Using control heuristics as a means to explore the educational potential of robotics kits

Ilaria Gaudiello[1], Elisabetta Zibetti[2]
i.gaudiello@gmail.com, ezibetti@univ-paris8.fr

[1] CHArt-LUTIN Laboratory (EA 4004 Cognitions Humaine & ARTificielle)
[2] Université Paris 8, EPHE, Cité des Sciences et de l'Industrie, Paris-France

Abstract. The educational potential of robotics kits as a form of control technology will remain undervalued until meaningful observation parameters are identified to enable a better understanding of children's control strategies. For this reason, this paper aims primarily to identify and classify the heuristics spontaneously applied by 6-10 year old children interacting with robotic devices containing specific transparency features (i.e. programmability) and interactivity features (i.e. immediacy of feedback). Two studies are described: an exploratory investigation into the control of a Lynx AL5A arm and a pilot study about the control of a Lego Mindstorms NXT®. Two issues relating to control heuristics are addressed: the heuristic shift and the perceived and objective level of task difficulty. The results demonstrate that three main types of heuristic emerge: (i) procedural-oriented, (ii) declarative-oriented, and (iii) metacognitive-oriented. Limitations of the difficulty indicators used and shift patterns proposed are discussed in relation to future research.

Keywords: educational robots, control heuristics, interactivity, transparency, Lego Mindstorms NXT®

Introduction: Identifying cognitive issues in control technology

Technological kits are longstanding tools in pre-school and school education (Papert & Harel, 1991). As a specific kind of technological kit, robotic kits are designed as constructible and programmable devices. This means that with the benefit of guidance from educators and manuals, children can shape their robot, design its mechanisms and command its sensors and actuators. Two inherent features of robotics kits are their *transparency*, which refers to the openly accessible programmability of the robot (Kynigos, 2008; Resnick, Martin, Sargent et al., 1996), and their *interactivity*. Traditionally defined as the set of processes, dialogues, and actions through which a human user employs and interacts with a computer (Baecker & Buxton, 1987), within the present work *interactivity* refers to the immediacy of the feedback given by the device when a child programs and executes the commands. These two features of *transparency* and *interactivity* give robotics kits high educational potential compared with other kinds of educational robots that are not - or that are only partially - constructible and programmable (Gaudiello & Zibetti, in press).

However, here we argue that this educational potential can only become fully developed once we acknowledge the cognitive strategies applied by children when controlling the robot. We can call such strategies *control heuristics*; these are special kinds of strategies that are meant, on the one hand, to modulate the inner hardware/software features of robotics kits on the basis of both a task's requirements and of an understanding of the device itself, and, on the other, to orient children toward specific categories of knowledge. Thus, this paper has two aims. The first aim is to identify children's control heuristics, by observing their emergence and assessing their robustness through two different kinds of task and with two different kinds of robotic device. In doing this, we aim to propose a methodological contribution to one of the most critical aspects of educational technology: the identification of appropriate variables to observe when children approach a new form of technology. This identification is crucial for the elaboration of clear interpretations and generalizations about the relationship between cognition and technological educational devices (Zuga, 2004). In our view, children's control heuristics can be considered as meaningful variables. For this reason, we investigate the identification of heuristics as well as the following heuristics-related issues: (i) heuristic shift, and ii) the perceived and objective level of task difficulty.

The second aim is to classify the identified control heuristics by anchoring them to a theoretical framework which accounts for the categories of knowledge acquired by children when they undertake robotics kit tasks. We believe this important in order to better understand how these types of robots could be exploited effectively for educational purposes.

Children's heuristics of robot control

Heuristics can be defined as general rules or strategies that guide our actions in a problem-solving task, and that take into account contextual constraints as well as the final goal of the task (Newell & Simon, 1972). In the case of robotic control, heuristics are represented by the general rules that guide our actions to control the robot, contextual constraints are represented by the inherent features of the robot, and the goal of the task is represented by the end-state solution. Control heuristics can thus be used by children to apply those actions that modulate the inherent features of the robots in order to achieve the solution to the task.

According to Anderson and colleagues (Anderson et al., 2001), children make use of particular types of cognitive processes when approaching a problem-solving task in a educational environment: remembering, which means retrieving knowledge from long-term memory; understanding, which is constructing meaning from instructional messages; applying, which is carrying out a procedure in a given situation; analyzing, which is breaking a whole into parts and apprehend their relation; evaluating, or making judgments based on criteria and standards; and creating, by putting elements together to form a coherent or functional whole (Anderson et al., 2001, p.68).

These processes result in four categories of knowledge: *factual knowledge*, relating to the basic elements needed to know about a discipline or to solve problems in it (i.e. knowledge of terminology and specific facts); *declarative knowledge*, concerning the interrelations among the basic elements within a larger structure that enable them to function together (i.e. concepts, categories, principles and models for this discipline); *procedural knowledge*, constituted of the procedures, techniques, and methods as well as the criteria for using them; and *metacognitive knowledge*, referring to knowledge about task demands, as well as strategies and one's ability to accomplish tasks. Together, declarative and conceptual knowledge represent knowledge of ''what'', while procedural and metacognitive knowledge represent knowledge of ''how to''.

