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Programming experience promotes higher STEM motivation among first-grade girls



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ABSTRACT

The gender gap in science, technology, engineering, and math (STEM) engagement is large and persistent. This gap is significantly larger in technological fields such as computer science and engineering than in math and science. Gender gaps begin early; young girls report less interest and self-efficacy in technology compared with boys in elementary school. In the current study ($N = 96$), we assessed 6-year-old children's stereotypes about STEM fields and tested an intervention to develop girls' STEM motivation despite these stereotypes. First-grade children held stereotypes that boys were better than girls at robotics and programming but did not hold these stereotypes about math and science. Girls with stronger stereotypes about robotics and programming reported lower interest and self-efficacy in these domains. We experimentally tested whether positive experience with programming robots would lead to greater interest and self-efficacy among girls despite these stereotypes. Children were randomly assigned either to a treatment group that was given experience in programming a robot using a smartphone or to control groups (no activity or other activity). Girls given programming experience reported higher technology interest and self-efficacy compared with girls without this experience and did not exhibit a significant gender gap relative to boys' interest and self-efficacy. These findings show that children's views mirror current American cultural messages about who excels at computer science and engineering and show the benefit of providing young girls with chances to experience technological activities.

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Introduction

Women's underrepresentation in science, technology, engineering, and math (STEM) is a complex issue. There are large variations in women's underrepresentation among STEM fields. In 2012, women earned 59% of bachelor's degrees in biological sciences, 43% in math and statistics, and 41% in physical sciences (National Science Foundation, 2015). In contrast, women's representation was much lower in technological fields such as computer science (18%) and engineering (19%). This means that many young women have fewer opportunities to contribute to and benefit from careers in computer science and engineering. Although many interconnected factors influence the gender gap in participation, research points to a gender difference in interest that begins early in elementary school (Ceci & Williams, 2010). Theory-based interventions that increase young girls' interest and self-efficacy in technology-related activities have the potential to reduce the gender gap in participation (Cheryan, Ziegler, Montoya, & Jiang, 2017; Master, Cheryan, & Meltzoff, 2016).

The current study had two aims. First, we examined whether 6-year-old girls and boys have stronger gender stereotypes about computer science and engineering compared with other STEM fields such as math and science. We examined children's stereotypes about computer science and engineering to address two questions: (a) whether 6-year-olds have stereotypes that boys are better than girls at computer science and engineering (i.e., programming and robotics) and (b) whether 6-year-olds' gender stereotypes about computer science and engineering are stronger than their gender stereotypes about math and science. We then examined possible consequences and correlates of gender stereotypes by assessing the relation between girls' stereotypes and their motivation in computer science and engineering.

Second, we examined as the central aim of this study an intervention that targeted girls' interest and self-efficacy in computer science and engineering in the face of potential negative stereotypes about their abilities. We tested whether providing 6-year-old girls and boys a brief experience in programming robots can affect girls' immediate interest and self-efficacy in computer science and engineering.

Gender gaps in technology motivation

Gender gaps in older children and adults exist in both STEM interest and self-efficacy, which are two different but related aspects of motivation (Eccles, 2011; Mantzicopoulos, Patrick, & Samarapungavan, 2008; Weisgram & Bigler, 2006). There are two types of interest that are relevant to this study. *Situational* interest is interest that is triggered within an immediate experience and may or may not last over time. *Individual* interest is a persistent inclination to engage with particular activities over time. The gender difference in individual interest begins by early elementary school, with girls reporting less interest in and liking for computers compared with boys (Cooper, 2006; McKenney & Voogt, 2010; Patrick, Mantzicopoulos, & Samarapungavan, 2009). Self-efficacy refers to confidence in one's ability to succeed on a specific task (Britner & Pajares, 2006). Girls report less confidence than boys about their science and computing abilities in elementary and middle school (Beghetto, 2007; Mumtaz, 2001).

Interests in science and technology are largely established by the end of elementary school (Maltese & Tai, 2010), suggesting the value of intervening at even earlier ages to foster emergence of these interests. It has been theorized that interest can develop from situational interest to individual interest (Hidi & Renninger, 2006). We argue that a first step toward increasing women's individual interest in computer science and engineering is to trigger young girls' situational interest in topics such as robotics. Many types of experiences in formal and informal learning environments, such as summer camps and conversations with parents in museums, can help to trigger children's situational interest in science and technology (Haden, 2010). Efforts by teachers and parents can develop students' interest from situational to individual, for example, by offering new challenges or opportunities. Once situational interest is triggered with an appropriate task, girls have the opportunity to build this situational interest into a more durable and strong individual interest (Crowley, Barron, Knutson, &

Martin, 2015). Without this first step of triggered situational interest, girls may be hesitant to begin to explore this field. Providing new STEM experiences to young girls can also create more opportunities for them to build self-efficacy in computer science and engineering.

Conceptual framework: Sources of gender gaps in motivation

Why are there early gender gaps in motivation to pursue computer science and engineering? In our theoretical model, we posit that two interacting sociocultural factors are particularly important in generating and maintaining the gender gap in technology motivation in young children: (a) cultural stereotypes and (b) gender differences in experiences (see Fig. 1). (See also Eccles, 2011 for a related model; for a review of possible biological factors, see Ceci & Williams, 2010; Halpern et al., 2007.)

How stereotypes contribute to the gender gap in motivation.

Girls may be affected by stereotypes about intellectual ability as early as 6 years of age, when they become less likely than boys to assume that someone who is “really, really smart” is their own gender and also start to avoid difficult tasks (Bian, Leslie, & Cimpian, 2017). Do children report gender-related stereotypes about math and science? From the youngest ages so far tested (kindergarten to second grade), North American and European children tend to report either that the genders are equal in ability (Steele, 2003) or that their own-gender group is better at math and science (Galdi, Cadinu, & Tomasetto, 2014; Heyman & Legare, 2004; Kurtz-Costes, Rowley, Harris-Britt, & Woods, 2008). (For work on the development of *implicit* gender stereotypes about STEM and how these relate to explicit measures, see Cvencek, Meltzoff, & Greenwald, 2011; Cvencek, Meltzoff, & Kapur, 2014.) Explicit stereotypes about math and science appear to emerge later in development. It is not clear from previous research precisely when girls explicitly endorse the stereotype that boys are better than girls at math, with some of the discrepancy in age estimates perhaps due to different methods of measuring stereotypes. Some research indicates that European girls explicitly endorse the stereotype that boys are better at math by fourth grade (Muzzatti & Agnoli, 2007), although Latin American girls seem to attribute less ability in math to girls compared with boys at 6 years of age (del Río & Strasser, 2013). However, other research using different methods suggests that European girls do not explicitly endorse this stereotype until adolescence (Martinot & Désert, 2007; Passolunghi et al., 2014).

What about gender stereotypes in STEM fields such as computer science and engineering? No study yet has systematically measured young children’s stereotypes across a variety of STEM fields; that is one of the aims and novel contributions of the current research. This question is of particular relevance because variations in adults’ masculine stereotypes about STEM fields correspond to women’s actual representation in those fields (Cheryan et al., 2017; Leslie et al., 2015). Do girls as young as 6 years differentiate among different STEM fields as adults do? Do they show gender stereotypes favoring boys over girls for the most highly stereotyped fields (programming and robotics)?

