ISBN: 978-989-8704-52-8

THE EFFECTS OF AGE AND LEARNING WITH EDUCATIONAL ROBOTIC DEVICES ON CHILDREN'S ALGORITHMIC THINKING

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ABSTRACT

Educational Robotics is increasingly used in elementary-school classrooms to develop students' algorithmic thinking and programming skills. However, most research appears descriptive and lacks experimental evidence on the effects of teaching interventions using robotics to develop algorithmic thinking. Using the robots Dash and Dot, this study examined algorithmic thinking development in groups of children aged 6, 9, and 12. The results showed a statistically significant main effect between the age of students and algorithmic thinking skills and a statistically significant main effect between intervention and algorithmic thinking. In conclusion, the findings underscore the necessity of providing learners with structured, scaffolded activities tailored to their age to effectively nurture algorithmic thinking skills when engaging in Dash and Dot activities.

KEYWORDS

Algorithmic Thinking, Robotics, Dash and Dot, Young Children

1. INTRODUCTION

In an increasingly technology-driven job market, algorithmic thinking and programming skills are in high demand (Semeraro, Griffiths, & Cangelosi, 2023). Early exposure equips students with essential tools for future careers in STEM-related fields. Developing algorithmic thinking and programming skills in elementary education is thus becoming increasingly recognized as a crucial aspect of preparing students for the digital world they will navigate.

A promising area for developing algorithmic thinking is the rapidly developing field of Educational Robotics (ER). Multiple studies found that robotics activities facilitated the development of algorithmic skills in young learners in various formal and informal learning contexts (Author). Hence, ER is increasingly used in primary classrooms to create interactive and engaging learning environments for developing algorithmic thinking in children (Su & Yang, 2023). Nonetheless, while the existing body of research includes a large number of descriptive studies reporting on children's interactions with robots (Merino-Armero et al., 2022), the field lacks systematic evidence on the experimental design and effects of interventions on the teaching of algorithmic thinking considering learners' age.

To this end, the study sought to examine the development of algorithmic thinking skills of 146 primary-school children aged 6, 9, and 12 during problem-solving activities with the robotic devices Dash and Dot within the context of two teaching interventions and a control group. Accordingly, the research sought to answer the following questions:

1. Given their initial performance on the pretest, did teaching intervention differentially affect children's performance on algorithmic thinking tasks?

2. Given their initial performance on the pretest, did age differentially affect children's performance on algorithmic thinking tasks?

3. Given the initial performance on the pretest, was there an interaction effect between teaching intervention and age on children's performance on algorithmic thinking tasks?

2. THEORETICAL FRAMEWORK

Algorithmic thinking involves breaking down complex problems into smaller, manageable steps (decomposition), designing step-by-step procedures to accomplish a task (algorithms), and debugging (recognition and correction of errors) (Sengupta et al., 2013). Algorithmic thinking also involves iterative problem-solving, where individuals test and refine their algorithms based on feedback and outcomes (Sengupta et al., 2013). In computer science, algorithmic thinking is fundamental to programming and computational problem-solving.

The framework for teaching algorithmic thinking leverages educational robots to enhance students' computational thinking skills and problem-solving abilities. This approach involves engaging students in hands-on activities where they program the robot to perform specific tasks and follow sequences of actions. This practical approach allows students to see the direct impact of their code on the robot's behavior, fostering a deeper understanding of algorithmic thinking (Hsu et al., 2019). Providing scaffolding and differentiated instruction is crucial in supporting students' learning.

In this study, the authors examined the effects of two teaching interventions with different types of scaffolds to develop elementary-school students' algorithmic thinking skills. Scaffolds included programming Dash with the help of Dot and Blockly, a programming application, and embodied learning activities facilitated by the researcher and Dot to teach about algorithmic thinking skills by performing bodily movements.

3. METHOD

3.1 Participants

One hundred forty-six participants aged 6, 9, and 12 participated in this study. The participants were recruited from different private and public schools in rural and urban areas in a European country. The participants' parents provided consent forms before their children participated in the research, and permission for the research was granted. All the participants had no previous experience with programming nor learning with the robots Dash and Dot.

3.2 Teaching Interventions

Each age group was randomly assigned into two intervention groups and a control group. Children participated in a 3 (age 6, 9, 12) X 3 (groups Dash and Dot, Dot and Researcher, Control) research design study. Group A (GA) and Group B (GB) formed the experimental groups, and Group C formed the control group (CC). The two teaching interventions involved problem-solving tasks by using robots. The CC had to execute the same tasks without receiving any teaching intervention. Each child worked individually in all phases of the research. In GA, children interacted with Dash and Dot and were guided by Dot on how to program Dash, using the Blockly application, to make Dash execute a task. In GB, children followed instructions given by Dot and interacted with the researcher by performing various bodily movements to form algorithms. On the contrary, the CC children had to explore Dash and Dot alone in a free-style play activity.