Due to the novelty of robotic kits as educational tools, it is premature to talk about the cognitive processes underpinning their use. However, a number of studies have investigated the cognitive strategies at work as children gain programming skills during problem solving tasks (Ribeiro, Coutinho, & Costa, 2011; Carver & Klahr, 1986; Highfield et al., 2008), as well as the scientific and technological knowledge acquired during these tasks (Sullivan, 2008; Alimisis 2009). However, in our view, these findings still represent a level of analysis that needs to be anchored to a better defined taxonomy, in order to unify the rich experimental data from these studies within a reasoned theoretical framework that can account for the impact of educational robotics on children's knowledge acquisition.

Table 1. The proposed classification system for children's control heuristics inspired by Anderson et al. (2001)

	Procedural-oriented heuristics	Declarative-oriented heuristics	Metacognitive-oriented heuristics
Description	**Task-driven** heuristics, in which sequences of actions are applied by children using a trial-and-error strategy, primarily to achieve the solution for the task by following an implicit procedure.	**Knowledge-driven** heuristics, in which single actions are applied by children through a reasoned strategy, mainly to seek explicit information about the rules of the task.	**Awareness-driven** heuristics, by which actions are applied by children through both trial and error and reasoned strategies, mainly to establish the limits of the task and to assess their own understanding of the task.

Moreover, if a considerable amount of literature has been devoted to the interactivity of computer interfaces (Rada & Michailidis, 1995; Svanæs, 2000) and of other kinds of technological devices (Kennewell et al., 2008; Yacci, 2000; Rose, 1999), no experimental study can be found that rely on control heuristics as a means to explore the educational potential of the interactivity feature in robotics kits. For this reason, we conducted an exploratory study using a robotic device of low transparency and high interactivity as a preliminary investigation for a subsequent pilot study, where the device children used during the task was characterized by higher transparency and lower interactivity. We aimed to develop a classification system for the control heuristics emerging in two different child-robot interaction contexts, based on Anderson's taxonomy (Anderson et al., 2001), in order to understand which strategies children apply to modulate the interactivity feature (transparency being a secondary concern in the present study). We considered Anderson's procedural, declarative and metacognitive knowledge categories to be particularly indicative of the kinds of knowledge that orient the strategies used by children when they control a robot in order to solve a problem (Table 1). The definition of the metacognitive-oriented heuristic used here is based on studies within the educational robotics literature that have demonstrated that educational robots enhance metacognitive attitudes (cf. Denis & Baron, 1993).

Before presenting the studies, we will discuss two heuristic-related issues, (i) heuristic shift, and (ii) the level of objective and perceived task difficulty.

Heuristic shift

The issue of shift phases in children's learning is indeed a central one. The reason is simple: learning requires change. A considerable variety of conceptual change models can be found in the literature (Harrison & Treagust, 2001). According to Sfard (1991), problem-solving consists in an intricate interplay between procedural and declarative knowledge. However, as Sfard highlights, procedural knowledge is, for most people, the first step. Borrowing from Piaget, who states that a process has been interiorized if it can be carried out through mental representations (Piaget, 1972, p.14). Sfard explains that the transition from procedural to declarative knowledge is a long and difficult process, accomplished through the interiorization of procedures and their consequent reification in explicit definitions. A further shift is needed to pass from procedural and declarative to metacognitive knowledge, since the latter implies a higher level of knowledge: awareness of one's knowledge.

Although this shift is considered to occur progressively in traditional educational settings, new educational settings such as educational robotics could demonstrate that it does not necessarily follow the same progression when children are confronted with technology with inherent hardware/software features that elicit primarily one type of knowledge rather than another, i.e. metacognitive knowledge in the case of robotics kit technology. In our opinion, it would thus be relevant to ascertain whether children persistently adopt one type of heuristic or if they shift between different types when repeating the same task twice. In particular, it would be pertinent to observe in which order this shift occurs, and whether it is progressive (i.e. a sequential use of control heuristics oriented to procedural knowledge, then to declarative knowledge, and finally to metacognitive) or non-progressive (a non-gradual use of control heuristics, e.g. from procedural to metacognitive). In relation to the literature reported previously, a progressive shift could be considered as an indication that the impact of the robotic learning environment on children's knowledge acquisition is not different from other traditional learning environments; in contrast, a non-progressive shift could indicate that the inherent features of educational robots produce specific control heuristics that elicit particular types of knowledge acquisition.

Perceived task difficulty

Task difficulty is a composite factor which plays an important role in children's mastery of educational technology. Established methods within Psychology of evaluating technology usability traditionally relies on quantitative indicators to assess the difficulty of the task, such as the number of errors, completion time, etc. These indicators are also usually employed in what has been named the Psychology of programming (Pea & Kurland, 1984). Diverse qualitative indicators have been introduced to educational robotics, ranging from the number of blocks making up the program (Caci, Cardaci & Lund, 2003), to the type of conditional rule that determines the adaptive behavior of the robot in an environment. This heterogeneity of indicators demonstrates that it is not clear how the objective difficulty of the task and the perceived difficulty of the task can be distinguished in robotics-based activities.

