, autonomously. The simple solution we proposed to the children was to program the robot to move forward as far as the infrared returned an obstacle ahead; in which case, children were instructed to make the robot turn by a certain degree, either rightward or leftward, until the way ahead was clear again. This behavior was enclosed within a *forever* loop. In addition, a button was programmed to stop every movement of Codey rocky when pressed.

Therefore, this lesson shows how programming instructions can be combined with information coming from sensors to program a somehow "intelligent" behaviour.

Follow a path. Programming Codey rocky to follow a path (i.e., a black solid line drawn on the ground), uses again the infrared sensor. However, the program is conceptually different. The challenge here is to exploit the information gathered from the sensor in order to take decisions (e.g., how to understand that the robot has to turn? in which direction? of which angle? when stop turning?). The strategy programmed by the children was to make the robot moving along the edge of the path, that is, at each step the robot detected either the black color (i.e., the path) or the white color (i.e., the background outside the path), and adjusted the direction of its next step, accordingly. In case, the subsequent step brought the robot outside the path (i.e., it kept reading the white color), the robot kept moving until it found the path again. Picture 2 was taken during the execution of this activity.

Listen and execute commands. In this lesson we used mBlock to understand vocal commands and send messages representing instructions to Codey rocky. We leveraged on the microphone, of which each tablet was equipped, and a specific mBlock library to convert vocal commands to strings. Children programmed Panda to listen to commands, transform them to string, check the string and send a corresponding message to Codey rocky. For instance, when receiving a "foreward" instruction, the robot was programmed to move forward. Similarly for other vocal commands.

Measures and Results

We used three measures at pre- and post-test: *i)* computational thinking test; *ii)* AMS scale (Manzi et al. 2020); and *iii)* AMOS 8-15 questionnaires (Cornoldi et al. 2005). In this section, we summarise the main results. Details, measures and scores can be found in the Appendix.

Computational Thinking Test

The first part of the test consists of twelve short exercises where children have to select one among a set of possible answers. Only one is correct. The exercises are taken from the literature, in particular half of them are taken from (Román-González, Moreno-León, and Robles 2019) and (code.org) and concern tasks that are more directly related to programming. The remaining six exercises are from the Bebras challenges (Calcagni et al. 2017), which are conceived to assess computational thinking capabilities.

The first six exercises concern the following topics: sequence (two exercises in which children have to select one command that completes a sequence of commands bringing a character from a starting position to a target one on a grid), loops and repeat *n* times (2 exercises), identify the output of a program (2 exercises). The Bebras exercises, which are selected for our target age, is taken from the collection of tests which is made available by the Bebras community and which is developed in the context of the annually international problem-solving challenge (Bebras). From a computational thinking perspective, according to the classification in (Izu et al. 2017), the exercises fall in the category *Algorithms and procedures*, whose main characteristics are to "verify if potential solutions are valid or invalid, debugging solutions to find errors, apply a set of rules to determine specific values". Partially, the exercises have also elements of *data representation*, specifically in "understanding the implication of a representation on the solution of a problem". From an AI perspective, the Bebras exercises concern the use of binary decision diagrams to answer questions, the application of planning to navigate a map satisfying some constraints, and, more in general, the solution of constraint satisfaction problems (i.e., finding the answer satisfying all the listed constraints).

Results. This part of the test was administered in a session lasting 25 to 30 minutes approximately and the score is calculated by summing the correct responses. We report the details of the analysis in the appendix. In summary, we observed a statistically significant improvement between the two tests, but there is no difference among the two groups. In other terms, children's performances from both groups improved from the pre-test to the post-test.

Conception of Artificial and Human Minds

To assess the development of accurate ideas about the functioning of the artificial mind and of human mind by children, we relied on two standardized tests, respectively the AMS scale (Manzi et al. 2020) and the AMOS 8-15 beliefs questionnaires (Cornoldi et al. 2005).

