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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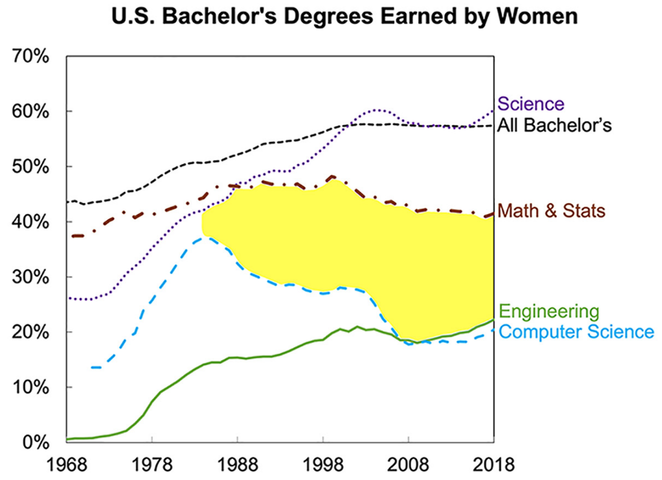

Fig. 1. Historical patterns in representation of bachelor's degrees earned in select STEM fields compared to all bachelor's degrees (STEM and non-STEM). The divergence gap between math/science and computer science/engineering degrees is highlighted in yellow to emphasize divergence since 1983. "Science" 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 (Ns = 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 ts > 10.93, Ps < 0.001, ds $= 0.28$ to 0.73. However, interest and ability stereotypes favored girls in math and language arts, one-sample ts < -4.19, Ps < 0.001, ds $= -0.68$ to -0.11. In science, interest and ability stereotypes favored girls, one-sample ts < -3.89, Ps < 0.001, ds $= -0.23$ 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 (Ms $= -0.35$ to -0.01) than stereotypes favoring boys in both computer science and engineering (Ms $= 0.41$ to 1.13) or favoring girls in language arts (Ms $= -0.96$ 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, Fs > 14.29, Ps < 0.001, η_p^2s > 0.20. This divergent pattern was also evident for students in elementary, middle, and high school, all Fs > 101.27, Ps < 0.001, η_p^2s> 0.18, although it appeared stronger for middle and high school students than elementary school students (Figs. 2–5).

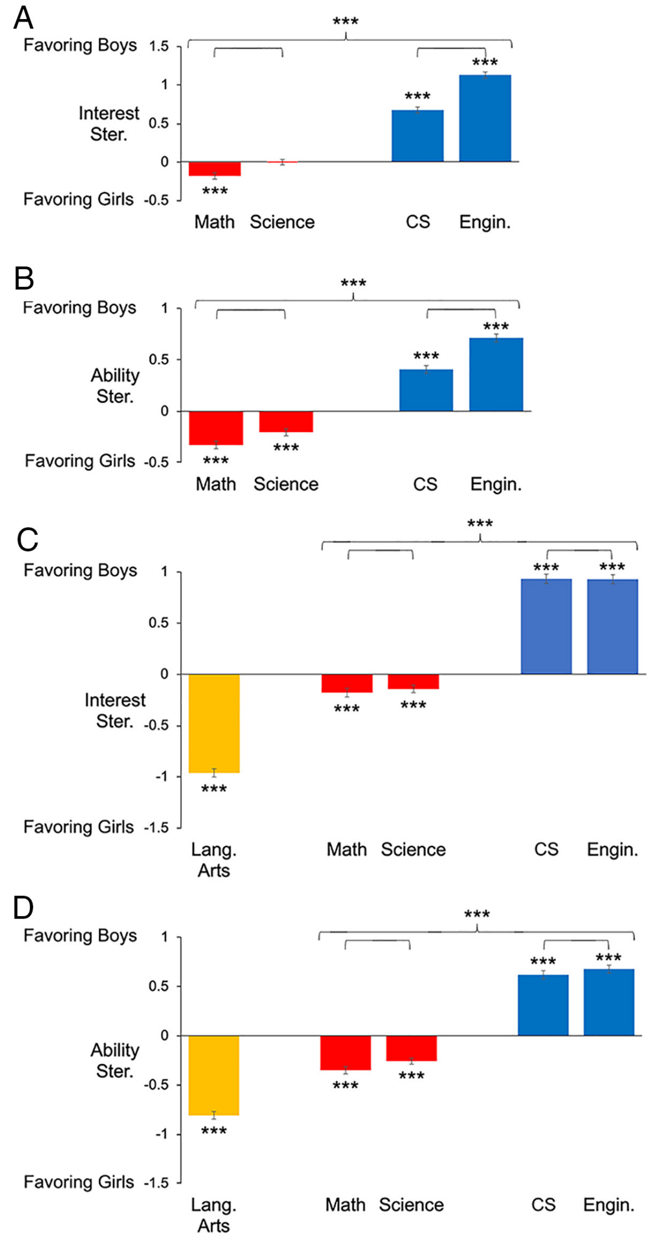

Fig. 2. Interest and ability stereotypes by field and study. Study 1 interest and ability stereotypes (*A* and *B*) and Study 2 interest and ability stereotypes (*C* and *D*) in language arts (yellow), math (red), science (red), computer science (blue), and engineering (blue), range −5 to 5. Positive 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. $^{***}P \leq 0.001$.

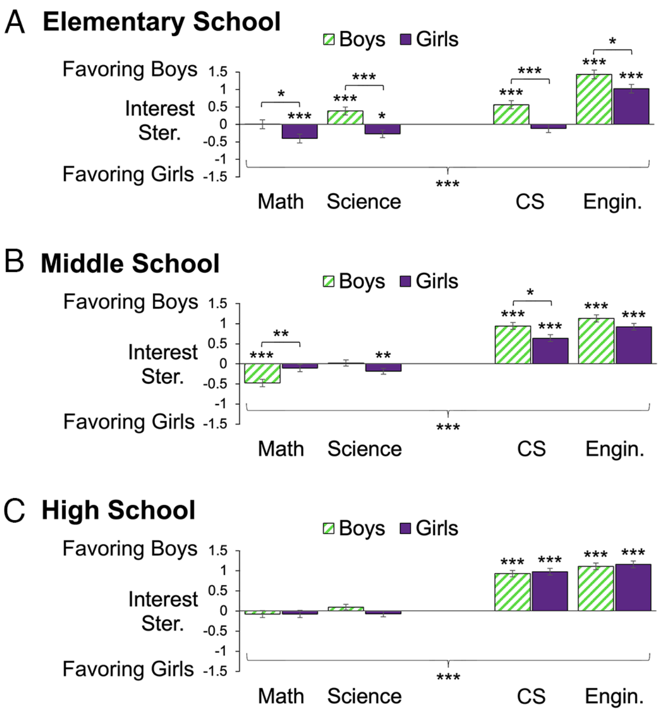

Fig. 3. Interest stereotypes by participant gender, field, and school level in Study 1. Results of Study 1 for elementary (*A*), middle (*B*), and high school (*C*) students for interest stereotypes. Girls' (solid purple) and boys' (striped green) stereotypes in math, science, computer science, and engineering (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, η_p^2s ≥ 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, η_p^2s ≤ 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, η_p^2s > 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, η_p^2s > 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, η_p^2s ≥ 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, η_p^2s ≥ 0.025, but gender differences in ability self-concepts for math and science were smaller, Fs > 4.19, Ps < 0.042, η_p^2s ≤ 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, η_p^2s > 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

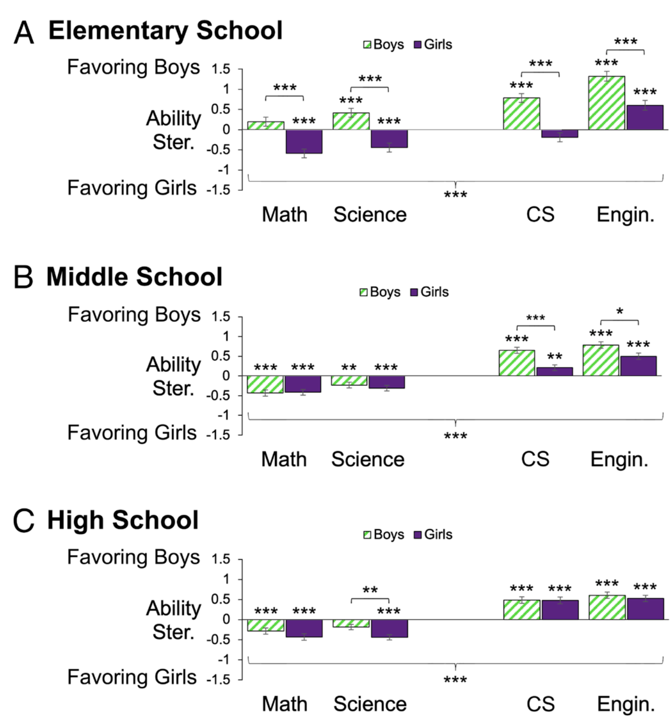

Fig. 4. Ability stereotypes by participant gender, field, and school level in Study 1. Results of Study 1 for elementary (*A*), middle (*B*), and high school (*C*) students for ability stereotypes. Girls' (solid purple) and boys' (striped green) stereotypes in math, science, computer science, and engineering (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.

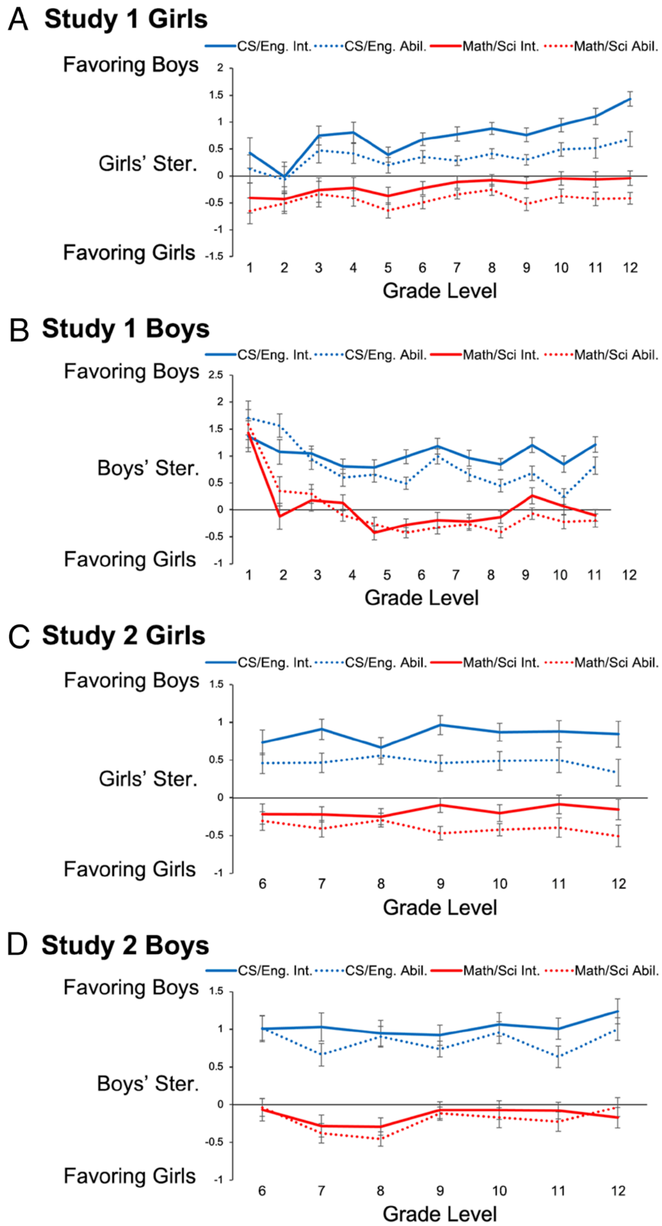

Fig. 5. Divergence in stereotypes by participant gender, grade level, and study. Study 1 girls' interest and ability (*A*), Study 1 boys' interest and ability (*B*), Study 2 girls' interest and ability (*C*), Study 2 boys' interest and ability (*D*), averaged across math/science (red lines) compared 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, *P*s ≤ 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, *P*s ≤ 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, *P*s ≤ 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, *P*s ≤ 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, *P*s < 0.001, with similar but less consistent effects for ability stereotypes (math [preregistered] and language arts: $rs = 0.24$ to 0.26, *P*s < 0.001, science: $rs = 0.05$ to 0.11, *P*s $= 0.003$ 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.

