Title: Peer tutoring of computer programming increases exploratory behavior in children

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1 **ABSTRACT**

2 There is growing interest to teach computer science and programming skills at schools. Here we
3 investigate the efficacy of peer-tutoring which is known to be a useful educational resource in other
4 domains, but never before examined in such a core aspect of applied logical thinking in children.
5 We compared (1) how children learn computer programming from an adult vs learning from a peer,
6 and (2) the effect of teaching a peer vs simply revising what has been learned. Our results indicate
7 that children taught by a peer showed comparable performance to their classmates taught by an
8 adult. However, learning from a peer promoted a more exploratory behavior, resulting in a less
9 conservative speed-accuracy trade-off, with shorter response times, at the expense of lower
10 accuracy. By contrast, no effects of teaching were found. Our results thus provide empirical
11 evidence in support of peer tutoring as a way to help teaching computer programming to children.
12 This could contribute to the promotion of a widespread understanding of how computers operate
13 and how to shape them, essential to our values of democracy, plurality and freedom.

14

15

16 **SIGNIFICANCE STATEMENT**

17 Computer programming is a skill so important to our world today that it has even been called a new
18 literacy, fundamental to the free and full exercise of our digital lives. However, although children
19 are skilled computer users, they do not necessarily understand how computers work.

20 For these reasons there is a growing interest to teach these skills at schools. However, properly
21 trained teachers are lacking, and it is not yet clear what teaching methods are better in which
22 circumstances. Empirical evidence is crucial for proper decision making in education. In this study
23 we therefore explore peer tutoring as an inexpensive way of teaching this fundamental skill, and
24 provide evidence of its effectiveness.

25

26 **INTRODUCTION**

27 Today's world is flooded by digital technologies. Computers surround us, in permanent and
28 increasing communication among them. This ever growing computer network is deeply intertwined
29 with our social network and underlies many aspects of our societies today (1–3). With computers at
30 the foundations of our worldwide society, understanding how they operate and how to shape them
31 turns us from passive into active actors (4) and is fundamental for freedom (5). Computer

32 programming is the way we, humans, have to communicate with these machines, and the networks
33 they belong to, and control what they do. It consists in designing and building sets of instructions
34 interpreted by a computer to accomplish a specific task (2, 6, 7). There is a variety of languages for
35 computer programming, and understanding them is becoming increasingly important (2, 8, 9). In
36 addition, learning to code not only improves computer programming skills, but there is evidence
37 that it also transfers to other general cognitive skills, such as creativity, spatial cognition,
38 mathematical skills, and reasoning (2, 4, 10, 11).

39 Children become software and hardware consumers earlier and earlier (12). However, being digital
40 native is not necessarily accompanied by learning how these technologies work (13). As a result,
41 there is growing interest in integrating programming courses at all educational levels (14, 15). It has
42 even been considered a new literacy, just like reading or math (8, 16–18), and many schools,
43 districts and countries have acknowledged the importance of including computer programming in
44 their curricula (2, 19–23). But, teaching children this new literacy is not an easy endeavor. Recently,
45 new programming languages have emerged which creatively managed to reduce the syntactic and
46 semantic difficulties of traditional ones (24), to the point of becoming completely visual. These
47 visual languages let users manipulate program elements graphically rather than specifying them
48 textually, and thus are particularly suitable for children (4, 25). However, teaching to code still
49 poses some difficulties on its own, such as the variability of teaching methods, without a clear
50 understanding of which are useful in what contexts; a lack of teaching standards and of trained
51 teachers (2); and a long tradition of Information Technology classes that focus on softer computer
52 skills instead, such as word processors, spreadsheets and other office tools (2, 4, 26).

53 There is no perfect recipe for learning a new skill. Whereas learning from a knowledgeable teacher
54 in a traditional setting promotes rapid and efficient learning, it also limits spontaneous exploration
55 and discovery (27). On the other hand, learning from a peer, or peer tutoring, has been shown to
56 benefit tutees as well as tutors (28–30) in a variety of knowledge domains (31, 32), and it is among
57 the most cost-effective teaching strategies (33). However, research in peer tutoring is not free of
58 contradictions. Results are highly variable, and they depend on a multitude of factors, such as the
59 targeted subject matter, the age of the participants, the availability and frequency of tutor training,
60 among many others (34). In addition, most studies have focused on math and reading, and although
61 peer tutoring has proved useful across all educational levels, the largest effects are usually found in
62 secondary school (34).

63 Collaborative approaches have also been considered by the software industry. Pair programming,
64 for example, is a practice which involves two developers collaborating as a single individual on the

65 design, coding and testing of the same programming task. This practice has been shown to be
66 productive and to render higher quality code than either developer may produce alone (35–39),
67 especially with novice programmers or challenging programming problems (35); and positive
68 effects have been found in educational contexts as well (40, 41). Another popular practice involves
69 explaining line by line what a nonworking piece of code is supposed to do. This forces the
70 programmer to clarify and structure the explanation, helping him or her to find where the cause of
71 the problem is. This technique would even work when the code is explained to an inanimate object,
72 and it is usually referred to *rubber duck debugging* (42, 43).