The AMS scale measures the mental states that children attribute to the robot. Specifically, the test presented a Codey rocky picture and a set of 26 questions. Children are asked to answer with a value from a 3-point scale (i.e., a lot, a little or not at all) to each question. For example, in response to the question, "Do you think that it can understand?", the range of responses is "a lot" (2 points), "a little" (1 point), and "not at all" (0 point). The total score is the sum of all responses (ranging from zero to 52). The lower the result, the better the conception of the artificial mind is.

The AMOS 8-15 beliefs questionnaires that we used contained assessments of *i)* Theory and Beliefs of Intelligence (4 items), *ii)* Self-Confidence (3 items), and *iii)* Mastery Goals (5 items). It consisted of twelve items in total, including questions, situations and pairs of alternatives. Examples of questions are 'Learning new things improves intelligence", "My intelligence is something about me that I cannot change" "I usually doubt that Im intelligent", and "When a new topic is covered at school, Im sure/Im not sure I understand it". Ratings are made on a Likert scale from 1 ("totally disagree") to 4 ("totally agree"). Scores are calculated separately for each questionnaire (Theory and Beliefs of Intelligence Questionnaire, Self-Confidence Questionnaire, and Mastery Goals Questionnaire).

Results. For what concerns these results, we can see an improvement between pre-test and post-test. This means that apparently, in most of the test categories, children improve the conception they have about human and artificial minds. However, this is a slight improvement only, which has no statistical significance. Moreover, the same tendency is recorded in both groups, meaning that there is no group in which children improve more than the others. See the appendix for a detailed analysis of the experimental results.

Discussions and Conclusions

In this paper, we have reported on the results collected during a preliminary study where we aimed at probing the effectiveness of a programming&AI course, hinging on AI activities and educational robots, in the development of AI conception in children. The case study was performed on twelve fifth and sixth grade classes, divided into two even groups: one attending a programming&AI path and one attending a programming path only (i.e., not performing AI based activities).

The results of the case study show that there is a statistically relevant improvement in the computational thinking test, but the two groups improve in a similar way. A possible interpretation of this result could be that activities included in the ministerial curriculum already contribute to improving logical reasoning and computational thinking. As a consequence, children who performed the additional AI activities did not improve more than the others. Thus the specific AI activities alone did not contribute in significantly improving the computational thinking level of children.

More surprising are the results concerning the human and artificial mind conceptions, where no improvement is observed in none of the groups. This is surprising since the AI block-based activities aim at teaching children that "intelligent" behaviour are actually programmed. Children themselves were able to develop such programs and execute them on the robots. However, human mental attitudes are, in many cases, still ascribed to the robot, even after performing the AI activities.

A possible explanation for this result is that the developed course may facilitate the acquisition of competences (e.g., programming constructs and the usage of AI libraries), rather than an understanding of the functioning of programmed intelligent behaviours. Understanding, however, is at the basis of AI awareness on the functioning of emerging AI-based technologies which, in turn, is one of the ingredients for developing a correct AI mindset.

It is worth noting that we are not claiming that teaching block-based programming and AI to children is not useful. We do believe that these courses represent an important experience in the learning path of children. However, our case study suggests that these courses should be complemented with other activities, aiming at fostering children reasoning, and hence comprehension, on how a smart machine actually works. This is in line with the approach in (Hitron et al. 2019), where the teaching method "uncovers the black boxes" of Machine Learning, with the explicit intent of allowing children to build accurate mental models about it.

As said earlier, this study is part of a broader project tackling the problem of how to convey AI awareness beside AI competences. To this aim, we developed a number of activities aiming at training AI attitudes and AI related abilities (such as the ability to plan). These abilities are present in humans since very young age. The idea is that by training those, children would be able to recognise and understand "artificial" intelligent behaviours in a very natural way, even when occurring in very different scenarios or contexts. Data about this part of the project are still being collected and analysed, we, thus, defer their discussion to a future work.