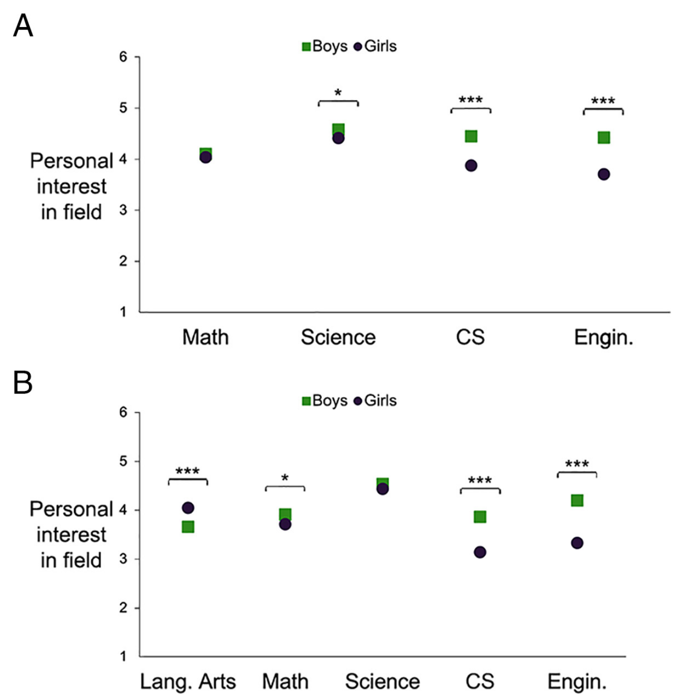

Fig. 6. Motivation (students' reports of their personal interest) by participant gender, field, and study. Studies 1 (*A*) and 2 (*B*). Girls' (purple dots) and boys' (green squares) personal interest in language arts (Study 2), math, science, computer science, and engineering (range 1 to 6). The main effects of gender and field were significant in both studies, *P*s < 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* ≤ 0.05 and ****P* ≤ 0.001.

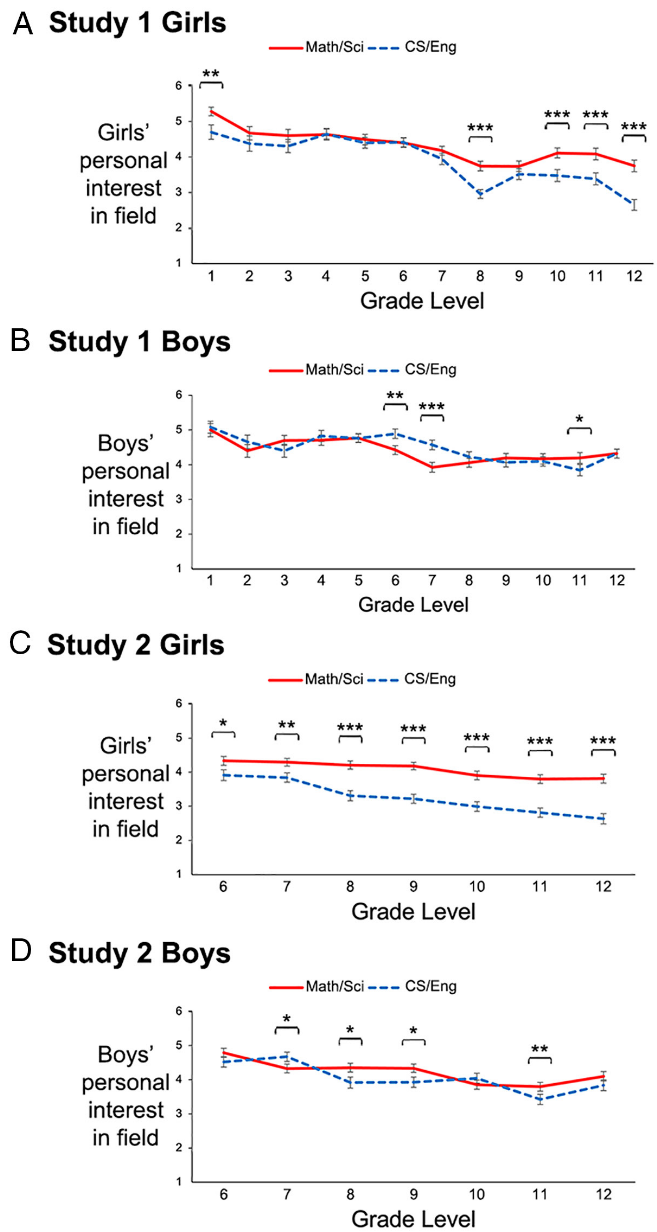

Fig. 7. Divergence in motivation as personal interest by participant gender, grade level, and study. Study 1 girls (*A*), Study 1 boys (*B*), Study 2 girls (*C*), and Study 2 boys (*D*), with motivation averaged across math/science (red lines) compared to CS/engineering (blue dashed lines). The range 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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Supporting Information for

Divergence in Children's Gender Stereotypes and Motivation Across STEM Fields

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Study 1

Participants

In consultation with officials in the Rhode Island Office of Innovation, STEAM Center, and Department of Education, the school district was selected based on district size, diversity, and participation in the CS4RI program, designed to bring computer science to all public schools in Rhode Island. In this district, elementary school students were typically exposed to coding and computational thinking in library classes once each week. Middle school students took a required series of technology courses ("Technology Education" in Grade 6, "Engineering and Design" in Grade 7, and "Introduction to Computer Science and Robotics" in Grade 8). High school students were required to take 0.5 credits in technology education as a graduation requirement (including options such as "Exploring Computer Science" and "Basic CAD for Engineering").

Before any exclusions, participants consisted of 1,954 students in Grades 1–12 (5.2 – 19.6 years old, M = 12.98, SD = 3.37; 47.7% boys, 46.6% girls, 3.6% unknown, 1% gender fluid, and 1.2% non-relevant answer; 36.4% White, 23.3% Hispanic/Latine, 13.8% multiracial, 9.0% Asian, 7.8% Black, 1.4% Native American, 0.7% other, and 7.5% missing race/ethnicity/other response). The final analytic sample was comprised of N = 1,497 students (Grade 1: 91, Grade 2: 89, Grade 3: 82, Grade 4: 86, Grade 5: 118, Grade 6: 155, Grade 7: 155, Grade 8: 182, Grade 9: 146, Grade 10: 130, Grade 11: 128, Grade 12: 135 students). There were no significant differences between the original sample and the final analytic sample in interest stereotypes, ability stereotypes, or personal interest in math, science, computer science, or engineering (see Table S16).

As noted in the main text, we used the Generalizer tool to examine how generalizable our samples were to the U.S. population for both studies. This tool helps educational researchers define an inference population of public schools using important geographic, demographic, and administrative features of the population. The Generalizer compared the specific schools in our studies to the relevant population of schools in the U.S. The website uses data provided by the Common Core of Data and American Community Survey (National Center for Education Statistics, 2024; United States Census Bureau, 2024). For Study 1, our sample was compared to an inference population of 24,934 schools that included Grades 1–12, were in suburban locations, and were regular, non-magnet, non-charter, non-shared time, Title I, or non-Title I schools. For Study 1, the Generalizability Index = 0.72. The Generalizer website notes that values between 0.7 and 0.9 are considered to have "high generalizability."

Procedure

Research assistants in the classrooms read all survey questions and responses out loud for first and second grade students. Of the 12 research assistants, six were women, two were men, and four had gender identities that were unable to be confirmed in 2024 (most likely three additional women and one additional man). A majority (58%) of the eligible children and adolescents in these schools completed the survey.

The survey included three measures of motivation: personal interest, sense of belonging, and ability self-concept. Interest was measured for all four STEM fields. Sense of belonging and ability self-concept were asked about three STEM fields (math, science, and computer science) to keep the survey length manageable for students.

For completeness and transparency, we also wish to note that our team has previously reported effects that use portions of the same dataset, and that the current questions and findings do not overlap with the ones reported earlier (Master et al., 2021; Tang et al., 2024). Table S17 provides a listing of the novelty of the current work and its separateness from these papers. In brief, compared to the 2021 paper, the current paper focuses on both interest and ability stereotypes and addresses a wholly different research issue (how stereotypes and motivation diverge across different STEM fields). In the current paper, we also provide measures from three new disciplines not examined in the 2021 paper (math, science, and language arts) and include a new study in the southern U.S. (Study 2). Compared to the 2024 paper, the current paper has quantitative comparisons about divergences in stereotypes in different STEM fields, comparisons to language arts, links between divergence in stereotypes and motivation, and a wider age range of children.

Deviations from Preregistration

Our initial intention was to report ability stereotypes for girls in Study 1 and interest stereotypes in Study 2. However, we decided that presenting the complete set of both interest and ability stereotypes for girls and boys for both Study 1 and Study 2 would create a stronger, more comprehensive manuscript with greater evidence of internal replication. In the sections below, we indicate which analyses and predictions are "parallel" to preregistered hypotheses (e.g., analyses of interest stereotypes in Study 1 and ability stereotypes in Study 2). Although they were not preregistered, they are in alignment with preregistered hypotheses.

In addition, we present exploratory analyses linking divergence in stereotypes to divergence in motivation. These analyses were not preregistered but may offer valuable insights into how patterns of stereotypes and motivation may be linked.

Some preregistered analyses were not reported in the main text due to space limitations and to focus on analyses related to divergence. All preregistered analyses not reported in the main manuscript are included in the Results section below.