An interesting proposal in relation to this was made by Levy & Mioduser (2008). According to these authors, when the task to be accomplished in interaction with the robot is perceived as easy, children tend to assume a technological perspective, that is, they employ a more engineering-related vocabulary in the spontaneous or enhanced questions and remarks that they address to peers and educators. The higher the level of difficulty of the task, the more the children shift to a psychological perspective, that is they use a more anthropomorphic vocabulary; for instance, they attribute states to the robot that are normally attributed to humans, such as intentions, volitions, fears, wishes, etc. Therefore, in order to capture both the objective and the perceived levels of task difficulty, we chose to measure both the number of errors made by children during programming and the type of engineering vs. anthropomorphic vocabulary employed during group interaction.

Identifying control heuristics for a Lynx AL5A robotic arm

In the first stage of our research, we conducted an exploratory study into children's control heuristics during the First Lego League® competition taking place at Drancy (a suburb of Paris) during winter 2011. In addition to the main competition program, various educational stands were set up for the purpose of testing several robotic devices, with educators setting micro-challenges to the First Lego League® participants and to children attending as visitors. Our exploratory study was realized in this context: we observed actions sequences used by children controlling a basic model Lynx AL5A2 robotic arm in one of these micro-challenges, and we classified into heuristics in order to test the relevance of our approach and our proposed classification system for general control heuristics.

Context, robotic devices and children's tasks

Our stand offered a simple activity with a Lynx AL5A robotic arm (Fig.1a), composed of a shoulder fixed to a table, a forearm, an arm, a wrist, a hand-gripper, an Arduino card, a motor for each of the five components and a knob for each motor (Fig.1b). Volunteers amongst the children at the competition or from the public could manipulate the robotic arm in order to grasp, lift and drop a sugar lump into a coffee cup. No programming was done: commands were given by manipulating the knobs. This kind of robotic device is thus not characterized by a high level of transparency, as its control merely requires the use of knobs to instruct the arm to move in four directions (up, down, left, right) and to open/close the hand gripper. In contrast, the fact that children can observe the effects of their commands in real time when manipulating the knobs engenders a high level of interactivity. Forty children (6-10 years old) volunteered for this activity during the all-day competition. Each trial for each child lasted 10 minutes. We were able to observe and classify children's control heuristics over the forty trials.

Data collection and coding

In order to observe if control heuristics were spontaneously deployed by children with this kind of robotic device and task, we recorded on an observational grid the nature of the actions performed by each child when he/she controlled the robot. We then coded the actions and defined the action sequences in terms of the types of heuristics outlined in Table 1. For this task and the Lynx AL5A robotic device, the action sequences were thus operationalized in terms of the three heuristics described in Table 2. The type of heuristic applied by a child was identified by two judges according to the type of action sequences he/she applied to the knobs.

Observed heuristics and outcomes

Three emergent heuristics were observed among the children.

(i) 60% of the children used the knobs to achieve a sequence of task-related commands for grasping, lifting and dropping an object. These children were mainly interested in applying a procedure in order to achieve the end-solution state, sometimes proceeding by trial-and-error strategies.

(a)

(b)

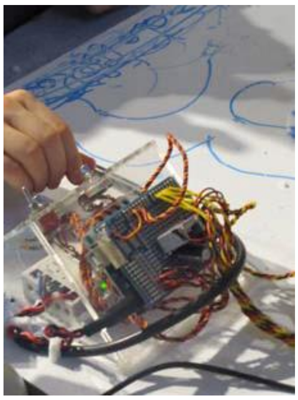

Figure 1. (a) The Lynx AL5A robotic arm being controlled by children during the exploratory study at the First ® League. (b) A child manipulating one of the five knobs corresponding to one of the five motors for the arm in order to pick up a sugar lump and put it in the coffee cup.

Table 2. Classification of the action sequences in terms of control heuristics used to control the Lynx AL5A

	Procedural-oriented heuristics	Declarative-oriented heuristics	Metacognitive-oriented heuristics
Action sequences	Children manipulated the knobs one after another, observing the corresponding motor activation and adjusting the movement in real time, in order to solve the task.	Children manipulated each of the five knobs and observed the corresponding motor activation. They only started to solve the task once they had understood the one-to- one correspondence between each knob and the related motor movement.	Children manipulated the knobs or a combination of knobs, observing the corresponding movement (i.e. the activation of more motors) in order to assess what they could and could not do with the robot. They only started to solve the task or proposed different or further tasks after this.

(ii) 30% of the children used the knobs in order, first to understand each knob's function (i.e. the one-to-one correspondence between knob manipulation and motor movement) and then to accomplish the task. These children were more interested in acquiring knowledge about task-related commands, in order to apply a reasoned (i.e. not trial-and-error) procedure afterwards.