73 Given the increasing importance attributed to learning to code, the growing interest to teach
74 computer programming from elementary school and even kindergarten, the recognized effectiveness
75 of peer tutoring in a variety of fields, and the experience from the software industry, it is surprising
76 that no previous studies have been made about peer tutoring of programming languages in children
77 and how it can help tackle some of the difficulties of teaching to code. Peer tutoring is particularly
78 appealing in this field, given that children are digital natives and sometimes they even outperform
79 some of their teachers in this subject matter (26).

80 In this study, we address peer tutoring as a way to help teaching programming languages to
81 children. To this end we use a custom adaptation of a programming platform designed for them.
82 First, we study whether children can teach other children to program by comparing coding skills
83 and resolution strategies developed by (i) children who were taught by an adult, and (ii) children
84 who learned from a peer. On the other hand, we also look into whether children benefit from having
85 to teach, by comparing (i) children who taught a naive peer, and (ii) children who revised the
86 teaching materials alone. Our results provide empirical evidence in support of peer tutoring to help
87 teaching programming languages to children.

88

89

90 **RESULTS**

91 **Effect of learning conditions**

92 In this study, some children were taught by an adult instructor in a group lesson (adult-taught
93 children), whereas others were taught by a peer in a one-to-one lesson (peer-taught children). First,
94 the effects of these two learning conditions on learning were evaluated. To do so, aggregate score in
95 the test stage was compared between groups; i.e., the sum of accuracies from all trials, regardless of
96 whether they were attempted and finished or not, in the 20 minutes available. A two-way analysis of

107 covariance (ANCOVA) was run, with group (i.e., *adult-taught* and *peer-taught* groups) and gender
108 as factors, and age as covariate. Children who were taught by a peer in the peer-tutoring stage
109 (*peer-taught* group), 68% CI [3.80, 4.61], performed equally well than children taught by an adult
100 instructor in the instruction stage (*adult-taught* group), 68% CI [3.62, 4.09], $F(37, 1)=.510$, $p=.480$
101 (Figure 1).

102

103 [Insert Figure 1]

104

105 Then, performance was analyzed trial by trial. In the 20 minutes available in the test stage, children
106 could spend as long as they decided on any one of the 10 trials, thus affecting the proportion of
107 trials finished. In addition, the trials differed in complexity (with later trials being more complex)
108 and trial complexity would presumably influence trial accuracy. Therefore, to compare the average
109 trial accuracy between subjects without bias, it was important to use only trials which were finished
110 by most subjects in all groups. Trials were hence divided into three even trial blocks: 1-3, 4-7 and 8-
111 10. On average, subjects finished almost all trials in the 1-3 trial block (on average, 94% for adult-
112 taught children, and 98% for peer-taught children), thus this block was selected to study
113 performance on a per trial basis. In the 4-7 trial block, in contrast, not only was the average
114 proportion of finished trials lower, but it was also significantly lower for adult-taught children, 68%
115 CI [0.33, 0.45], than for peer-taught children, 68% CI [0.57, 0.73], as shown by a Kruskal-Wallis
116 test, $H(1)=5.510$, $p=0.019$ (Figure 2A, left). In fact, peer-taught children spent significantly less
117 time per trial (seconds) in trial block 1-3, $n=13$, 68% CI [113.94, 138.24], than adult-taught
118 children, $n=25$, 68% CI [172.43, 201.24], as shown by a three-way ANCOVA, with group and
119 gender as between factors, trial as within factor, and age as covariate, $F(1, 33)=7.601$, $p=.009$
120 (Figure 2A, right). The fact that peer-taught children spent less time per trial (around 60 seconds
121 less) in trial block 1-3 may explain why they finished more trials in the 4-7 block.

122

123 [Insert Figure 2]

124

125 In contrast, peer-taught children were significantly less accurate per trial (trial accuracy), 68% CI
126 [0.62, 0.69], than adult-taught children, 68% CI [0.75, 0.79], in trial block 1-3, as shown by a two-
127 way ANCOVA, with group and gender as factors, and age as covariate, $F(36, 1)=9.065$, $p=.005$.

128 This speed-accuracy trade-off, with lower trial times -which result in more finished trials (Figure
129 2A)- countered by lower trial accuracies (Figure 2B), may explain why peer-taught children's
130 aggregate score was indistinguishable from adult-taught children's (Figure 1).

