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Gender equity and motivational readiness for computational thinking in early childhood

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ABSTRACT

Learning coding during early childhood is an effective way for children to practice computational thinking. Aspects of children's motivation can increase the likelihood that children approach computational thinking activities with enthusiasm and deep engagement. Gender inequities may interfere with children's readiness to take advantage of opportunities to build computational thinking skills through activities such as coding. Societal stereotypes can reduce young girls' motivation to engage with computer science, preventing them from gaining benefits from coding activities designed to support computational thinking. This study examined children's gender stereotypes as well as children's own motivation for computer coding in 363 first- through third-grade children. We assessed gender differences in both stereotypes and motivation, as well as links between the stereotypes that individual children held and their own motivation. Children generally endorsed stereotypes about interest and ability for computer coding that favored their own-gender group, although third-grade girls reported gender-egalitarian beliefs about interest in coding. There were no gender differences in children's motivation for computer coding in terms of their own interest, sense of belonging, or ability self-concepts. Children's stereotypes about their own-gender group were significantly positively correlated with their own motivation for computer coding. These findings suggest that early childhood represents an excellent age for children to begin building computational thinking skills, before girls endorse negative stereotypes about their gender's interest in computer science.

Learning coding during early childhood is one effective way for children to practice computational thinking and improve other cognitive skills (Bers, 2018; Grover & Pea, 2018; Scherer et al., 2019). Computational thinking is a core thinking and problem-solving process that can be embedded within a broad range of academic subjects (Grover & Pea, 2018; Henderson et al., 2007). Wing (2006) advocated for all students to learn computational thinking and cited the importance of computational thinking in both problem solving and system design. Berry (2013) further broke down computational thinking into more basic concepts and approaches. In elementary education, the most common concepts are algorithms, abstraction, decomposition, and patterns, and the most common approaches are tinkering, debugging, persevering, collaboration, and creating (Berry, 2013; Prottsman, 2019). Integrating computational thinking into curriculum not only provides students with experience in real-world problem solving (Denning & Tedre, 2019; Weintrop et al., 2016), but also results in deeper understanding of the content at hand (Ketelhut et al., 2020). Yet, gender inequities may interfere with children's readiness to take advantage of opportunities to build computational thinking skills (Early Childhood STEM Working Group, 2017; Ketelhut et al., 2020; Master et al., 2017b; Mercier et al., 2006; Sullivan, 2021).

Gender equity is necessary to consider because the field of computer science shows gender disparities (Ashcraft et al., 2012; Beyer, 2014; J. Wang et al., 2015). Although computational thinking is taught across academic subjects, the most common approach is embedding computational thinking within computer science (Grover & Pea, 2013; Hsu et al., 2018; Relkin et al., 2021). Only about 7% of elementary school students in the U.S. are enrolled in computer science courses, but many more are introduced to computer science in other ways, including Hour of Code (Code.org Advocacy Coalition, Computer science teachers association, & expanding computing education pathways alliance, 2021; Yauney et al., 2022). Exposure to computer programming can promote young chil-

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dren's motivation to engage with computer science materials, especially for girls (Master et al., 2017b). Computer science classes in elementary school are more likely than those in middle or high school to have equal representations of girls and boys (Code.org Advocacy Coalition, Computer science teachers association, & expanding computing education pathways alliance, 2021), which reduces girls' underrepresentation as a cue that they do not belong in computer science (Murphy et al., 2007). Early, positive exposure to computer science can help counter the impact of negative societal stereotypes about girls and computer science (Code.org Advocacy Coalition & Computer Science Teachers Association, 2018; Master et al., 2017b; Sullivan, 2021) and can come at a critical time in their development when positive associations are easier to form and can leave long-lasting impressions (Wang & Degol, 2017). Young children's motivation for computer science sets the stage for their learning and engaging in computational thinking embedded within computer science education (diSessa, 2000).

However, significant concerns arise when teaching computational thinking through the use of computer science. As a field, computer science is associated with many societal stereotypes that can be transmitted by people (such as teachers) and environmental cues (Cheryan et al., 2015; Mercier et al., 2006). One concern is that many teachers have low self-efficacy in their ability to teach computer science (Thorsnes et al., 2020; Zhou et al., 2020). A nationwide survey of more than 3,500 computer science teachers found that elementary school teachers reported lower levels of confidence in teaching computer science compared to middle and high school teachers (Koshy et al., 2021). In elementary education, most teachers are women (De Brey et al., 2021), and 78% of elementary school computer science teachers are women (Koshy et al., 2021). Historically, women have experienced fewer opportunities in computer science (Beyer, 2014; Papastergiou, 2008; J. Wang et al., 2016), and fewer computer science role models (Cheryan et al., 2013; Dasgupta & Stout, 2014; Meelissen & Drent, 2008). Thus, they are likely to have had less exposure to computer science than men, leading to lower self-confidence in their ability to teach computer science (Tate et al., 2018; J. Wang et al., 2015). In addition, teachers are not immune to implicit bias and may unconsciously perpetuate stereotypes that computer science is for boys, decreasing the amount of instructional time and opportunities for girls (Barker & Aspray, 2006; Tate et al., 2018).

A second concern is that many environmental cues can send a stereotypical message about computer science. Girls have been shown to be less motivated (with lower interest and a lower sense of belonging) than boys in classrooms whose design reflects highly stereotypical perceptions of computer science (e.g., with Star Trek posters; Cheryan et al., 2011; Master et al., 2016). Stereotypical portrayals of computer scientists as men in media such as television shows or news articles can negatively impact girls (Cheryan et al., 2013; Lyda Hill Foundation & Geena Davis Institute on Gender in Media, 2021). In addition, some computer science curricula can perpetuate the stereotype of computer science as an abstract, isolating field, which can deter girls away in search of more applied and communal fields (Ashcraft et al., 2012; Diekman et al., 2011). When computer science is framed as "not for girls," gender inequities can form within the classroom that limit girls' access to, and engagement with, computational thinking opportunities (Hand et al., 2012). If young children are already being influenced by gender stereotypes about computer science, then it would be useful for teachers to address gender stereotypes before introducing computational thinking to their classrooms through coding. We discuss ways to address gender stereotypes further in the Discussion section below.

1. Children's gender stereotypes

Societal stereotypes about both gender and academic fields can directly affect young children. Stereotypes are beliefs that link social groups with certain traits (Master et al., 2021). Societal stereotypes about coding may begin to take hold at an early age, although early exposure to coding can help mitigate those stereotypes in young children (Master et al., 2017b). Given that computer science is often the avenue in which computational thinking is taught (Cator et al., 2017), stereotypes that surround who is associated with computer science are important to consider. Even though girls and boys are equally successful at learning computational thinking and coding (Relkin et al., 2021; Sullivan & Bers, 2012), many children as young as first grade believe that boys have higher ability than girls in computer coding, and many children as young as third grade believe that boys are more interested than girls in coding (Master et al., 2021). Both types of stereotypes have important implications for young girls' motivation to take advantage of computer science opportunities. Stereotypes that boys are more talented than girls and more interested than girls in computer science may have negative implications for girls' perceptions of their own ability and sense of belonging in computer science (Master, 2021; Master et al., 2017b; Master et al., 2021).