Appendix 1: In-Depth Analysis of Measures

Computational Thinking

At the pre-test no difference emerged among the performances of the two groups (score range = 0 – 12. *programming&AI group*. mean score = 8.21; SD = 2.32; *programming group*, mean score = 8.00; SD = 2.57; F(1,91) = 0.35, p = 0.56). A mixed repeated measures 2x2 ANOVA (two groups by two time points) were performed on Computational thinking test total score to explore any difference between the two groups from pre- to post-test. The mean scores at the post-test were 9.00 (SD = 2.11) for the *programming&AI group*, and 8.73 (SD = 2.10) for the *programming group*. A significant main effect of the time, F(1,191) = 26.94, $p < 0.001$, η2p = 0.12 was found indicating that all children increased their performance over time; no effect of the group and of the time by group interaction was found.

Conception of Artificial and Human Minds

Regarding the conception of Artificial mind, the results showed that at the pre-test no difference emerged among the performances of the two groups in the AMS scale total score (*programming&AI group*, mean score = 20.77; SD = 9.28; *programming group*, mean score = 22.01; SD = 9.03; F(1,91) = 0.86, p = 0.356). A mixed repeated measures 2x2 ANOVA (two groups by two time points) were provided to explore any difference between the two groups from pre- to post-test. Although both the groups changed their conception of artificial mind decreasing in attribution of mental states to robot from pre- to post-test (the mean scores at the post-test were 19.78 (SD = 10.43) for the *programming&AI group*, and 20.43 (SD = 10.29) for the *programming group*), no statistically significant effect of the time, neither of the group, and nor of time by group interaction was found.

Regarding the conception of Human mind, we recall that scores are calculated separately for each questionnaire. Score range = 0 16 for the Theory and Beliefs of Intelligence Questionnaire, 0 12 for the Self-Confidence Questionnaire, 0 20 for the Mastery Goals Questionnaire. Pattern of results similar to the Artificial mind result was found. No difference emerged among the performances of the two groups in the three questionnaires at the pre-test (Theory and Beliefs of Intelligence Questionnaire mean score: *programming&AI group* = 12.50, SD = 2.71; *programming group* = 11.74, SD = 2.55, F(1,91) = 3.85, p = 0.052; Self-Confidence Questionnaire mean score: *programming&AI group* = 8.71, SD = 2.61; *programming group* = 8.94, SD = 1.90, F(1,91) = 0.46, p = .500; Mastery Goals Questionnaire mean score: *programming&AI group* = 15.18, SD = 3.19; *programming*

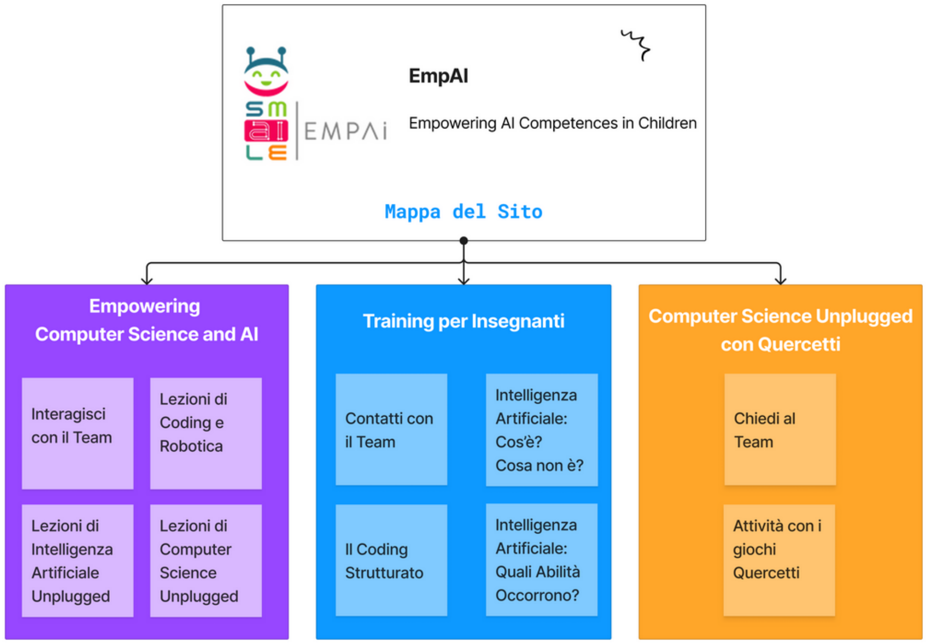

Figure 3: The Web site of EmpAI@SMaILE.