131 In summary, from the perspective of aggregate score –i.e., the sum of the accuracy from all trials–
132 children who were taught by a peer were indistinguishable from children who were taught by an
133 adult in a group lesson. However, a closer look reveals that in fact peer-taught children were faster,
134 spending less time per trial and thus finishing more trials per session, although less accurate, with
135 lower trial accuracy.

136

137 **Teaching effect**

138 Our second hypothesis argued that children would benefit from their role as tutors. To examine this,
139 after evaluating them for the first time in the test stage, some of the children (tutors) who had
140 learned from an adult were asked to teach a naive classmate, whereas others were asked to revise
141 the instruction materials alone (controls). Finally, both groups were evaluated again in the retest
142 stage (see Methods section). To compare aggregate score between stages (test and retest) and groups
143 (controls and tutors), a repeated measures three-way ANCOVA was done, with group and gender as
144 between factors, stage as within factor, and age as covariate. A significant stage effect was found,
145 with aggregate score increasing from test to retest for both controls (test: 68% CI [3.83, 4.25],
146 retest: 68% CI [5.44, 6.04]), and tutors (test: 68% CI [3.33, 4.09], retest: 68% CI [4.84, 5.68];
147 $F(1,22)=54.978$, $p=2.04E-07$). However, we found no significant interaction between stage and
148 group, $F(1, 22)=.207$, $p=.654$ (Figure 3). Hence, the increase in aggregate score does not seem to
149 have emerged as a result of teaching a peer, but rather due to a retest effect and/or an effect of
150 revising the instruction materials (either in pairs or alone).

151

152 [Insert Figure 3]

153

154 A detailed analysis revealed that this increase in aggregate score in both groups was not only due to
155 a small increase in mean trial accuracy, but mainly due to a decrease in total trial times, which thus
156 led to more finished trials (see Supplementary Results 1).

157 In short, although children improved from test to retest, this improvement was not tied to teaching a
158 peer and thus it was the same for controls and tutors.

159

160

161 **DISCUSSION**

162 In this study we approached the problem of teaching programming languages to children by
163 considering the potential role of peer tutoring. We studied both whether children could learn a
164 programming language from a peer; and if children would benefit from teaching others. To do so,
165 we examined their performance in a series of programming tasks.

166

167 *Learning from a peer*

168 To test whether children could learn from a peer, we first compared adult-taught and peer-taught
169 children on their aggregate score. Aggregate scores are regularly used in school tests, where
170 children are given a certain number of questions, and they have a fixed amount of time to answer
171 them all. At the end, the question scores are summed up, so that not only does it matter how well
172 children responded each question, but also how many they managed to respond. In this scenario, a
173 question left blank due to lack of time gets zero points, just as a question left unanswered because
174 of lack of the necessary knowledge. Analogously, our first approach to measure performance
175 involved aggregating accuracy scores along 10 trials of a programming task, irrespective of whether
176 children managed to try them or not in the 20 minutes they had available. Remarkably, according to
177 this first coarse measure of performance, children who were taught by a peer performed as well as
178 children taught by an adult.

179 But this result does not necessarily mean that adult-taught and peer-taught children are
180 indistinguishable. Therefore, a finer grained approach to performance was taken, examining trial
181 accuracy and trial time separately. With this approach children were found to differ in their speed-
182 accuracy trade-off: peer-taught children seem to have adopted a less conservative strategy, with
183 faster response times than their adult-taught classmates, but at the expense of lower trial accuracies.
184 This finding is surprisingly similar to a previous study showing that, when facing a stronger
185 opponent, chess players adopt a more conservative strategy (44). According to the regulatory focus
186 theory (45), people can be set in a *promotion mode*, where focus is on seeking to approach a desired
187 state (such as winning a chess game or, in our case, successfully solving a programming task), or in
188 a *prevention mode*, where focus is on avoiding undesired states instead (e.g. making mistakes). In
189 promotion mode, people would be eager to achieve the desired state, increasing speed and
190 decreasing accuracy (44). By analogy with how instruction can change exploratory policies in

191 children, limiting spontaneous exploration and discovery (27), our results could be interpreted using
192 the regulatory focus theory. Under this framework, adult-taught children, who learned from a much
193 more knowledgeable and authoritative figure, could have adopted the prevention mode, reflecting a
194 cautious way of playing and avoiding errors, whereas peer-taught children could have been set in
195 promotion mode instead, taking more risks through trial and error. We speculate, then, that these
196 results may suggest that children taught by a peer may develop a different understanding of how to
197 use new knowledge, which could be some kind of interaction between peer-tutoring and children's
198 epistemic beliefs. This may have resulted from different expectations as to why they were learning
199 first, and why they were playing later. Children taught by an adult may have expected to be
200 evaluated, whereas children taught by a peer may have expected they would just play. Future
201 studies manipulating children's expectations may help further understand these results.