Girls' stereotypes about ability and interest are linked to their own lower interest in computer science (Master et al., 2017b; Master et al., 2021). In early childhood, children are often described as "gender detectives," who seek and identify the preferences and expectations for their gender group (Halim & Ruble, 2010; see Wang et al., 2021, for evidence that gender norms powerfully change young children's behavior and engagement). If young girls perceive that computer science is a topic that their gender group is not interested in or good at, they are likely to choose to avoid learning opportunities involving this subject or not fully engage, even when participation is mandatory. Gaining a better understanding of young children's stereotypes and motivation for computer science is important for helping children develop their identity as learners of computational thinking (Grover & Pea, 2013).

2. Children's motivation in computer science

Engaging young girls in computing is important for efforts to reduce gender gaps in the field of computer science (Grover & Pea, 2013). Indeed, gender gaps in motivation for computer science emerge during elementary school (Cooper, 2006; Master et al., 2021; McKenney & Voogt, 2010). "Motivation" refers to the factors that energize students in school, including their *cognitions* (e.g., self-perceptions and beliefs about belonging), *affective* and emotion-related responses (e.g., interest and enjoyment), and *behaviors* (e.g., persistence and academic choices; Dweck & Leggett, 1988; Master, 2021). The current study takes a comprehensive view and measures three key motivational outcomes: interest, sense of belonging, and ability self-concepts.

Studies have found that girls report lower interest in computer science compared to boys in elementary school, as early as first grade (Cooper, 2006; Master et al., 2017b; McKenney & Voogt, 2010). Young children's self-reported interest is linked to important behaviors, including children's choice of whether to do a computer science activity (Master et al., 2021). "Interest," as we will use it within this paper, refers to an individual's *maintained* interest, for example, a repeated inclination to engage with computer science activities over time (Hidi & Renninger, 2006). This is distinguished from *situational* interest, which is triggered within an immediate learning experience and may not last over time. Situational interest in computer science is known to be malleable, with positive experiences and social connections supporting young children's immediate interest in STEM activities (Master et al., 2017a; Master et al., 2017b).

Although opportunities to engage in computational thinking activities provide the chance to spark girls' situational interest in computing, a more critical goal for educators and society is to develop girls' *maintained* individual interest in computer science to encourage their repeated engagement in this topic. Maintained interest in scientific fields often emerges by the end of elementary school (Maltese & Tai, 2010), supporting the importance of focusing on early childhood computer science education. However, more research is needed, using a wider variety of measures of interest to gain a better understanding of how interest in computer science develops and is shaped by young children's stereotypical beliefs and experiences.

Ability self-concepts represent a central aspect of children's motivational beliefs. Girls report lower beliefs about their own abilities in computer science compared to boys by first grade (Master et al., 2017b). We use the term "ability self-concepts" to refer to children's stable beliefs about how good they are in a field; this is broader than self-efficacy, which refers to students' beliefs about their success on a specific task (Eccles & Wigfield, 2020). Ability self-concepts are one of the key factors determining whether children choose to engage in a topic (Eccles & Wigfield, 2020; Master & Meltzoff, 2020). If young children think they will be good at computer science, they are more likely to choose to engage in these opportunities and build their individual interest in this topic over time. We need a better understanding of how young children develop ability self-concepts about general topics such as computer science, and how those might overlap or be distinct from self-efficacy for more specific tasks (such as programming a robot during a class activity).

A "sense of belonging" is also linked to children's interest in computer science by elementary school (Master et al., 2021). Sense of belonging refers to children's sense that they would belong, fit in, and have a positive relationship with others in an environment (Master, 2021). Although few studies have examined the development of children's sense of belonging in computer science, gender differences seem to emerge during middle school, with girls reporting lower sense of belonging than boys (Master et al., 2021). However, even younger children's sense of belonging is sensitive to information about gender in certain contexts. Elementary-school girls feel a lower sense of belonging for a computer science activity when it is described as one that "girls are much less interested in than boys," compared to an activity for which girls and boys show equal interest (Master et al., 2021). Very little is known about how young children's own sense of belonging in computer science is linked to their stereotypical beliefs.

3. Why motivation matters for computational thinking

When students learn computational thinking, they are learning to think like computer scientists (Grover & Pea, 2018). But how motivated are children to become computer scientists? Motivation for computer science sets the stage for learning computational thinking, because computational thinking is often embedded within computer science education (Cator et al., 2017). Given that motivational variables such as interest, sense of belonging, and ability self-concept represent a key part of children's readiness to learn, lower motivation for computer science could create barriers in learning computational thinking. Students who are motivated (whether they are children or adults) more easily pick up content matter and are more likely to embed the practice for further use (Jiang & Wong, 2017; Shanmugam et al., 2019; Yadav et al., 2011). That is, if students are motivated to learn computational thinking (and see its relevance in their lives), they may be more likely to use it as an approach to thinking across disciplines. This would then support the primary purpose of computational thinking (Cator et al., 2017; Weintrop et al., 2016). It is also important to gain a better understanding of children's motivation in computer science across educational contexts, including among children who have or do not have exposure to computer science curricula. Even children who engage in formal computer science instruction may receive varied exposure to different aspects of computer science (including coding and/or robotics) and computational thinking.

What about computational thinking embedded in disciplinary content other than computer science? Elementary school teachers may integrate computational thinking in many other topics, such as when teaching pattern recognition in math or rules of grammar in language (Grover, 2021). Integrating computational thinking into other topics can range from coding activities that have little relation with domain content to full integration (Lee et al., 2020; Ottenbreit-Leftwich & Yadav, 2021). In early-elementary grade levels, integration may primarily involve the use of computational thinking *language*, such as talking about data when graphing the growth of lima beans or talking children through the processes of experimentation and iteration, rather than actively extending learning through computational thinking (Coenraad, Cabrera, Killen, Plane, & Ketelhut, 2021; Jacob, Parker, & Warschauer, 2021; Ottenbreit-Leftwich & Yadav, 2021). In these situations, motivation in computer science could be more or less relevant depending on how teachers label and frame the learning situation and how students perceive it (Conlin et al., 2020; Rich et al., 2020). If teachers and students explicitly connect activities to the field of computer science itself (e.g., when using algorithms and debugging), then children's stereotypes and motivation for computer science are likely to drive how much they engage and learn in that situation. In contrast, if teachers and students explicitly frame activities solely in terms of the other domain, then stereotypes and motivation for that domain should be most influential (Huguet & Régner, 2007, 2009).