Results

Ability Stereotypes by Field and Gender (Hypothesis Preregistered). A preregistered (for girls) 4 (Field: math vs. science vs. computer science vs. engineering) × 2 (Gender: boy vs. girl) two-way mixed analysis of variance (ANOVA) examined how ability stereotypes differed across STEM fields and gender (see Figure 2B). When the assumption of sphericity was not met for ANOVAs, corrections were made using the Huynh-Feldt method. All P-values are two-tailed unless explicitly stated otherwise. We use the symbol "/" throughout to designate analyses where fields were combined using planned contrasts. Students' ability stereotypes significantly differed across the four STEM fields, $F(2.82, 4175.29) = 260.73$, $P < 0.001$, $\eta_p^2 = 0.15$. Beliefs in ability stereotypes favoring boys in STEM fields were significantly higher among boys than girls, $F(1,1480) = 53.67$, $P < 0.001$, $\eta_p^2 = 0.03$. The interaction between field and gender was not significant, $P = 0.31$. To compare ability stereotypes in math/science to computer science/engineering, we contrasted these pairs of fields within the ANOVA. Students' ability stereotypes were significantly lower for math/science than for computer science/engineering, $F(1,1480) = 548.57$, $P < 0.001$, $\eta_p^2 = 0.27$. Students were more likely to believe that girls were better at math/science, but boys were better at computer science/engineering. In support of preregistered hypothesis H2A, girls reported significantly stronger ability stereotypes favoring boys for computer science/engineering than for math/science, $F(1,739) = 271.05$, $P < 0.001$, $\eta_p^2 = 0.27$. In terms of students, 38% and 48% believed that girls had less ability than boys in computer science and engineering, respectively, compared to only 17% and 18% of students who believed that girls had less ability than boys in math and science, respectively.

To test our preregistered hypothesis H2B, a one-way ANOVA with a planned contrast between math/science and computer science/engineering was conducted to examine ability stereotypes for girls in Grades 1 and 2. In support of our prediction, girls' ability stereotypes about computer science/ engineering were significantly stronger than math/science by Grade 2, $F(1, 88) = 7.40$, $P = 0.008$, $\eta_p^2 = 0.08$ (see Figure 5), although this effect was driven by the difference between engineering and math stereotypes.

Interest Stereotypes by Field and Gender (Exploratory Analysis). This analysis is parallel to preregistered hypothesis H2A, with the substitution of interest stereotypes for ability stereotypes. A 4 (Field: math vs. science vs. computer science vs. engineering) × 2 (Gender: boy vs. girl) two-way mixed ANOVA examined how interest stereotypes differed across STEM fields and gender (see Figure 2A). Students' interest stereotypes significantly differed across the four STEM fields, $F(2.87, 4241.22) = 317.34$, $P < 0.001$, $\eta_p^2 = 0.18$. Interest stereotypes favoring boys in STEM fields were significantly higher among boys than girls, $F(1, 1479) = 15.19$, $P < 0.001$, $\eta_p^2 = 0.01$. The interaction between field and gender was significant, $F(2.87, 4241.22) = 4.61$, $P = 0.004$, $\eta_p^2 = 0.003$. To compare interest stereotypes in math/science to computer science/engineering, we contrasted these pairs of fields to each other within the ANOVA. In line with predictions, students' interest stereotypes were significantly lower for math/science than for computer science/engineering, $F(1, 1479) = 696.57$, $P < 0.001$, $\eta_p^2 = 0.32$. Students believed that girls were more interested than boys in math/science, and that conversely boys were more interested than girls in computer science/engineering. Looking at individual students, 51% and 63% of students believed that girls were less interested than boys in computer science and engineering, respectively, compared to 26% and 28% of students who believed that girls were less interested than boys in math and science, respectively. Similar to preregistered hypothesis H2A and in line with the predictions concerning H2A (see Table S1), girls reported significantly stronger interest stereotypes favoring boys for computer science/ engineering than for math/science, $F(1, 738) = 328.98$, $P < 0.001$, $\eta_p^2 = 0.31$.

Parallel to preregistered hypothesis H2B (see Table S1), a one-way ANOVA with a planned contrast between math/science and computer science/engineering was conducted to examine first and second grade girls' interest stereotypes. In line with the H2B predictions, girls' interest stereotypes about computer science/engineering were significantly stronger than math/science by second grade, $F(1,89) = 8.81$, $P = 0.004$, $\eta_p^2 = 0.09$. Girls' stereotypes about computer science changed from egalitarian/neutral stereotypes in elementary school to strongly favoring boys in middle school (see Figure 5).

Personal Interests by Field and Gender (Hypothesis Preregistered). A 4 (Field: math vs. science vs. computer science vs. engineering) × 2 (Gender: girl vs. boy) two-way mixed analysis of variance (ANOVA) examined how personal interest differed across STEM fields and gender. Students' personal interest significantly differed across the four STEM fields, $F(2.85, 4242.91) = 44.27$, $P < 0.001$, $\eta_p^2 = 0.03$. In support of preregistered hypothesis H3A, the results revealed a significant interaction between field and gender for interest, $F(2.85, 4242.91) = 26.14$, $P < 0.001$, $\eta_p^2 = 0.02$ (see Figure 6). The planned contrast for interest in math/science vs. computer science/engineering for the interaction between field and gender was significant, $F(1,1490) = 61.02$, $P < 0.001$, $\eta_p^2 = 0.04$. In terms of the simple effects of gender, results were consistent with preregistered hypothesis H3C. Gender differences in math ($\eta_p^2 = 0.00$) and science ($\eta_p^2 = 0.003$) were smaller than those in computer science ($\eta_p^2 = 0.03$) and engineering ($\eta_p^2 = 0.05$). Looking at the interaction the other way, in terms of the simple effects of field for each gender, we conducted two one-way ANOVAs (one for girls and one for boys) with planned contrasts that compared interest for math/science and for computer science/engineering rather than directly testing simple effects of gender or field from the mixed ANOVA. As predicted in H3B, girls' interest in math/science was significantly higher than computer science/engineering, $F(1, 742) = 78.98$, $P < 0.001$, $\eta_p^2 = 0.10$. In contrast, the difference between boys' interest in the two sets of fields was smaller, $F(1, 748) = 4.05$, $P < 0.05$, $\eta_p^2 = 0.01$.

Linking Divergence in Stereotypes with Divergence in Motivation (Exploratory Analysis). As reported in the main text, larger divergences in stereotypes predicted larger divergences in motivation (with lower personal interest in computer science/engineering relative to math/science for girls, and higher personal interest in computer science/engineering relative to math/science for boys). For this analysis, we used latent difference score models. "Divergence" and "difference scores" are used interchangeably throughout this section. We first created latent divergence score variables (in Step 1) and then examined correlations between latent divergence scores for stereotypes and personal interest (in Step 2).

In Step 1, we created three initial models for the latent divergence scores for (a) personal interest, (b) interest stereotypes, and (c) ability stereotypes. First, in terms of personal interest, we created two latent factors, one representing latent interest in math and science (measured by observed interest in math and science) and the other representing latent interest in computer science and engineering (measured by observed interest in computer science and engineering). The personal interest latent divergence score reflected the difference between those two latent factors. The path of interest in math/science on interest in computer science/engineering was fixed to 1. The influence of interest in math/science on the latent difference score was also fixed to 1. This defined the latent divergence as a direct subtraction to avoid arbitrary scaling; it also allowed the model to partition the variance of interest in math/science into two components: one directly attributable to interest in computer science/engineering and the other to the overall personal interest divergence. The stereotype latent divergence score models were computed in the same way as the personal interest latent divergence score model.

In Step 2, we examined the relationships between (a) the latent personal interest divergence score and the latent interest stereotype divergence score, and (b) the latent personal interest divergence score and the latent ability stereotype divergence score. The models were examined separately for girls and boys. First, for the model including the interest stereotype divergence scores, model fit indices suggested the model fit the data well for girls and boys (girls: χ^2 = 9.818, *df* = 8, *P* = 0.278, CFI = 0.998; TLI = 0.994; RMSEA = 0.017, CI [0.000, 0.048]; SRMR = 0.014; boys: χ^2 = 14.617, *df* = 8, *P* = 0.067, CFI = 0.992; TLI = 0.971; RMSEA = 0.033, CI [0.000, 0.060]; SRMR = 0.019). Second, for the model including the ability stereotype divergence scores, model fit indices suggested the model fit the data well for girls and boys (girls: χ^2 = 28.503, *df* = 12, *P* = 0.005, CFI = 0.984; TLI = 0.964; RMSEA = 0.043, CI [0.023, 0.063]; SRMR = 0.030; boys: χ^2 = 19.425, *df* = 12, *P* = 0.079, CFI = 0.992; TLI = 0.981; RMSEA = 0.029, CI [0.000, 0.051]; SRMR = 0.023). Degrees of freedom varied based on the different covariances of the observed items. For girls, the more that their stereotypes diverged (with computer science/engineering stereotypes more likely to favor boys than math/science), the more that their personal interest in these fields diverged (with lower personal interest in computer science/engineering than math/science), interest stereotypes ρ = -0.70, *P* < 0.001; ability stereotypes ρ = -0.37, *P* < 0.001. 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), the more they were personally interested in computer science/engineering compared to math/science, interest stereotypes ρ = 0.36, *P* < 0.001; ability stereotypes ρ = 0.30, *P* < 0.001. See Fig. S7.

Correlations between Ability Stereotypes and Personal Interest (Hypothesis Preregistered). As predicted, the more that individual girls reported ability stereotypes favoring boys in a particular field, the lower their own personal interest in that field (with significant correlations for computer science and engineering, the fields with the strongest stereotypes favoring boys). In contrast, the more that individual boys reported ability stereotypes favoring boys in a particular field, the higher their personal interest in that field (with significant correlations for math, science, and engineering; see Table S5).

Moreover, as we predicted, correlations between ability stereotypes and interest were significantly more negative for girls than for boys in these fields (preregistered hypothesis H1; see Tables S1 and S5).

Correlations between Interest Stereotypes and Personal Interest (Exploratory Analysis). This analysis is parallel to preregistered hypothesis H1 with the substitution of interest stereotypes for ability stereotypes. Similar to preregistered hypothesis H1 and in line with predictions (see Table S1), the more that individual girls reported interest stereotypes favoring boys in a particular field, the lower their own personal interest in pursuing that field. In contrast, the more that individual boys reported interest stereotypes favoring boys in a particular field, the higher their personal interest in that field (see Table S5).

Moreover, consistent with H1, correlations between interest stereotypes and personal interest in the field were significantly more negative for girls than for boys in these fields (see Table S5).

Study 2

Participants

Before any participant exclusions, participants were 1,629 students in Grades 6–12 (11–22 years old, *M* = 14.15, *SD* = 2.03; 44% boys, 48% girls, 7% unknown, 1% gender fluid or used another word; 31.1% White, 27.6% Hispanic/Latine, 13.9% multiracial, 13.5% Black, 5.6% Asian, 0.7% Native American, 0.2% other, and 7.4% missing race/ethnicity/other response). Demographic data found in the Common Core of Data (NCES) was used to define this population. To facilitate research and recruitment, this population of schools was divided into strata using k-means cluster analysis (Tipton, 2014). Character Lab then recruited schools (and their students) within each of these strata and matched researchers and studies to specific strata.