202 Although hasty decisions often lead to poor choices, accurate decisions are ineffective if they take
203 too long (46). For example, adopting a conservative strategy against a stronger opponent actually
204 reduces the chances to win in chess (44). So, what is the best speed-accuracy trade-off? It would
205 probably depend on the situation at hand whether to prefer teaching methods that promote the more
206 conservative prevention mode, with a focus on avoiding mistakes, or methods that promote the less
207 conservative promotion mode, focusing on results instead and allowing some trial and error.

208 Also, it is worth considering some limitations of our experimental approach. First, as children could
209 have learned the basics of the language while they were taking the test, it is possible that the peer-
210 taught condition was merely a non-adult-taught condition, indistinguishable from children not
211 taught at all. To evaluate this possibility, we conducted a complementary study where we compared
212 two conditions: (1) peer-taught vs (2) non-taught children, and successfully found that children
213 taught by a peer were significantly more accurate than children not taught at all (see Supplementary
214 Discussion 1). On the other hand, our experimental procedure was aimed at making the peer- and
215 adult-taught conditions as comparable as possible. For example, children taught their peers using
216 the exact same instruction materials used by the adult instructor. However, it is worth noting that
217 conditions differed not only in whether children were taught by an adult or by a peer, but also in
218 whether classes were in groups or one-on-one, respectively. It is a possibility that one-on-one
219 instruction would increase trial accuracy in adult-taught children (47), hence widening the
220 difference with peer-taught children.

221 Another aspect we wanted to examine was whether children exhibited different behaviors or
222 strategies depending on who had taught them, irrespective of their performance. For example, all
223 trial videos required children to clear any image or text in the programmable environment's virtual

224 screen at the end of their programs. To do so, children had to use the corresponding command
225 blocks with an empty argument (see Methods and Supplementary Methods 3). This was
226 demonstrated by the adult instructor in the adult-taught condition. Interestingly, while half the
227 children taught by an adult tried to reset the virtual screen in at least one of the programs they built,
228 no children taught by a peer did this. This is compatible with tutors not simply imitating their adult
229 instructors, but rather digesting the information provided to them, and then elaborating their own
230 teaching (48). Further analysis of the peer interactions should be conducted to support this
231 hypothesis.

232 In summary, our study shows that children can learn computer programming from a peer. Peer-
233 taught and adult-taught children were indistinguishable using aggregate scores such as those
234 frequently used in school tests. Nonetheless, children who learned from a peer showed a less
235 conservative speed-accuracy trade-off, with shorter response times, at the expense of lower trial
236 accuracy.

237

238 *The effect of teaching a peer*

239 Peer tutoring has been found to benefit not only tutees, but tutors as well (28, 29, 49, 50). However,
240 there is no clear consensus about the conditions under which this tutor effect is evident, and some
241 studies have failed to find it (31, 51, 52). Then, the effect of teaching on performance was
242 examined. Our design was aimed at making peer-tutoring and self-revision conditions as
243 comparable as possible, with the only two differences being (i) *social*: in one case children were
244 interacting with a peer, whereas in the self-revision condition they were alone; and (ii) *motivational*:
245 in one case the goal was to teach a classmate so she could play too, whereas in the other it was to
246 revise the material to perform better the next time. Our results showed that children improved their
247 aggregate score the second time they were tested. This increase was not only due to a small increase
248 in mean trial accuracy, but mainly due to shorter response times in retest, which in turn led to more
249 trials finished (Supplementary Results 1). However, this improvement was not significantly greater
250 for tutors than for controls, thus failing to support the tutor effect hypothesis on learning.

251 A variety of reasons may underlie our failure to identify a tutor effect on performance. First,
252 tutoring a peer has been hypothesized to help tutors metacognitively reflect upon their own
253 expertise and comprehension through explanation and questioning (52). However, although this
254 better understanding of their own knowledge could undermine subjects' confidence, it may not
255 immediately translate into learning benefits until they are given the chance to identify or construct a

256 correct answer. Therefore, tutors in our study may have become aware of gaps in their knowledge
257 while teaching, without having a chance to fill them before retest. Further studies including an
258 additional revision instance between peer-tutoring and retest stages could help test this hypothesis.
259 Second, some authors suggest that cognitive benefits of teaching actually result from expecting to
260 teach, rather than from teaching itself, and the associated greater effort to select the relevant
261 elements and organize them into a meaningful representation (49, 53, 54). Prompting this
262 expectation to teach before peer-tutoring may help test this hypothesis. Finally, two aspects of our
263 study may have biased tutors to unproductive knowledge-telling (52). On the one hand, although
264 there is evidence that tutor training is not necessary (28, 34), with some authors even proposing that
265 teaching is a natural cognitive skill (55–57), previous studies have shown that peer tutoring works
266 best if tutor training is provided (32). The fact that our study implied no tutor training on teaching,
267 may have led to unproductive knowledge-telling bias (52). On the other hand, even though the
268 availability of instruction materials makes our study a case of structured peer tutoring, which is
269 known to show greater benefits than unstructured tutoring (32), the presence of teaching materials
270 may have biased tutors to knowledge-telling as well, preventing them from learning by retrieval
271 (58).