Gender stereotypes have negative consequences for girls’ performance in STEM, a phenomenon known as “stereotype threat” (Flore & Wicherts, 2015; Régner et al., 2014), and for adults’ motivation

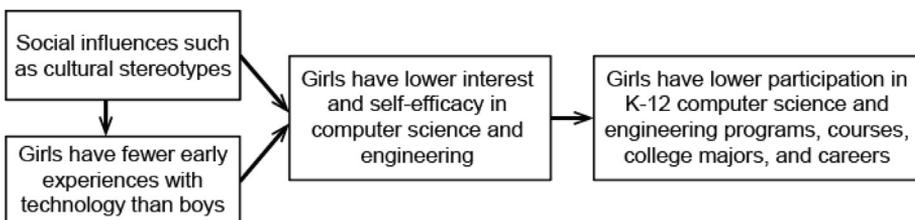


Fig. 1. Cultural stereotypes and gender differences in early experiences contribute to gender differences in motivation in computer science and engineering. These compound over time to lead to a participation gap in computer science and engineering as boys gain more experience, interest, and self-efficacy than girls in technological fields.

in STEM (Thoman, Smith, Brown, Chase, & Lee, 2013). The prevalence of STEM–gender stereotypes may be an important social factor influencing girls' interest in STEM (Kessels, 2015; Master et al., 2016). Stereotypes about STEM may act as “gatekeepers” and deter girls from pursuing interests in computer science and engineering (Cheryan, Master, & Meltzoff, 2015). If children hold stereotypes that boys are better than girls at computer science and engineering, girls may anticipate doing poorly and be deterred from related activities.

How experiences contribute to the gender gap in motivation.

Another possible reason why girls may show lower motivation than boys for computer science and engineering is because they have fewer experiences with technology to generate their interest and build self-efficacy (Barker & Aspray, 2006; Martin & Dinella, 2002). As early as elementary school, girls spend less time playing with computer games and technological toys (Cherney & London, 2006) and are less likely to play with spatial and science-related games and toys than boys (Jirout & Newcombe, 2015). By sixth grade, boys spend more time than girls playing with electric toys and fuses outside of school (Jones, Howe, & Rua, 2000). Young boys spend more time interacting with age-appropriate technology activities, which could give them more opportunities to gain self-efficacy (Nugent et al., 2010; Terlecki & Newcombe, 2005).

Girls' insufficient early experience with computer science and engineering may contribute to gender gaps in later participation (Cheryan et al., 2017). States and countries that require both girls and boys to take more STEM coursework have lower gender gaps in STEM participation in college (Charles & Bradley, 2009; see also Federman, 2007). Correlational research with older students shows that stronger math and science curricula are correlated with high school girls' intentions to major in STEM fields (Legewie & DiPrete, 2014).

Goals of the current research

The current work investigated three interrelated questions: (a) whether 6-year-old children hold stronger gender stereotypes about computer science and engineering (programming and robotics) compared with math and science, (b) whether girls who believe that boys are better than girls at computer science and engineering report lower motivation for these subjects, and (c) whether girls in a treatment group who experience a child-friendly robot programming activity show higher technology motivation than girls in control groups.

We hypothesized that 6-year-old children would hold stereotypes that boys are better at robotics and programming and that these stereotypes would be stronger than stereotypes about math and science. We also predicted that girls' stereotypes that boys are better at robotics and programming would correlate with lower motivation for these domains. Finally, and most importantly, we predicted that girls who were randomly assigned to the treatment group would report significantly higher motivation than girls in the control groups. We also predicted there would be fewer gender differences in motivation for children in the treatment group than children in the control groups. We did not expect that our specific treatment would influence the cultural stereotypes that children held because it was not designed to do so; rather, we expected that the treatment would result in higher technology interest and self-efficacy for girls in the treatment group compared with the control groups.

Method

Participants

Participants were 96 6-year-old children (48 girls and 48 boys; $M_{\text{age}} = 6$ years 10 months, range = 6 years 8 months to 6 years 11 months; 79% White, 3% Asian American, 1% Black, 1% Latino, 1% other, and 15% multiple ethnicities). Most were middle or upper-middle class (93% of mothers were college graduates). No participants were excluded from analyses. Conditions were balanced across child gender and experimenter gender using stratified random sampling to condition (the experimenter was male for half of the participants and female for the other half). Preliminary analyses confirmed that

the random assignment worked as expected and that conditions did not differ in age, family income, mother's education level, or minutes per day that children spent using devices such as smartphones, computers, and video games.

Procedure

Children were tested individually in the laboratory. Children were randomly assigned to one of three independent groups: (a) the “robot” experimental treatment group, (b) a control group that completed a parallel “storytelling” activity not involving technology, and (c) a “no-activity” control group. All children then responded to measures of technology motivation and STEM–gender stereotypes.

Robot treatment group

Children who were randomly assigned to this group spent 20 min playing a game in which they chose a specially designed “pet” robot and used a smartphone to program the robot. Smartphones are mobile devices that include all the features of a phone as well as features like touch-screen capabilities. Past research indicates that even very young children can learn to program (Kazakoff & Bers, 2014; Wyeth, 2008) and use robots (Bers et al., 2014; Mioduser & Levy, 2010). The goal was to make the robot navigate an experimentally specified spatial path made out of hexagonal tiles that could be laid out in different spatial designs (see Fig. 2). Children used drag-and-drop visual programming to program the robot to move forward, turn left or right, and create loops to repeat instructions. The researcher demonstrated how to program the robot to navigate four different spatial paths, and then children programmed the robot to navigate up to eight additional paths. The eight additional paths

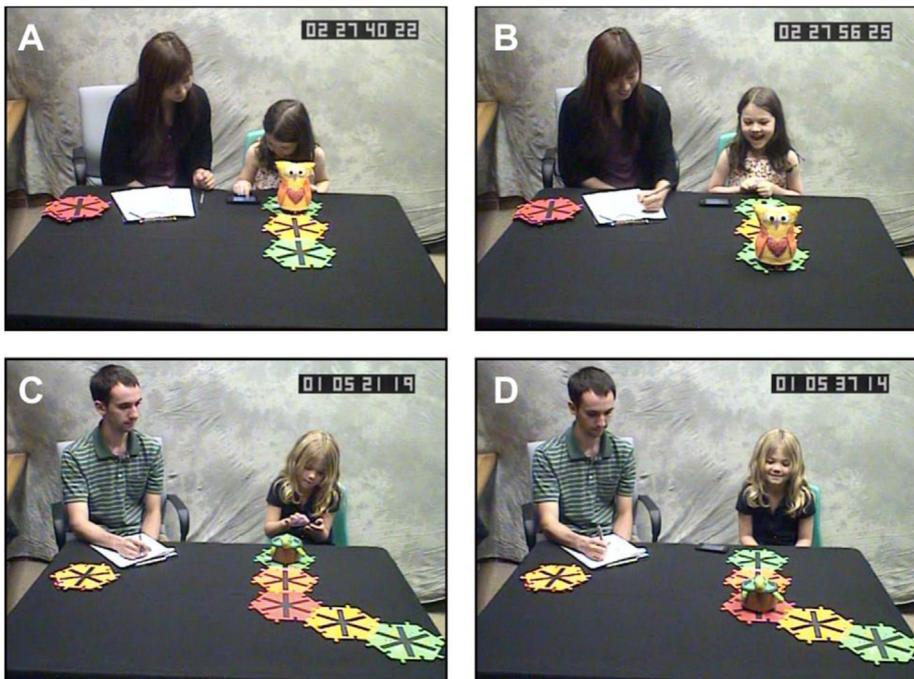


Fig. 2. Six-year-old girls in the robot treatment group: (A and C) programming a robot animal using a smartphone to move along different spatial paths; (B and D) watching the robot execute the programmed commands. (The authors received signed consent for the experimenter and children's likenesses to be published in this article.) Links to movies are available here: <https://youtu.be/-bVdDlyD9Ec> and <https://youtu.be/rirZjzPtErQ>.

required children to generalize what they had learned during the practice paths. The mean number of additional paths children completed within 20 min was 6.41 ($SD = 1.34$).