This study was conducted with students at schools in a stratum (selected by the researchers) defined as "large, diverse, suburban and urban schools." Schools in this stratum represent 15% of all middle schools and 13% of all high schools in the U.S. This stratum was purposefully selected to recruit a diverse sample, as most students in the U.S. attend schools that are not diverse (54% of middle school students and 62% of high school students attend schools with mostly White students; 12% of middle and high school students attend schools with mostly Black students; and 19% of middle school students and 13% of high school students attend schools with mostly Hispanic/Latine students). In all districts that approved our study, all students in attendance at schools in the relevant stratum during the predetermined data collection window were invited to participate in Character Lab research activities, but not all were randomly assigned to our study. Students had an equal chance of being randomized to any of the studies running in their school. As noted in the main text, we used the Generalizer tool to compare our sample to the U.S. population, with a Generalizability Index of 0.78. For Study 2, our sample was compared to an inference population of 12,498 schools that included Grades 6-12, were in suburban locations, and were regular/non-magnet, non-charter, non-shared time, Title I, or non-Title I schools.

Although computer science courses were not mandatory in this district, 51% of participants (647 students; 52% of middle school students and 50% of high school students) reported some previous experience with computer science and/or engineering, with 116 students mentioning middle school technology courses ("Information & Communications Technology" or "Digital Information Technology"), 79 students mentioning "Project Lead The Way" (a STEM curriculum that involves coding and engineering), and 37 students mentioning high school AP computer science courses.

The final analytic sample was comprised of N = 1,268 students (Grade 6: 164, Grade 7: 173, Grade 8: 194, Grade 9: 188, Grade 10: 189, Grade 11: 175, Grade 12: 184 students; missing: 1 student).

Results

Interest Stereotypes by Field and Gender (Hypothesis Preregistered). A 5 (Field: language arts vs. math vs. science vs. computer science vs. engineering) × 2 (Gender: girl vs. boy) two-way mixed ANOVA examined how interest stereotypes differed across STEM fields and gender. In line with preregistered hypothesis H2 (see Table S1), students' interest stereotypes significantly differed across the five fields, $F(3.30, 4134.91) = 479.40$, $P < 0.001$, $\eta_p^2 = 0.28$. Interest stereotypes did not significantly differ between boys and girls, $F(1, 1252) = 2.44$, $P = 0.12$, $\eta_p^2 = 0.002$. The interaction between field and gender was significant, $F(3.30, 4134.91) = 5.08$, $P = 0.001$, $\eta_p^2 = 0.004$ (see Figure 2C).

Next, we compared specific sets of fields using preregistered planned comparisons. First, we compared computer science/engineering to math/science. A planned within-subjects contrast within the ANOVA tested whether students' interest stereotypes about computer science/engineering were significantly more likely to favor boys than math/science. In line with preregistered hypothesis H2A, students' interest stereotypes about computer science/engineering favoring boys were significantly higher than math/science, indicating that students were more likely to report that boys were more interested than girls in computer science/engineering, $F(1, 1252) = 667.82$, $P < 0.001$, $\eta_p^2 = 0.35$ (see Figure 2C).

Second, we compared language arts to math and science. A planned within-subjects contrast within the ANOVA tested whether students' interest stereotypes about language arts were significantly more likely to favor girls than math/science. In accordance with preregistered hypothesis H2B, students' interest stereotypes about language arts were significantly more likely to favor girls than math/science, $F(1, 1252) = 313.96$, $P < 0.001$, $\eta_p^2 = 0.20$ (see Figure 2C).

Third, we compared language arts to computer science and engineering. A planned within-subjects contrast tested whether students' interest stereotypes about language arts were significantly more likely to favor girls than computer science/engineering. In accordance with preregistered hypothesis H2C, students' interest stereotypes about language arts were significantly more likely to favor girls than computer science/engineering, $F(1, 1252) = 1059.28$, $P < 0.001$, $\eta_p^2 = 0.46$ (see Figure 2C).

Examining the data at the level of individual students, 56% believed that girls had less interest than boys in both computer science and engineering, compared to 23% of students who believed that girls had less interest than boys in both math and science, and 58% of students who believed that girls had more interest than boys in language arts.

Ability Stereotypes by Field and Gender (Exploratory Analysis). This analysis is parallel to preregistered H2 with the substitution of ability stereotypes for interest stereotypes. A 5 (Field: language arts vs. math vs. science vs. computer science vs. engineering) × 2 (Gender: girl vs. boy) two-way mixed ANOVA examined how ability stereotypes differed across STEM fields and gender. Parallel to preregistered hypothesis H2 (see Table S1), students' ability stereotypes significantly differed across the five fields, $F(3.00, 3739.85) = 420.72$, $P < 0.001$, $\eta_p^2 = 0.25$. There was a significant interaction between field and gender, $F(3.00, 3739.85) = 5.41$, $P = 0.001$, $\eta_p^2 = 0.004$ (see Figure 2D). Beliefs in ability stereotypes favoring boys were significantly higher among boys than girls, $F(1,1247) = 22.80$, $P < 0.001$, $\eta_p^2 = 0.02$.

Next, we compared specific sets of fields in planned comparisons (parallel to preregistered hypothesis H2B with the substitution of ability stereotypes for interest stereotypes). First, we compared computer science and engineering to math and science. A planned within-subjects contrast tested whether students' ability stereotypes about computer science/engineering were significantly more likely to favor boys than math/science. In line with preregistered hypothesis H2A predictions (see Table S1), students' ability stereotypes about computer science/engineering favoring boys were significantly higher than math/science, indicating that students were more likely to report that boys were better than girls in computer science and engineering, $F(1, 1247) = 604.48$, $P < 0.001$, $\eta_p^2 = 0.33$.

Second, we compared language arts to math and science. A 3 (Field: language arts vs. math vs. science) × 2 (Gender: girl vs. boy) two-way mixed ANOVA with planned within-subjects contrast tested whether students' ability stereotypes about language arts were significantly more likely to favor girls than math/science. In line with preregistered hypothesis H2B predictions, students' ability stereotypes about language arts were significantly more likely to favor girls than math/science, $F(1, 1247) = 188.34$, $P < 0.001$, $\eta_p^2 = 0.13$.

Third, we compared language arts to computer science and engineering. A planned within-subjects contrast tested whether students' ability stereotypes about language arts were significantly more likely to favor girls than computer science/engineering. In line with preregistered hypothesis H2C predictions, students' ability stereotypes about language arts were significantly more likely to favor girls than computer science/engineering, $F(1, 1247) = 811.72$, $P < 0.001$, $\eta_p^2 = 0.39$.

Examining data at the level of individual students, 44% and 45% believed that girls had less ability than boys in computer science and engineering, respectively, compared to 15% and 13% of students who believed that girls had less ability than boys in math and science, respectively, and 51% of students who believed that girls had more ability than boys in language arts.

Motivation by Field and Gender (Hypothesis Preregistered). We conducted 5 (Field: language arts vs. math vs. science vs. computer science vs. engineering) × 2 (Gender: girls vs. boys) ANOVAs with planned contrasts separately for the four measures of motivation: identification, sense of belonging, ability self-concept, and personal interest in classes and activities. In accordance with our preregistration, we separated the five fields and used planned contrasts rather than averaging across fields due to low reliability across fields. In support of preregistered hypothesis H3A (see Table S1), there were significant interactions between field and gender for: a) identification, $F(3.20, 3976.60) = 42.11$, $P < 0.001$, $\eta_p^2 = 0.03$; b) sense of belonging, $F(3.17, 3990.72) = 42.57$, $P < 0.001$, $\eta_p^2 = 0.03$; c) ability self-concept, $F(3.16, 3905.13) = 28.90$, $P < 0.001$, $\eta_p^2 = 0.02$; and d) personal interest, $F(3.40, 4238.30) = 50.57$, $P < 0.001$, $\eta_p^2 = 0.04$, see Figure S7 and Figure 6.

Next, we compared specific simple effects in planned comparisons. First, we compared language arts to math/science separately for girls and boys using planned contrasts. For girls, the results for H3B provided mixed support for the preregistered prediction (see Table S18). Although girls' sense of belonging and ability self-concepts for language arts were significantly higher than for math/science, Ps < 0.001, there were no significant differences across these fields for identification and interest, Ps = 0.23 to 0.68. In support of preregistered hypothesis H3E, boys' identification, sense of belonging, ability self-concept, and interest were each significantly lower for language arts than for math/science, Ps < 0.001 (see Table S19).

Second, we compared language arts to computer science/engineering. For girls, in support of preregistered hypothesis H3C, all four motivational variables were significantly higher for language arts than for computer science/engineering, Ps < 0.001 (see Table S18). For boys, in support of preregistered hypothesis H3E, all four motivational variables were significantly lower for language arts than computer science/engineering, Ps < 0.05 (see Table S19).

Third, we compared math/science to computer science/engineering. For girls, in support of preregistered hypothesis H3D, all four motivational variables were significantly higher for math/science than for computer science/engineering, Ps < 0.001 (see Table S18). For boys, motivation was significantly higher for math/science than for computer science/engineering, but these differences were smaller than the differences for girls' motivation, which supported our prediction (see Table S19).

Looking at the interaction the other way, we examined simple effects of gender for each field. In support of preregistered hypotheses H3F and H3G, gender differences in motivation in math/science were smaller than in computer science/engineering, and also smaller than gender differences in motivation in language arts. In terms of simple effects of gender (H3F), results showed that gender differences in math/science motivation (math, Ps < 0.04, $\eta_p^2 = 0.004$ to 0.01; science, Ps = 0.04 to 0.65, $\eta_p^2 < 0.004$) were smaller than gender differences in computer science/engineering (computer science, Ps < 0.001, $\eta_p^2 = 0.03$ to 0.05; engineering, Ps < 0.001, $\eta_p^2 = 0.04$ to 0.07), Ps < 0.001 except ability self-concepts, P = .054. Likewise, gender differences in math/science were smaller than those in language arts (language arts, Ps < 0.003, $\eta_p^2 = 0.008$ to 0.02), Ps < 0.001.

Linking Divergence in Stereotypes with Divergence in Motivation (Exploratory Analysis). As reported in the main text, at the level of individual participants, larger divergences in stereotypes predicted larger divergences in motivation (with lower interest in computer science/engineering relative to math/science for girls, and higher interest in computer science/engineering relative to math/science for boys). As in Study 1, we used latent difference score models. We fixed all loadings in the same ways as Study 1.

First, for the model including the interest stereotype divergence scores, model fit indices suggested acceptable model fit for girls and that the model fit the data well for boys (girls: $\chi^2 = 52.703$, $df = 11$, $P < 0.001$, CFI = 0.967; TLI = 0.917; RMSEA = 0.077, CI [0.057, 0.099]; SRMR = 0.060; boys: $\chi^2 = 11.278$, $df = 8$, $P = 0.186$, CFI = 0.996; TLI = 0.988; RMSEA = 0.027, CI [0.000, 0.060]; SRMR = 0.014). Second, for the model including the ability stereotype divergence scores, model fit indices suggested acceptable model fit for girls and boys (girls: $\chi^2 = 18.838$, $df = 12$, $P = 0.093$, CFI = 0.996; TLI = 0.990; RMSEA = 0.030, CI [0.000, 0.055]; SRMR = 0.016; boys: $\chi^2 = 56.352$, $df = 13$, $P < 0.001$, CFI = 0.958; TLI = 0.908; RMSEA = 0.077, CI [0.057, 0.098]; SRMR = 0.035). For girls, the more that their stereotypes diverged (with computer science/engineering stereotypes more likely to favor boys than math/science), the more that their personal interest in these fields diverged (with lower personal interest in computer science/engineering than math/science), interest stereotypes $\rho = -0.37$, $P < 0.001$; ability stereotypes $\rho = -0.26$, $P = 0.005$. 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), the more they were personally interested in computer science/engineering compared to math/science, interest stereotypes $\rho = 0.29$, $P = 0.036$, ability stereotypes $\rho = 0.29$, $P = 0.002$. See Fig. S7.