272 In addition, as teaching may have an effect on long-term retention (52, 59–63), we evaluated all
273 groups again two years later. However, although most children reported that they remembered the
274 game, the performance was the same across groups, and indistinguishable from children who were
275 not taught at all (see Supplementary Discussion 2). Future studies in the field with shorter retention
276 times may help test this hypothesis as well.

277 In short, although our study failed to find beneficial effects of teaching on performance, no learning
278 impairment in tutors was found either. Future studies may help identify conditions under which the
279 effect of teaching on performance is evident, as well as other aspects it may contribute to.

280

281 *Can we talk about gender differences?*

282 Another aspect that emerged from our study was gender differences. Many studies have described
283 differences in performance and interest in technical domains between male and female participants
284 (64–66). Most (if not all) of these differences are the by-product of social convention stereotypes
285 (for example, see Beilock et al., 2010; Dar-Nimrod & Heine, 2006). In this study, we expected that
286 children may be free from these biases, given their young age and what we hoped to be a limited
287 cultural indoctrination regarding gender stereotypes. Nevertheless, we found that girls had lower

288 aggregate score than boys (see Supplementary Discussion 3). Similar results were found by Sullivan
289 and Bers (69) in a robotics program involving kindergarten children. However, a closer look at our
290 results revealed that their lower aggregate score was not because of lower trial accuracies, but rather
291 because they were slower and finished less trials (see Supplementary Discussion 3). This is in line
292 with previous findings that girls are less likely to take risks to achieve a goal when programming
293 with LOGO than boys, exhibiting a more cautious or careful approach to task solution (70), and
294 raises a sign of warning that apparent lower performance may hide equivalent accuracy.

295

296 *Final remarks*

297 Peer tutoring has been found useful in a wide variety of settings. However, results are highly
298 variable, and they depend on a multitude of factors, such as the targeted subject matter, the age of
299 the participants, the availability and frequency of tutor training, among many others (34). Given the
300 growing interest in teaching computer science at schools, it is surprising that peer tutoring of
301 computer programming in children has not been experimentally studied so far. Children are digital
302 natives and it is impossible to deny that most of the time they outperform their teachers in this field
303 (26). This makes peer tutoring of programming languages among children even more interesting to
304 complement traditional education at schools. Some studies have come close to the topic, but none of
305 them have made it the focus of their attention. For example, some studies have addressed attainment
306 of basic computer literacy by unattended groups of young children, but they have not covered
307 computer programming (71). On the other hand, there are a few studies about peer tutoring and peer
308 assessment of computer programming, but they focus on older -secondary school and college-
309 students (72, 73), and some of them are exploratory, not experimental (64).

310 Our study would be the first experimental study to focus on peer tutoring of programming
311 languages in children. It provides empirical results favoring peer tutoring as a complementary
312 means of teaching programming languages, bringing further evidence to how peer tutoring can help
313 promote learning in fields where learning is difficult to achieve (31). Interestingly, learning to code
314 not only improves computer programming skills, but there is evidence that it also transfers to other
315 general cognitive skills (2, 4, 10, 11, 17), some of which are collectively referred to as
316 Computational Thinking (74, 75). Our study therefore opens new possibilities in this research field
317 as well, which is far from settled and is still an ongoing effort (10). In addition, teaching computer
318 programming through peer tutoring may also result in benefits specific to peer tutoring, such as

319 metacognitive benefits (32), advantages in social and communication skills (76), and in affective
320 functioning (77).

321 Computers and computer networks lie at the foundations of our worldwide society. All in all, our
322 study contributes to the widespread understanding of how these foundations operate and how to
323 shape them, both essential to the values of democracy and plurality, as a way of freeing future
324 generations from the infertile grounds of technological dependency, and leading them toward
325 technological sovereignty instead.

326

327 **METHODS**

328 **Participants**

329 A total of 44 second graders (28 female) from a private medium-to-high-SES bilingual school in
330 Buenos Aires, Argentina participated in the study. Data from only two children (both female) had to
331 be eliminated, one because her test session had to be interrupted, and the other because she had
332 difficulties understanding the game. Ages of the 42 remaining children ranged from 7 years and 1
333 month to 8 years and 4 months, with a mean age of 7 years and 10 months. Sessions took place
334 outside of the classroom in a quiet room provided by the school for the purpose of this study.