4. Importance of diversity and intersectionality for young children's motivation

Another important issue relevant to examining young children's motivation for computational thinking is their racial/ethnic and socioeconomic background. There are disparities in access to K-12 computer science education, with schools less likely to offer foundational computer science courses if they have higher percentages of socioeconomically disadvantaged and Black, Hispanic/Latinx, and Native American students (Code.org Advocacy Coalition, Computer science teachers association, & expanding computing education pathways alliance, 2021). Even larger disparities emerge when considering the intersectionality among different demographic characteristics, including gender, race/ethnicity, and geographic location (Warner, Childs, Fletcher, Martin, & Kennedy, 2021). On the bright side, learning computational thinking in childhood may be one important way to address issues of equity (Grover et al., 2021). There are fewer racial/ethnic disparities for K-8 students in computer science than older students. For instance, elementary school students who take foundational computer science are generally representative of the race/ethnicity of their state's student population (Code.org Advocacy Coalition, Computer science teachers association, & expanding computing education pathways alliance, 2021). Integrating computational thinking into domains outside of computer science can also help to expand the number of children who gain opportunities to experience this type of learning situation (Ottenbreit-Leftwich & Yadav, 2021; Weintrop et al., 2016). Thus, attending to the recruitment of diverse young students into computational thinking opportunities is relevant for issues of educational equity (Warner, Childs, Fletcher, Martin, & Kennedy, 2021), as is understanding their perceptions of and motivations for embracing or avoiding such opportunities.

5. Rationale for current work

Given that computational thinking is fundamental in how well students solve problems (Wing, 2006) and that computer science is the way in which computational thinking is often taught (Grover & Pea, 2013; Hsu et al., 2018; Relkin et al., 2021), it is important to understand students' *stereotypical beliefs* and *motivation* for coding. The current paper examined gender differences and links between stereotypes and motivation for coding in first through third grades.

This paper includes secondary analyses of a large cross-sectional dataset (from which some findings have been published; Master et al., 2021); here, we analyze new aspects of the larger dataset that have not yet been examined (see Table S1). More specifically, the current paper provides: (a) novel analyses, including the addition of more variables (stereotype ratings about girls and boys separately, sense of belonging, and ability self-concepts); (b) new analyses examining the relations among these variables; (c) the implications of these findings for theories of early childhood motivation and cognition; and (d) broader implications for educators who aim to promote computational thinking. Our research questions included:

1 What are young children's stereotypes about how much most girls and boys are interested in and good at computer science, and about which gender group is relatively *more* interested in and good at computer science?
2 Are there gender differences in young children's motivation for computer science, including their interest, sense of belonging, and ability self-concepts in computer science?
3 Are young children's gender stereotypes about computer science related to their own motivation?

These research questions are important when considering how to integrate and frame computational thinking activities in early childhood. If girls endorse gender stereotypes that predict their lower motivation, then educators should address gender stereotypes before introducing computational thinking to their classrooms through coding.

6. Methods

Participants were from four elementary schools in a diverse school district in New England that provided opportunities for all students to engage with coding. Elementary-school students were typically exposed to coding and computational thinking in library classes once each week. Children beginning in first grade were taught applied logic in the form of basic algorithms, by considering inputs and outputs of basic tasks. First and second-grade students were introduced to coding and computational thinking through the online platform Kodable, and third-grade students used Scratch. The participating school district was selected by officials in the state's Department of Education, based on district size, diversity (see Participants section, below), and participation in the statewide initiative to promote computer science education in K-12 schools.

Institutional review board (IRB) approval was obtained to conduct this research. Information letters were sent to parents and guardians, allowing them to opt their children out of participating in the surveys. In addition, research with children younger than age 18 typically obtains youths' *assent* (Lindeke et al., 2000). Assent is defined as an affirmation or agreement to participate in research (Lindeke et al., 2000; Miller et al., 2004). All children in the current study were given information about what the study involved before they gave their informed assent to participate. We surveyed 363 students (181 girls, 182 boys) in Grades 1-3 (120 first grade, 115 second grade, and 128 third grade; 37% White, 17% Hispanic/Latinx, 9% Multiracial, 7% Black, 6% Asian, 24% Other or no response). The mean age of the sample was $M = 8.00$, $Sd = 0.91$ (Grade 1: $M = 7.01$, $Sd = 0.50$, range 5.46 to 8.08 years old; Grade 2: $M = 7.95$, $Sd = 0.46$, range 6.06 to 9.18 years old; Grade 3: $M = 8.94$, $Sd = 0.36$, range 8.18 to 10.11 years old). In this school district during this school year, 43% of students received free/reduced-price lunch (Rhode Island Department of Education, n.d.). Participants identified their own gender by selecting between the options, "Girl," "Boy," or "I use another word," with a text box to enter their preferred gender identity. An additional five children identified their gender as something other than girl or boy (e.g., "awesome") and 56 children left this item blank; these were excluded from the count of 363 participants and from analyses. Excluding these 61 participants does not change the overall mean value for any stereotype or motivation measure, $ps > .63$.

Surveys were completed using Qualtrics within the classroom with research assistants reading survey items out loud to first and second graders, who entered their own responses into the computer with help from researchers as needed. This procedure was implemented following a recommendation from the project's superintendent-appointed school liaison, who was the library media program supervisor for the district. This type of additional support is common for cross-sectional studies that include early elementary-school children (Harris et al., 2018; Wigfield et al., 1997). The third graders completed the survey items independently, although a researcher was available in the classroom to help as needed.

Gender stereotypes about computer science were assessed by measuring beliefs about boy targets' and girl targets' interest (e.g., "How much do most girls like computer coding?") and ability (e.g., "How good are most girls at computer coding?") on 1-6 Likert scales. Stereotypes were analyzed as separate "raw" scores as well as by creating difference scores, with positive scores reflecting beliefs favoring boys. We defined coding for all children by saying, "Computer coding means to write instructions for a computer, robot, tablet, or phone app to do a task." We asked children about coding because we expected children to be more familiar with this than the broader academic discipline of computer science. *Motivational measures* included assessments of the child's own *interest* (two items, $\alpha = .79$, e.g., "I like to do computer coding activities"), *sense of belonging* (three items, $\alpha = .65$, e.g., "I feel like I belong when I do computer coding classes and activities at school"), and *ability self-concepts* (two items, $\alpha = .76$, e.g., "I am good at computer coding activities"), on 1-6 Likert scales. Each measure demonstrated good reliability for scales with less than 10 items (Price et al., 2015). The amount of missing data per variable ranged from 0.80% to 4.10%. Expectation–maximization (EM) algorithm estimated statistics indicated the missing pattern was missing completely at random (Little's Missing Completely at Random test: $\chi^2 = 81.19$, $df = 96$, $p > .05$). The complete list of survey items is included in the electronic supplementary materials. Other measures and other STEM fields (science, math, and engineering) were also collected in the survey, but were not the focus of this paper. Following the initial survey sessions, we realized the survey length was too challenging for first grade students and reduced the total number of survey questions for the remaining first grade participants ($N = 65$) from 120 to 57. All measures reported in this paper were included for all participants.

7. Results

7.1. Stereotypes

Stereotypes were examined in two ways: raw stereotype ratings about girl targets and boy targets separately and as difference scores. "Targets" refer to children's ratings of "most girls" and "most boys" as the focus of the stereotype. Raw stereotype scores provide specific information about children's beliefs about each gender group separately, and difference scores provide information about beliefs about members of each gender group relative to the other. Examining both types of stereotype measures allows us to understand children's beliefs about gender groups in a more comprehensive manner than taking one measure alone (as is sometimes done in studies).