(iii) Only 10% of the children used the knobs in order to explore the general functioning of the robotic arm. These children were more interested in becoming aware of what they could do and could not do, in terms of possibilities (e.g. combining different knobs to obtain specific robotic arm movements) and limitations (e.g. checking the maximum rotation of a motor beyond which the robotic arm blocked); thus they did not restrict their attention to task-related commands.

These first results showed that the majority of children seemed to pay more attention to achieving the solution and to acquiring knowledge about the functioning of the task-related commands, rather than to gaining a general awareness of the possibilities and limitations offered by the robotic device. This is coherent with those studies that show that trial-and-error strategies are predominant when children approach a new technology (Ribeiro et al., 2011) and that they relate to procedural knowledge (Anderson et al., 2001; Sfard, 1991). Moreover, the emergence of overt and diverse types of heuristics enabled an initial validation of our approach, which consisted in recording and classifying the nature of action sequences performed by the children (Table 2). Using Anderson's taxonomy (2001), we were able to link these action sequences to the type of knowledge acquisition favored by the use of such heuristics when children controlled the robotic device (Table 1). This coding procedure and the initial results encouraged us to investigate children's control heuristics further in a later study on a different task and with a different robot (Lego Mindstorms NXT®).

Pilot study: control heuristics for Lego Mindstorms NXT® kits

Our pilot study was designed to verify, as a first aim, whether the proposed classification (Table 1) was also relevant in a different device and problem-solving context. For this reason we used a different kind of robotic kit, Lego Mindstorms NXT®, and a different kind of problem-solving task. The Lego robotic kit includes a programming interface with a graphic code: drag and drop icons are used to program sensors and actuators. Compared with the Lynx AL5A robotic arm, Lego Mindstorms NXT® has a higher level of transparency: all the sensors and the actuator can be programmed using dedicated icons with stylized symbols on them (e.g. a stylized wheel on the motor programming icon, a stylized sun on the light sensor programming icon) and by setting the parameters of these icons (e.g. the speed of the motor or intensity of the light), so that children do not have to guess which icon corresponds to each command, nor what the effect of such a command might be. Moreover, Lego Mindstorms NXT® has a lower level of interactivity than the Lynx AL5A robotic arm. Moreover, in the pilot study we were able to better control experimental procedure so to investigate the two issues of heuristic shift and perceived task difficulty as a second aim. In order to meet these aims, we refined the definition of the three heuristics identified in the exploratory study by adapting them to the specific Lego robotic device and task. The three heuristics were thus operationalized as outlined in Table 3. Finally, we wanted to assess if the proposed task was perceived as easy or difficult, and if the proposed indicators (number of errors and type of vocabulary) were appropriate to test the level of task difficulty and perceived task difficulty respectively.

Hypothesis and Expectations

We expected children to demonstrate at least three types of programming heuristics when controlling the robot (Table 3): (i) Procedural-oriented; (ii) Declarative-oriented and (iii) Metacognitive-oriented. Other heuristics, specific to the robotics device, could possibly emerge. In particular, since trial-and-error strategies have been observed to predominate when children approach a new technology (Ribeiro et al., 2011) and since these strategies typically relate to procedural knowledge as the first kind of knowledge to be acquired (Anderson et al., 2001; Sfard, 1991), we expected procedural-oriented heuristics to occur more frequently than the others.

In relation to heuristic shift, because several studies have highlighted the role of Lego robotics kits in enhancing metacognitve attitudes (see Danis & Baron, 1993), we expected a non-progressive shift between different control heuristics; that is, we expected children to pass from procedural to metacognitive-oriented heuristics, without passing through declarative-oriented heuristics, or to start directly with metacognitive oriented heuristics. In relation to task difficulty, we expected children using procedural oriented heuristics making more errors because this kind of heuristic mostly implies trial and errors procedures.

Table 3. Classification of action sequences in terms of control heuristics used to control the Lego Mindstorms NXT®

	Procedural-oriented heuristics	Declarative-oriented heuristics	Metacognitive-oriented heuristics
Action sequences	Children drag and drop several programming icons onto the software workspace and they execute the whole sequence of icons (i.e. the program).	Children drag and drop a programming icon onto the workspace and they execute it individually before adding the subsequent programming icons needed to complete the program.	Children drag and drop one or more ? programming icons ? onto the workspace, they set the parameters and they execute the program more times, trying different parameters.

(a) (b)

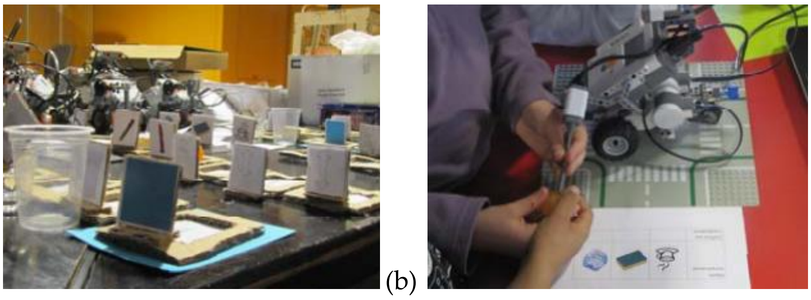

Figure 2. (a) The materials used in the pilot study: colored objects (blue, red, and yellow paper), objects with different temperatures (an ice cube, a glass of hot water and a glass of room temperature water), and objects producing different sounds (a bell, a whistle and a percussion stick). (b) Children testing a temperature sensor on a plastic ice cube.