335 All children's parents or legal guardians gave signed voluntary consent previously authorized by an
336 Ethical Committee - Comité de Ética de la Dirección de Investigación del Centro de Educación
337 Médica e Investigación Clínica "Norberto Quirno" (CEMIC), Unidad Asociada del CONICET,
338 Protocol N° 683.

339

340 **Programming platform**

341 The LEGO Education WeDo set (78) was used, marketed for children from seven years old (79),
342 and already used in previous studies with children around this age (80, 81). This programming
343 platform comprises (i) a programming language, (ii) a program editor, (iii) an interpreter and (iv) a
344 programmable environment. The programming language is a visual, icon-based language, similar to
345 MIT's Scratch Jr (82). It includes a series of blocks, each conveying a different command. In the
346 program editor, blocks are dragged from the blocks' panel onto the editor's canvas and snapped one
347 next to the other to build block sequences or programs (Figure 4A). These programs are read by the
348 interpreter to operate on the platform's programmable environment, which is comprised of (i) a
349 virtual screen, located near the top left corner of the computer's screen, (ii) the computer's speakers,

350 and (iii) a LEGO-brick physical robot built by us with a rotating arm, resembling a clock facing
351 upwards.

352

353 [Insert Figure 4]

354

355 The programming language can be understood as operating on five different variables, which
356 describe the state of the programmable environment at any one moment. (1) The image (img)
357 variable describes the image content of the environment's screen, and it can take values 1 to 20,
358 each representing a different image, or 0 for a white/empty image. (2) The text (txt) variable
359 describes the text content of the environment's screen, and it can take any string value given by the
360 user. (3) The position (pos) variable describes the position of the robot's arm in degrees, and it can
361 take values 0 to 360. (4) The rotation (rot) variable describes if the robot's arm is rotating and in
362 which direction, and it can take values +1, -1 or 0 for clockwise, counterclockwise or no rotation,
363 respectively. (5) The sound (snd) variable describes the sound being played by the computer's
364 speakers, and it can take values 1 to 20, each representing a different sound, or 0 for no sound.

365 The programmable environment is initialized with state [img=0, txt="" (empty string), pos=0,
366 rot=0, snd=0] for all trials. A two-sided cardboard catalog was printed with all images available and
367 their corresponding values (including 0 for white/empty image) on one side, and all sounds
368 (represented with icons) and their values, on the other (see Supplementary Methods 1).

369 Block sequences (programs) are built on the editor's canvas by attaching command blocks one next
370 to the other. Eight command blocks were available in this study; some of them (transitive) accept an
371 additional argument block attached below, to further define the command (see Supplementary
372 Methods 2). The interpreter reads block sequences from left to right and updates the state of the
373 programmable environment accordingly (Figure 4B). For example, the image block updates the img
374 variable when read by the interpreter. Changes in the programmable environment's state are referred
375 to as events.

376

377 **User interface**

378 For this study, we developed a user interface laying between the user and the WeDo programming
379 platform. Its purpose was to avoid undesired interactions with the platform, and to provide an

adequate frame, including a series of exercises or trials to evaluate participants' learning of the programming language (Figure 4A).

Regarding control of user interaction, to simplify the programming language, a limited subset of blocks from the editor's block panel was made available, while the rest were concealed and disabled behind the overlay interface. In addition, other undesired user interactions with the programming platform and with the computer's operating system were blocked, such as closing the program editor's block panel, the programmable environment's screen, or the programming platform altogether, adjusting the computer's volume, turning the computer off, among many others.

On the other hand, to provide an adequate evaluation frame, we also included a video player and a trial navigator (Figure 4A). The video player showed one video per trial, each presenting a series of events (changes in the programmable environment's state), which children had to reproduce programmatically by building block sequences (see Figure 4B and Trial videos section). The video player provided a play/pause button to start, pause and resume playback as many times as desired, and a reload button to restart playback from the beginning. The trial navigator included next and previous buttons to go back and forth through the trials as desired. Each time one trial was accessed through the trial navigator it was counted as one attempt for that trial, and block sequences placed on the editor's canvas were remembered between attempts of the same trial. Participants could reinitialize the programmable environment's state at any time with a reset button (Figure 4A).

As participants could go to the next trial at any moment, regardless of their performance, a self assessment screen was included to discourage compulsive "next-clicking". For each trial's first attempt, when the next trial button was clicked the user was presented with the self assessment screen for that trial. It asked the user if they were able to successfully copy the video of the trial they had just attempted, and provided three buttons with a traffic light icon each: "yes" (green light), "so so" (yellow light) and "no" (red light). If the user responded "yes", the self assessment screen was closed and the next trial (if any) was presented. If the user responded "so so" or "no", they were asked to confirm if they wanted to proceed to the next trial, or return to the previous trial instead.

The overlay user interface could be run in one of three modes: *introduction* and *training* modes, used in the *instruction* and *peer-tutoring/self-revision* stages; and *test/retest* modes, used in the *test* and *retest* stages (see Procedure section below, and Supplementary Methods 2).

