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Divergence in children's gender stereotypes and motivation across STEM fields

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STEM disciplines are traditionally stereotyped as being for men and boys. However, in two preregistered studies of Grades 1 to 12 students in the United States (*N* = 2,765), we find a significant divergence in students' gender stereotypes about different STEM fields. Gender stereotypes about computer science and engineering more strongly favored boys than did gender stereotypes about math and science. These patterns hold across genders, intersections of gender and race/ethnicity, and two geographical regions. This divergence between different STEM fields was evident, although smaller, for children in elementary school compared to adolescents (students in middle school and high school). The divergence in stereotypes predicted students' divergence in motivation for entering these fields. Gender stereotypes on average slightly favored girls in math and were egalitarian or slightly favored girls in science, while boys remained strongly favored for computer science and engineering, with implications for educational equity and targeted interventions.

STEM | gender | stereotypes | motivation | diversity

Significance

All STEM fields are not the same. Gender stereotypes about computer science and engineering strongly diverge from those about math and science, and this holds across racially and socioeconomically diverse students in Grades 1 to 12. Importantly, we found that the divergence in stereotypes significantly predicted divergence in motivation for entering these fields, with implications for educational equity. We also present the finding that math stereotypes show notable variation in direction and slightly favored girls rather than boys among many students. These findings could help promote equity in STEM by ensuring greater focus on the fields in which women and girls are most underrepresented and negatively stereotyped.

The gender gap in participation in STEM is a large and persistent educational problem (1). For example, women are granted only 21% of computer science and engineering degrees in the United States (2). Crucially, STEM fields significantly vary in their representation of women (e.g., women are granted more than 60% of degrees in biological sciences), highlighting the need to document and understand reasons for differences between STEM disciplines. One prominent explanation for gender gaps is negative gender stereotypes—socially shared beliefs that men and boys have greater talent and interest than women and girls in certain fields (3–5). In the current paper, we examine whether children's and adolescents' gender stereotypes are distinct in different STEM fields and the potential consequences of these stereotypes. Investigating this broad age range allows us to assess the early presence of differences in these gendered beliefs across fields and to test for differences along the K-12 educational trajectory.

Gender Stereotypes Across STEM Fields

Pervasive and strongly held negative stereotypes about women's and girls' interests and abilities have been observed in computer science and engineering (6, 7). Negative stereotypes about women's and girls' abilities have also been observed in math and general science (8, 9). However, studies with nationally representative samples of US high school students indicate that adolescents' math and science stereotypes may only slightly favor boys, be egalitarian, or even slightly favor girls, especially among girls in early adolescence and racially/ethnically diverse samples (9, 10; see also refs. 11 and 12). For example, Black girls hold weaker ability stereotypes favoring boys than White girls across STEM fields (8).

A few studies have compared gender stereotypes about STEM fields to one another. A meta-analysis of 98 studies found that children's and adolescents' ability stereotypes about computer science, engineering, and physics (combined) were significantly more likely to favor boys than either math or general science stereotypes, which both only slightly favored boys (8). In another study, 6-y-old children's ability stereotypes about robots were significantly stronger than their stereotypes about math, science, and programming (6). Two other examinations of children's/adolescents' stereotypes that did not statistically test for differences among STEM fields found that stereotypes consistently favored boys in computer science and engineering (7, 13), and stereotypes in math and science were more variable in direction (tending toward weakly boy-favoring, egalitarian, or girl-favoring).

In the present work, we empirically compare interest and ability stereotypes for computer science and engineering to stereotypes for math and science. Children's stereotypes are actively constructed based on input from their environment (14, 15). Gender

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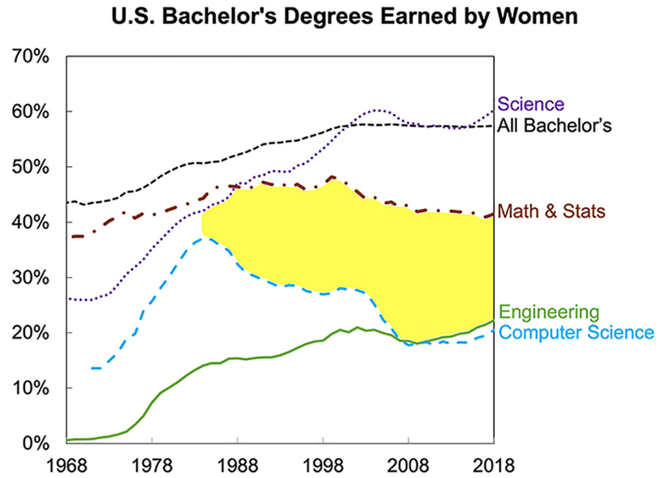

Fig. 1. Historical patterns in representation of bachelor's degrees earned in select STEM fields compared to all bachelor's degrees (STEM and non-STEM). The divergence gap between math/science and computer science/engineering degrees is highlighted in yellow to emphasize divergence since 1983. "Science" is a composite of chemistry, biological sciences, and earth sciences. Source: https://nces.ed.gov/ipeds/.

representation in STEM has measurably changed in the past 50 y (Fig. 1 and ref. 16). Women in the United States earn 63% of bachelor's degrees in biological sciences, 51% in chemistry, and 42% in math and statistics (17). Girls reliably receive higher grades than boys in Grades 1 to 12 and many college classes and perform equally on achievement tests in math in Grades 3 to 8 (18–20). Girls are as likely as boys to take math, chemistry, and biology in US public schools (21, 22). Given that girls and women show success in math and science, we expected that children and adolescents' stereotypes about these fields should diverge from their stereotypes about computer science and engineering, with implications for psychological theory and educational practice: All STEM stereotypes may not be considered the same.

Gender Gaps in Motivation across Different STEM Fields

Importantly, gender stereotypes may have consequences for girls' and boys' *motivation* for STEM fields. Meta-analyses have shown that gender gaps in interest and expectations of success among children and adults are different across fields, such that gaps favor boys and men in computer science, engineering, general science, and math and are equal or favor girls and women in biological science and verbal domains (23, 24). Studies examining math and science motivation (e.g., ability self-concepts, expectations of success, task values) have found small or no gender gaps favoring boys in math and small or no gender gaps favoring girls in science (25; see also ref. 26), with larger gaps in self-efficacy in computer science than in math, general science, and biology (27, 28). Gender differences in college major or career intentions favor boys for computer science and engineering but not biological sciences or math fields (10, 29; see also 4, 30–32).

Motivation has been predicted by students' math and science ability stereotypes (9, 33, 34) and their computer science and engineering interest and ability stereotypes (5). For example, stereotypes favoring boys' interest in computer science correlate with and cause lower interest in the field for girls, with some stronger links for older students (5). There is some evidence that boys experience higher motivation in line with stereotype boost (35) for computer science/engineering (5).