3.3 Research Materials

GA used Dash and Dot, the iPad applications *Go* and *Blockly*, and a city-mat for Dash to execute the tasks. GB children only had the mat and Dot at their disposal. In this group, the researchers used printed arrow cards to explain the steps in writing an algorithm. The students in the CC used Dash and Dot in an exploratory free-play fashion to discover their functions. The researcher used specific scripts for all phases to ensure consistent data collection and kept a researcher diary.

3.4 Dash and Dot Robots

Dash and Dot, shown in Figure 1, are two different robots with different features. Dot is a smaller robotic device with a spherical blue shape, one eye and two ears. Dot can speak, change eye and ears color, make noises, and reproduce recordings through programming using *the Go* application. Dash is larger than Dot, has a blue color, and has the shape of four spherical parts - three parts on the bottom and one part on the top. The robot has one eye and two ears on its head, which can change colors through programming. Dash can be programmed using the *Blockly* application.

Figure 1. Dash and Dot

3.5 The Mat and Problem-Solving Tasks

Students in all three groups solved the same tasks. All tasks involved using a floor mat, visually representing a city with various locations such as a school, post office, bank, department store, playground, and residences. Students had to figure out the commands of a path to move from one location to another. Participants in the Dash and Dot group followed instructions from Dot to program Dash to move from one location to another. Students in the Dot group used Dot as a buddy to instruct them to walk using their bodies on the mat and move from one location to another. Finally, students in the control group followed written instructions on a script to move on the mat from one location to another in a free-style play activity.

3.6 Instruments

All participants completed a pretest before the interventions and a posttest at the end of the study. The time allowed to complete the test on each occasion was 30-min. The pretest and the posttest were the same and consisted of four sections on aspects of algorithmic thinking. Each part had two different problem-solving subtasks. The first part evaluated sequencing, the second part evaluated decomposition, the third part focused on the skill of debugging and the fourth part on the skill of repetition (control flow).

3.7 Research Procedures

Data collection for the experimental groups was completed in three phases: A, B, and C. The control group completed only phases A and C. Phase A lasted for 20 minutes and was an exploration phase for all children to become familiar with the materials and the robots. Phase B was the intervention phase for GA and GB and lasted for 40 minutes. GA children were instructed by Dot how to use the application *Blockly* to write and code algorithms so that Dash can execute a task. On the contrary, GB children followed instructions by Dot and the researcher and used bodily movements by stepping and moving on the mat to simulate the algorithm and used printed arrow cards to visualize the steps of the algorithm. Finally, phase C was the assessment phase for all groups (30 minutes). Children were asked to write the steps of an algorithm or show the steps of the algorithm using the printed cards. For each phase, the researcher recorded the child's number of efforts to develop the correct algorithm and the extent to which the child used the skills of decomposition and debugging.

4. RESULTS

The researchers developed the rubric shown in Table 1 to assess participants' algorithmic thinking. The rubric evaluated the solutions participants proposed for each problem-solving task, considering various factors such as the number of failing attempts, decomposition of commands, and debugging. Analytically, children's algorithmic thinking was assessed based on the correctness of their sequences of instructions expressed in *Blockly* command language (i.e., *MOVE FORWARD*, *MOVE BACKWARD*, *TURN LEFT*, *TURN RIGHT*, *REPEAT)* and other symbolic systems they used to express the steps of an algorithm. Table 1 shows the rubric that emerged from the inductive data analysis.

Table 1. Algorithmic thinking rubric

Code	Description	Points received
1	Success without decomposition from first attempt	21
2	Success with decomposition into two from first attempt	20
3	Success with decomposition into three from first attempt	19
4	Success with decomposition into four from first attempt	18
5	Success without decomposition from second attempt	17
6	Success with decomposition into two from second attempt	16
7	Success with decomposition into three from second attempt	15
8	Success with decomposition into four from second attempt	14
9	Success without decomposition from third attempt	13
10	Success with decomposition into two from third attempt	12
11	Success with decomposition into three from third attempt	11
12	Success with decomposition into four from third attempt	10
13	Success without decomposition from fourth attempt	9
14	Success with decomposition into two from fourth attempt	8
15	Success with decomposition into three from fourth attempt	7
16	Success without decomposition from fifth attempt	6
17	Success with decomposition into two from fifth attempt	5
18	Success with decomposition into four from fifth attempt	4
19	Success with decomposition into three from sixth attempt	3
20	Success without decomposition from seventh attempt	2
21	Success with decomposition into two from seventh attempt	1

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Table 2 shows descriptive statistics for students' scores on the pretest, posttest, and the tasks in the third phase of the research. As shown in Table 2, 12-year-old students' scores were higher than all other scores, whereas 6-year-old students' scores were the lowest. Also, as shown in Table 2, students in the Dash and Dot group outperformed all other groups.