For the raw scores, we used a 2 (participant gender, between subjects: girl participants or boy participants) × 2 (target gender, within subjects: girl targets or boy targets) × 3 (grade level, between subjects: first, second, or third grade) analysis of variance (ANOVA) to examine whether there were gender differences in stereotypes about girl and boy targets by grade level. Both girls and boys generally reported positive beliefs about each gender's interest and ability in computer science, see Fig. 1 and Tables 1-2, although they reported the most positive beliefs about their own gender group.

For the difference scores, we first examined whether each gender and grade level group significantly endorsed stereotypes using a one-sample t-test compared to an egalitarian/neutral value of 0. We then used a 2 (participant gender, between subjects: girl participants or boy participants) × 3 (grade level, between subjects: first, second, or third grade) mixed-model ANOVA to examine whether there were gender differences in stereotype difference scores by grade level. Both girls and boys generally reported stereotypes favoring their own gender group, see Fig. 2 and Tables 1-2. Thus, boys' stereotypes were more similar to adults' societal stereotypes favoring boys, but girls' stereotypes were generally counter to traditional stereotypes.

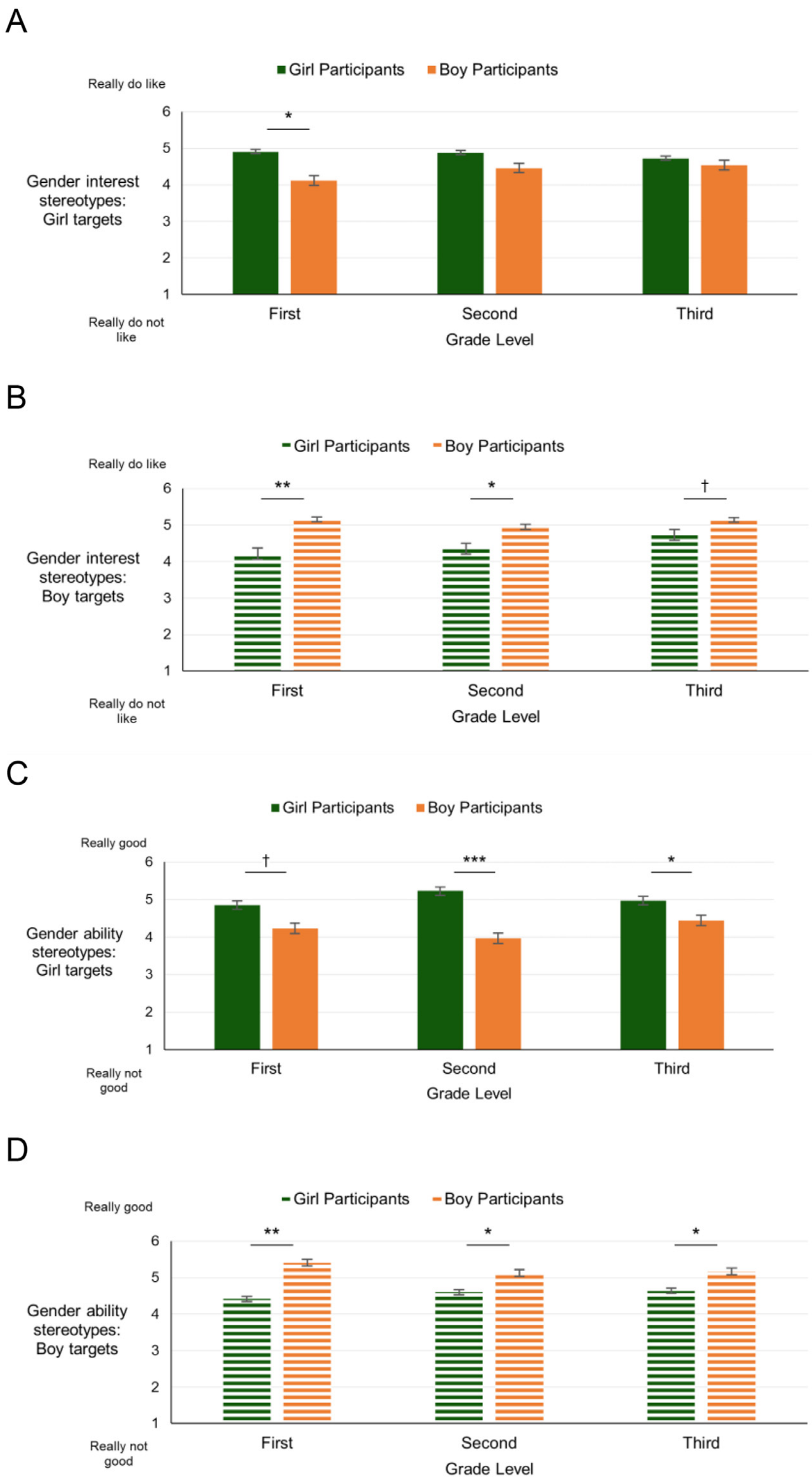

Fig. 1. Raw Stereotype Scores by Grade Level and Participant Gender

Note. Gender-interest raw stereotype scores for girl targets in solid bars (A) and boy targets in striped bars (B), and gender-ability raw stereotype scores for girl targets (C) and boy targets (D) by grade level and participant gender. Error bars represent ±1 *SE*. Gender differences: $^{\dagger}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

7.2. Raw stereotype scores

7.2.1. Gender-interest stereotypes

In terms of gender-interest raw stereotype scores, the 2 (participant gender, between subjects: girl or boy participants) × 2 (target gender, within subjects: girl or boy targets) × 3 (grade level, between subjects: first, second, or third grade) ANOVA revealed a significant two-way interaction between participant gender and target gender, $F(1, 350) = 29.76$, $p < .001$, $\eta_p^2 = .08$, see Fig. 1A and 1B. Girl participants rated girl targets as more interested than boy targets, and boy participants rated boy targets as more interested than girl targets. In terms of the simple effects, there were significant participant gender differences for ratings of girl targets, $p = .006$ (with girl participants rating them as more interested than boy participants did), and ratings of boy targets (with boy participants rating them as more interested than girl participants did), $p < .001$. Looking at this interaction the other way, both girl participants, $p = .005$, and boy participants, $p < .001$, showed significant differences in their ratings of girl targets and boy targets (with girl participants rating girl targets as more interested than boy targets, and boy participants rating boy targets as more interested than girl targets). The

Table 1
Gender-interest stereotypes by gender and grade level.

Grade	Stereotypes	Girl Participants			Boy Participants			Participant Gender Difference		
		N	*M*	*SD*	*N*	*M*	*SD*	*t*	*p*	Cohen's *d*
First	Girl Targets	64	4.91	1.71	51	4.12	2.13	-2.15	.034	0.41
	Boy Targets	65	4.22	1.87	52	5.15	1.53	2.99	.003	0.54
	Difference Score	63	-0.71*	2.50	51	1.02**	2.59	3.63	.000	0.68
Second	Girl Targets	52	4.88	1.23	63	4.46	1.59	-1.61	.110	0.30
	Boy Targets	52	4.35	1.68	63	4.95	1.38	2.12	.036	0.39
	Difference Score	52	-0.54*	1.88	63	0.49*	1.68	3.10	.002	0.58
Third	Girl Targets	62	4.73	1.38	65	4.54	1.19	-0.82	.413	0.15
	Boy Targets	62	4.73	1.34	66	5.14	1.19	1.83	.069	0.32
	Difference Score	62	0.00	1.55	65	0.58***	1.18	2.40	.018	0.42

Note. Girl target and boy target means were on a scale from 1-6. Significance levels for difference score means are for the comparison to an egalitarian value of 0.
* $p < .05$.
** $p < .01$
*** $p < .001$.