Children had no difficulty with the phone itself, which is unsurprising given that children's toys involving mobile apps and technology are becoming increasingly common (Montgomery, 2015). In a parental survey (completed by 80% of participating families), 100% reported owning either a smartphone or tablet computer. Other research indicates that 75% of families with children age 8 years and under have access to a smart device (including smartphones and tablet computers) at home and that 83% of 5- to 8-year-olds have used a mobile device at some point (Rideout, 2013). The researcher provided assistance as needed (see online supplementary material for more details).

Two control groups

Two control groups were used: "storytelling" and "no activity." In the storytelling control group, children spent 20 min playing a storytelling card game (adapted from the card game "Once Upon a Time") where they were given a series of cards with a person, an object, or an idea and were asked to tell a brief story involving those cards. This group helped to control for the experience of playing a sequential game with the researcher. The researcher demonstrated how to tell a story using four sets of picture cards that were arranged on the table, and then children told their own stories for eight additional sets of cards (all children completed all eight sets within 20 min). In the no-activity control group, children did not play any games. We did not expect any differences between control groups on outcome measures, but combining both controls provides the most rigorous comparison against the experimental treatment.

Dependent measures

Practice items. To help children get used to the scales assessing interest and self-efficacy, children first responded to two practice items. These items were designed to introduce children to the positive and negative dimensions of the scale. Each item was asked in two steps (known as "branching"; Krosnick & Presser, 2010) to keep the number of choices simple and age appropriate (Master et al., 2017, 2012). In the first step, to familiarize children with the positive side of the scale, we asked children whether playing outside is *fun* or *not fun*, accompanied by a card with one smiling face and one frowning face. Depending on their choice, in a second step they were asked how much it was fun or how much it was not fun—a *little*, *medium*, or *a lot*—with a second card showing faces with three sizes of smiles (or frowns). To familiarize children with the negative side of the scale, we asked children whether getting hurt is fun or not fun and then how much it was or was not fun. The steps were combined to create a 6-point scale with three positive values and three negative values.

Technology motivation. We measured technology motivation with three items assessing interest in programming (how fun is programming), interest in robots (how fun are robots), and self-efficacy with robots (how good are you with robots), all measured in two steps to create a scale from 1 to 6, as described above. Items were adapted from other scales assessing young children's interest and liking for math and science (Arnold et al., 2002; Mantzicopoulos et al., 2008). We defined programming for all children by saying, "Programming is when you tell a computer or a robot or a phone what to do."

STEM-gender stereotypes. We measured explicit stereotypes about whether boys or girls are "better" at robots and programming (as well as science and math for comparison)—for example, "Who is better at programming, girls or boys? Are girls/boys a little better or a lot better?" We coded each of these on a 4-point scale so that higher numbers indicated belief that boys are better and a score of 0 reflected chance responses if children were equally likely to choose boys and girls as better. We purposely asked this question comparatively, rather than asking children to evaluate girls and boys separately, to help highlight any contrasts between the genders (Heyman & Legare, 2004; Kurtz-Costes et al., 2014). We did not offer children a neutral option because children may default to neutral response options without fully considering their answer, leading to less reliable responses (Borgers, Hox, & Sikkels, 2004).¹

¹ We also measured children's spatial cognition (see supplementary material for details).

Results

Preliminary analyses

Correlations

Table 1 provides the correlations across measures. We focus on the programming–gender and robotics–gender stereotypes to highlight the stereotypes most relevant to technology motivation. (For means and standard deviations for all four stereotypes, see Table 3 below.)

Control groups

As expected, results showed that the two control groups did not differ for any of the technology motivation items, $t_s < 1.23$, $p_s > .22$, $d_s < .31$, so we collapsed across control groups for analyses.

Effect of treatment on technology motivation

Because the three technology motivation items were moderately correlated (average inter-item correlation = .20), we analyzed them using a multivariate analysis of variance (MANOVA). A 2×2 (Gender \times Group [robot treatment or controls]) MANOVA on technology motivation revealed significant main effects of both gender, Pillai's trace = .19, $F(3, 88) = 6.82$, $p < .001$, $\eta_p^2 = .19$, and group, Pillai's

Table 1
Correlations among dependent measures by gender.

Measure	1	2	3	4	5
1. Programming interest	–	.12	.23	.32 [*]	.27
2. Robot interest	–.23	–	.15	–.05	.15
3. Robot self-efficacy	.05	.51 ^{***}	–	.15	.36 [*]
4. Programming–gender stereotype	–.37 [*]	–.03	–.29 [*]	–	.26
5. Robotics–gender stereotype	.12	–.37 ^{**}	–.32 [*]	.02	–

Note. Correlations for girls ($n = 48$) are presented below the diagonal, and correlations for boys ($n = 48$) are presented above the diagonal. Stereotypes were scored such that positive scores indicated the stereotype that boys were better and negative scores indicated that girls were better.

^{*} $p \leq .05$.

^{**} $p \leq .01$.

^{***} $p \leq .001$.

Table 2
Technology motivation by experimental condition and gender.

Measure	Robot treatment	Controls			<i>d</i>
		Combined	Storytelling	No activity	
<i>Programming interest</i>					
Girls	5.00 (1.41)	3.88 (1.66)	3.69 (1.82)	4.06 (1.53)	.73
Boys	5.60 (0.63)	5.00 (1.24)	5.07 (1.03)	4.94 (1.44)	.61
Overall	5.29 (1.13)	4.43 (1.56)	4.35 (1.62)	4.50 (1.52)	.63
<i>Robot interest</i>					
Girls	5.06 (1.24)	4.44 (1.70)	4.87 (1.54)	4.00 (1.79)	.42
Boys	5.87 (0.35)	5.19 (1.17)	5.07 (1.34)	5.31 (1.01)	.78
Overall	5.45 (0.99)	4.81 (1.50)	4.97 (1.43)	4.66 (1.58)	.50
<i>Robot self-efficacy</i>					
Girls	4.88 (0.96)	3.59 (1.97)	3.88 (1.86)	3.31 (2.09)	.83
Boys	5.13 (0.74)	4.81 (1.25)	5.07 (0.88)	4.56 (1.50)	.32
Overall	5.00 (0.86)	4.19 (1.75)	4.45 (1.57)	3.94 (1.90)	.59

Note. Means (and standard deviations) on a scale from 1 (*really not*) to 6 (*really*) are shown. Effect sizes correspond to the difference between the robot treatment and the combined control groups.