group = 15.76, SD = 3.09, F(1,91) = 1.56, p = 0.213). A mixed repeated measures 2x2 ANOVA (two groups by two time points) were provided to explore any difference between the two groups from pre- to post-test. The results showed no main effect of the time, neither of the group, and nor of time by group interaction in all the three questionnaires administered. The mean scores at the post-test were as follow: Theory and Beliefs of Intelligence Questionnaire mean score: *programming&AI group* = 12.56, SD = 2.69; *programming group* = 11.72, SD = 2.85; Self-Confidence Questionnaire mean score: *programming&AI group* = 8.64, SD = 2.46; *programming group* = 8.60, SD = 2.15; Mastery Goals Questionnaire mean score: *programming&AI group* = 15.50, SD = 3.27; *programming group* = 15.48, SD = 3.12).

Appendix 2: Web site

The material designed and developed for the Programming and for the AI block-based lessons is collected in a moodle-based web site (EmpAI 2021) (in Italian only). The main purpose of the website is to support teachers in replicating all or part of the lessons. Figure 3 shows the organization of the material on the web site. For each lesson we provide:

1. A video of duration up to 10 minutes meant to serve as a teacher guide. Here, one of the orchestrators who performed the activity in class explains the objective of the lesson, the main parts in which it is structured and the main concepts which are explained.
2. A pdf file meant to serve as a teacher guide as well. On the one hand it presents the information in a different format (which could be more suitable to bring in class when actually performing the activity) and, on the other hand, it provides a higher level of detail.
3. The power point of the lesson that has been used by the orchestrator in class. Being a power point file, teachers can adapt or modify the content at wish, for instance to shrink lessons for a shorter duration, or to target younger or older learners.

Leveraging on the functionalities supported by the moodle platform, we created a course which can be used by teachers as a forum to discuss about the lessons, ask questions to the team, report on their experience and such like.

The web site also contains other sections were teachers can find material developed in the EmpAI@SMaILE (EmpAI 2021) and AI-LEAP (AI-LEAP 2023) projects (not described in this paper). Among this, we collected material for activities aiming at training Computer Science-related and AI-related capabilities in children (presented in (Baldoni et al. 2022). One section is dedicated to teachers, presenting a course of three lessons on *i)* coding and AI concepts; *ii)* introduction to artificial intelligence; and *iii)* training of AI-related abilities in children (Baldoni et al. 2021). Finally, one sections presents the activities developed in collaboration with the Italian company for educational toys Quercetti, aiming at understanding how real problems can be translated into programs, developing problem solving capabilities and introducing children to cryptography.

Acknowledgments

This work was supported by the project *SMaILE: Simple Methods for Artificial Intelligence Learning and Education* (E19C20001400007) financed by Fondazione Compagnia di San Paolo, and the project *AI-LEAP: LEArning Personalization with AI and of AI* (D13C23001280007) financed by Fondazione Compagnia di San Paolo and Cassa Depositi e Prestiti.

References

AI-LEAP. 2023. LEarning Personalization with AI and of AI. https://ai-leap.di.unito.it/ (Last access 19 December 2023).

Akram, B.; Yoder, S.; Tatar, C.; Boorugu, S.; Aderemi, I.; and Jiang, S. 2022. Towards an AI-Infused Interdisciplinary Curriculum for Middle-Grade Classrooms. *Proceedings of the 36th AAAI Conference on Artificial Intelligence, AAAI 2022*, 36: 12681 12688.