Trial videos

412 Trial videos show a series of *events*, each involving one or more of the `img`, `txt`, `pos`, `rot` and
413 `snd` variables, which participants have to reproduce by building block sequences or programs
414 (Figure 4B). Trial videos contain: (i) a copy of the programmable environment's screen in the top
415 left corner, to indicate changes in the `img` and `txt` variables; (ii) an area in the top right corner
416 where the icons which represent sounds may appear, accompanied by their corresponding sound, to
417 indicate changes in the `snd` variable; and (iii) a top-view representation of the robot and its rotating
418 arm, to indicate changes in the `pos` and `rot` variables. All videos start with the programmable
419 environment's initial state [`img`=0, `txt`="", `pos`=0, `rot`=0, `snd`=0]; the first event occurs at 1
420 seconds and the remaining every 2 seconds (see Figure 4B for an example; full videos available in
421 <blinded>).

422 In test and retest stages, 10 videos were presented in the same order to all participants, and showing
423 increasingly complex series of events (see Supplementary Methods 3). Videos in retest were
424 isomorphic to videos in test, meaning they showed events involving the same variables but with
425 different values, to promote engagement (83). For example, if the second event in test video 3
426 involved changing `img` from 0 to 5 (image of the woods), then the second event in retest video 3
427 involved a change in `img` as well, but from 0 to 7 (image of a desert), instead.

428

429 **Procedure**

430 *Instruction stage.* First, two thirds of the participants in each class were assigned to the adult-taught
431 condition (n=27). In same-class mixed-gender groups of four to five children, they were given a 20-
432 minute tightly scripted lesson by an adult instructor. Children sat at the table one next to the other,
433 facing a notebook's screen, with the instructor standing to their left. The lesson consisted of two
434 parts. In the first part, the basics of the programming language were taught, following a 23-page
435 instruction book (see Supplementary Methods 1) and using the user interface in *introduction* mode,
436 without video player or trial navigator. The robot remained out of sight to avoid distractions, until it
437 was revealed by the instructor when necessary. In the second part, the user interface was used in
438 *training* mode and two example trials were presented. The adult instructor paused the sample videos
439 on each of the *events* and built the block sequence that reproduced them. At the end of each trial, the
440 correct solution was shown in an examples' book (see Supplementary Methods 1) and checked
441 against the sequence built. Mouse, keyboard and instruction materials were under sole control of the
442 adult instructor in both parts.

443 *Test stage.* Then, on average 4 days later (min=2, max=7) children taught by an adult were
444 evaluated individually on 10 trials, with the user interface in *test* mode. Following a tight script, the
445 participant was told she had to use the blocks from the editor's block panel to copy what appeared
446 in the videos. The video player, trial navigator and self assessment buttons were explained as well.
447 Then, the researcher gave the participant the images and sounds catalog (see Supplementary
448 Methods 1), opened trial 1, and left the room. The researcher reentered the room when the session
449 was over, 20 minutes later, and rapidly reviewed the child's responses by simply congratulating the
450 participant for her work in each trial, without giving extra feedback about her performance.

451 *Peer-tutoring / self-revision stage.* Next, adult-taught children were divided into two groups of
452 equivalent performance: tutor (n=15) and control (n=12) groups. A third group included children
453 who had not participated in the preceding *instruction* and *test* stages: peer-taught group (n=15).
454 Children in the tutor group were paired with same-gender classmates of the peer-taught group, and
455 were asked to teach their peer so she could play as well (peer-tutoring condition; 7 days after test
456 stage, on average). The tutor was given the same instruction materials used by the adult instructor in
457 the *instruction* stage, and up to forty minutes were provided (see Supplementary Methods 2). On the
458 other hand, children in the control group were asked to revise the instruction materials on their own
459 so they would play even better next time (self-revision condition; 7 days after test stage, on
460 average). The procedure ensured that the self-revision condition was as similar as possible to the
461 peer-tutoring condition, with the only differences being (i) social: individual vs paired, and (ii)
462 motivational: revising to improve performance vs teaching to let a peer play as well.

463 *Final stage.* In this stage, all children were evaluated. *Peer-taught children's test:* Peer-taught
464 children were evaluated for the first time, with the same test that their peers were given in the *test*
465 stage. On average, this took place 5 days after being taught by a peer (min=2, max=7). *Adult-taught*
466 *children's retest:* On the other hand, controls and tutors were evaluated for the second time with the
467 user interface in *retest* mode. Trial videos in this mode were different but isomorphic to videos in
468 the *test* mode (see Trial videos section). On average, this took place 9 days after peer-tutoring for
469 tutors, and 8 days after self-revision for controls.