Concerning perceived task difficulty, as recent studies in robot-child interaction have shown that children who find a task difficult use anthropomorphic language while children who find it easy use technological language (Levy & Mioduser 2008), we expected children using more anthropomorphic terms because they had never used robotics kits before, so some difficulties could emerge in their first approach to this technology.

Participants and materials

Twenty-six children (6-10 years old) participated in the study (17 boys and 9 girls). Thirteen participants were aged 6-7 years and thirteen participants were aged 8-10 years. Three children worked on each robotic device (a Lego® Mindstorms NXT kit including light, sound and temperature sensors, and a computer provided with Lego software). Children of different ages were grouped in order to balance age differences. Each group was accompanied by an educator who guided the activity and an experimenter who took notes on an observational grid without intervening in the activity. No child had used a Lego robot before. The task consisted in making the robot's actuators (i.e. the motor) react when a defined intensity of light, sound, and temperature was detected by the sensors. To achieve this aim, children were first taught to use the NXT iconic language to calibrate the sensors (i.e. to define a threshold beyond which the robot had to react). Pencils and papers were distributed to enable children to note values detected by the sensors. The educational activity presented to the children was designed to portray the robot as an inquiry tool to investigate the properties of light, sound and temperature, using an introductory analogy between human senso-motricity and the robot's sensors and actuators. The scenario (Gaudiello, Zibetti & Pinaud, 2012) was specifically improved and adapted within a joint frame including the Carrefour Numérique educational seminars at the Cité des Sciences et de l'Industrie in Paris, and the Pri-Sci-Net European Project. The aim of the Carrefour Numérique educational seminars is to disseminate scientific and technological information to a broad public. The objective of the Pri-Sci-Net European Project is to implement Inquiry Based Learning (IBL) for Scientific Education in primary schools.

Tasks, procedure and data collection

The experiment included an introductory phase, in which educators engaged children in a discussion about the differences between automats and robots by showing them images selected by the experimenters. This phase was designed to investigate the children's prior knowledge of robotics and to provide a general understanding of the robot as a particular type of machine, which can be programmed to sense and act in order to accomplish multiple tasks, depending on the current state of the surroundings. A second phase followed in which children were prompted to form groups, with each group choosing the kind of sensor (light, sound, or temperature) they wanted to program. Initially, the educator demonstrated how to use the programs already stored in the intelligent brick. Subsequently he/she outlined the functioning of the NXT icon programming language: the meaning of the programming icons, the parameters, how to create a basic program by joining several programming icons, how to download and execute the program. Then the children were introduced to the target problem: how to make the robot react to information detected by the sensor. For the light sensor group, the target was to make the robot go forward if it detected a green light and to go backwards if it detected a red light. For the sound sensor group, the target was to make the robot say "shhh!" if the detected sound exceeded a defined threshold. For the temperature group, the target was to make the robot say "hot" if the temperature sensor detected a temperature value exceeding 40° degrees. Each child within the group was encouraged to complete a programming trial. Afterwards, the children were invited to program the sensor to solve the target problem. Once the task had been completed, the children could have further trials or ask for a different sensor to program. Task execution for each group lasted on average 60 minutes. Each group completed on average 6 trials on different sensors (on average 2 for each child). The problem-solving phase lasted on average 30 minutes. Finally, all groups were collectively invited to discuss their views on the activity and their suggestions for how future activities could be improved.

Behavioral data were collected by the experimenters throughout the activity. Actions, errors and verbalizations between children as well as between children and educators were collected during the programming phase using an observational grid for each child in each group. A colored label was placed on each child's hand, in order for the experimenters to be able to identify the participants on the observational grid. The educators were instructed to refer to the children using their assigned color when interacting verbally. Screen capture software (CamStudio) was used to register cursor actions on the screen,the order in which actions occurred when children programmed the robot as well as verbalizations. This information was used only to confirm descriptive analysis or to complete missing data. The type of heuristic applied by a child was identified by two judges according to the type of action sequences (Table 3) he/she applied during the programming. Errors were coded by counting each time a child used an incorrect icon or an incorrect icon sequence. Language was coded by noting when children referred to the robot using anthropomorphic terms (e.g. verbs indicating intentions, worries or other psychological states normally attributed to humans) and engineering terms (e.g. names of specific kit components or explanations of procedures and terms using technical vocabulary, such as cable, sensors, computer-robot relations, etc.).