Table 3
Descriptive statistics for STEM-Gender stereotypes.

Field	Overall		Girls		Boys	
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
Robots	.73 ^{***}	.88	.81 _a	.90	.65 _a	.85
Programming	.24 [†]	.96	.04 _b	.97	.46 _c	.92
Science	.08	.88	-.16 _d	.87	.33 _e	.82
Math	.07	.93	-.38 _f	.73	.54 _g	.89

Note. Range = -1.5 (girls a lot better) to 1.5 (boys a lot better). Means for each stereotype sharing a common subscript are not statistically different at $p \leq .05$. Overall significantly different from 0: [†] $p < .05$; ^{***} $p < .001$.

trace = .18, $F(3,88) = 6.22$, $p = .001$, $\eta_p^2 = .18$, and a nonsignificant interaction, Pillai's trace = .04, $F(3,88) = 1.06$, $p = .37$, $\eta_p^2 = .035$; see Table 2 for means and standard deviations and Fig. 3. Boys reported significantly higher motivation than girls for all three items: (a) programming interest, $p = .005$, $d = .67$, (b) robot interest, $p = .008$, $d = .58$, and (c) robot self-efficacy, $p = .023$, $d = .60$. Children who experienced the robot treatment reported significantly higher motivation than children in the controls for all three items: (a) programming interest, $p = .005$, $d = .63$, (b) robot interest, $p = .027$, $d = .50$, and (c) robot self-efficacy, $p = .013$, $d = .59$. The lack of interaction indicates that the size of the treatment effect was not significantly different for boys and girls for any item, $ps = .38$, $.93$, and $.14$ and $\eta_p^2s = .008$, $< .001$, and $.025$, respectively.

Because there were a priori hypotheses, we also examined the simple effects as a function of gender. We expected that (a) girls who experienced the robot treatment would report significantly higher motivation than girls in the control conditions and (b) the robot experience would eliminate significant gender differences in motivation.

As predicted, we found that girls who experienced the robot treatment had significantly higher technology motivation compared with girls in the controls, Pillai's trace = .16, $F(3,88) = 5.47$, $p = .002$, $\eta_p^2 = .16$. Girls who experienced the robot treatment reported significantly higher motivation than girls in the controls for two of the three items: programming interest, $p = .008$, $d = .73$, and robot self-efficacy, $p = .005$, $d = .83$, but not robot interest, $p = .12$, $d = .42$. The robot treatment did not significantly affect boys' motivation, Pillai's trace = .06, $F(3,88) = 1.90$, $p = .14$, $\eta_p^2 = .06$, which appeared to be close to ceiling on this scale (≥ 4.8 on the 6-point scale) and was nonsignificant for all three items, $ps = .17$, $.11$, and $.47$ and $ds = .61$, $.78$, and $.32$, respectively.

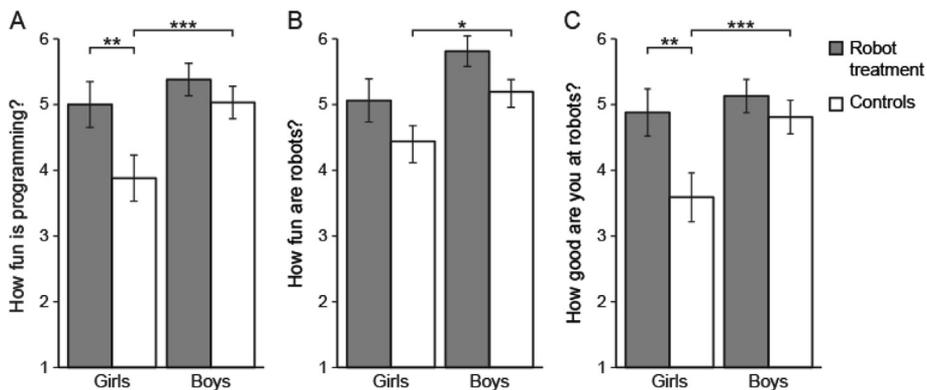


Fig. 3. Technology motivation: (A) programming interest; (B) robot interest; (C) robot self-efficacy. All were measured on a scale from 1 (really not fun/good) to 6 (really fun/good). Error bars show standard errors. Brackets show pairwise comparisons. Girls in the control groups showed particularly low technology motivation compared with boys and with girls in the robot treatment group. [†] $p < .05$; ^{**} $p < .01$; ^{***} $p < .001$.

Also as predicted, the gender difference (with boys showing more technology motivation than girls) was significant in the controls, Pillai's trace = .22, $F(3,88) = 8.23$, $p < .001$, $\eta_p^2 = .22$, but not in the robot treatment group, Pillai's trace = .06, $F(3,88) = 1.84$, $p = .15$, $\eta_p^2 = .06$. For children who experienced the robot treatment, the gender difference was not significant for any of the three items, $ps = .22$, .09, and .62 and $ds = .30$, .82, and .30, respectively. In the control groups, boys reported significantly higher motivation than girls for all three items: (a) programming interest, $p = .001$, $d = .79$, (b) robot interest, $p = .025$, $d = .52$, and (c) robot self-efficacy, $p = .001$, $d = .74$.

For simple effects using univariate tests, see Table 2 and Fig. 3.²

We also repeated these analyses controlling for children's spatial cognition and found the same pattern of results (see supplementary material).

STEM–gender stereotypes

We first compared children's stereotypes with chance (0). Results showed that 6-year-olds were significantly more likely than chance to report stereotypes that boys were better than girls at robots, $t(95) = -8.15$, $p < .001$, 95% confidence interval (CI) $[-.91, -.55]$, and programming, $t(93) = -2.47$, $p = .015$, 95% CI $[-.44, -.05]$ (see Table 3). There were no significant effects for science and math at this age, $ts < 0.89$, $ps > .37$, 95% CIs $[-.26, .10]$ and $[-.27, .12]$.

We conducted a 2×2 (Gender \times Group [robot treatment or controls]) repeated-measures analysis of variance (ANOVA) on children's stereotypes. There was a main effect of stereotype field, $F(3,267) = 11.25$, $p < .001$, $\eta_p^2 = .11$, a main effect of gender, $F(1,89) = 17.55$, $p < .001$, $\eta_p^2 = .17$, and a significant interaction between stereotype field and gender, $F(3,267) = 6.07$, $p = .001$, $\eta_p^2 = .06$. Follow-up Bonferroni-corrected tests found that children's stereotypes about robots were significantly stronger (i.e., children were more likely to say that boys were better) than their stereotypes about science, math, and programming, $ps \leq .001$. Boys were more likely than girls to say that boys were better at these fields.

We examined the interaction between field and gender in two ways, again using Bonferroni-corrected tests. First, boys were significantly more likely than girls to say that boys were better than girls at science, $F(1,89) = 5.35$, $p = .023$, $\eta_p^2 = .06$, math, $F(1,89) = 28.43$, $p < .001$, $\eta_p^2 = .24$, and programming, $F(1,89) = 5.20$, $p = .025$, $\eta_p^2 = .06$. There were no significant gender differences for stereotypes about robots, $F(1,89) = 0.85$, $p = .36$, $\eta_p^2 = .009$, because both girls and boys said that boys were better than girls at robots. Second, follow-up tests found that girls' stereotypes about robots were significantly stronger than their stereotypes about science, programming, and math, $ps < .001$.