Table 2. Descriptive statistics for pretest, posttest and performance in Phase 3

	Intervention											
	Dash and Dot			*Dot and Researcher*			*Control*			*Total*		
	Pretest											
Age	*Mean*	*SD*	*n*	*Mean*	*SD*	*n*	*Mean*	*SD*	*n*	*Mean*	*SD*	*n*
6 years	9.40	3.16	24	8.91	3.12	28	8.33	3.28	18	8.93	3.15	70
9 years	11.75	3.35	16	10.75	2.83	14	10.47	3.91	15	11.01	3.37	45
12 years	11.70	3.22	10	10.06	2.21	9	12.83	2.32	12	11.66	2.78	31
Total	10.61	3.38	50	9.62	2.97	51	10.24	3.70	45	10.15	3.35	146
	Posttest											
Age	*Mean*	*SD*	*n*	*Mean*	*SD*	*n*	*Mean*	*SD*	*n*	*Mean*	*SD*	*n*
6 years	11.02	3.34	24	9.96	3.48	28	9.51	4.01	18	10.21	3.58	70
9 years	13.97	2.26	16	12.93	2.32	14	12.60	3.09	15	13.19	2.60	45
12 years	14.75	1.51	10	12.78	2.39	9	13.83	1.99	12	13.82	2.07	31
Total	12.71	3.16	50	11.27	3.31	51	11.69	3.70	45	11.89	3.42	146
	Phase 3 performance											
Age	*Mean*	*SD*	*n*	*Mean*	*SD*	*n*	*Mean*	*SD*	*n*	*Mean*	*SD*	*n*
6 years	332.67	45.79	24	311.96	62.51	28	286.72	72.69	18	312.57	62.01	70
9 years	360.75	24.19	16	368.71	31.33	14	315.33	64.22	15	348.09	48.59	45
12 years	363.00	38.91	10	343.78	28.55	9	335.25	37.77	12	346.68	36.58	31
Total	347.72	40.69	50	333.16	55.87	51	309.20	64.15	45	330.76	55.95	146

A MANCOVA was then conducted to examine whether there were statistically significant differences in the phase 3 performance and scores on the posttest between the three age groups across all three research groups taking into consideration the scores on the pretest. The results showed that performance on the pretest was a statistically significant covariate for both phase 3 performance ($F(1, 146) = 10.47$, $p<.05$) and posttest scores ($F(1, 146) = 117.46$, $p<.05$). The results also revealed statistically significant differences between the three age groups for both phase 3 performance ($F(2,146) = 4,81$, $p<.05$), and posttest scores ($F(2, 146) = 9.58$, $p<.05$). In regards to the age differences on phase 3 performance, 12-year-old-students, and 9-year-old-students outperformed 6-year-old-students. Regarding statistically significant differences in the posttest performance, the same results were observed, namely that 12-year-old students and 9-year-old students outperformed 6-year-old students.

The results also revealed statistically significant differences between the two interventions and the control group for both phase 3 performance ($F(2,146) = 7,40$, $p<.05$) and posttest scores ($F(2, 146) = 2.31$, $p<.05$). Specifically, the Dash and Dot group outperformed all other groups, and the Dot and Researcher group outperformed the control group.

5. DISCUSSION

The study's findings demonstrated statistically significant main effects between the age of students, intervention, and algorithmic thinking. The findings concur with recent research on robotics activities with Dash and Dot that reported on the importance of structured, scaffolded activities over free play in fostering algorithmic thinking skills. For example, a study by Mabie, McGill, and Huerta (2023) found that learners engaged in structured, scaffolded activities with Dash and Dot showed notable improvements in algorithmic thinking abilities. In contrast, learners participating in free-play activities demonstrated limited progress in algorithmic thinking. This finding is also consistent with a study by De Santo et al. (2022), which emphasized the significance of scaffolded interventions in enhancing algorithmic thinking skills in robotics.

Additionally, age has been identified as a critical factor influencing the development of algorithmic thinking skills with Dash and Dot. The study's findings align with the research findings reported by Kanaki and Kalogiannakis (2022), revealing that older learners showed higher levels of algorithmic thinking proficiency as their cognitive capabilities and problem-solving strategies matured with age.

In conclusion, these findings underscore the necessity of providing learners with structured, scaffolded activities tailored to their age to effectively nurture algorithmic thinking skills when engaging with robotics activities involving Dash and Dot. Educators can utilize these findings to design age-appropriate curricula and instructional strategies, promoting meaningful learning experiences that empower students in their technological journey.

6. CONCLUSION

In the dynamic interplay between technology and education, robots like Dash and Dot offer a glimpse into the future of learning. However, to harness their full potential, a structured approach is crucial. Scaffolded interventions, tailored to children's needs and paced to their learning trajectories, ensure that algorithmic thinking isn't just a buzzword but a tangible skill that they internalize and carry forward. In this blend of technology, pedagogy, and structured support, lies the promise of an empowered generation, ready to navigate and shape the digital landscapes of the future.

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