Correlations between Interest Stereotypes and Motivation (Hypothesis Preregistered). In support of preregistered hypothesis H1, stereotypes favoring boys were linked to lower motivation for girls for each of the five fields and higher motivation for boys for four of the five fields. The more that individual girls reported interest stereotypes favoring boys in a particular field (with stereotypes most strongly favoring boys in the fields of computer science and engineering), the lower their motivation for that field (in support of preregistered hypothesis H1A). Put another way, the more that girls reported interest stereotypes favoring girls in a field (with stereotypes most strongly favoring girls in the field of language arts), the higher their motivation for that field. Similarly, the more that individual boys reported interest stereotypes favoring boys, the higher their motivation in that field (with the exception of engineering), while boys who believed that girls were more interested than boys in a field (with stereotypes most strongly favoring girls in the field of language arts) reported lower motivation for that field.

All 13 correlations predicted in the preregistration were supported (see Table S6). Moreover, correlations between stereotypes and motivation were more negative for girls than for boys in all five fields, Zs > 2.29, Ps ≤ 0.01 (supporting preregistered hypothesis H1B; see Table S7).

Correlations between Ability Stereotypes and Motivation (Hypothesis Preregistered). In support of preregistered hypothesis H1 (which explicitly included ability stereotypes), stereotypes favoring boys were linked to at least one measure of lower motivation for girls in each of five fields and higher motivation for boys in four of five fields. The more that individual girls reported ability stereotypes favoring boys in a particular field (with stereotypes most strongly favoring boys in the fields of computer science and engineering), the lower their motivation for that field (in support of preregistered hypothesis H1A). Put another way, the more that girls reported ability stereotypes favoring girls in a field (with stereotypes most strongly favoring girls in the field of language arts), the higher their motivation for that field (with correlations most significant for sense of belonging and ability self-concept). Similarly, generally the more that individual boys reported ability stereotypes favoring boys, the higher their motivation in that field (with stereotypes most strongly favoring boys in the fields of computer science and engineering), while boys who reported ability stereotypes favoring girls (with stereotypes most strongly favoring girls in the field of language arts) reported lower motivation for that field. However, these correlations were significant only for language arts (all motivation variables), math (all motivation variables), science ability self-concept, computer science ability self-concept, and computer science interest (see Table S6).

All four correlations predicted in the preregistration were supported. Moreover, correlations between stereotypes and motivation were more negative for girls than for boys in all five fields, Zs > 1.75, Ps < 0.10 (in support of preregistered hypothesis H1B, see Table S7).

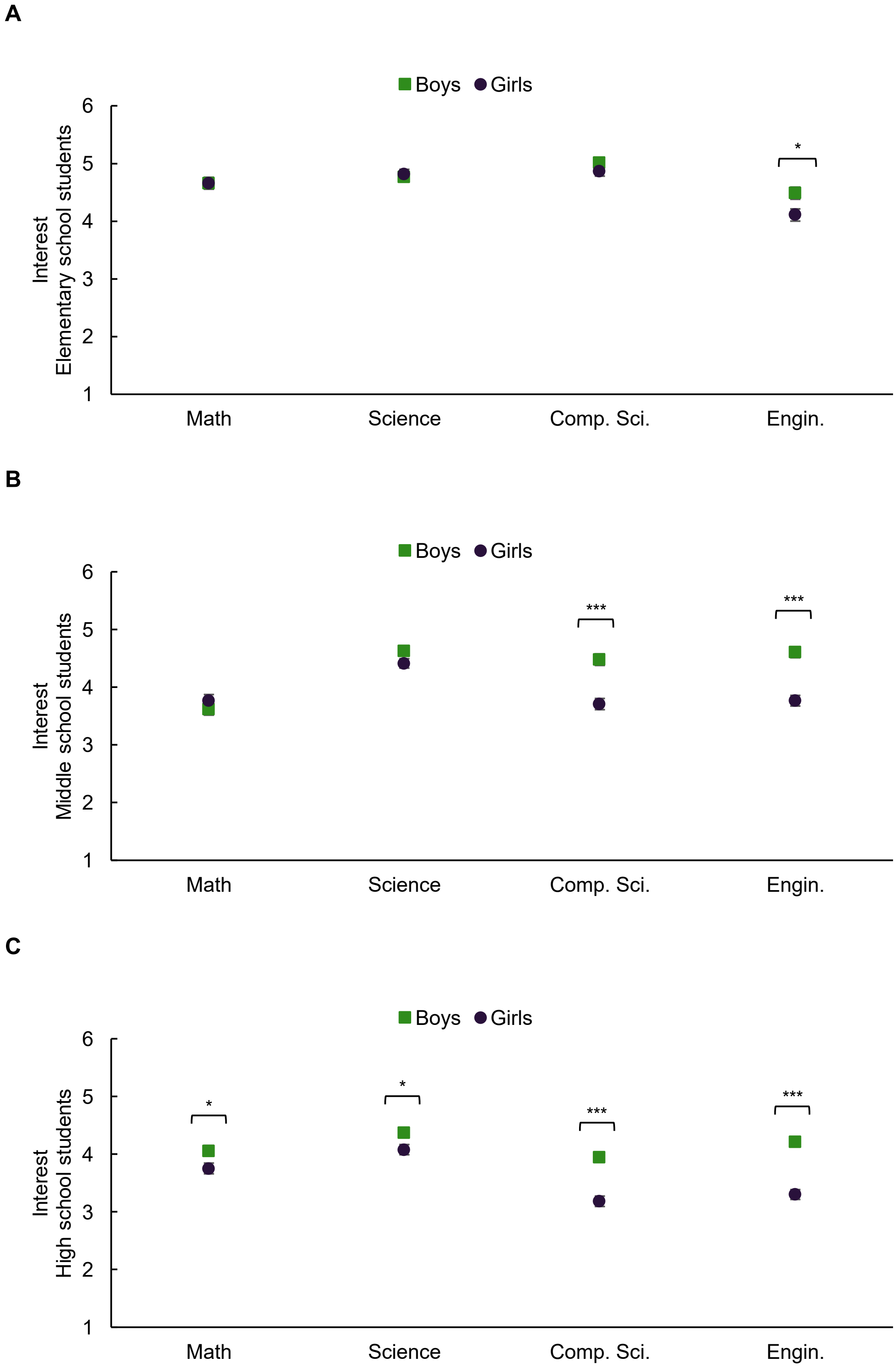
Supplemental Discussion

Contextual Influences on Stereotypes

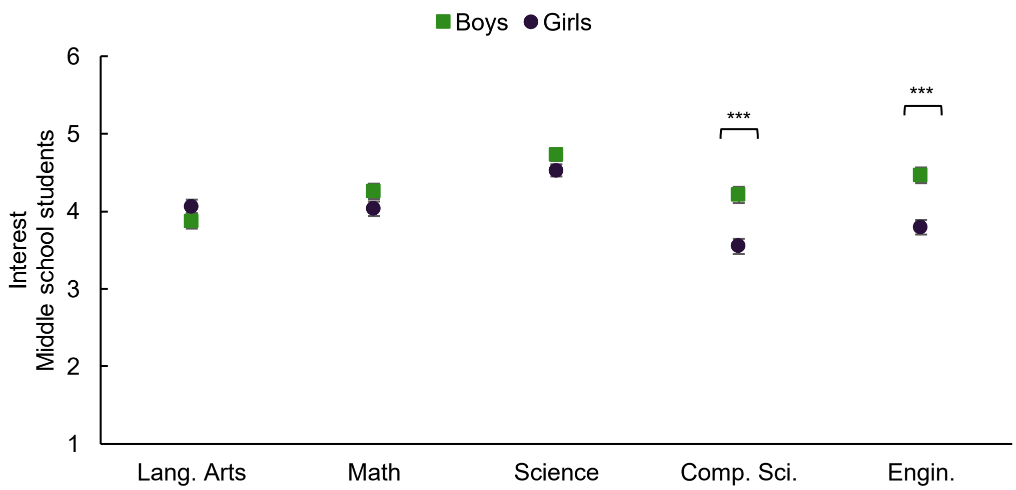
Although overall patterns of divergence replicated across Studies 1 and 2, it is possible that different contexts of the samples impacted similarities and differences in results. For example, Study 1 was conducted in a school district with mandatory coding and technology courses, and Study 2 was conducted in a district where fewer students had experienced coursework in coding and technology (only 51% reported experience with computer science/engineering). Other differences included geographic region (Study 1 in New England and Study 2 in the South) and grade levels in the sample (with Study 2 including only middle and high school students).

In terms of discrepancies across studies, high school girls in Study 2 appeared to report stronger science-interest stereotypes favoring girls than high school girls in Study 1. This difference may reflect salient experiences in courses such as biology rather than physics for girls in Study 2. In Study 2, we asked students to report what kind of science they were thinking about (we did not ask students this question in Study 1 so we cannot compare across studies). Indeed, many high school girls in Study 2 reported thinking about fields including biology, marine science, and earth/environmental science, which may be subfields in which stereotypes are less likely to favor boys. In addition, boys reported stronger divergence than girls for ability stereotypes in Study 2. (There were no interactions between participant gender and stereotype divergence in Study 1 or for interest stereotypes in Study 2.) This effect appeared to be driven by boys' strongly boy-favoring computer science and engineering ability stereotypes in Study 2. This could be related to fewer classroom experiences of observing girls' academic success in these domains. One longitudinal study of children's STEM stereotypes found that stereotypes generally changed toward favoring girls over a calendar year, especially for younger students and domains in which students had more experiences (math, science, and in this sample, computer coding), potentially due to the visibility of girls' greater academic success in the classroom on average (Tang et al., 2024).