Table 2
Gender-ability stereotypes by gender and grade level.

Grade	Stereotypes	Girl Participants			Boy Participants			Participant Gender Difference		
		N	*M*	*SD*	*N*	*M*	*SD*	*t*	*p*	Cohen's *d*
First	Girl Targets	67	4.85	1.61	52	4.23	2.04	-1.80	.075	0.34
	Boy Targets	65	4.42	1.88	51	5.41	1.13	3.53	.001	0.64
	Difference Score	65	-0.42	2.38	51	1.18**	2.25	3.52	.001	0.69
Second	Girl Targets	52	5.23	1.17	63	3.97	1.62	-4.86	.000	0.89
	Boy Targets	52	4.60	1.40	63	5.13	1.20	2.19	.031	0.41
	Difference Score	52	-0.63*	1.75	63	1.16***	1.98	5.10	.000	0.96
Third	Girl Targets	61	4.97	1.08	65	4.45	1.23	-2.53	.013	0.45
	Boy Targets	61	4.64	1.37	65	5.17	1.13	2.38	.019	0.42
	Difference Score	61	-0.33	1.58	65	0.72***	1.38	3.99	.000	0.71

Note. Girl target and boy target means were on a scale from 1-6. Significance levels for difference score means are for the comparison to an egalitarian value of 0.
* $p < .05$.
** $p < .01$.
*** $p < .001$.

3-way interaction between participant gender, target gender, and grade level was not significant, $F(2, 350) = 2.65$, $p = .072$, $\eta_p^2 = .02$. There were no significant main effects of grade level, participant gender, or target gender, *ps* > .17.

7.2.2. Gender-ability stereotypes

In terms of gender-ability raw stereotype scores, the 2 (participant gender, between subjects: girl or boy participants) × 2 (target gender, within subjects: girl or boy targets) × 3 (grade level, between subjects: first, second, or third grade) ANOVA again revealed a significant 2-way interaction between participant gender and target gender, $F(1, 351) = 51.34$, $p < .001$, $\eta_p^2 = .13$. Similar to the measure of gender-interest stereotypes, girl participants rated girl targets as better than boy targets at coding, and boy participants rated boy targets as better than girl targets at coding. In terms of the simple effects, there were significant participant gender differences for ratings of girl targets (with girl participants rating them as better than boy participants did), $p < .001$, and ratings of boy targets (with boy participants rating them as better than girl participants did), $p < .001$. Looking at this interaction the other way, both girl participants, $p = .002$, and boy participants, $p < .001$, showed significant differences in their ratings of girl targets and boy targets (with girl participants rating girl targets as better than boy targets, and boy participants rating boy targets as better than girl targets). The 3-way interaction between participant gender, target gender, and grade level was not significant, $p = .31$. There was a significant main effect of target gender, $F(1, 351) = 7.05$, $p = .008$, $\eta_p^2 = .02$, with boy targets overall rated as significantly better than girls at coding. The main effects of grade level, participant gender, and their interaction were not significant, *ps* > .11.

7.3. Stereotype difference scores

7.3.1. Gender-interest stereotypes

In terms of gender-interest stereotype difference scores, children reported gender-interest stereotypes that significantly favored their ingroup among first-grade girls, first-grade boys, second-grade girls, second-grade boys, and third-grade boys, see Table 1. Third-grade girls did not favor either gender. The gender difference in gender-interest stereotypes was significant among first graders, $t(112) = 3.63$, $p < .001$, $d = 0.68$, second graders, $t(113) = 3.10$, $p = .002$, $d = 0.58$, and third graders, $t(125) = 2.40$, $p = .018$, $d = 0.42$, with boys more likely than girls to report stereotypes favoring boys' interest in coding. Thus, boys' stereotypes were more similar to adults' societal stereotypes favoring boys, but first- and second-grade girls' stereotypes were counter to traditional stereotypes and favored their own-gender group.

7.3.2. Gender-ability stereotypes

In terms of gender-ability stereotype difference scores, children reported gender-ability stereotypes that significantly favored their ingroup among first-grade boys, second-grade girls, second-grade boys, and third-grade boys, see Table 2. The first-grade and third-grade girls did not significantly favor either gender. The gender difference in gender-ability stereotypes was significant among first graders, $t(114) = 3.52$, $p = .001$, $d = 0.69$, second graders, $t(113) = 5.10$, $p < .001$, $d = 0.96$, and third graders, $t(124) = 3.99$, $p < .001$, $d = 0.71$, with boys