We found no significant effects of group (robot treatment or control groups) on any of these measures of children's stereotypes, $F(1,89) = 0.32$, $p = .57$, and no significant interactions between group and gender or stereotype field, $Fs < .79$, $ps > .50$.

Correlations between stereotypes and motivation

Four of six possible correlations were significant for girls between the two stereotype measures (programming–gender stereotypes and robotics–gender stereotypes) and programming interest, robot interest, and robot self-efficacy (see Table 1, bottom two rows). The size of these four correlations indicates a small to moderate relationship ($r \approx -.34$) between stereotypes and STEM motivation. To control for multiple comparisons, we used the Benjamini–Hochberg procedure to control the false discovery rate for these six correlations (with $Q = .10$); the four significant correlations remained significant (Benjamini & Hochberg, 1995). In particular, the correlations between self-efficacy and both types of stereotypes were significantly negative, indicating that girls who held stereotypes that boys were better than girls at robots and programming also reported lower self-efficacy.

² Although the pattern for each univariate test was similar to the multivariate test, there was no significant difference between girls who experienced the robot treatment and girls in the control groups for the robot interest item taken by itself, possibly because the mean for girls in the control groups was higher than for the other two items (programming interest and robot self-efficacy).

Discussion

Despite a growing use of technology in daily life, there is a persistent gender gap in participation in computer science and engineering as measured in college degrees, graduate degrees, and the workforce. Girls in contemporary U.S. culture face cultural stereotypes that girls have lower ability in technological fields compared with boys. They also receive less exposure to technology-related activities compared with boys, and this starts early in development.

In this experiment, children were randomly assigned to an experimental treatment group or control groups to examine whether a brief learning experience with technology could lead to changes in girls' interest and self-efficacy in computer science and engineering. Indeed, the robot treatment had the desired effect. Because we used random assignment with well-controlled treatment and control conditions, we can infer that the robot treatment led to higher technology motivation than that of children in the control groups, which has implications for developmental and social psychological theory as well as educational practice. The current research points to strategies that may be effective when designing programs to promote early STEM motivation.

Malleability of technology motivation in children

We found that girls randomly assigned to spend 20 min playing an intentionally designed programming game had significantly higher technology motivation compared with girls in the control groups. As expected, children in the control groups showed the typical pattern in which boys reported higher technology interest and self-efficacy compared with girls. However, children who were provided the experimental treatment showed no significant gender differences for interest in programming, interest in robots, or self-efficacy with robots. These findings suggest that gender differences in children's technology motivation are not set in stone; instead, they are malleable and open to influence from specific experiences.

On the whole, the results show that providing positive experiences with technology to girls can lead to higher technology motivation. Girls who encounter intentionally designed experiences showed higher interest in programming and higher self-efficacy than girls without these encounters, with no significant differences from boys' interest and self-efficacy. This is important because enjoyment of a field and a sense of self-efficacy can lead children to seek out further opportunities in that area and help them to build a well-developed sense of individual interest in that area.

Technology–gender stereotypes

To our knowledge, this is the first research to show that 6-year-old children already hold stereotypes that boys are better than girls at robotics and programming. In particular, the stereotype about boys being better than girls at robotics was held by *both* boys and girls and was stronger than children's stereotypes about other fields. This pattern mirrors that of adult women's participation across STEM fields, with women more underrepresented in computer science and engineering than in math and biological sciences (Cheryan et al., 2017). It is of interest that children at this young age already show stereotypes that reflect the adult stereotypes and the adult participation pattern. Further research is needed to understand exactly why children, both boys and girls, showed such strong stereotypes about robots in particular and how girls' familiarity with each field affects their stereotypes. The mechanism by which stereotypes and biases are “caught” or develop in very young children is an important and growing topic in experimental child psychology (e.g., Skinner, Meltzoff, & Olson, 2017).

Although our treatment was effective in leading to higher technology motivation than controls, it is worth noting that we did not find evidence that the robot treatment activity was a “cure all”; it did not change girls' stereotypes about programming or robotics. Changing stereotypes is difficult (Rothbart, 2001), even among children (Bigler, 1999; Steele, 2003). Thus, it is unsurprising that a brief experience—not intentionally designed to change stereotypes but rather designed to result in higher technology motivation—did not seem to shift their stereotypes. Rather than changing stereotypes,

positive experiences may help to act as a buffer for girls against negative effects of strong stereotypes about their ability (Stout, Dasgupta, Hunsinger, & McManus, 2011). Other types of experiences, such as watching a female role model succeed at and enjoy programming robots, may be more likely to change children's stereotypes (Galdi et al., 2014; Shin et al., 2016).

There was some correlational evidence (i.e., four of six correlations in the bottom section of Table 1 in the small to moderate range, with $r_s \approx -.34$) that girls who held stronger stereotypes that boys were better than girls at programming and robotics had lower motivation, particularly lower self-efficacy. However, the direction of causality is unclear. Perhaps belief in these stereotypes made girls feel less interested and efficacious. Alternatively, perhaps girls who already felt higher interest in and self-efficacy for technology were more likely to reject those cultural stereotypes. A girl who believes robots are fun may infer that "girls are good with robots" (i.e., a projection from self to other people who are "like me"; Meltzoff, 2013). If this latter idea is true, then sufficient positive experiences in technology might also help to change girls' beliefs about the ability of other girls; of course, the direction of causality may also go in both directions (Miller, Trautner, & Ruble, 2006).

Two empirical approaches could be taken to provide further insights into the causal pathways. First, longitudinal studies of the same children over time could assess the emergence of technology stereotypes and interest/self-efficacy. If stereotypes develop at a time prior to a decrease in girls' interest and self-efficacy, then children's assimilation of cultural stereotypes may affect girls' motivation. Second, targeted experiments on either side of the equation (cultural stereotypes or motivation) might help to sort out the causal pathways. Experimenters could teach children stereotypes about a novel field and then measure motivation (Cimpian, 2010; Miller, 2008) or could examine whether systematic interventions to increase motivation subsequently change stereotypes. In the future, researchers could also examine the psychological processes through which girls assimilate such stereotypes (e.g., Cvencek et al., 2011) and the degree to which such stereotypes can be changed over time when girls gain new experiences.

Creating technology activities with broad appeal

One design feature of the programming activity used in the current study is that it was created to appeal to girls and boys. Others have attempted to increase girls' interest in STEM by making STEM activities explicitly feminine (e.g., by using pink materials or very feminine role models; Khazan, 2012). However, such gendered approaches can backfire for three reasons. First, activities that divide children by gender can lead to increased gender stereotyping (Hilliard & Liben, 2010). Research also suggests that girls are less interested in STEM when these activities are segregated by gender, perhaps due to the reinforcement of gender stereotypes (Legewie & DiPrete, 2014). Second, attempts to make STEM superficially appealing to girls can lead to unintended consequences such as implying that girls and women in STEM must also be hyperfeminine (Betz & Sekaquaptewa, 2012; Liben, 2016). Third, there are large individual differences within *both* genders and highly overlapping distributions, such that many girls are more interested than many boys in technology. Thus, designing technology activities with inclusive appeal, as we have attempted to do here, may result in higher interest for some boys as well. Based on other related work, we posit that broadening the appeal of computer science and engineering, and the image of who belongs and succeeds in computer science and engineering, has the potential to benefit a larger set of students and may be the preferred approach for educational interventions (Cheryan et al., 2015; Master & Meltzoff, 2017; Master et al., 2016).