Results and interpretation

Twenty-one of twenty-six children programmed the robot – with the remaining five children tending to participate more in terms of manipulating hardware (e.g. connecting sensors to the processor) or proposing and evaluating solutions. Forty-two programming trials were carried out during the study (mean: 2 trials per child; 6 trials per group). Only a preliminary, exploratory descriptive data analysis was performed.

Which heuristics are spontaneously developed by children engaged in the control of Lego Mindstroms® robotic kits?

Across the 42 trials we observed a total of 37 heuristics. Overall, our results show that all three heuristics were observed (Table. 3). Across the 42 trials, procedural-oriented heuristics were observed most frequently (49%), followed by metacognitive heuristics (30%) and declarative heuristics (21%). In line with our expectations, procedural heuristics were applied most often by children, i.e. they represented almost half the sampled data. Thus, procedural-oriented heuristics appear to represent the most frequently kind of action sequence adopted by children approaching this kind of problem-solving task. This kind of heuristic typically involves trial and error strategies. Furthermore, the distribution of the three heuristics and the predominance of procedural heuristics are consistent with most findings in the literature: procedural heuristics, which are mainly task-driven, orient children towards the acquisition of procedural knowledge, which is known to precede declarative ("knowing what to do to execute a task") and meta-cognitive ("knowing about knowing") knowledge acquisition (Sfard, 1991; Piaget, 1972). In contrast with previous findings, we observed more metacognitive than declarative-oriented heuristics across all trials. There are two possible ways to interpret this result: in terms of the curiosity stimulated by the novelty of the device, or in terms of Lego robotics kits' reputed key role in enhancing metacognitive attitudes. The novelty effect constitutes a bias often encountered in studies involving the impact of new technologies on children's learning attitudes. Further analysis of heuristic shift should enable greater understanding of these results.

How do children shift from one heuristic to another?

In order to answer this question, we considered the type of heuristic used by each child in the first and second trials as the unit of analysis (Table 4). Among the twenty-one children who programmed the robot, 38% used only one type of heuristic in the two trials, while 62% (thirteen out of twenty-one children) used more than one type. However among this last group, a majority of children made non-progressive heuristic shifts, that is they started with procedural-oriented heuristics and directly shifted to metacognitive (Table 4).

Although two trials per child represent a limited data set from which to draw rigorous conclusions, the data trend shows that procedural-oriented heuristics predominated, non-progressive shifts occurred more frequently than progressive shifts, and metacognitive-oriented heuristics were applied more extensively than declarative-oriented heuristics. However, the surprisingly high occurrence of metacognitive-oriented heuristics still requires an explanation. In particular, if the frequent occurrence of metacognitive-oriented heuristics is due to the novelty effect of the robotic device, then we would expect this kind of heuristic to be used more frequently as the initial or sole approach to the robot. If, in contrast, the use of metacognitive-oriented heuristics is specifically triggered by the particular kind of robotic device, then we would expect metacognitive heuristics to be used later on, after procedural or declarative-oriented heuristics. As the descriptive analysis shows, only one child used metacognitive-oriented heuristics as the initial and sole approach, while the other children seemed to apply it later on, through progressive or non-progressive shift. In this sense, the study seems to confirm claims within the literature about the potential of educational robots to enhance metacognitive attitudes. Further analysis using larger sets of programming trials is planned to reinforce these initial findings.

Table 4. Percentage of progressive and non-progressive heuristic shifts between the two trials when children controlled a Lego Mindstorms NXT

Use of single heuristics (no shift) 38% (n = 8 children)			**Progressive heuristic shifts 24% (n = 5 children)**		**Non - Progressive heuristic shifts 38% (n = 8 children)**
Procedural	Declarative	Metacognitive	Procedural/ Declarative	Declarative/ Metacognitive	Procedural/ Metacognitive
28%	5%	5%	16%	8%	38%

Is the problem perceived as easy or difficult?

In order to investigate how much the children understood about a kit they had never used before, we decided to break the difficulty factor down into two indicators. The first indicator related to children's performance in terms of the number of errors made during problem-solving. We considered any incorrect programming icon or sequence of icons to be an error.

The second indicator related to children's verbalizations (the use of engineering vocabulary when the task was perceived as easy and anthropomorphic vocabulary when the task was perceived as difficult).

Performance – number of errors: Over the 42 trials (84 blocks, each trial requiring two blocks) and across the 37 heuristics, we observed a total of 27 errors during programming.
52% of errors occurred with procedural-oriented heuristics, 33% with metacognitive-oriented heuristics and 15% with declarative-oriented heuristics. This result, partially coherent with our hypothesis can be attributed to the fact that not only procedural but also metacognitive-oriented heuristics basically involves a trial-and-error approach, with the former heuristic leading to different trials being carried out in order to attain the task goal and the latter used to understand the robot's possibilities and limitations. In contrast, declarative-oriented heuristics did not lead to frequent errors, since these heuristics are applied in order to achieve an exact understanding of each task-related command, so that errors can be identified step-by-step rather than sought after the entire sequence has been executed.