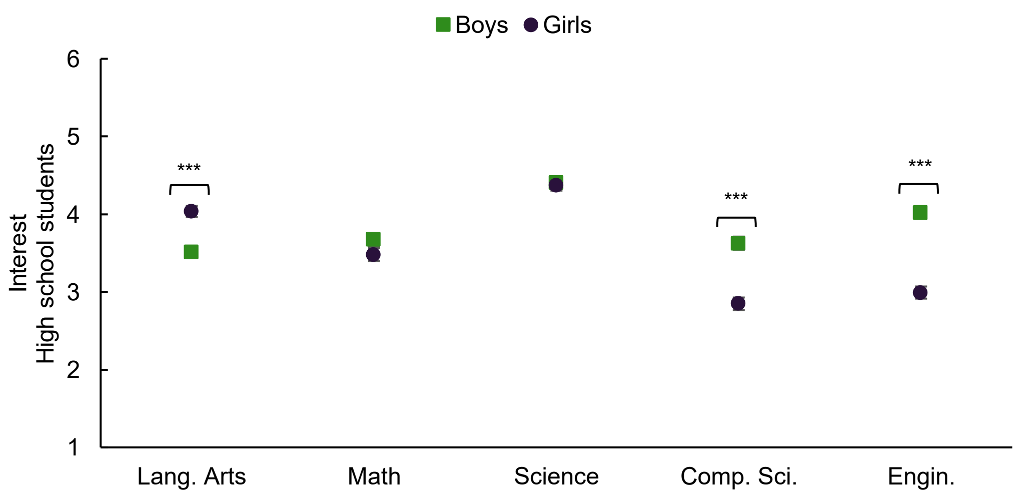
Fig. S1


A
Boys Girls
Interest
Elementary school students
1
2
3
4
5
6
Math
Science
Comp. Sci.
Engin.
*
B
Boys Girls
Interest
Middle school students
1
2
3
4
5
6
Math
Science
Comp. Sci.
Engin.
***
***
C
Boys Girls
Interest
High school students
1
2
3
4
5
6
Math
Science
Comp. Sci.
Engin.
*
*
***
***

D

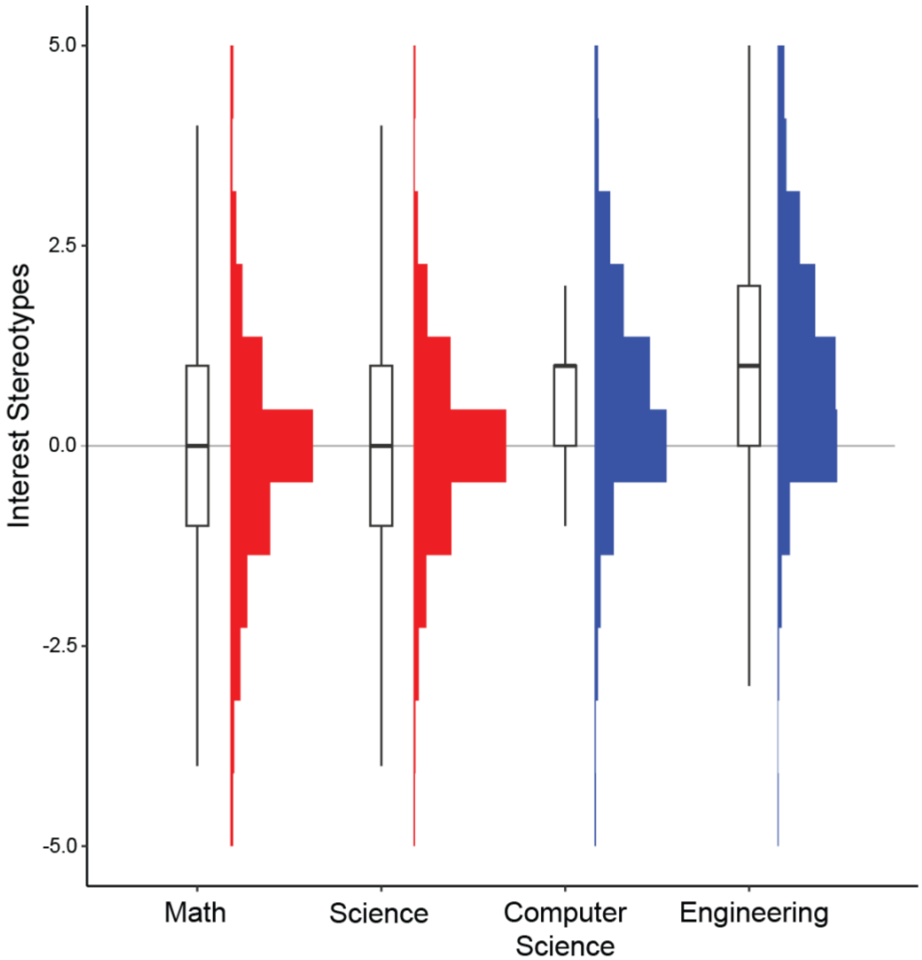


E



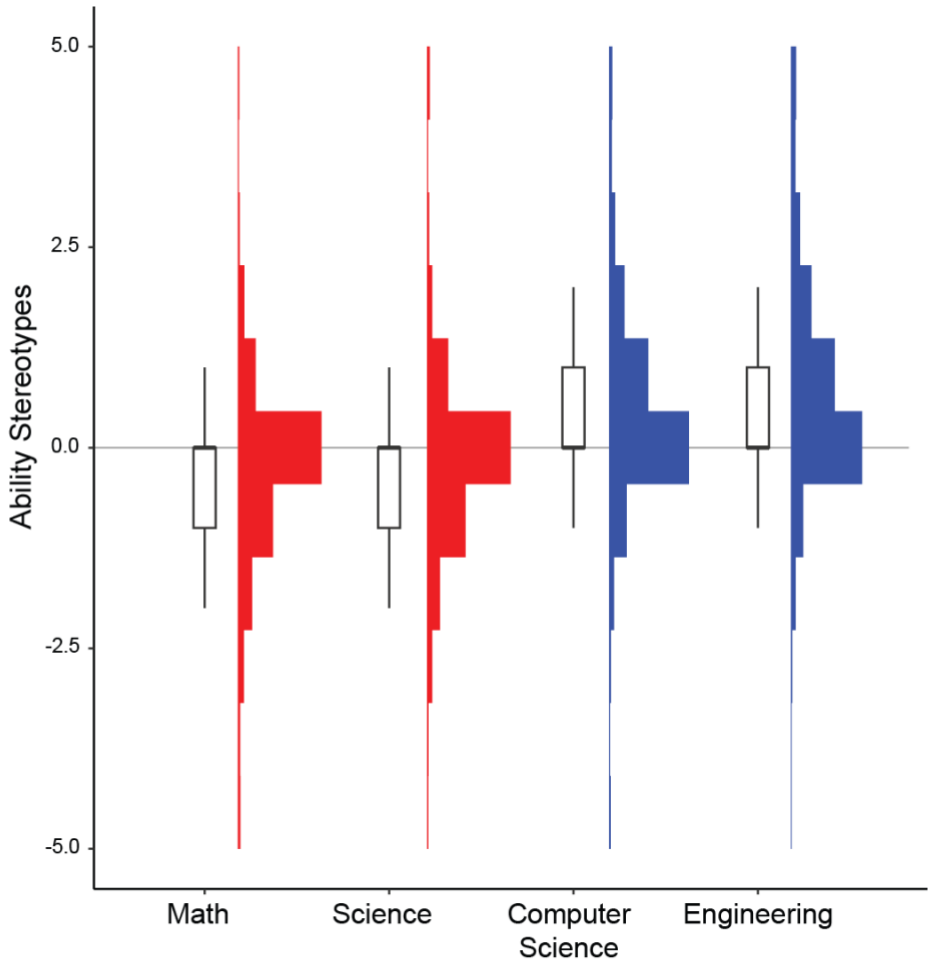
Study 1 elementary school (**A**), middle school (**B**), and high school (**C**), and Study 2 middle school (**D**) and high school (**E**). The range of interest is from 1 to 6. Higher values indicate more interest in the field and lower values indicate less interest in that field. Comp. Sci. indicates computer science; Engin. Indicates engineering; Lang. indicates language. Error bars represent SE. The main effect of field was significant for students in all school levels, *P*s < .001. The main effect of gender was significant for middle and high school students in Study 1 and Study 2, *P*s < 0.001, but not for elementary school students, *P* = 0.18. **P* ≤ 0.05, ***P* ≤ 0.01, ****P* ≤ 0.001.

Fig. S2



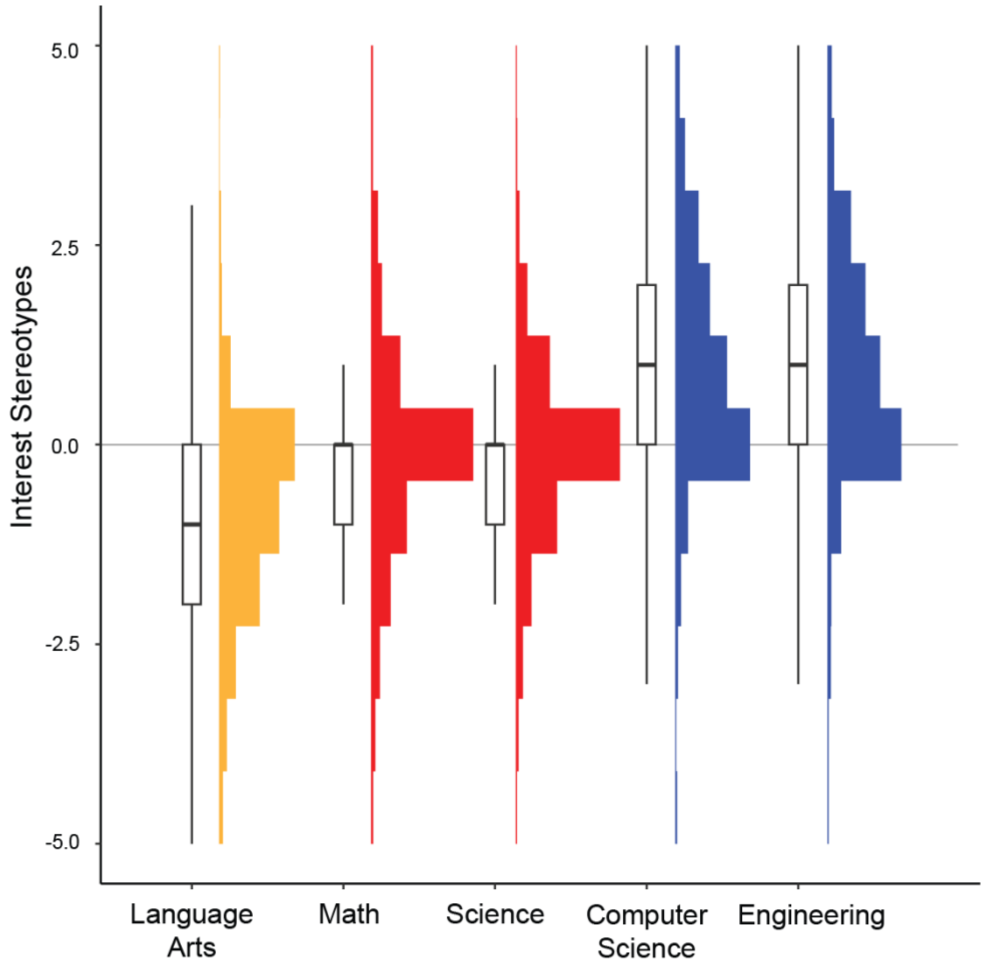
Boxplot of Study 1 interest stereotypes by field. The thick line of the boxplot represents the median, while the edges of the box represent the interquartile range (25th and 75th percentiles). When the median and 25th or 75th percentiles are the same value, the corresponding box is not visible. The "whiskers" show the minimum and maximum values. The histograms show the frequency of responses at each value. Math and science histograms are in red; computer science and engineering histograms are in blue.