Baldoni, M.; Baroglio, C.; Bucciarelli, M.; Capecchi, S.; Gandolfi, E.; Gena, C.; Ianì, F.; Marengo, E.; Micalizio, R.; and Rapp, A. 2021. Empowering AI competences in children: A training program based on simple playful activities. In *Proceedings of the Third Symposium on Psychology-Based Technologies, Virtual Event, Naples, Italy, 4-5 October, 2021*, volume 3100 of *CEUR Workshop Proceedings*. CEUR-WS.org.

Baldoni, M.; Baroglio, C.; Bucciarelli, M.; Gandolfi, E.; Ianì, F.; Marengo, E.; and Ras, I. N. 2022. Empowering AI Competences in Children: The First Turning Point. In *Methodologies and Intelligent Systems for Technology Enhanced Learning, Workshops, 12th International Conference, MIS4TEL 2022, L'Avila, Italy, 13-15 July 2022*, volume 538 of *Lecture Notes in Networks and Systems*, 171–181. Springer.

Bebras. 2020. bebras.org. (Last access 3 July 2023).

Belpaeme, T.; Kennedy, J.; Ramachandran, A.; Scassellati, B.; and Tanaka, F. 2018. Social robots for education: A review. *Science Robotics*, 3(21).

Calcagni, A.; Lonati, V.; Malchiodi, D.; Monga, M.; and Morpurgo, A. 2017. Promoting Computational Thinking Skills: Would you use this Bebras Task? In *Informatics in Schools: Focus on Learning Programming: 10th International Conference on Informatics in Schools: Situation, Evolution, and Perspectives, ISSEP 2017, Helsinki, Finland, November 13-15, 2017, Proceedings 10*, 102–113. Springer.

code.org. 2020. Code.org. (Last access 3 July 2023).

Cornoldi, C.; De Beni, R.; Zamperlin, C.; and Meneghetti, C. 2005. *AMOS 815. Strumenti di valutazione di abilit e motivazione allo studio per studenti dagli 8 ai 15 anni. [AMOS 815: Assessment of the study skills and motivation for students from 8- to 15-year-olds].* Trento, Italy: Erickson.

Druga, S.; Vu, S.; Likhith, E.; Oh, L.; Qui, T.; and Breazeal, C. 2018. Cognimates. http://cognimates.me/home (Last access 19 January 2024).

EmpAI Project. 2021. Empowerment of AI competences. https://empai.di.unito.it/ (Last access 19 December 2023).

European Commission. 2021-2027. Digital Education Action Plan. https://education.ec.europa.eu/focus-topics/digital-education/action-plan (Last access 23 August 2023).

Hitron, T.; Orlev, Y.; Wald, I.; Shamir, A.; Erel, H.; and Zuckerman, O. 2019. Can Children Understand Machine Learning Concepts? The Effect of Uncovering Black Boxes. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*.

Informatics for All. 2023. Mission. Informatics for All. https://www.informaticsforall.org/members/ (Last access 23 August 2023).

Innovation for Education. 2020. STEAM on Board. https://www.innovationforeducation.it/academy/steam-on-board/ (Last access 3 July 2023).

Izu, C.; Mirolo, C.; Settle, A.; Mannila, L.; and Stupuriene, G. 2017. Exploring Bebras Tasks Content and Performance: A Multinational Study. *Informatics Education*, 16(1): 39–59.

Kahn, K.; and Winters, N. 2017. Child-friendly programming interfaces to AI cloud services. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 10474 LNCS: 566–570.

Kim, S.; Jang, Y.; Kim, W.; Choi, S.; Jung, H.; Kim, S.; and Kim, H. 2021. Why and What to Teach: AI Curriculum for Elementary School. In *AAAI*, 15569–15576. AAAI Press.

Long, D.; and Magerko, B. 2020. What is AI Literacy? Competencies and Design Considerations. *Conference on Human Factors in Computing Systems - Proceedings*.

Makeblock. 2020a. Codey Rocky. https://education.makeblock.com/product/codey-rocky/ (Last access 3 July 2023).