Current Studies

We report two large-scale, preregistered studies on racially and socioeconomically diverse students in Grades 1 to 12 (*N*s = 1,497 and 1,268) that measure gender stereotypes and motivation across five fields. These include four STEM fields (math, science, computer science, and engineering) and language arts. Including language arts enables a comparison to a field with a high representation of women (2, 36), in which girls on average significantly outperform boys (19) and that is often stereotyped as favoring girls (37). We examine two stereotypes: beliefs about which gender is more interested (*interest stereotypes*) and which gender has more ability (*ability stereotypes*) in STEM. Both stereotypes may cause gender differences in motivation and influence critical educational choices (5, 38, 39), but one recent study found that interest stereotypes are a stronger predictor of students' own motivation than ability stereotypes (5). We also examine four measures of motivation: personal interest, ability self-concepts, sense of belonging, and identification. These key aspects of motivation support students' persistence in academic pathways (40).

We tested students in two racially/ethnically and socioeconomically diverse regions in New England (Study 1) and the South (Study 2). Studying students across a broad range of ages and demographic backgrounds prior to college is critical (25). Young students are learning about academic fields and beginning to choose career paths as early as middle school, making these important ages to influence their interest in pursuing STEM (41). Though our focus is on explaining stereotypes of girls and boys, children's gender identity is not binary or fixed (42).

The contributions of the current work are to, within a single set of preregistered studies, a) provide rigorous and high-powered estimates for the divergence of math/science stereotypes from computer science/engineering stereotypes, b) provide such estimates for students' motivation as well, c) empirically link the divergences in stereotypes to the divergences in motivation, and d) examine how the divergence in stereotypes and motivation differ across gender, race/ethnicity, school level (i.e., elementary, middle, high), and race/gender intersections.

We predicted that gender stereotypes and gender disparities in motivation favoring boys would be larger in computer science/engineering than in math/science. We also investigated whether patterns of stereotype divergence across fields (i.e., a greater difference between computer science/engineering versus math/science stereotypes) predict gendered patterns of motivation divergence across fields. That is, for girls, greater stereotype divergence may predict a larger divergence in motivation with lower interest in computer science/engineering; for boys, it may predict the opposite.

In Study 1 (some hypotheses and analyses preregistered; see *SI Appendix*), we investigated gender stereotypes and motivation in math, science, computer science, and engineering in Grades 1 to 12. Study 2 (some hypotheses and analyses preregistered) replicated and generalized Study 1 by adding a non-STEM field, language arts, in Grades 6 to 12. According to the Generalizer tool (43, 44), results from schools in Studies 1 and 2 have high generalizability to regular US suburban public schools when considering factors like gender, free/reduced lunch, English-speaking-only, and race/ethnicity (Generalizability Index = 0.72 and 0.78, respectively). See *SI Appendix* for more details about the Generalizer tool. In addition, the large sample sizes provide adequate power to analyze based on gender, race/ethnicity, and gender by race/ethnicity intersections.

Results

Preregistered target sample sizes, procedures, hypotheses, and analyses, as well as materials, data, and code for both studies, are available on the Open Science Framework at https://osf.io/4r7sb/. See *SI Appendix*, Table S1 for all preregistered hypotheses and *SI Appendix*, Table S17 for uniqueness from other studies using portions of one dataset (5, 13). Some preregistered analyses and additional exploratory analyses related to divergence are presented below. Preregistered hypotheses are indicated; all others were exploratory. Results from all preregistered analyses, deviations from the preregistrations, and full results can be found in *SI Appendix*. We also repeated analyses using multiple imputation, and results remained consistent; see *SI Appendix*, Tables S20–S23. All survey items are listed in *SI Appendix*, Table S8.

Divergence in Gender Stereotypes. We assessed divergence in gender stereotypes between computer science/engineering compared to math/science using planned contrasts in a mixed-model ANOVA. Students showed significant divergence in gender stereotypes between computer science/engineering compared to math/science (preregistered for girls' ability stereotypes in Study 1 and girls' and boys' interest stereotypes in Study 2; see *SI Appendix*, Table S1). This result held for both interest stereotypes and for ability stereotypes: interest stereotypes: Study 1, $F(1, 1{,}479) = 696.57$, $P < 0.001$, $\eta_p^2 = 0.32$, Study 2, $F(1, 1{,}252) = 667.82$, $P < 0.001$, $\eta_p^2 = 0.35$ (preregistered); ability stereotypes: Study 1, $F(1, 1{,}480) = 548.57$, $P < .001$, $\eta_p^2 = 0.27$, Study 2, $F(1, 1247) = 604.48$, $P < 0.001$, $\eta_p^2 = 0.33$ (Fig. 2 and *SI Appendix*, Table S2 and Figs. S2–S5). All *P*-values are two-tailed unless stated otherwise. Interest and ability stereotypes significantly favored boys in both computer science and engineering, one-sample *t*s > 10.93, *P*s < 0.001, *d*s = 0.28 to 0.73. However, interest and ability stereotypes favored girls in math and language arts, one-sample *t*s < −4.19, *P*s < 0.001, *d*s = −0.68 to −0.11. In science, interest and ability stereotypes favored girls, one-sample *t*s < −3.89, *P*s < 0.001, *d*s = −0.23 to −0.11, or were neutral (Study 1 interest stereotypes), $t(1{,}486) = -0.15$, $P = 0.88$, $d = -0.004$. Stereotypes favoring girls in both math and science were smaller on average (*M*s = −0.35 to −0.01) than stereotypes favoring boys in both computer science and engineering (*M*s = 0.41 to 1.13) or favoring girls in language arts (*M*s = −0.96 to −0.81; all preregistered in Study 2). See *SI Appendix*, Tables S9 and S10 for all differences between pairs of fields, *SI Appendix*, Table S11 for effects by grade level and gender, and *SI Appendix*, Table S12 for prevalence of stereotypes favoring girls, boys, or neither.