Language – type of vocabulary: We registered a total of 58 occurrences of both engineering markers (e.g. "the robot is programmed to", "the computer tells the robot to do that", "it does not work because the cable is not plugged-in", etc.) and anthropomorphic markers (e.g. "the robot wants" or "he does not want" and "he is scared", etc.). We did not register any specific language marker for six children and for one child we registered 8 markers. The remaining nineteen children used between 2 and 4 markers on average. Across the 58 markers recorded across all groups of children, 29% were anthropological markers and 71% were engineering markers. Contrary to our hypothesis, the predominance of engineering markers might suggest that the task was perceived as easy.

General discussion and conclusions

To summarize, the observations and measures carried out during the Lynx AL5A robotic arm study and the Lego Mindstorms NXT® pilot study allow us to draw the following conclusions. Classifying and analyzing the action sequences performed by children during their interactions with robotic devices within a control heuristics typology and defining the corresponding type of knowledge gain can be an insightful way to highlight the educational benefits of such devices within a learning framework. Across the two different kinds of robotics device and task, three types of heuristics emerged: procedural-oriented, declarative-oriented and metacognitive-oriented. Specifically, procedural-oriented heuristics occurred more frequently in both studies. Furthermore, metacognitive-oriented heuristics occurred more frequently than declarative-oriented heuristics with the Lego robot. The extensive use of metacognitive-oriented heuristics and the non-progressive heuristic shift observed when children controlled Lego robots seem to confirm evidence in the literature that this kind of technological device should increase metacognitive attitudes during knowledge acquisition. However, more in depth analysis is needed to ensure that the exploration of the robot's general functioning (i.e. the metacognitive-oriented heuristic) is not attributable to the use of a specific heuristic, but merely to the device's novelty effect; that is, to the curiosity elicited in children during their first encounter with the robot. Moreover, two trials per child do not constitute a sufficiently representative data set to enable us to assess whether a shift from one heuristic category to another has actually taken place. Finally, we must consider possible interaction effects between errors and adopted heuristics: children might have shifted from one heuristic to another in order to counteract errors they had committed rather than to voluntarily change their approach.

The proposed methodology based on a combination of control heuristics and language marker and error number indicators has encouraged us to pursue this type of analysis and refine these indicators in order to investigate child-robot interaction further; however, with relation to level of perceived task difficulty, the surprisingly high use of technological language observed among children leads us to interpret these results with a certain degree of caution. The fact that children today are widely exposed to technological vocabulary may bias an attempt to fully exploit traditional linguistic markers as indicators; traditional language markers need to be updated in order to reflect and control for the language evolution affecting the future generation of “digital native” children.

Limitations of the pilot study

First, although this study mainly addressed the use of control heuristics in relation to the low level of interactivity that characterizes Lego, we need to acknowledge the fact that Lego’s high transparency can also affect children’s heuristics. Thus, if on the one hand low interactivity may prompt children to exploit declarative heuristics that can reduce feedback time, high transparency may on the other hand prompt children to pass straight to metacognitive heuristics in order to fully explore the robot.

Second, the three different sensors included in the Lego robotics kit might have presented different levels of difficulty. For example, the temperature sensor displayed the registered temperature for several minutes, such that it was not clear that repeated measurements needed to be taken in order to calibrate the sensor.

Third, although we tried to balance age differences across the groups of children, we did not control for the level of logical skills, scientific knowledge or technological fluency of each child allocated to a group.

Fourth, the present analysis of sample data did not take into account group dynamics (e.g. collaboration, competition, leader-attitude etc.) that might have promoted or impeded task completion and knowledge acquisition.y determined by group dynamics or might be related simply to the children’s age.

Fifth, different scaffolding styles were applied by different educators within each group, with some educators showing a preference for strongly structured guidance and others being more open to children’s own initiatives.

Sixth, we only performed descriptive analysis, since the data set (in terms of the number of trials per child) was too limited to enable us to generalize our initial results using statistical analysis. Therefore, these initial outcomes need to be intepreted with prudence, since at this stage we are unable to state that the observed differences are statistically significant. Moreover, we need to replicate this experiment to enable better control of children’s profiles, group dynamics and number of trials.

Future perspectives

Overall, the results of the present investigation support the need for further studies to be conducted in order to develop several of the proposed issues, provide more detailed results and answer the questions raised in this pilot study. An extended set of trials is required and a rigorous experimental design needed to measure the effects of age, of different levels of scientific, logical and technological knowledge and skills, and of group dynamics. To achieve this, children could be pre-tested and post-tested using questionnaires delivered before and after the robotics activity. Finally, more pertinent indicators of perceived task difficulty should be specified and stronger distinctions between task difficulty and device difficulty introduced. In summary, this study has sought to provide two contributions to the field of Educational Robotics: a methodological contribution in terms of the identification of meaningful variables in child-robot interactions (i.e. control heuristics and knowledge-related language), and the elaboration of a framework to be developed and implemented to assess the impact of robotics kits on children's learning.