Makeblock. 2020b. mBlock 5. https://www.mblock.cc/en/ (Last access 3 July 2023).

Manzi, F.; Peretti, G.; Di Dio, C.; Cangelosi, A.; Itakura, S.; Kanda, T.; Hiroshi, I.; Massaro, D.; and Marchetti, A. 2020. A Robot Is Not Worth Another: Exploring Children's Mental State Attribution to Different Humanoid Robots. *Frontiers in Psychology*, 11: 1–12.

MIM. 2022. Piano Nazionale Scuola Digitale (Ministero dell'Istruzione e del Merito). https://www.miur.gov.it/web/guest/scuola-digitale (Last access 21 August 2023).

Papert, S.; and Solomon, C. 1971. Twenty things to do with a computer. *Twenty Things to Do with a Computer*, 248.

Román-González, M.; Moreno-León, J.; and Robles, G. 2019. Combining Assessment Tools for a Comprehensive Evaluation of Computational Thinking Interventions. *Computational Thinking Education*, 79–98.

Sabuncuoglu, A. 2020. Designing One Year Curriculum to Teach Artificial Intelligence for Middle School. In *Proceedings of the 2020 ACM Conference on Innovation and Technology in Computer Science Education*, ITiCSE '20, 96102. Association for Computing Machinery.

Song, J.; Zhang, L.; Yu, J.; Peng, Y.; Ma, A.; and Lu, Y. 2022. Paving the Way for Novices: How to Teach AI for K-12 Education in China. *Proceedings of the 36th AAAI Conference on Artificial Intelligence, AAAI 2022*, 36: 12852 12857.

Tedre, M.; Toivonen, T.; Kahila, J.; Vartiainen, H.; Valtonen, T.; Jormanainen, I.; and Pears, A. 2021. Teaching Machine Learning in K-12 Classroom: Pedagogical and Technological Trajectories for Artificial Intelligence Education. *IEEE Access*, 9: 110558–110572.

Touretzky, D.; Gardner-McCune, C.; Martin, F.; and Seehorn, D. 2019. Envisioning AI for K-12: What should every child know about AI? *33rd AAAI Conference on Artificial Intelligence, AAAI 2019, 31st Innovative Applications of Artificial Intelligence Conference, IAAI 2019 and the 9th AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2019*, 9795 9799.

UNICEF. 2019. Workshop Report: AI and Child Rights Policy.

United States Government. 2023. National Artificial Intelligence Initiative: Overseeing and Implementing the United States National AI Strategy. AI GOV. https://www.ai.gov/ (Last access 23 August 2023).

Van Mechelen, M.; Smith, R. C.; Schaper, M.-M.; Tamashiro, M.; Bilstrup, K.-E.; Lunding, M.; Graves Petersen, M.; and Sejer Iversen, O. 2023. Emerging Technologies in K12 Education: A Future HCI Research Agenda. *ACM Trans. Comput.-Hum. Interact.*, 30(3).

Williams, R.; Breazeal, C.; MacHado, C.; Maes, P.; and Druga, S. 2018. "My doll says it's ok": A study of children's conformity to a talking doll. *IDC 2018 - Proceedings of the 2018 ACM Conference on Interaction Design and Children*, 625–631.

Williams, R.; Park, H. W.; Oh, L.; and Breazeal, C. 2019. Popbots: Designing an artificial intelligence curriculum for early childhood education. *33rd AAAI Conference on Artificial Intelligence, AAAI 2019, 31st Innovative Applications of Artificial Intelligence Conference, IAAI 2019 and the 9th AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2019*, 9729 9736.

Wong, G.; Ma, X.; Dillenbourg, P.; and Huen, J. 2020. Broadening artificial intelligence education in K-12: Where to start? *ACM Inroads*, 11(1): 20–29.

Yang, W. 2022. Artificial Intelligence education for young children: Why, what, and how in curriculum design and implementation. *Computers and Education: Artificial Intelligence*, 3.