We found that this same divergent pattern held among various demographic breakdowns of the sample: It was evident within gender, racial/ethnic groups, their intersections, and school level. The divergence between computer science/engineering versus math/science stereotypes was evident among girls (preregistered for Study 1 ability stereotypes and Study 2) and boys (preregistered for Study 2), with no significant interaction with gender in Study 1, interest stereotypes, $F(1, 1{,}479) = 0.77$, $P = 0.38$, $\eta_p^2 = 0.001$, ability stereotypes, $F(1, 1{,}480) = 0.75$, $P = 0.39$, $\eta_p^2 = 0.001$, or for interest stereotypes in Study 2, $F(1, 1{,}252) = 3.64$, $P = 0.057$, $\eta_p^2 = 0.003$. Boys had a stronger divergence than girls for Study 2 ability stereotypes, $F(1, 1{,}247) = 5.54$, $P = 0.019$, $\eta_p^2 = 0.004$. (There were also main effects of gender--boys had significantly stronger STEM stereotypes than girls for ability stereotypes in both studies and for interest stereotypes in Study 1 but not Study 2, *SI Appendix*.) The divergent pattern between computer science/engineering versus math/science stereotypes was robust and consistent for participants within race/gender intersections, with White girls, White boys, Hispanic/Latina girls, Hispanic/Latino boys, Asian girls, Asian boys, Black girls, Black boys, Multiracial girls, and Multiracial boys all showing the divergence in stereotypes, *F*s > 14.29, *P*s < 0.001, η_p^2s > 0.20. This divergent pattern was also evident for students in elementary, middle, and high school, all *F*s > 101.27, *P*s < 0.001, η_p^2s> 0.18, although it appeared stronger for middle and high school students than elementary school students (Figs. 2–5).

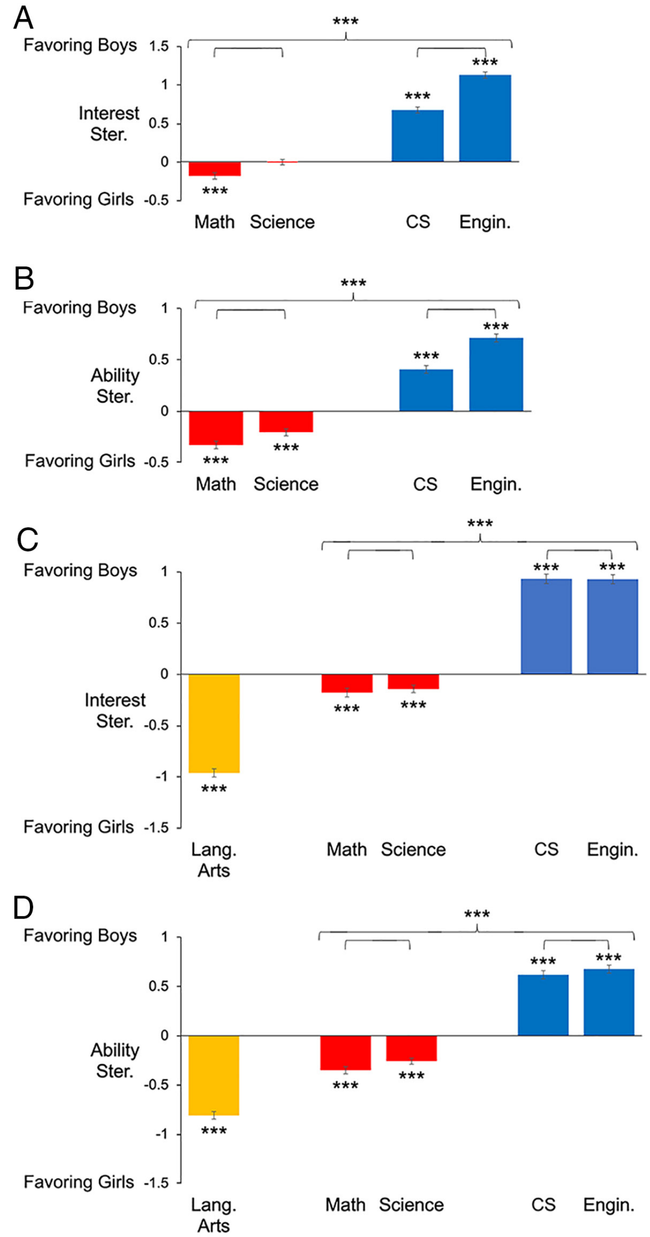

Fig. 2. Interest and ability stereotypes by field and study. Study 1 interest and ability stereotypes (*A* and *B*) and Study 2 interest and ability stereotypes (*C* and *D*) in language arts (yellow), math (red), science (red), computer science (blue), and engineering (blue), range −5 to 5. Positive values indicate stereotypes favoring boys, and negative values indicate stereotypes favoring girls. A score of 0 represents neutral/egalitarian stereotypes. Stereotypes strongly favored boys for computer science and engineering, strongly favored girls for language arts, and generally favored girls for math and science. Significance for each bar represents difference from 0; significance with brackets indicates significance of the contrast between math/science and computer science/engineering. Ster. indicates stereotype; CS indicates computer science; Engin. indicates engineering; Lang. indicates language. Error bars represent 95% SE. ****P* ≤ 0.001.

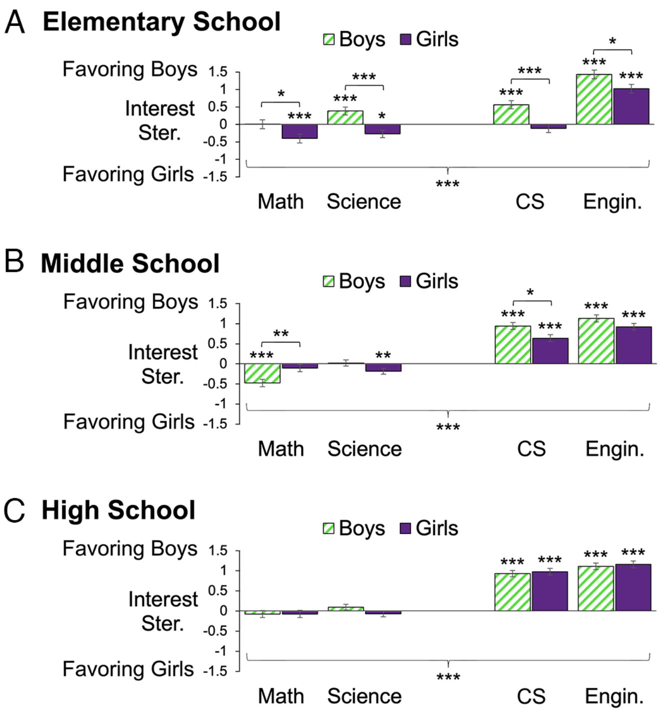

Fig. 3. Interest stereotypes by participant gender, field, and school level in Study 1. Results of Study 1 for elementary (*A*), middle (*B*), and high school (*C*) students for interest stereotypes. Girls' (solid purple) and boys' (striped green) stereotypes in math, science, computer science, and engineering (range −5 to 5). Positive values indicate stereotypes favoring boys, and negative values indicate stereotypes favoring girls. Significance for each bar represents difference from 0; significance of the bracket for a pair of bars indicates significance of the gender difference; significance for the large bracket indicates significance of the main effect of field. Ster. indicates stereotype; CS indicates computer science; Engin. indicates engineering; Error bars represent 95% SE. **P* < 0.05, ***P* < 0.01, and ****P* < 0.001.