Fig. S3



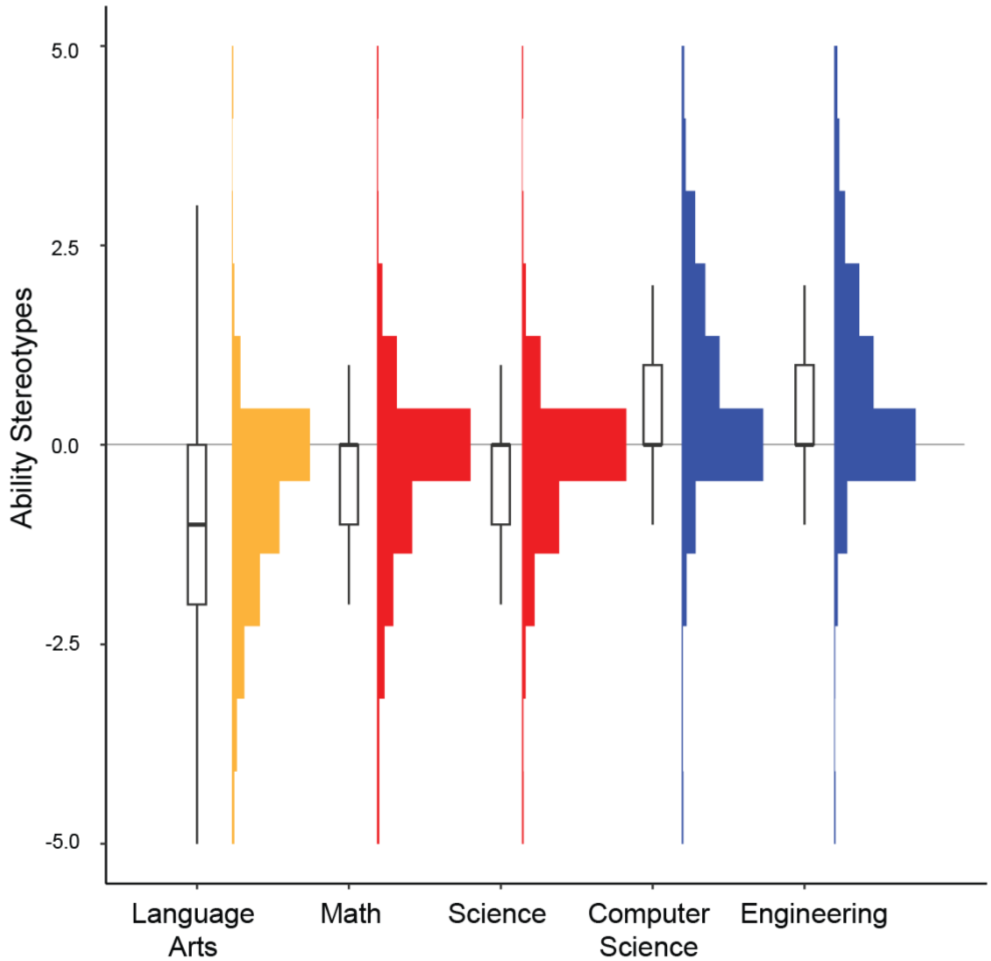
Boxplot of Study 1 ability stereotypes by field. The thick line of the boxplot represents the median, while the edges of the box represent the interquartile range (25th and 75th percentiles). When the median and 25th or 75th percentiles are the same value, the corresponding box is not visible. The “whiskers” show the minimum and maximum values. The histograms show the frequency of responses at each value. Math and science histograms are in red; computer science and engineering histograms are in blue.

Fig. S4



Boxplot of Study 2 interest stereotypes by field. The thick line of the boxplot represents the median, while the edges of the box represent the interquartile range (25th and 75th percentiles). When the median and 25th or 75th percentiles are the same value, the corresponding box is not visible. The "whiskers" show the minimum and maximum values. The histograms show the frequency of responses at each value. Language arts histogram is in yellow; math and science histograms are in red; computer science and engineering histograms are in blue.

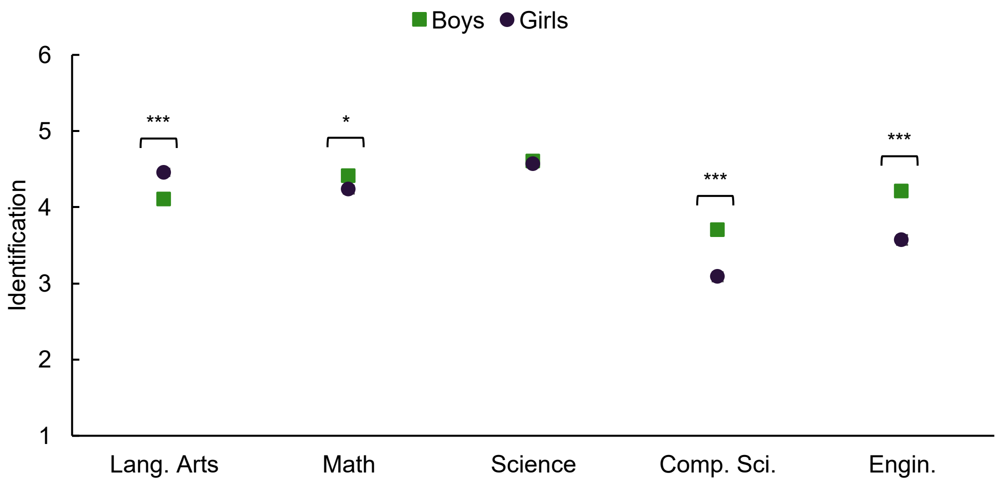
Fig. S5



Boxplot of Study 2 ability stereotypes by field. The thick line of the boxplot represents the median, while the edges of the box represent the interquartile range (25th and 75th percentiles). When the median and 25th or 75th percentiles are the same value, the corresponding box is not visible. The "whiskers" show the minimum and maximum values. The histograms show the frequency of responses at each value. Language arts histogram is in yellow; math and science histograms are in red; computer science and engineering histograms are in blue.

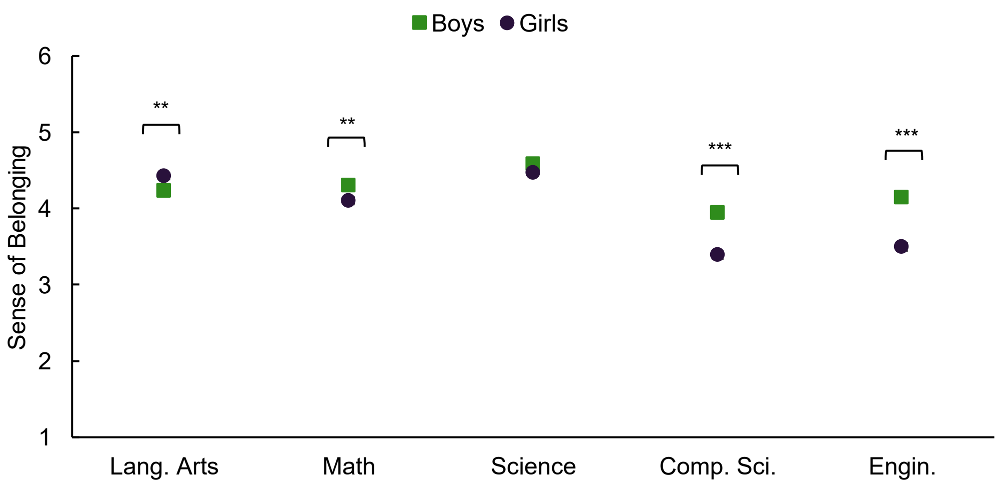
Fig. S6

A



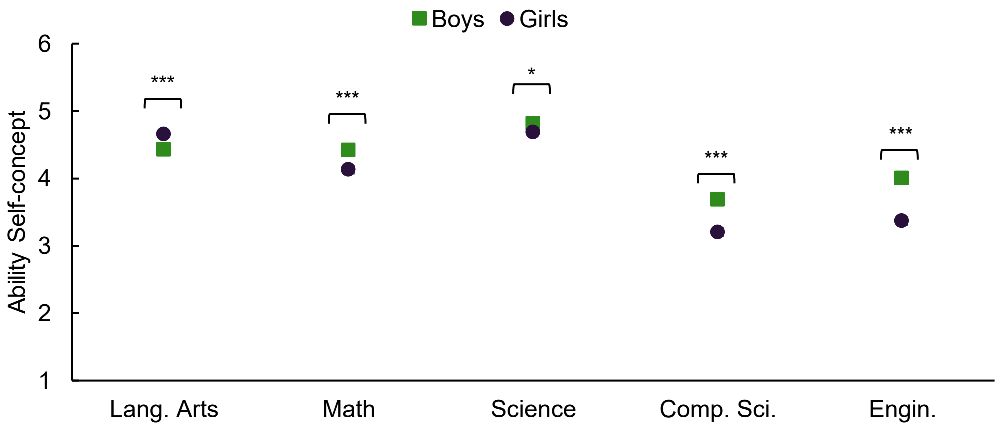
Boys
Girls
6
5
4
3
2
1
Identification
***
*
***
***
Lang. Arts
Math
Science
Comp. Sci.
Engin.

B



Boys
Girls
6
5
4
3
2
1
Sense of Belonging
**
**
***
***
Lang. Arts
Math
Science
Comp. Sci.
Engin.

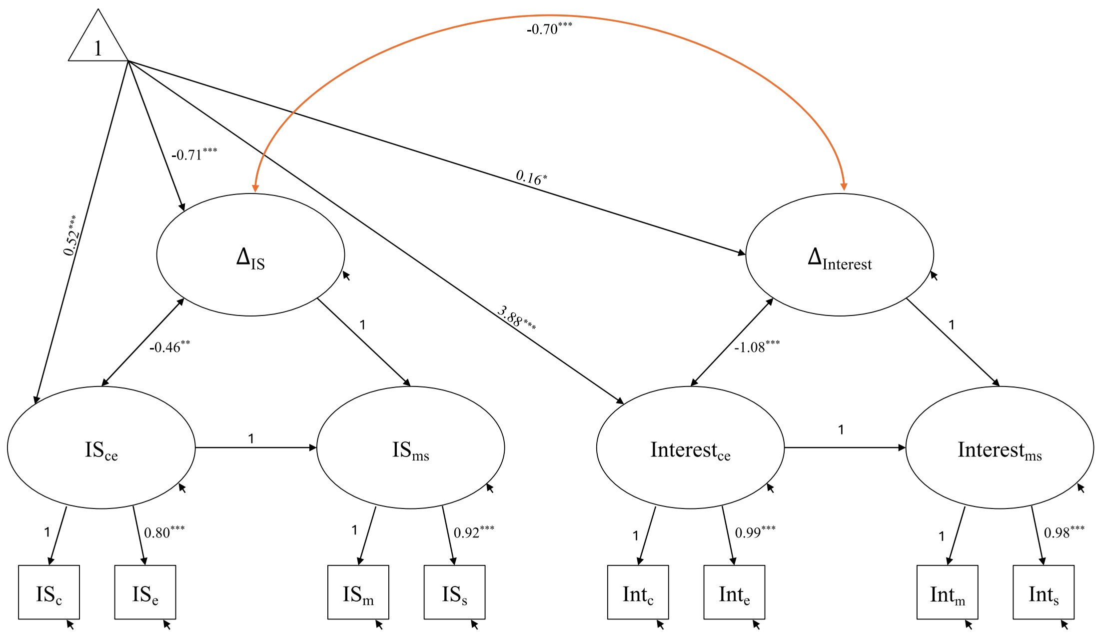
C



Other measures of motivation for Study 2. Study 2 identification (**A**), sense of belonging (**B**), and ability self-concepts (**C**) across fields. The range of identification is from 1 to 6. Higher values indicate greater likelihood of identifying oneself as a person in the field and lower values indicate lower likelihood of identifying oneself as a person in that field. The range of sense of belonging is from 1 to 6. Higher values indicate a greater sense of belonging in the field and lower values indicate a lower sense of belonging in that field. The range of ability self-concept is from 1 to 6. Higher values indicate more confidence in the field and lower values indicate less confidence in that field. Asterisks represent significant gender differences. The main effect of field was significant for all motivational measures. Comp. Sci. indicates computer science; Engin. indicates engineering; Lang. indicates language. Error bars represent 95% SE. *$P \leq 0.05$, **$P \leq 0.01$, ***$P \leq 0.001$.