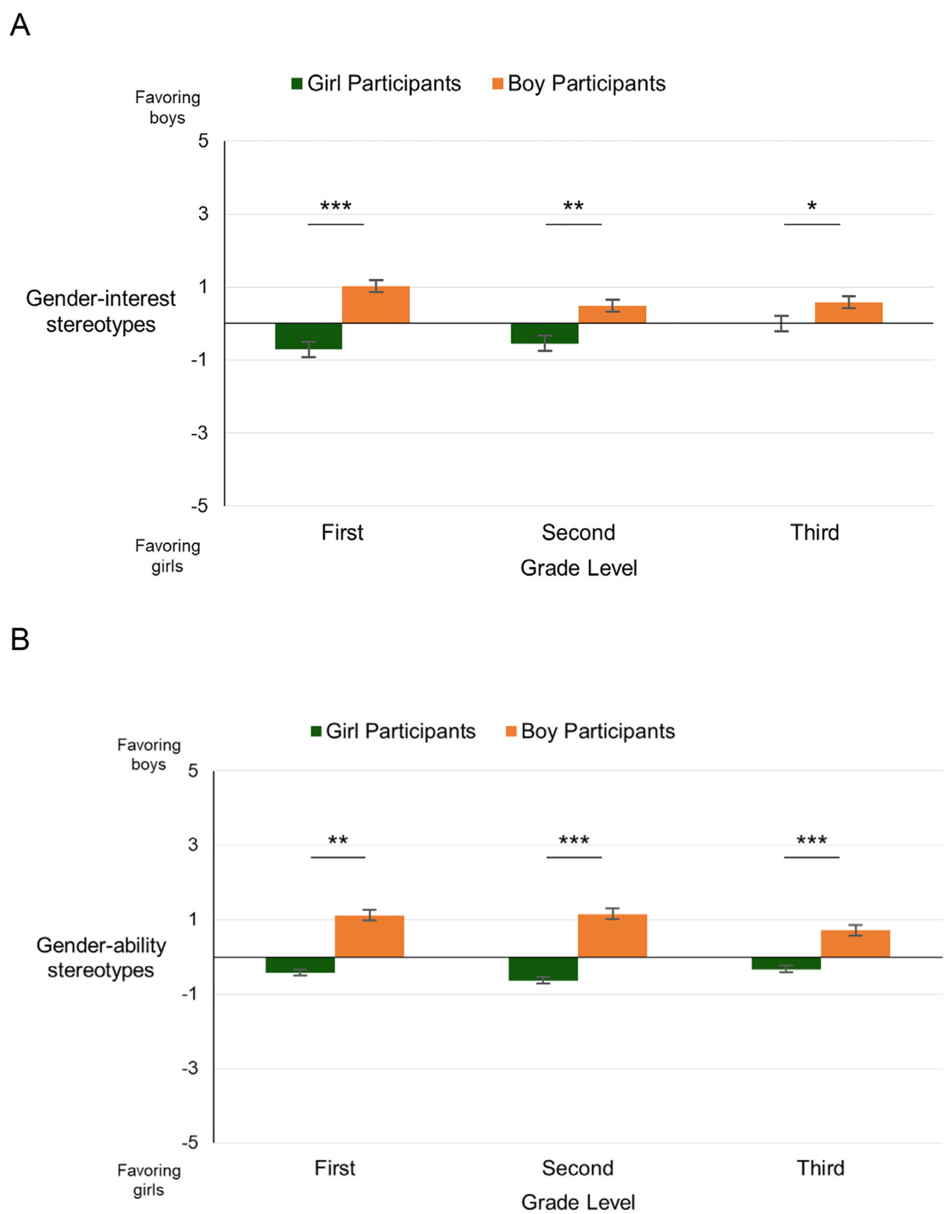

Fig. 2. Stereotype Difference Scores by Grade Level and Participant Gender
Note. Gender-interest (A) and gender-ability (B) difference score stereotypes by grade level and participant gender. Positive numbers represent stereotype difference scores favoring boys, and negative numbers represent stereotype difference scores favoring girls (possible range -5 to 5). Error bars represent ±1 *SE*. Gender differences: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

more likely than girls to report stereotypes favoring boys' ability in coding. Thus, boys' stereotypes were more similar to adults' societal stereotypes favoring boys, but second-grade girls' stereotypes were counter to traditional stereotypes and favored their own-gender group.

7.4. Motivation

Motivation in the individual was examined in terms of gender and grade level differences for each measure.

7.4.1. Children's own interest

We ran a 2 (participant gender, between subjects: girl or boy participant) × 3 (grade level, between subjects: first, second, or third grade) ANOVA. We found no significant differences in children's own interest in coding activities based on gender, $F(1, 342) = 0.39$, $p = .53$, $\eta_p^2 = .001$, or the interaction between gender or grade level, $F(2, 342) = 0.15$, $p = .86$, $\eta_p^2 = .001$, see Fig. 3A, with most children reporting that they had high interest. There was a marginally significant main effect of grade level, $F(2, 342) = 2.91$, $p = .056$, $\eta_p^2 = .02$. Second-grade students reported lower interest in computer science than first-grade students, $p = .021$.

7.4.2. Children's sense of belonging

We found no significant differences for children's sense of belonging during coding activities based on gender, $F(1, 347) = 0.11$, $p = .74$, $\eta_p^2 = .00$, grade level, $F(2, 347) = 0.31$, $p = .74$, $\eta_p^2 = .002$, or the interaction between them, $F(2, 347) = 0.25$, $p = .78$, $\eta_p^2 = .001$, see Fig. 3B, with most children reporting a high sense of belonging.

7.4.3. Children's ability self-concepts

We found no significant differences for children's ability self-concepts in coding based on gender, $F(1, 347) = 0.29$, $p = .59$, $\eta_p^2 = .001$, grade level, $F(2, 347) = 0.66$, $p = .52$, $\eta_p^2 = .004$, or the interaction between them, $F(2, 347) = 0.24$, $p = .79$, $\eta_p^2 = .001$, see Fig. 3C, with most children reporting high ability self-concepts.

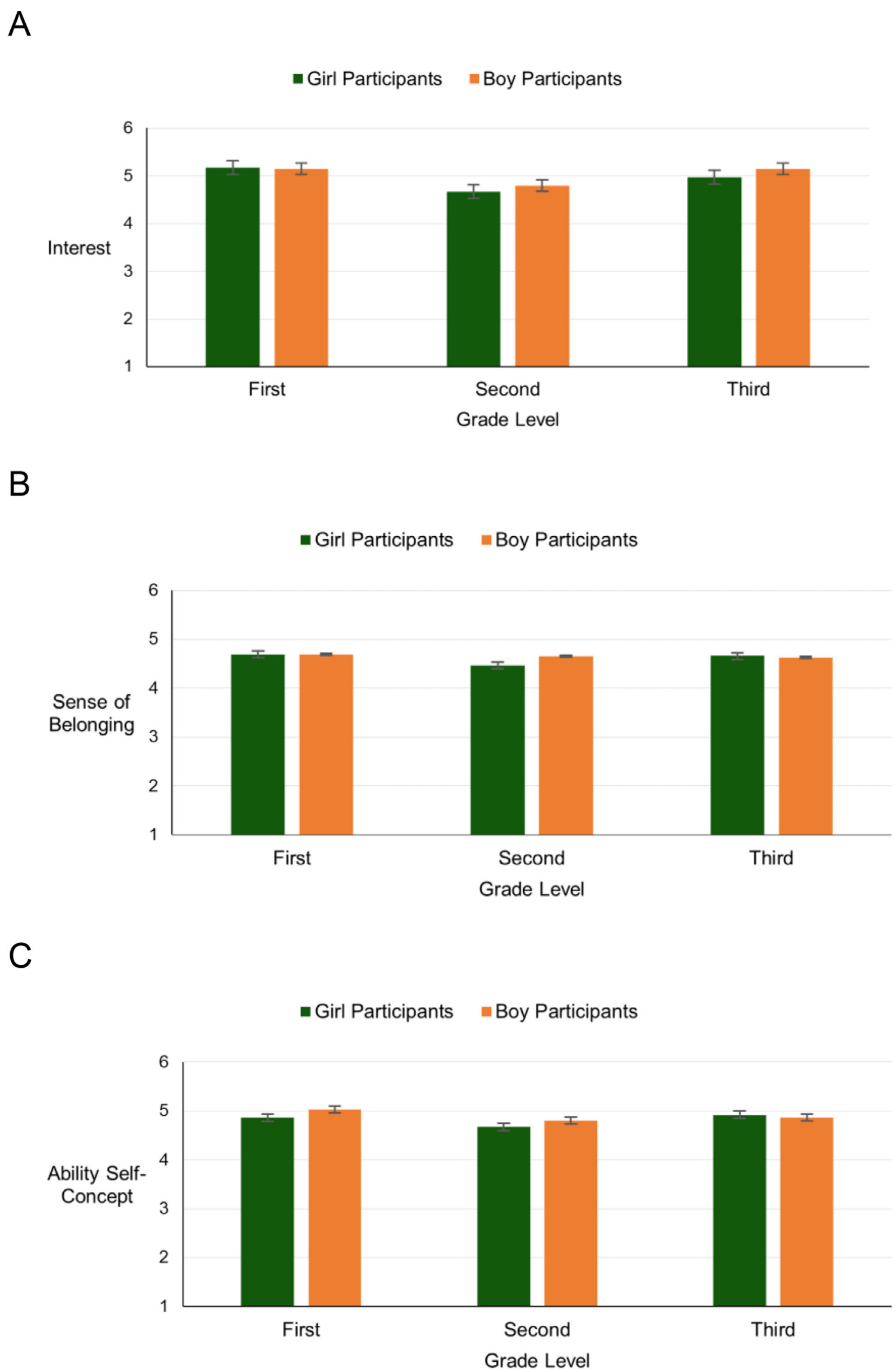

Fig. 3. Motivation by Grade Level and Participant Gender
Note. Interest (A), sense of belonging (B), and ability self-concept (C) by grade level and participant gender. All were measured on a scale from 1 (*Strongly disagree*) to 6 (*Strongly agree*). Error bars represent ±1 *SE*.