Gender Divergence in Motivation. Motivation (i.e., students' reports of their personal interest in classes and activities in school) showed a gendered divergence between computer science/engineering versus math/science, Study 1, $F(1, 1{,}490) = 61.02$, $P < 0.001$, $\eta_p^2 = 0.04$, Study 2, $F(1, 1{,}245) = 60.72$, $P < 0.001$, $\eta_p^2 = 0.05$ (preregistered; Fig. 6 and *SI Appendix*, Table S3). Boys reported significantly more interest than girls in both computer science and engineering, Fs > 50.33, Ps < 0.001, $\eta_p^2\text{s} \geq 0.03$, but there were small or nonsignificant differences between girls' and boys' interest in both math and science, Fs < 5.15, Ps > 0.023, $\eta_p^2\text{s} \leq 0.004$ (preregistered; *SI Appendix*, Tables S13 and S14). Girls reported more interest than boys in language arts, $F(1, 1{,}245) = 23.61$, $P < 0.001$, $\eta_p^2 = 0.02$ (preregistered; Fig. 6*B* and *SI Appendix*, Table S14). Gender gaps in math and science (η_p^2s = 0.000 to 0.004) were smaller on average than gender gaps in computer science and engineering (η_p^2s = 0.03 to 0.07), and smaller than language arts ($\eta_p^2 = 0.02$; preregistered). Girls were significantly less interested in computer science/engineering than the other three fields, Fs > 78.98, Ps < 0.001, $\eta_p^2\text{s} > 0.09$ (preregistered).

In exploratory analyses, we found that the same pattern of gendered divergence in personal interest held among various demographic breakdowns of the sample, including White students, Black students, Hispanic/Latine students, and Multiracial students, Fs > 6.12, Ps < 0.02, $\eta_p^2\text{s} > 0.02$, as well as Asian students in Study 1, $F(1, 143) = 8.99$, $P = 0.003$, $\eta_p^2 = 0.06$ (Study 2, $F[1, 76] = 3.85$, $P = 0.053$, $\eta_p^2 = 0.05$).

Similarly, exploratory analyses showed that this pattern was also generally evident across ages for students in elementary, middle, and high school, Fs > 5.92, Ps < 0.016, $\eta_p^2\text{s} \geq 0.01$, see Fig. 7 and *SI Appendix*, Fig. S1. High school students showed stronger gendered patterns of divergence in personal interest compared to elementary or middle school students, with girls in high school showing the strongest divergence between computer science/engineering and math/science in personal interest (*SI Appendix*, Table S3). *SI Appendix*, Tables S13 and S14 provide further detailed comparisons of gender differences in personal interest broken down by racial/ethnic group and school level for each field and comparisons between individual fields.

Motivation in terms of students' ability self-concepts also showed a gendered divergence between computer science/engineering versus math/science, Study 2, $F(1, 1{,}237) = 20.72$, $P < 0.001$, $\eta_p^2 = 0.016$ (preregistered; *SI Appendix*, Fig. S6 and Table S4). Boys had significantly higher ability self-concepts than girls in both computer science and engineering, Fs > 32.58, Ps < 0.001, $\eta_p^2\text{s} \geq 0.025$, but gender differences in ability self-concepts for math and science were smaller, Fs > 4.19, Ps < 0.042, $\eta_p^2\text{s} \leq 0.012$ (preregistered). Girls reported higher ability self-concepts than boys in language arts, $F(1, 1{,}237) = 13.15$, $P < 0.001$, $\eta_p^2 = 0.011$ (*SI Appendix*, Fig. S6 and Table S15). Girls reported significantly lower ability self-concepts in computer science/engineering than the other three fields, Fs > 442.04, Ps < 0.001, $\eta_p^2\text{s} > 0.40$ (preregistered). See *SI Appendix*, Fig. S6 for similar preregistered patterns among other motivational variables in Study 2, including identification and sense of belonging.

Links between Divergence in Stereotypes and Motivation. In further exploratory analyses, we used latent difference score analyses (in this case, latent divergence scores) to examine whether

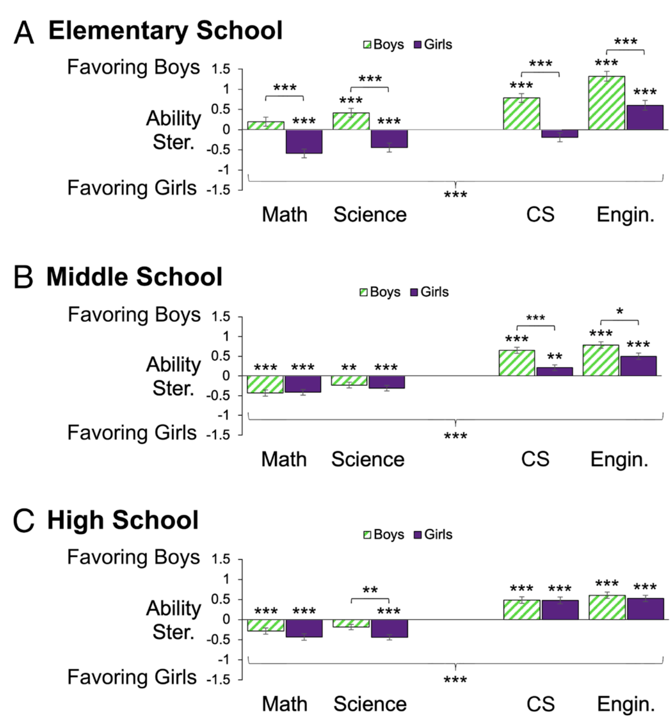

Fig. 4. Ability stereotypes by participant gender, field, and school level in Study 1. Results of Study 1 for elementary (*A*), middle (*B*), and high school (*C*) students for ability stereotypes. Girls' (solid purple) and boys' (striped green) stereotypes in math, science, computer science, and engineering (range −5 to 5). Positive values indicate stereotypes favoring boys, and negative values indicate stereotypes favoring girls. Significance for each bar represents difference from 0; significance of the bracket for a pair of bars indicates significance of the gender difference; significance for the large bracket indicates significance of the main effect of field. Ster. indicates stereotype; CS indicates computer science; Engin. indicates engineering; Error bars represent 95% SE. **P* < 0.05, ***P* < 0.01, and ****P* < 0.001.