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References

Alimisis, D. (ed.) (2009). *Teacher Education on Robotics-Enhanced Constructivist Pedagogical Methods*. Athens: School of Pedagogical and Technological Education.

Anderson, L.W., Krathwohl, D.R., Airasian, P.W., Cruikshank, K.A., Mayer, R.E., Pintrich, P.R., Raths, J., & Wittrock, M.C. (2001). *A taxonomy for learning, teaching, and assessing: a revision of Bloom's taxonomy of educational objectives*. New York: Longman.

Baecker, R. M., & Buxton, W.A.S. (1987). *Readings in human-computer interaction : a multidisciplinary approach*. San Mateo, CA: Kaufmann.

Caci, B., Cardaci, M., & Lund, H.H. (2003). Assessing educational robotics by the robot edutainment questionnaire. *Technical Reports 3*. The Maersk McKinley Moeller Institute for Production Technologies, University of Southern Denmark.

Carver, S. M., & Klahr, D. (1986). Assessing children's LOGO debugging skills with a formal model. *Journal of Educational Computing Research*, 4, 487-525.

Denis, B., & Baron, G.L. (Eds.) (1994). Regards sur la Robotique pédagogique. Actes du quatrième colloque sur la robotique pédagogique. Liège, 5-8 juillet. Paris: INRP.

Gaudiello, I., Zibetti, E., & Pinaud, C-A. (2012). Control heuristics for educational robots: a pilot study. *Proceedings of 3rd International Workshop Teaching Robotics, Teaching with Robotics. Integrating Robotics in School Curriculum* (pp. 67-75). Trento, Italy: Riva del Garda.

Gaudiello, I., & Zibetti, E. (in press). La robotique Educationnelle: Etat des lieux et Perspectives. *Psychologie Française*. Retrieved 12 March 2013, from http://dx.doi.org/10.1016/j.psfr.2012.09.006.

Harrison, A. G., & Treagust, D. F. (2001). Conceptual change using multiple interpretive perspectives: Two case studies in secondary school chemistry. *Instructional Science*, 29, 45-85.

Highfield, K., Mulligan, J., & Hedberg, J. (2008). Early mathematics learning through exploration with programmable toys. *Proceedings of the Joint Meeting of PME 32 and PME-NA* (pp. 169-176). Mexico: International Group for the Psychology of Mathematics.

Kennewell, S., Tanner, H., Jones, S., & Beauchamp, G. (2008). Analysing the use of interactive technology to implement interactive teaching. *Journal of Computer Assisted Learning*, 24(1), 61–73.

Kynigos, C. (2008). Black-and-white-box perspectives to distributed control and constructionism in learning with robotics. *Workshop Proceedings of International Conference on Simulation Modeling and Programming for Autonomous Robots (SIMPAR)* (pp. 41-49). Venice, Italy.

Levy, S., & Mioduser, D. (2008). Does it ''want'' or ''was it programmed to…''? Kindergarten children's explanations of an autonomous robot's adaptive functioning. *International Journal of Technology and Design Education*, 18(4), 337–359.

Newell, A., & Simon, H.A. (1972). *Human problem solving*. NJ: Englewood Cliffs Prentice.

Papert, S., & Harel, I., (eds.) (1991). *Constructionism*. NJ: Ablex Publishing Corporation.

Pea, R.D., & Kurland, D. (1984). On the cognitive effect of learning computer program. *New Ideas in Psychology*, 2(2), 137-168.

Piaget, J. (1972). *The principles of genetic epistemology*. London: Routledge & Kegan Paul.

Rada, R., & Michailidis, A. (1995). *Interactive media*. New York: Springer-Verlag.

Resnick, M., Martin, F., Sargent, R., & Silverman, B. (1996). Programmable bricks: Toys to think with. *IBM Systems Journal*, 35(3-4), 443-452.

Ribeiro C., Coutinho, C., & Costa, M.F. (2011). Proposal for the evaluation of educational robotics in basic schools. *Proceedings of International Study Association on Teachers and Teaching (ISATT)* (pp. 831-839). Rose, E. (1999). Deconstructing interactivity in educational computing. *Educational Technology*, 39(1), 43-49.

Sfard, A. (1991). On the dual nature of mathematical conception: reflection on processes and objects as different sides of the same coin. *Educational Studies in Mathematics,* 22, 1-36.

Sullivan, F. V. (2008). Robotics and science literacy: Thinking skills, science process skills and systems understanding. *Journal of Research in Science Teaching*, 45(3), 373-394.

Svanæs, D. (2000). *Understanding Interactivity: Steps to a Phenomenology of Human-Computer Interaction*. Unpublished PhD thesis. NTNU, Norway, Retrieved 5 November 2012, http://tinyurl.com/und-int.

Yacci, M. (2000). Interactivity Demystified: A Structural Definition for Distance Education and Intelligent CBT. *Educational Technology*, 40(4), 5-16.

Zuga, K. (2004). Improving technology education research on cognition. *International Journal of Technology and Design Education*, 14, 79-87.

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