Interventions, translational science, and early STEM: Limitations and future directions

These results suggest that young girls' situational interest in technology is not set in stone but rather is malleable and can be changed through interventions. Important questions remain, however, from both theoretical and translational viewpoints. First, it is unclear whether a brief experience of higher motivation for girls can translate into behavioral changes such as seeking out future opportunities in robotics and programming. Although a recent meta-analysis on motivation interventions suggests that effects on behavioral outcomes are similar to effects on self-reported outcomes (Lazowski & Hulleman, 2016), this is an important direction for future empirical research. In the future, researchers

should also make sure that girls' reports of higher motivation in the current research were not due to social desirability effects, given that the researcher who measured technology motivation was the same one who guided children in the technology activity.

Second, in the future researchers should investigate the durability of the effect, including how to promote the development of girls' interest in STEM from situational to individual interest and how to sustain feelings of self-efficacy in STEM. Interest can decrease over time if there are no opportunities to continue to reengage with that topic (Hidi & Renninger, 2006), so girls may need to become involved in longer-term programs to prevent them from losing interest in robotics and programming. Although interventions that target skill building tend to have effects that fade over time, interventions that target motivation have the potential to create longer-lasting educational benefits, especially when that motivation shapes students' self-concepts (Bailey et al., 2017; Cohen et al., 2006; Murayama et al., 2013). Researchers should also examine how these laboratory results could be scaled up into a larger-scale practical intervention to boost technology interest in young girls. Might we add this type of activity to existing programs and curricula such as classroom-based computer science and engineering programs? How long should such programs last, and how can these programs maintain girls' interest over longer periods of time?

Third, what specific aspects of girls' experiences are most important for fostering technology motivation? Not all experiences with computers and programming lead to positive changes in beliefs and attitudes toward technology (Krendl et al., 1989; Lang et al., 2015). The addition of a social element, such as collaboration with a friend or group programming, could increase girls' interest as well (Hanks, Fitzgerald, McCauley, Murphy, & Zander, 2011). Preschool children show more interest and persistence in spatial and math activities when they feel that they are part of a social group engaged in the same activity (Master et al., 2017). Incorporating creative elements into programming can also motivate girls (Kelleher, Pausch, & Kiesler, 2007). It is important to ensure that these experiences do not reinforce stereotypes about the masculine culture of computer science and engineering (Cheryan et al., 2017).

Fourth, a related question for future research is to compare actual technology experience with different control groups to specify the necessary and sufficient ingredients of the treatment. It is possible that a less direct exposure to technology might have similar effects. For example, could watching a video of the robot moving, or of another girl programming the robot, create as high interest and self-efficacy as when girls do the programming themselves? Researchers could also examine the effectiveness of pair programming, in which children take turns being the active programmer (the "driver") or watching for errors (the "navigator") (Lewis, 2011). Another potential comparison could be whether a nonprogramming activity related to STEM (e.g., a spatial game like Tetris) influences children's technology motivation. We believe that the current control using a storytelling activity still remains valuable; for many children, the choice of whether to pursue a technology activity is contrasted with pursuing a nontechnology activity.

Finally, this study should be replicated with a larger sample size. Some of the effects that were non-significant in this study may become significant with greater power.

Conclusions

The gender gap in participation in STEM, and computer science and engineering in particular, is a persistent issue in U.S. culture (Cheryan et al., 2015). Girls have fewer experiences than boys with robotics and computing and report less interest in these activities. There are also pervasive U.S. stereotypes that boys have more ability in STEM (Beilock, Gunderson, Ramirez, & Levine, 2010; Else-Quest, Hyde, & Linn, 2010; Nosek et al., 2009).

However, the current research also suggests malleability; positive experiences with programming can lead to higher motivation in robotics and programming for girls compared with girls without these experiences. Teachers, parents, and policymakers who create positive STEM experiences for girls have the potential to put girls on academic trajectories that can lead to more participation in computer science and engineering. Although we did not systematically compare technology experiences at earlier or later ages, evidence from other research indicates that providing girls with experiences at an

early age is an important consideration for theory and practice. In one retrospective survey of professional scientists, 66% of women reported that their interests in science were galvanized prior to middle school (Maltese & Tai, 2010). Although simply an initial step in a larger program to motivate more girls to enter STEM, the current findings highlight the importance of rich educational experiences in sparking girls' motivation in STEM.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.jecp.2017.03.013>.

References

- Arnold, D. H., Fisher, P. H., Doctoroff, G. L., & Dobbs, J. (2002). Accelerating math development in Head Start classrooms. *Journal of Educational Psychology, 94*, 762–770.
- Bailey, D., Duncan, G. J., Odgers, C., & Yu, W. (2017). Persistence and fadeout in the impacts of child and adolescent interventions. *Journal of Research on Educational Effectiveness, 10*, 7–39.
- Barker, L. J., & Aspray, W. (2006). The state of research on girls and IT. In J. M. Cohoon & W. Aspray (Eds.), *Women and information technology: Research on underrepresentation* (pp. 3–54). Cambridge, MA: MIT Press.
- Beghetto, R. A. (2007). Factors associated with middle and secondary students' perceived science competence. *Journal of Research in Science Teaching, 44*, 800–914.
- Beilock, S. L., Gunderson, E. A., Ramirez, G., & Levine, S. C. (2010). Female teachers' math anxiety affects girls' math achievement. *Proceedings of the National Academy of Sciences of the United States of America, 107*, 1860–1863.
- Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: A practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society, 57*, 289–300.
- Bers, M. U., Flannery, L., Kazakoff, E. R., & Sullivan, A. (2014). Computational thinking and tinkering: Exploration of an early childhood robotics curriculum. *Computers and Education, 72*, 145–157.
- Betz, D. E., & Sekaquaptewa, D. (2012). My fair physicist? Feminine math and science role models demotivate young girls. *Social Psychological and Personality Science, 3*, 738–746.
- Bian, L., Leslie, S.-J., & Cimpian, A. (2017). Gender stereotypes about intellectual ability emerge early and influence children's interests. *Science, 355*, 389–391.
- Bigler, R. S. (1999). The use of multicultural curricula and materials to counter racism in children. *Journal of Social Issues, 55*, 687–705.
- Borgers, N., Hox, J., & Sikkel, D. (2004). Response effects in surveys on children and adolescents: The effect of number of response options, negative wording, and neutral mid-point. *Quality and Quantity, 38*, 17–33.
- Britner, S. L., & Pajares, F. (2006). Sources of science self-efficacy beliefs of middle school students. *Journal of Research in Science Teaching, 43*, 485–499.
- Ceci, S. J., & Williams, W. M. (2010). Sex differences in math-intensive fields. *Current Directions in Psychological Science, 19*, 275–279.
- Charles, M., & Bradley, K. (2009). Indulging our gendered selves? Sex segregation by field of study in 44 countries. *American Journal of Sociology, 114*, 924–976.
- Cherney, I. D., & London, K. (2006). Gender-linked differences in the toys, television shows, computer games, and outdoor activities of 5- to 13-year-old children. *Sex Roles, 54*, 717–726.
- Cheryan, S., Master, A., & Meltzoff, A. N. (2015). Cultural stereotypes as gatekeepers: Increasing girls' interest in computer science and engineering by diversifying stereotypes. *Frontiers in Psychology, 6*. <http://dx.doi.org/10.3389/fpsyg.2015.00049>.
- Cheryan, S., Ziegler, S. A., Montoya, A., & Jiang, L. (2017). Why are some STEM fields more gender balanced than others? *Psychological Bulletin, 143*, 1–35.
- Cimpian, A. (2010). The impact of generic language about ability on children's achievement motivation. *Developmental Psychology, 46*, 1333–1340.
- Cohen, G. L., Garcia, J., Apfel, N., & Master, A. (2006). Reducing the racial achievement gap: A social-psychological intervention. *Science, 313*, 1307–1310.
- Cooper, J. (2006). The digital divide: The special case of gender. *Journal of Computer Assisted Learning, 22*, 320–334.
- Crowley, K., Barron, B., Knutson, K., & Martin, C. K. (2015). Interest and the development of pathways to science. In K. A. Renninger, M. Nieswandt, & S. Hidi (Eds.), *Interest in mathematics and science learning* (pp. 297–313). Washington, DC: American Educational Research Association.
- Cvencek, D., Meltzoff, A. N., & Greenwald, A. G. (2011). Math-gender stereotypes in elementary school children. *Child Development, 82*, 766–779.