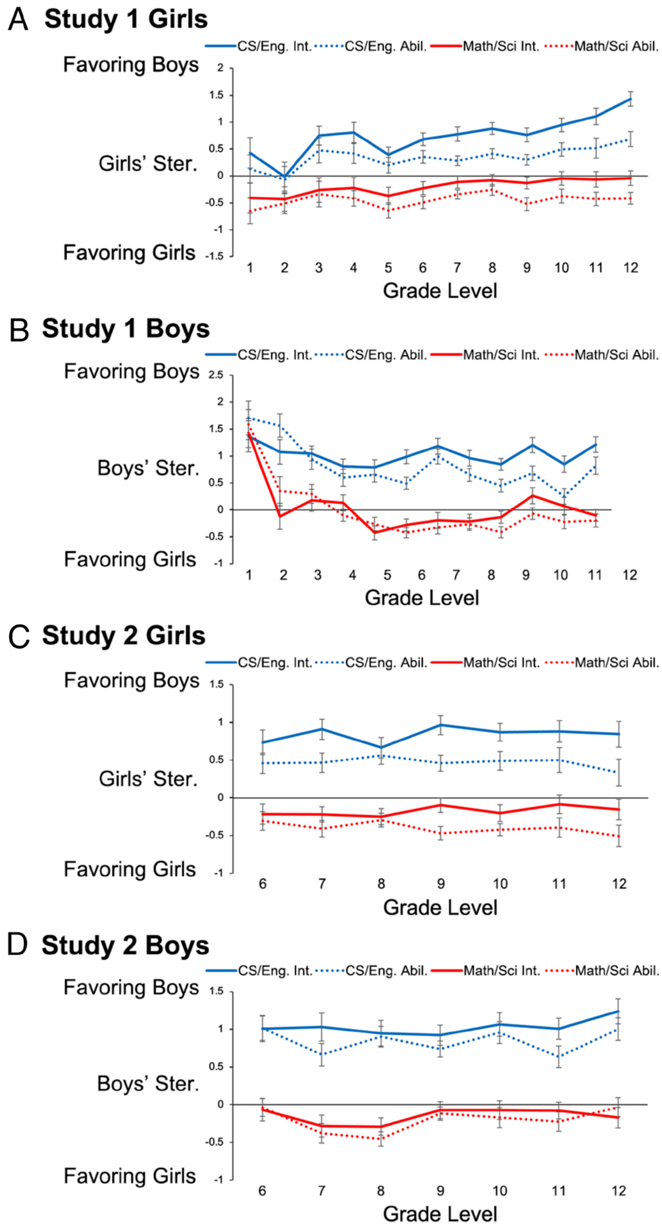

Fig. 5. Divergence in stereotypes by participant gender, grade level, and study. Study 1 girls' interest and ability (*A*), Study 1 boys' interest and ability (*B*), Study 2 girls' interest and ability (*C*), Study 2 boys' interest and ability (*D*), averaged across math/science (red lines) compared to computer science (CS)/engineering (blue lines). Interest stereotypes are shown in solid lines and ability stereotypes are shown in dotted lines. Positive values indicate stereotypes favoring boys, and negative values indicate stereotypes favoring girls. Both girls and boys showed significant divergence in both interest and ability stereotypes between math/science and CS/engineering by Grade 2 for boys and Grade 3 for girls, $Ps \leq 0.001$. Ster. indicates stereotype; Int. indicates interest; Abil. indicates ability; CS indicates computer science; Eng. indicates engineering; Sci. indicates science. Error bars represent 95% SE.

divergence in stereotypes predicted divergence in personal interest. We first created latent divergence score variables for math/science and computer science/engineering and then examined correlations between latent divergence scores for stereotypes and personal interest. For girls, the more that their stereotypes diverged (with computer science/engineering stereotypes more likely to favor boys than math/science stereotypes), the more that their personal interest in these fields diverged (with lower personal interest in computer science/engineering than math/science), $\rho s = -0.70$ to -0.26, $Ps \leq 0.005$. For boys, the divergence links went the opposite direction: The more their stereotypes diverged (with computer science/engineering stereotypes more likely to favor boys than math/science stereotypes), the more they were personally interested in computer science/engineering compared to math/science, $\rho s = 0.29$ to 0.36, $Ps \leq 0.036$. See *SI Appendix*, Fig. S7 and further details in *SI Appendix*.

Examining the five individual fields separately, the more that individual girls reported interest and ability stereotypes favoring boys for computer science and/or engineering, the lower their own personal interest in pursuing these fields, $rs = -0.32$ to -0.10, $Ps \leq 0.008$ (preregistered). The more that boys reported interest stereotypes that favored girls in math (preregistered), science, and language arts, the lower their personal interest in pursuing these fields, $rs = 0.17$ to 0.24, $Ps < 0.001$, with similar but less consistent effects for ability stereotypes (math [preregistered] and language arts: $rs = 0.24$ to 0.26, $Ps < 0.001$, science: $rs = 0.05$ to 0.11, $Ps = 0.003$ to 0.19) (Table 1).

Discussion

Stereotypes about different STEM fields are not identical and do not exclusively favor boys. Across two large-scale studies of Grades 1 to 12 students, we found that stereotypes of computer science and engineering differed in both strength and content (strongly favoring boys) from stereotypes of math and science (egalitarian or slightly favoring girls). Children and adolescents held strong and consistent stereotypes that boys are more interested and capable than girls in computer science and engineering but simultaneously did not hold these negative stereotypes about girls in math and science. Children and adolescents in both studies on average reported that girls are more interested and capable than boys in math and in science.