470

471 **Performance**

472 Accuracy was calculated for each trial by quantifying the difference between (i) the block sequence
473 built by the participant and (ii) the correct sequence for that trial; i.e., the shortest block sequence
474 which recreated the series of events portrayed in the trial video (see Supplementary Methods 3). To

do so, the Levenshtein distance was used, which counts the number of steps to go from one sequence to another; i.e. the number of blocks that have to be removed or inserted (84, 85). In general, the sequence at the end of a trial's last attempt was taken as the participant's response for that trial (see Supplementary Methods 2). If more than one sequence were available on the editor's canvas, the best matching sequence was used.

To easily measure the Levenshtein distance between sequences, command and argument blocks were translated into ASCII characters, according to a translation table (see Supplementary Methods 4), such that one block = one character. Levenshtein distances can take values from 0 to the sum of the lengths of the sequences being compared. To work with values which are independent from sequence lengths, the following ratio r was used:

$$(1) \ r = \frac{1-d}{\text{len}(\text{seq1}) + \text{len}(\text{seq2})},$$

where d is the Levenshtein distance between sequences seq1 and seq2, and len(seq) is the length of sequence seq. Ratio r ranges from 0, if seq1 and seq2 share nothing in common, to 1, if they match perfectly. See Supplementary Methods 2 for full details of the Levenshtein distance implementation used.

A trial was marked as "finished" if the following two conditions were met: (i) at least one block was dragged onto the editor's canvas in at least one of the trial's attempts, and (ii) the next trial button was clicked at least once in that trial. Two measures of performance were defined. The aggregate score is the sum of all trial accuracies, regardless of whether they were finished or not in the 20 minutes available per session. The mean trial accuracy, on the other hand, is the average accuracy across trials. To make sure that the mean trial accuracy unbiasedly represented children's intended responses, unfinished trials were excluded as time could have run out while children were still building their sequences, or even before attempting the trial at all. However, as trials have different difficulty, it was desired to calculate the mean trial accuracy using a set of trials finished by most participants. Therefore, only trials in the 1-3 trial block were used, as the mean proportion of finished trials in this block was above 90% for all groups.

501

502 **Trial time**

Trial time is the sum of the time (in seconds) spent in all attempts of a trial. As it is usually the case with response times, trial time distribution was positively skewed (86), and therefore its logarithm was used instead. Only trials in the 1-3 trial block were used to calculate mean trial time, as done

506 with mean trial accuracy (see *Performance* section), and sessions with one or more unfinished trials
507 in the 1-3 trial block were excluded (sessions from 2 tutors and from 2 peer-taught children).

508

509 **Data analysis**

510 Data and statistical analysis and visualizations were run with Pandas (<https://pandas.pydata.org/>),
511 Seaborn (<https://seaborn.pydata.org/>), StatsModels (<https://www.statsmodels.org/>), SciPy
512 (<https://www.scipy.org/>), afex (<https://afex.singmann.science/>), and other Python and R libraries,
513 using Jupyter Notebook (<https://jupyter.org/>).

514

515 **Data availability**

516 The data sets generated are available from the corresponding authors upon request.

517

518 **Ethical compliance**

519 All children's parents or legal guardians gave signed voluntary consent previously authorized by an
520 Ethical Committee - Comité de Ética de la Dirección de Investigación del Centro de Educación
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523

524

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537 **Figures**

538

539 **Figure 1.** Aggregate score.

540 Aggregate score is the sum of accuracies from all trials, including unattempted (with accuracy = 0).

541 Children who learned from a peer (*peer-taught* group) performed as good as children who learned

542 from an adult (*adult-taught* group). (ns: non-significant. Error bars represent 68% bootstrap

543 confidence intervals).

544

545 **Figure 2.** Performance on a per trial basis.

546 (a) Left: Proportion of finished trials. Children who learned from a peer finished more trials in the
547 test stage than children who learned from an adult.

548 Right: Time spent per trial. Children who learned from a peer spent less time per trial than children
549 who learned from an adult. Trial times (seconds) follow a log-normal distribution, and thus a
550 logarithmic transformation was applied to them. Subjects who did not finish all trials 1-3 were
551 excluded.

552 (b) Trial accuracy. Children who learned from a peer had lower accuracies per trial than children
553 who learned from an adult. Excluded one subject who did not finish any of trials 1-3.

554 (*: $p < .05$, **: $p < .01$. Error bars represent 68% bootstrap confidence intervals).

555

556 **Figure 3.** Teaching effect.

557 Both controls and tutors improved in retest, but no evidence was found that teaching provided an
 558 extra benefit (or detriment) to tutors, on performance. (***: $p < .001$. Error bars represent 68%
 559 bootstrap confidence intervals).

575 videos. *Bottom:* beneath the video frames, it is shown the block sequence or program which
576 recreates the series of events depicted in the video. Duck clipart designed by brgfx / Freepik.