- Cvencek, D., Meltzoff, A. N., & Kapur, M. (2014). Cognitive consistency and math-gender stereotypes in Singaporean children. *Journal of Experimental Child Psychology*, *117*, 73–91.
- del Río, M. F., & Strasser, K. (2013). Preschool children's beliefs about gender differences in academic skills. *Sex Roles*, *68*, 231–238.
- Eccles, J. (2011). Gendered educational and occupational choices: Applying the Eccles et al. model of achievement-related choices. *International Journal of Behavioral Development*, *35*, 195–201.
- Else-Quest, N. M., Hyde, J. S., & Linn, M. C. (2010). Cross-national patterns of gender differences in mathematics: A meta-analysis. *Psychological Bulletin*, *136*, 103–127.
- Federman, M. (2007). State graduation requirements, high school course taking, and choosing a technical college major. *The B.E. Journal of Economic Analysis & Policy*, *7*, 1–34.
- Flore, P. C., & Wicherts, J. M. (2015). Does stereotype threat influence performance of girls in stereotyped domains? A meta-analysis. *Journal of School Psychology*, *53*, 25–44.
- Galdi, S., Cadinu, M., & Tomasetto, C. (2014). The roots of stereotype threat: When automatic associations disrupt girls' math performance. *Child Development*, *85*, 250–263.
- Haden, C. A. (2010). Talking about science in museums. *Child Development Perspectives*, *4*, 62–67.
- Halpern, D. F., Benbow, C. P., Geary, D. C., Gur, R. C., Hyde, J. S., & Gernsbache, M. A. (2007). The science of sex differences in science and mathematics. *Psychological Science in the Public Interest*, *8*, 1–51.
- Hanks, B., Fitzgerald, S., McCauley, R., Murphy, L., & Zander, C. (2011). Pair programming in education: A literature review. *Computer Science Education*, *21*, 135–173.
- Heyman, G. D., & Legare, C. H. (2004). Children's beliefs about gender differences in the academic and social domains. *Sex Roles*, *50*, 227–239.
- Hidi, S., & Renninger, K. A. (2006). The four-phase model of interest development. *Educational Psychologist*, *41*, 111–127.
- Hilliard, L. J., & Liben, L. S. (2010). Differing levels of gender salience in preschool classrooms: Effects on children's gender attitudes and intergroup bias. *Child Development*, *81*, 1787–1798.
- Jirout, J. J., & Newcombe, N. S. (2015). Building blocks for developing spatial skills: Evidence from a large, representative U.S. sample. *Psychological Science*, *26*, 302–310.
- Jones, M. G., Howe, A., & Rua, M. J. (2000). Gender differences in students' experiences, interests, and attitudes toward science and scientists. *Science Education*, *84*, 180–192.
- Kazakoff, E. R., & Bers, M. U. (2014). Put your robot in, put your robot out: Sequencing through programming robots in early childhood. *Journal of Educational Computing Research*, *50*, 553–573.
- Kelleher, C., Pausch, R., & Kiesler, S. (2007). Storytelling Alice motivates middle school girls to learn computer programming. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems—CHI '07* (pp. 1455–1464). New York: Association for Computing Machinery. doi:10.1145/1240624.1240844.
- Kessels, U. (2015). Bridging the gap by enhancing the fit: How stereotypes about STEM clash with stereotypes about girls. *International Journal of Gender, Science, and Technology*, *7*, 280–296.
- Khazan, O. (2012, June 22). E.U.'s "Science, it's a girl thing" campaign sparks a backlash. *The Washington Post*.
- Krendl, K. A., Broihier, M. C., & Fleetwood, C. (1989). Children and computers: Do sex-related differences persist? *Journal of Communication*, *39*, 85–93.
- Krosnick, J. A., & Presser, S. (2010). Question and questionnaire design. In P. V. Marsden & J. D. Wright (Eds.), *Handbook of survey research* (2nd ed., pp. 263–313). Bingley, UK: Emerald Group.
- Kurtz-Costes, B., Copping, K. E., Rowley, S. J., & Kinlaw, C. R. (2014). Gender and age differences in awareness and endorsement of gender stereotypes about academic abilities. *European Journal of Psychology of Education*, *29*, 603–618.
- Kurtz-Costes, B., Rowley, S. J., Harris-Britt, A., & Woods, T. A. (2008). Gender stereotypes about mathematics and science and self-perceptions of ability in late childhood and early adolescence. *Merrill-Palmer Quarterly*, *54*, 386–409.
- Lang, C., Fisher, J., Craig, A., & Forgasz, H. (2015). Outreach programmes to attract girls into computing: How the best laid plans can sometimes fail. *Computer Science Education*, *25*, 257–275.
- Lazowski, R. A., & Hulleman, C. S. (2016). Motivation interventions in education: A meta-analytic review. *Review of Educational Research*, *86*, 602–640.
- Legewie, J., & DiPrete, T. A. (2014). The high school environment and the gender gap in science and engineering. *Sociology of Education*, *87*, 259–280.
- Leslie, S.-J., Cimpian, A., Meyer, M., & Freeland, E. (2015). Expectations of brilliance underlie gender distributions across academic disciplines. *Science*, *347*, 262–265.
- Lewis, C. M. (2011). Is pair programming more effective than other forms of collaboration for young students? *Computer Science Education*, *21*, 105–134.
- Liben, L. S. (2016). We've come a long way, baby (but we're not there yet): Gender past, present, and future. *Child Development*, *87*, 5–28.
- Maltese, A. V., & Tai, R. H. (2010). Eyeballs in the fridge: Sources of early interest in science. *International Journal of Science Education*, *32*, 669–685.
- Mantzicopoulos, P., Patrick, H., & Samarapungavan, A. (2008). Young children's motivational beliefs about learning science. *Early Childhood Research Quarterly*, *23*, 378–394.
- Martin, C. L., & Dinella, L. M. (2002). Children's gender cognitions, the social environment, and sex differences in cognitive domains. In A. V. McGillicuddy-DeLisi & R. De Lisi (Eds.), *Biology, society, and behavior: The development of sex differences in cognition* (pp. 207–239). Westport, CT: Ablex.
- Martinot, D., & Désert, M. (2007). Awareness of a gender stereotype, personal beliefs, and self-perceptions regarding math ability: When boys do not surpass girls. *Social Psychology of Education*, *10*, 455–471.
- Master, A., Cheryan, S., & Meltzoff, A. N. (2016). Computing whether she belongs: Stereotypes undermine girls' interest and sense of belonging in computer science. *Journal of Educational Psychology*, *108*, 424–437.
- Master, A., Cheryan, S., & Meltzoff, A. N. (2017). Social group membership increases STEM engagement among preschoolers. *Developmental Psychology*, *53*, 201–209.