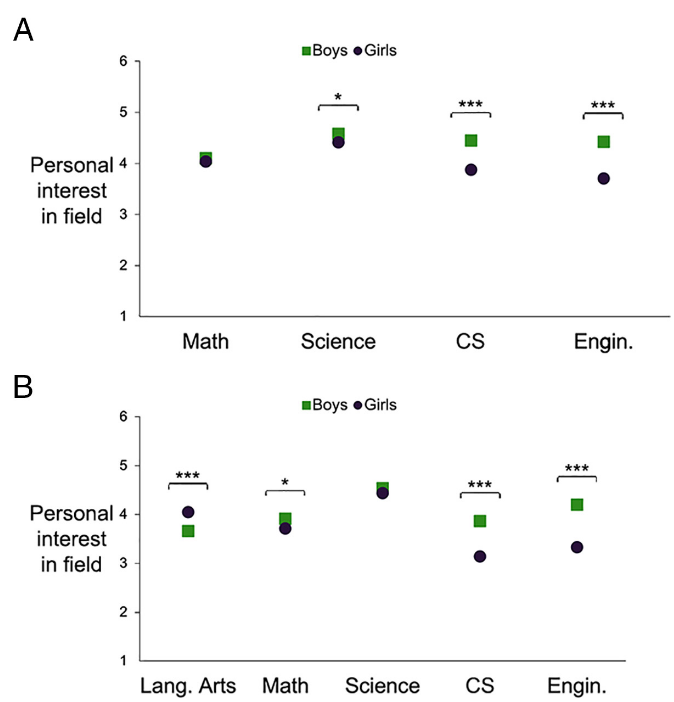

Fig. 6. Motivation (students' reports of their personal interest) by participant gender, field, and study. Studies 1 (*A*) and 2 (*B*). Girls' (purple dots) and boys' (green squares) personal interest in language arts (Study 2), math, science, computer science, and engineering (range 1 to 6). The main effects of gender and field were significant in both studies, $Ps < 0.001$. Gender gaps were largest in fields with stronger gender stereotypes (computer science, engineering, and language arts). CS indicates computer science; Engin. indicates engineering; Lang. indicates language. Error bars represent 95% SE but are not visible due to small size of SE compared to markers. Gender difference: $^*P \leq 0.05$ and $^{***}P \leq 0.001$.

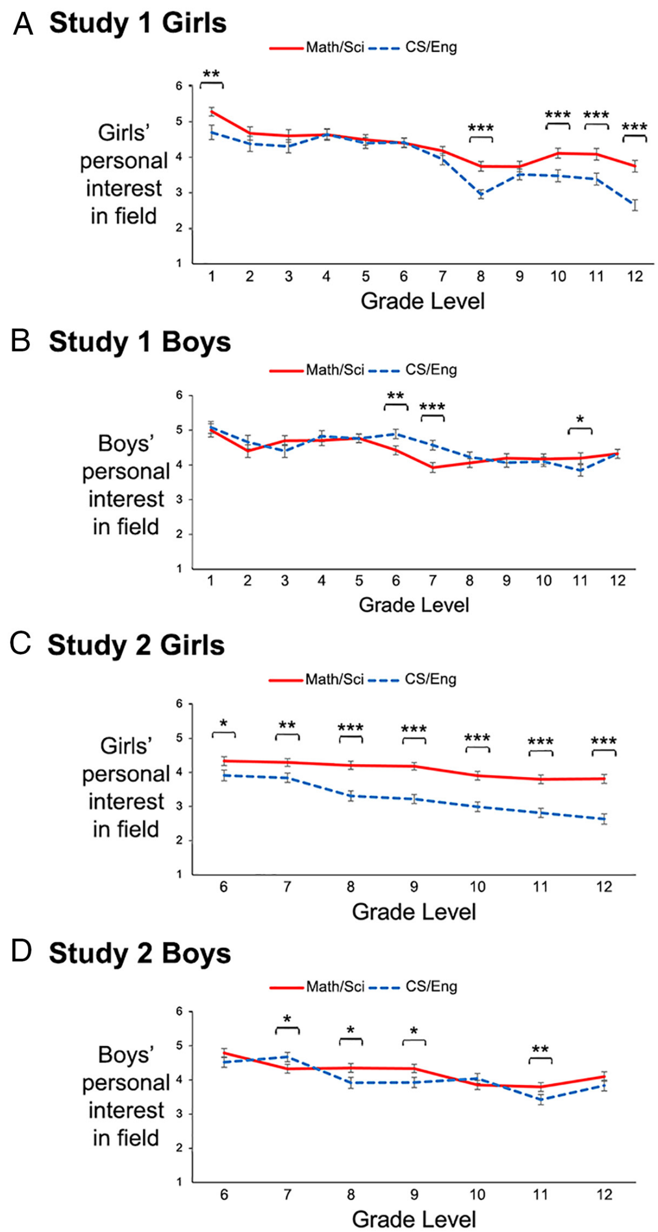

Fig. 7. Divergence in motivation as personal interest by participant gender, grade level, and study. Study 1 girls (*A*), Study 1 boys (*B*), Study 2 girls (*C*), and Study 2 boys (*D*), with motivation averaged across math/science (red lines) compared to CS/engineering (blue dashed lines). The range of interest is from 1 to 6. Higher values indicate more personal interest in the fields and lower values indicate less personal interest in those fields. Divergence in motivation is gendered, with greatest divergence for girls in middle and high school. CS indicates computer science; Eng. indicates engineering. Error bars represent 95% SE. Significance represents significant differences between math/science and CS/engineering motivation. $^{*}P \leq 0.05$, $^{**}P \leq 0.01$, and $^{***}P \leq 0.001$.

Table 1. Key findings in this paper

Key findings	Supporting evidence
STEM stereotypes diverge: Stereotypes about computer science and engineering strongly favor boys, while stereotypes about math and science are largely egalitarian or slightly favor girls.	Figs. 2–5 and *SI Appendix*, Table S2: see bars representing stereotypes about computer science and engineering, which show stereotypes strongly favoring boys, while bars representing stereotypes about math and science show stereotypes slightly favoring girls or near the neutral value (0).
Motivation for STEM fields diverges: Gender gaps are larger in computer science and engineering and smaller in math and science.	Figs. 6 and 7 and *SI Appendix*, Tables S3 and S4: see gaps between motivation for girls and boys across fields.
Stereotypes predict motivation for *individuals*: Girls who report stereotypes favoring boys in computer science and engineering are less motivated in those fields; boys who report stereotypes favoring girls in math, science, and language arts are less motivated in those fields.	Main text and *SI Appendix*, Tables S5–S7.
Stereotypes predict motivation *across fields*: Gender gaps in motivation are largest in the fields with the strongest gender stereotypes (computer science, engineering, and language arts).	Figs. 2 and 6.
Pattern of divergence (with computer science/engineering diverging from math/science) is consistently evident within girls and boys, and within multiple racial/ethnic and gender intersections.	Main text and Fig. 5.
Pattern of divergence (with computer science/engineering diverging from math/science) is consistently evident across school levels, although smallest for elementary school students.	Main text, Fig. 5, and *SI Appendix*, Tables S2–S4 and Fig. S1.

Note: An overview of key findings and location of supporting evidence in the paper.

This divergence between students' stereotypes of computer science/engineering versus math/science was observed among both girls and boys. The same divergence was also observed among White, Hispanic/Latine, Asian, Black, and Multiracial students. Our large datasets also enabled us to examine patterns at the intersections of gender and race/ethnicity, and we found similar divergence for all tested race/gender intersections. Examining intersections of race and gender is important to combat "single-axis thinking" that potentially overlooks effects of interconnected systems of bias (ref. 45, p. 787). Finally, divergence for different STEM fields was evident across elementary, middle, and high school students but appeared weaker among elementary school students.