7.5. Links between stereotypes and motivation

7.5.1. Raw stereotype scores

Raw stereotype ratings about girl and boy participants were significantly correlated with girls' and boys' motivation, especially for ratings of their own gender ingroup. Girl participants' gender-interest stereotypes about girl targets were significantly correlated with their own interest, sense of belonging, and ability self-concepts, *ps* < .001; see Table 3. Girl participants' gender-ability stereotypes about girl targets were also significantly correlated with their own interest, *p* = .006, sense of belonging, *p* < .001, and ability self-concepts, *p* < .001. The correlations between motivation and girl participants' ratings of the ingroup/girl targets (gender-interest stereotypes, *rs* = .38 – .46; gender-ability stereotypes, *rs* = .21 – .35) were generally stronger than the correlations for girl participants' ratings of the outgroup/boy targets (gender-interest stereotypes, *rs* = .20 – .27; gender-ability stereotypes, *rs* = .16 – .17).

Boy participants' gender-interest stereotypes about boy targets were significantly correlated with their own interest, sense of belonging, and ability self-concepts, *ps* < .001. Boy participants' gender-ability stereotypes about boy targets were also significantly correlated with their own interest, sense of belonging, and ability self-concepts, *ps* < .001. The

Table 3
Correlations between stereotypes and motivation by gender.

Variable	1	2	3	4	5	6	7	8	9
1. Raw gender-interest stereotypes about girl targets	—	.15*	-.59***	.29***	.09	-.14†	.46***	.38***	.42***
2. Raw gender-interest stereotypes about boy targets	.25**	—	.71***	.12	.37***	.21**	.20*	.27***	.27***
3. Gender-interest stereotype difference scores	-.70***	.51***	—	-.11	-.25**	.28***	-.14†	-.03	-.07
4. Raw gender-ability stereotypes about girl targets	.27***	.10	-.17*	—	.10	-.59***	.21**	.31***	.35***
5. Raw gender-ability stereotypes about boy targets	.17*	.47***	.19*	.12	—	.74***	.17*	.17*	.16*
6. Gender-ability stereotype difference scores	-.12†	.22**	.27***	-.79***	.51***	—	-.01	-.10	-.12
7. Interest	.30***	.49***	.10	.21**	.37***	.03	—	.66***	.77***
8. Sense of belonging	.44***	.44***	-.07	.23**	.31***	-.02	.61***	—	.63***
9. Ability self-concept	.37***	.49***	.03	.25**	.43***	.03	.67***	.57***	—

Note. The results for girl participants (ns = 163 – 178) are shown above the diagonal. The results for boy participants (ns = 177 – 182) are shown below the diagonal. Stereotype difference scores are calculated by using ratings about boy targets minus ratings about girl targets, with positive values indicating stereotypes favoring boys (range -5 to 5).
† $p < .10$.
* $p < .05$.
** $p < .01$.
*** $p < .001$.

correlations between motivation and boy participants' ratings of the ingroup/boy targets (gender-interest stereotypes, rs = .44 – .49; gender-ability stereotypes, rs = .31 – .43) were generally stronger than the correlations for boy participants' ratings of the outgroup/girl targets (gender-interest stereotypes, rs = .30 – .44; gender-ability stereotypes, rs = .21 – .25).

7.5.2. Stereotype difference scores

Stereotype difference scores were not significantly correlated with girls' or boys' motivation, -.14 < rs < .10, ps > .05, see Table 3.

8. Discussion

Activities such as coding are the predominant way to teach computational thinking to young children (Grover & Pea, 2013; Hsu et al., 2018; Relkin et al., 2021). If children endorse gender stereotypes that are linked to girls' lower motivation, then it may be judicious for teachers to address gender stereotypes before introducing computational thinking to their classrooms through coding (see *Gender Equity and Computational Thinking* section below). We found that this was not the case: girls did not yet endorse negative stereotypes about their group. Children's stereotypes about whether members of their own-gender group were interested in and good at computer science were linked to children's own motivation in computer science. However, these stereotypical beliefs generally reflected positive beliefs about the interest and ability of their own gender, and we found no gender differences in young children's motivation for coding. Girls and boys in these early grade levels reported similar levels of their own interest in coding, sense of belonging, and ability self-concepts.

8.1. What are young children's stereotypes about computer science?

In terms of stereotypes, the pattern of findings about young children's ability stereotypes replicates previous findings that 6-year-old boys reported ability stereotypes favoring boys in technology, but 6-year-old girls did not significantly favor either group (Master et al., 2017b). Despite methodological differences, these results align with other findings that young boys strongly favor their ingroup's ability in certain domains while young girls do not (Bian et al., 2017). This may be because girls' tendency for ingroup bias is counteracted by societal stereotypes depicting boys and men as more naturally brilliant and talented in STEM fields (Bian et al., 2018; Chestnut et al., 2021; Cvencek et al., 2016).

The pattern for children's gender-interest stereotypes was slightly different from that of ability stereotypes. First- and second-grade girls believed that girls were more interested than boys in computer science, but this appeared to change for third-grade girls, who did not favor either gender. Cross-sectional data on children's endorsement of interest stereotypes about computer science suggests that these beliefs increasingly favor boys as children progress through primary and secondary school (Master et al., 2021). As girls get older, they may experience more cues that boys are perceived as more enthusiastic and excited than girls about computer science (Moorman & Johnson, 2003; Sullivan, 2021). Such cues can come from television shows, books, and other media showing men as computer scientists (Cheryan et al., 2015; Cheryan, Plaut, et al., 2013; Lewis et al., 2022; Lyda Hill Foundation & Geena Davis Institute on Gender in Media, 2021; Steinke, 2017), the underrepresentation of girls at computer science afterschool programs and summer camps (Google Inc. & Gallup Inc., 2015; Murphy et al., 2007), and from parental or societal gender stereotypes (del Río et al., 2019; Lily, 1994; Tenenbaum & Leaper, 2002; J. Wang et al., 2015).