- Master, A., Markman, E. M., & Dweck, C. S. (2012). Thinking in categories or along a continuum: Consequences for children's social judgments. *Child Development, 83*, 1145–1163.
- Master, A., & Meltzoff, A. N. (2017). Building bridges between psychological science and education: Cultural stereotypes, STEM, and equity. *Prospects, 8*. <http://dx.doi.org/10.1007/s11125-017-9391-z>.
- McKenney, S., & Voogt, J. (2010). Technology and young children: How 4–7 year olds perceive their own use of computers. *Computers in Human Behavior, 26*, 656–664.
- Meltzoff, A. N. (2013). Origins of social cognition: Bidirectional self–other mapping and the “Like-Me” hypothesis. In M. R. Banaji & S. Gelman (Eds.), *Navigating the social world: What infants, children, and other species can teach us* (pp. 139–144). New York: Oxford University Press.
- Miller, C. F. (2008). The influence of gender stereotypes on children's performance: A developmental exploration of mechanisms and vulnerability factors. *Dissertation Abstracts International B: The Sciences and Engineering, 68*, 8430.
- Miller, C. F., Trautner, H. M., & Ruble, D. N. (2006). The role of gender stereotypes in children's preferences and behavior. In L. Balter & C. Tamis-LeMonda (Eds.), *Child psychology: A handbook of contemporary issues* (2nd ed., pp. 293–323). New York: Psychology Press.
- Mioduser, D., & Levy, S. T. (2010). Making sense by building sense: Kindergarten children's construction and understanding of adaptive robot behaviors. *International Journal of Computers for Mathematical Learning, 15*, 99–127.
- Montgomery, K. (2015). Children's media culture in a big data world. *Journal of Children and Media, 9*, 266–271.
- Mumtaz, S. (2001). Children's enjoyment and perception of computer use in the home and the school. *Computers & Education, 36*, 347–362.
- Murayama, K., Pekrun, R., Lichtenfeld, S., & vom Hofe, R. (2013). Predicting long-term growth in students' mathematics achievement: The unique contributions of motivation and cognitive strategies. *Child Development, 84*, 1475–1490.
- Muzzatti, B., & Agnoli, F. (2007). Gender and mathematics: Attitudes and stereotype threat susceptibility in Italian children. *Developmental Psychology, 43*, 747–759.
- National Science Foundation (2015). Bachelor's degrees awarded, by sex and field: 2002–2012 [Table 5–1] <http://www.nsf.gov/statistics/2015/nsf15311/tables/pdf/tab5-1.pdf>.
- Nosek, B. A., Smyth, F. L., Sriram, N., Lindner, N. M., Devos, T., Ayala, A., et al (2009). National differences in gender–science stereotypes predict national sex differences in science and math achievement. *Proceedings of the National Academy of Sciences of the United States of America, 106*, 10593–10597.
- Nugent, G., Barker, B., Grandgenett, N., & Adamchuk, V. I. (2010). Impact of robotics and geospatial technology interventions on youth STEM learning and attitudes. *Journal of Research on Technology in Education, 42*, 391–408.
- Passolunghi, M. C., Rueda Ferreira, T. I., & Tomasetto, C. (2014). Math–gender stereotypes and math-related beliefs in childhood and early adolescence. *Learning and Individual Differences, 34*, 70–76.
- Patrick, H., Mantzicopoulos, P., & Samarapungavan, A. (2009). Motivation for learning science in kindergarten: Is there a gender gap and does integrated inquiry and literacy instruction make a difference. *Journal of Research in Science Teaching, 46*, 166–191.
- Régner, I., Steele, J. R., Ambady, N., Thinus-Blanc, C., & Huguet, P. (2014). Our future scientists: A review of stereotype threat in girls from early elementary school to middle school. *Revue Internationale de Psychologie Sociale, 27*, 13–51.
- Rideout, V. (2013). *Zero to eight: Children's media use in America 2013*. Common Sense Media. <https://www.commonsensemedia.org/research/zero-to-eight-childrens-media-use-in-america-2013>.
- Rothbart, M. (2001). Category dynamics and the modification of outgroup stereotypes. In R. Brown & S. L. Gaertner (Eds.), *Blackwell handbook of social psychology: Intergroup processes* (pp. 45–64). Oxford, UK: Blackwell.
- Shin, J. E. L., Levy, S. R., & London, B. (2016). Effects of role model exposure on STEM and non-STEM student engagement. *Journal of Applied Social Psychology, 46*, 410–427.
- Skinner, A., Meltzoff, A. N., & Olson, K. R. (2017). “Catching” social bias: Exposure to biased nonverbal signals creates social biases in preschool children. *Psychological Science, 28*, 216–224.
- Steele, J. (2003). Children's gender stereotypes about math: The role of stereotype stratification. *Journal of Applied Social Psychology, 33*, 2587–2606.
- Stout, J. G., Dasgupta, N., Hunsinger, M., & McManus, M. A. (2011). STEMing the tide: Using ingroup experts to inoculate women's self-concept in science, technology, engineering, and mathematics (STEM). *Journal of Personality and Social Psychology, 100*, 255–270.
- Terlecki, M. S., & Newcombe, N. S. (2005). How important is the digital divide? The relation of computer and videogame usage to gender differences in mental rotation ability. *Sex Roles, 53*, 433–441.
- Thoman, D. B., Smith, J. L., Brown, E. R., Chase, J., & Lee, J. Y. K. (2013). Beyond performance: A motivational experiences model of stereotype threat. *Educational Psychology Review, 25*, 211–243.
- Weisgram, E. S., & Bigler, R. S. (2006). The role of attitudes and intervention in high school girls' interest in computer science. *Journal of Women and Minorities in Science and Engineering, 12*, 325–336.
- Wyeth, P. (2008). How young children learn to program with sensor, action, and logic blocks. *Journal of the Learning Sciences, 17*, 517–550.