While the current findings for computer science and engineering are consistent with a recent meta-analysis of ability stereotypes among more than 145,000 students (8), the math stereotype finding slightly differs, in that the meta-analysis found a small stereotype slightly favoring boys' ability on average across ages. Ability stereotypes may differ based on whether they assess beliefs about success in school versus innate talent (38). Measuring stereotypes about school subjects may have led participants in the current studies to rate stereotypes as more girl-favoring than they would have if the stereotype measure had asked about natural ability in each domain. (However, identical wording was used across STEM fields, thus this should not affect the measurement of divergence across fields in the present studies.) In the current studies, math and science stereotypes also showed variability in direction across specific groups of students (*SI Appendix*, Tables S2 and S11). One nationally representative US high school sample reported that girls in Grade 9 held math stereotypes slightly favoring girls on average, although boys in Grades 9 and 11 and girls in Grade 11 held math stereotypes that slightly favored boys (9). This heterogeneity suggests that even large-scale studies may find slight variation in stereotypes depending on the gender, age, and racial/ethnic composition of their samples, how stereotypes are measured, and variability in individual students' exposure to stereotype cues by socializers and media (8, 13).

Math stereotypes favoring girls among some adolescents have been documented in other research (7, 9, 10). The current work adds to the recent meta-analysis (8) showing that math stereotypes favoring girls exist even among some younger children, particularly young girls. Despite the evidence for many students holding egalitarian or girl-favoring beliefs about math rather than a traditional math stereotype, such evidence remains largely unrecognized in broader US culture (e.g., refs. 46 and 47). People who have long been aware of explicit math stereotypes favoring boys may be likely to ignore or distort information that does not match their existing stereotypes (48).

Gender differences in motivation differed across fields. Boys reported greater motivation than girls in computer science and engineering, but gender differences in motivation were smaller or nonexistent in math and science. Girls at all school levels (except for Study 1 girls in Grades 4 to 6) reported lower motivation for computer science and engineering than math and science, but divergence was strongest among high school girls. The relatively lower divergence among late elementary school girls and higher divergence among high school girls accords with findings that middle school is a crucial period during which girls lose motivation for STEM (49, 50), with the current data suggesting the greatest loss of motivation for computer science and engineering. Gendered patterns of divergence in motivation were evident across all schooling levels and all racial/ethnic groups.

Patterns of divergence in stereotypes across groups and individuals predicted students' motivation. Larger divergence in stereotypes was linked to larger divergence in girls' and boys' motivation, with girls less motivated and boys more motivated for computer science/engineering relative to math/science. For individual girls, believing stereotypes favoring boys in computer science/engineering relative to math/science predicted their own lower motivation in computer science/engineering. For individual boys, the pattern flipped, such that believing stereotypes favoring girls in math/science/language arts predicted their own lower motivation in these fields.

Comparing across STEM fields reveals that math and many subfields of science may have fewer gender disparities in education to rectify than do computer science and engineering. Strong efforts have been made to reduce gender disparities in math and science, and these efforts could now be applied to computer science and engineering. In 2021, the NSF spent $1.07 billion on efforts to broaden participation in STEM generally, with only 8% ($83 million) specifically designated for computer science or engineering programs (51). Similarly, a Google Scholar search for "gender disparities in:" in April 2024 returned the most results for science (2,030), followed by STEM (949), with fewer results for computer science (545) and engineering (205). National efforts to improve equity in STEM education (52) may benefit from placing increased focus on the fields in which women and girls are most underrepresented and negatively stereotyped. Attempts to improve motivational cultures in STEM may similarly need to focus on how daily practices and institutional contexts can make computer science and engineering more welcoming for women to increase a sense of belonging in those fields (53, 54). Increases in the number of girls interested and pursuing computer science and engineering would likely lead to societal benefits, including a reduction in products and services that overlook or unintentionally harm women and children (55).

Future work could turn to the question of the origins of stereotypes and why gender stereotypes about different STEM fields are so varied in strength and content. Researchers could investigate whether images in the media display a divergence of gendered depictions in different STEM fields, whether messages from parents and teachers play a role, whether K-12 students are attuned to changes to gender representation in college and occupations, and whether personal experience with certain STEM fields in school influences stereotype divergence (9).

In sum, computer science and engineering continue to be heavily stereotyped as fields for boys, but math and science are stereotyped by many children and adolescents in Grades 1 to 12 in the United States as fields in which girls have greater or equal interests and capabilities when compared to boys. This divergence between stereotypes for different STEM fields predicts students' own motivation for these fields and may, in part, account for why disparities in gender representation among high school and college students continue to exist in computer science and engineering but have largely closed or reversed in certain subfields in math and science in the United States.

Materials and Methods

Study 1.

Participants. The final analytic sample included $N = 1{,}497$ students (50% girls, 50% boys; 37% White, 24% Hispanic/Latine, 15% Multiracial, 10% Asian, 8% Black, 1% Native American, 5% missing/other response) in Grades 1 to 12 in a racially/ethnically diverse suburban public school district in Rhode Island in which 10% of students live in poverty. Adhering to our preregistered criteria, 411 participants were excluded from analyses for failing the attention check. An additional 46 participants were excluded from analyses for identifying their gender as something other than "girl" or "boy," leaving a final analytic sample of $N = 1{,}497$ students with 82 to 182 students per grade.

Determining sample size. Our preregistered sample size was based on the estimate that 126 students per grade (18 per classroom) would agree to participate across six schools in 12 grades (84 classrooms), for an estimated sample size of 1,512. Based on estimated effect size $d_z = 0.80$ from ref. 6, two-tailed, $\alpha = 0.05$, and power = 0.80, G*Power 3.1 suggested a sample size of 12 girls for the preregistered difference between math/science and computer science/engineering ability stereotypes. Based on effect size $f = 0.22$ from a pilot study, $\alpha = 0.05$, power = 0.80, two groups, two measurements, a correlation among repeated measures $r = 0.36$, and nonsphericity correction = 1, G*Power 3.1 suggested a sample size of 54 students for the preregistered Gender × Field mixed-model ANOVA on personal interest. Based on a pilot study, G*Power 3.1 suggested a sample size of 374 to test the preregistered equality of correlation coefficients for girls and boys (*SI Appendix*).

Procedure. The University of Washington Institutional Review Board and district superintendent's office approved all procedures. Parents were sent opt-out information letters and students gave informed assent. Students completed online surveys during school using classroom computers from January to March 2019.

The survey included a) an attention check requesting that participants mark a particular response, b) endorsement of interest and ability stereotypes; c) personal interest; and d) demographics (gender, race/ethnicity, and grade level). Stereotypes and interest were measured for four STEM fields (math, science, computer science, and engineering). The order of STEM fields for each measure followed a random order counterbalanced across participants, and each individual student saw the fields presented in the same order for all questions. The survey included other measures outside the scope of the current research questions and analyses (*SI Appendix*, Table S8). The survey referred to computer science using the term "computer coding" and to engineering using the term "engineering."