Beliefs that boys are more interested than girls in computer science can have meaningful causal consequences (Master et al., 2021). Studies have indicated that girls (as a group) perceive computer science as a socially isolating field that lends itself to boys, those who lack social skills, and/or are considered "nerds" or "geeks" (Archer et al., 2013; Master et al., 2016, 2021; Papastergiou, 2008). This perception can discourage individual girls from themselves engaging in opportunities to explore computational thinking through computer science as they grow older and become more likely to endorse these beliefs (Cundiff et al., 2013; Master et al., 2021; Schimpf et al., 2015). Indeed, 49% of students enrolled in foundational computer science courses in elementary school are girls, compared to 44% in middle school, 31% in high school, and 33% in college (Code.org Advocacy Coalition, Computer science teachers association, & expanding computing education pathways alliance, 2021; Sax et al., 2017).

8.2. Are there gender differences in young children's motivation?

In term of the findings about motivation, this lack of gender differences in young children's own motivation for computer science differs, on the surface, from reports that 6-year-old girls report lower interest and self-efficacy than boys (Master et al., 2017b). However, several key differences between studies may help explain these findings. First, the current work examined ability self-concepts, which involve more general beliefs about a domain, whereas the previous study measured self-efficacy particularly in terms of robotics, which is a more specific topic. Young children's lack of familiarity with robotics may have reduced girls' feelings of efficacy in that study. Future research examining gender and children's beliefs and attitudes about robotics in comparison to computer science is needed. Second, the current work measured interest using questions about "liking to do" activities and feeling "interested" in them, whereas the previous study measured interest using a single item about "fun." It is possible that the wording of the items in the current study might tap into children's perceptions of more durable or trait-like maintained interest, yet assessing "fun" might tap into more unstable situational interest. A third important difference could involve the participant samples. The current work examined motivation among young children in a school district in Rhode Island which all K-12 schools specifically offered exposure to computer science, including required courses in computer science from first through eighth grade and several electives in high school. As experience with computer science can have a positive impact on young children's beliefs and attitudes (Cheryan et al., 2017; Master et al., 2017b), it is possible that the school district's policies promoted positive motivation among all children.

8.3. Are individual children's stereotypes related to their own motivation?

We found interesting patterns for the links between young children's stereotypes about social groups and their own motivation. Stereotypes about the ingroup were correlated with children's own motivation in computer science for both girls and boys, more than stereotypes about the outgroup. However, stereotypes about the outgroup were also positively correlated with motivation. This was true for both stereotypes about interest and stereotypes about ability in coding, although correlations overall were higher for interest stereotypes than ability stereotypes. This pattern suggests that the findings are not due to a generalized positivity bias in young children's responses (Stipek & Mac Iver, 1989), because there was meaningful variation between ratings of the ingroup and the outgroup.

In contrast to the raw stereotype scores, the stereotype difference scores were not correlated with children's motivation. Previous research on older children suggests that girls' stereotype difference scores are significantly linked to lower interest in computer science during middle school (Master et al., 2021). This raises the possibility of a developmental change such that perceptions of the ingroup are more central for young children's motivation than comparisons with the outgroup, with comparisons to the outgroup gaining importance during secondary school. If so, then efforts to increase young girls' willingness to engage in computational thinking opportunities may benefit more from directly targeting perceived group norms for girls ("girls like coding") than from comparisons with boys ("both girls and boys like coding"). This pattern of findings suggests that young children may use their perceptions of themselves as the basis for inductive inferences about their gender group members (Master, 2021).

8.4. Implications for computational thinking and education

The overall pattern of findings supports the argument that early childhood represents an excellent age for children to begin building computational thinking skills, before negative stereotypes begin to deter girls. In this study, girls in Grades 1-3 reported high motivation for computer coding. They said that they liked and were interested in computer coding activities, that they felt comfortable and belonged when they did coding activities, and that they understood and were good at coding activities. They held positive beliefs about other girls' interest and ability in computer science, reporting that other girls also liked and were good at computer coding. Girls across all grade levels had more positive views about girls' ability in computer science compared to boys' ability. First- and second-grade girls also had more positive views about girls' interest in computer science compared to boys' interest.

However, it remains important for future research to examine whether children's stereotypes and motivation differ based on the measures used to assess stereotypes and motivation. Although adult experts and some elementary school teachers can distinguish between the concepts of coding, computer science, and computational thinking (Cator et al., 2017; Garvin et al., 2019), delineating how young children construe and differentiate these terms is necessary for better understanding their motivation to engage in activities related to each or all of these. In terms of computational thinking integrated with other domains, children's stereotypes and motivation for the other domains may be salient as well, depending on how the integrated learning opportunities are framed by teachers and perceived by students (Huguet & Régner, 2007, 2009).

It is also worth recalling the larger school context of the study reported here. Girls in this study attended elementary schools in a district where computer science and computational thinking were introduced to students in primary school, in a state whose governor launched an initiative to promote computer science in primary and secondary education (http://cs4ri.org). Although the students in this study could not be compared to a control group without such experiences, these findings suggest that girls in this district were building positive interest and ability self-concepts for computer science and felt that they belonged in this educational setting. Such early and positive experiences may be very important to help set young girls on a positive trajectory for building individual interest in computer science in a way that helps them maximize benefits from computational thinking learning experiences (Sullivan, 2021). Future research could examine variations in district-wide policies and their effects on young children's gender stereotypes and motivation for computer science.

8.5. Gender equity and computational thinking

The current findings carry equity-related implications for elementary-school educators. Teachers can inadvertently transmit their own biases, stereotypes, and anxiety surrounding STEM to students, and some women teachers in particular can pass along negative attitudes about STEM to girls (Beilock et al., 2010). For example, girls are less likely than boys to report being told by a teacher that they would be good at computer science (Google Inc. & Gallup Inc., 2016; see also Pantic & Clarke-Midura, 2019; Vekiri, 2010). On the other hand, teachers who encourage their students and send cues that they believe in their students' potential promote positive motivation for young women in STEM (LaCosse et al., 2021). Teachers who assume that boys are more interested or capable than girls in computer science might send cues of these beliefs that promote the development of stereotypes favoring boys. Over time, this can reinforce girls' perceptions that they do not belong or will not be successful in computer science. Girls with these beliefs may avoid or disengage from opportunities to learn computational thinking (Master et al., 2021). Important directions for future research in educational science include examining teachers' gender biases related to computer science and computational thinking, the link between teachers' gender biases and classroom behaviors, how these predict children's stereotypes and motivation, and how such biases can be effectively reduced.

9. Conclusions

Computer science is the most common way to teach computational thinking to young children (Grover & Pea, 2013; Hsu et al., 2018; Relkin et al., 2021). Computational thinking promotes students' deep conceptual thinking and problem-solving skills (Denning & Tedre, 2019; Ketelhut et al., 2020; Weintrop et al., 2016). When students feel interested and capable during computational activities, they are more likely to show cognitive and behavioral engagement in those activities, with improved learning outcomes (Jiang & Wong, 2017; Shanmugam et al., 2019; Yadav et al., 2011). They are also better able to use this approach to thinking in other domains. Although societal stereotypes about computer science can negatively impact older girls' motivation for computer science and other computational activities (Master et al., 2021), we found that girls in Grades 1-3 held positive beliefs about their gender ingroup and high motivation for these activities. Supporting and nurturing young children's enthusiasm for learning computational thinking can have broad educational benefits.

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CRediT authorship contribution statement

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Supplementary materials

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