Measures. Interest stereotypes were measured using Likert scales from 1 (*Really do not like*) to 6 (*Really like*). Two items measured beliefs in boys' and girls' interest ("How much do you think that most [boys/girls] like the following subjects?") for the four STEM fields. Interest stereotypes were calculated as a difference score with beliefs in boys' interest minus girls' interest for each field (56, 57). Positive scores indicated stereotypes favoring boys (that boys were more interested than girls), and negative scores indicated stereotypes favoring girls (that girls were more interested than boys).

Ability stereotypes were measured using Likert scales from 1 (*Really not good*) to 6 (*Really good*). Two items measured beliefs in boys' and girls' ability ("How good do you think that most [boys/girls] are at the following subjects?") for each field. As in interest stereotypes, ability stereotypes were calculated as a difference score with beliefs in boys' ability minus girls' ability for each field. Measuring ability stereotypes using difference scores may reduce participants' social desirability concerns about having to rate one group as "better."

Personal interest was measured with two items, e.g., "I am interested in [subject] activities," from 1 (*Strongly disagree*) to 6 (*Strongly agree*). Interest showed satisfactory internal reliability for each field (αs = 0.89 to 0.92) so was averaged. This type of interest during adolescence is the strongest predictor of pursuit of STEM degrees during college (58), representing students' continued interest in pursuing these fields.

As specified in the preregistration, we first examined whether it was possible to average stereotypes and personal interest across math and science, as well as across computer science and engineering, to examine the contrast between the two pairs of fields. However, the average scores showed unsatisfactory reliability for gender stereotypes in math and science, αs = 0.51 to 0.57, and for computer science and engineering, αs = 0.49 to 0.60. Likewise, average scores showed unsatisfactory reliability for personal interest in math and science, $\alpha = 0.52$. Thus, as specified in the preregistration, we used specific contrasts in statistical analyses to compare students' gender stereotypes and motivation across the planned fields rather than averages.

Study 2.

Participants. The final analytic sample included $N = 1{,}268$ students (53% girls, 47% boys; 34% White, 30% Hispanic/Latine, 15% Multiracial, 14% Black, 6% Asian, 1% Native American, 1% missing/other response) from a large, diverse, urban/suburban school district in the South in which 17% of students live in poverty (comparable to the 17% of children ages 0 to 18 who live in poverty in the United States; ref. 59), selected in consultation with the Character Lab Research Network. Character Lab was an organization that aimed to recruit a broad population of US public middle and high school students. According to our preregistration exclusion criteria, 299 participants were excluded for failing the attention check. An additional 62 participants were excluded for identifying as a gender other than girl or boy, leaving a final analytic sample of $N = 1{,}268$ students, with 164 to 194 students per grade.

Determining sample size. Sample size was determined by power calculations conducted by Character Lab. Given $\alpha = 0.05$ and an expected effect size $d = 0.12$, Character Lab assigned 1,090 students per between-subjects condition to fully powered studies, which provides 80% power to detect an effect size $d = 0.12$ for any pairwise difference. The current study was considered to contain one condition under their guidelines. For the power analysis, schools were treated as fixed (60). The power analysis took into account the degree to which classrooms within schools were clustered using intraclass correlation coefficients derived from Character Lab's school data collected in 2018 to 2020. Based on the G*Power analyses in our preregistration, we predicted that the necessary sample size for predicted effects ranged from 10 to 1,068 students.

Procedure. Research services were provided through the Character Lab Research Network. This study was approved as part of their Institutional Review Board approval through Advarra with students providing informed assent. Participants completed an online Qualtrics survey during school time on classroom or home computers in October 2020. The survey included a) an attention check requesting that participants mark a particular response; b) endorsement of interest and ability stereotypes; c) four motivational variables: identification, sense of belonging, ability self-concept, and interest. All stereotypes and motivation items were asked about five fields (language arts, math, science, computer science, and engineering) following a random order that was consistent from question to question and counterbalanced across participants. The order of interest and ability stereotype questions was counterbalanced. Participants either saw all interest stereotype questions followed by the ability stereotype questions, or vice versa.

Measures. Two stereotype variables (interest and ability) and four motivation variables (identification, sense of belonging, ability self-concept, and interest) for language arts and four STEM fields were each measured on a six-point Likert scale.

Interest stereotypes included two items measuring beliefs in boys' and girls' interest ("How much do you think that most [boys/girls] like these subjects?") from 1 (*Really do not like*) to 6 (*Really do like*). Interest stereotypes were again calculated as a difference score (57).

Likewise, ability stereotypes included two items measuring beliefs in boys' and girls' ability ("How good do you think that most [boys/girls] are at these subjects?") from 1 (*Really not good*) to 6 (*Really good*) in the given fields. Difference scores were calculated in the same way.

Identification was measured with two items, e.g., "How much do you feel like you are a [field] person?" from 1 (*Strongly disagree*) to 6 (*Really agree*). Identification showed satisfactory internal reliability for each field (αs = 0.70 to 0.83) and was averaged.

Sense of belonging was measured with three items (e.g., "How much do you feel like you belong when you do these classes and activities at school?") from 1 (*Really not belong*) to 6 (*Really belong*). Sense of belonging showed satisfactory internal reliability for each field (αs = 0.80 to 0.86) and was averaged.

Ability self-concept was measured with two items, e.g., "How good are you at these classes and activities?" from 1 (*Really not good*) to 6 (*Really good*). Ability self-concept showed satisfactory internal reliability for each field (αs = 0.87 to 0.92) and was averaged. Ability self-concepts in engineering were not measured in Study 1.

Personal interest was measured with two items, e.g., "How interested are you in these activities?" from 1 (*Really not interested*) to 6 (*Really interested*). Interest showed satisfactory internal reliability for each field (αs = 0.91 to 0.94) and was averaged.

As in Study 1, the variables showed unsatisfactory reliability across math and science, αs = 0.47 to 0.67, although they showed acceptable reliability across computer science and engineering, αs = 0.75 to 0.86. Thus, as specified in our preregistration, specific contrasts were again used in statistical analyses.

Data, Materials, and Software Availability. Anonymized CSV datafiles, preregistered target sample sizes, procedures, hypotheses, and analyses, as well as materials, data, and code data have been deposited in Open Science Framework (https://osf.io/4r7sb/). Previously published data were used for this work (some of Study 1 has overlap with refs. 5 and 13: https://osf.io/ve6n9/).

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