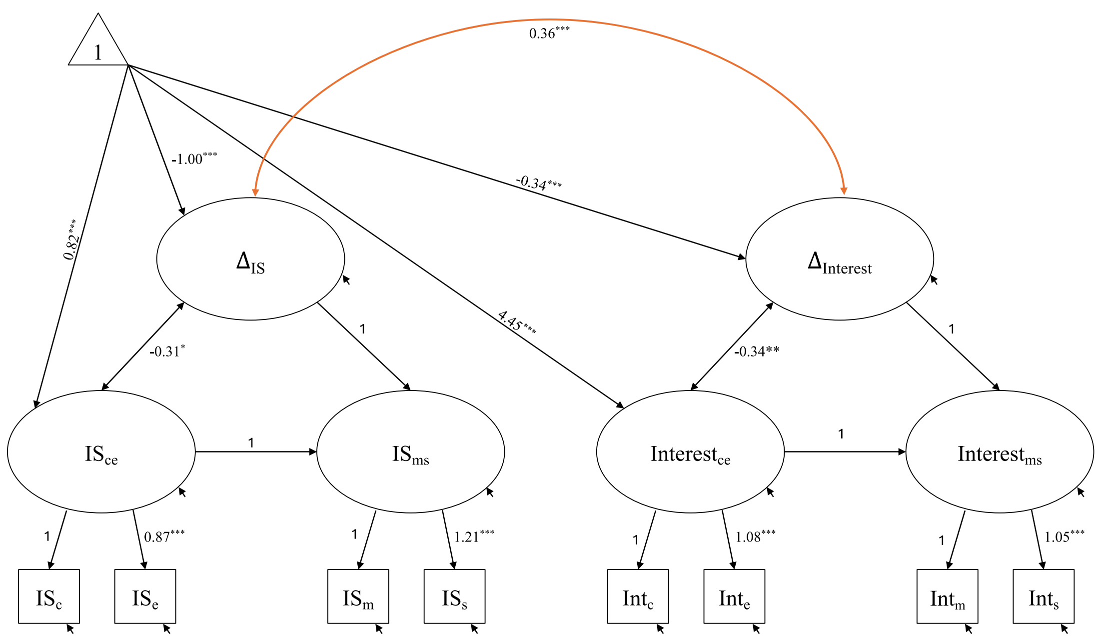
Fig. S7

A



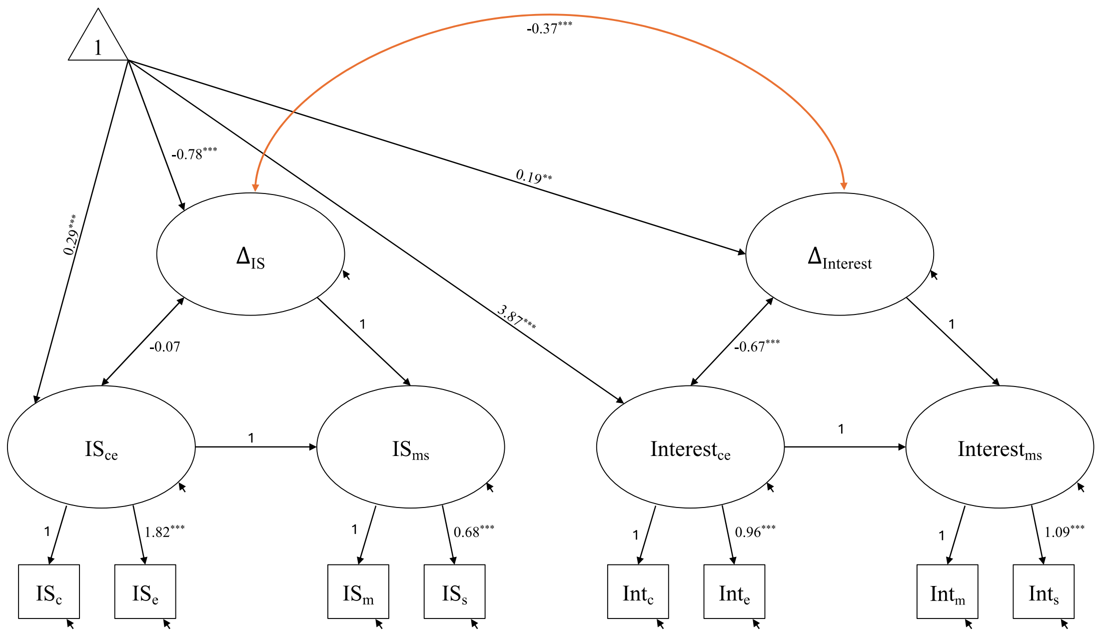
1
-0.70***
-0.71***
0.16*
0.52***
Δ_IS
Δ_Interest
3.88***
1
1
-0.46**
-1.08***
IS_ce
1
IS_ms
Interest_ce
1
Interest_ms
1
0.80***
1
0.92***
1
0.99***
1
0.98***
IS_c
IS_e
IS_m
IS_s
Int_c
Int_e
Int_m
Int_s

B

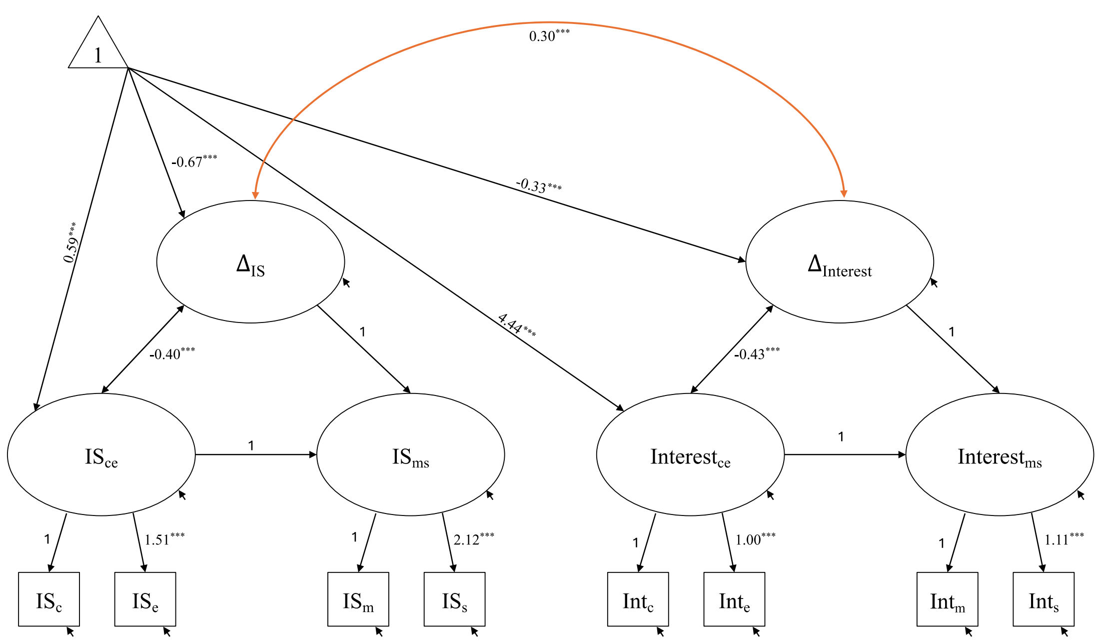


1
0.36***
-1.00***
-0.34***
0.82***
Δ_IS
Δ_Interest
4.45***
1
1
-0.31*
-0.34**
IS_ce
1
IS_ms
Interest_ce
1
Interest_ms
1
0.87***
1
1.21***
1
1.08***
1
1.05***
IS_c
IS_e
IS_m
IS_s
Int_c
Int_e
Int_m
Int_s

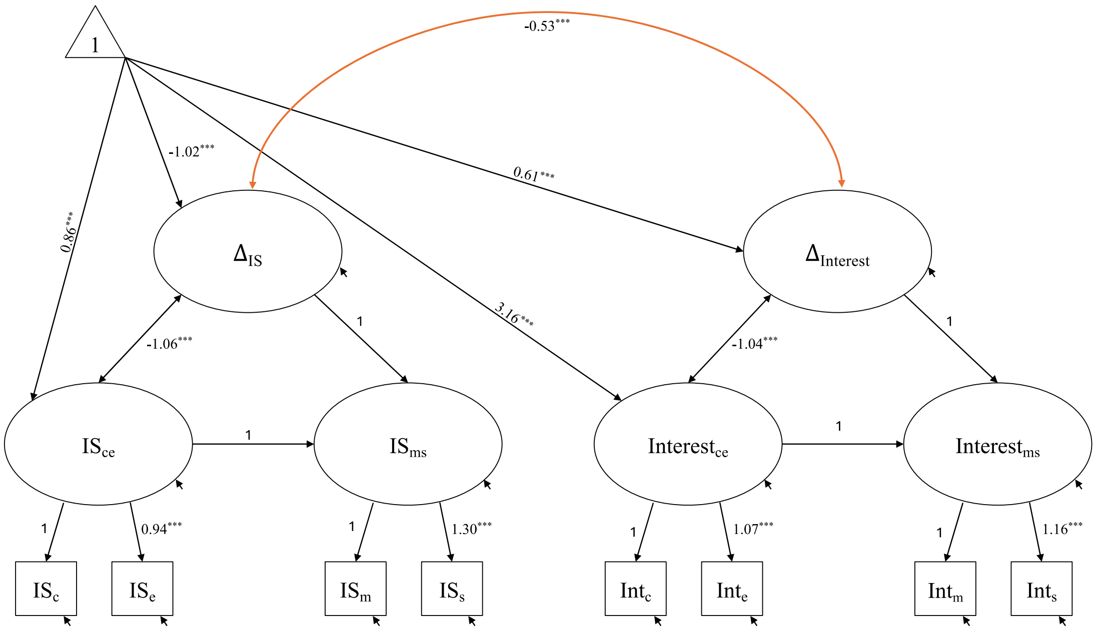
C


1
-0.37***
-0.78***
0.19**
0.29***
ΔIS
ΔInterest
3.87***
1
-0.07
-0.67***
1
ISce
1
ISms
Interestce
1
Interestms
1
1.82***
1
0.68***
1
0.96***
1
1.09***
ISc
ISe
ISm
ISs
Intc
Inte
Intm
Ints

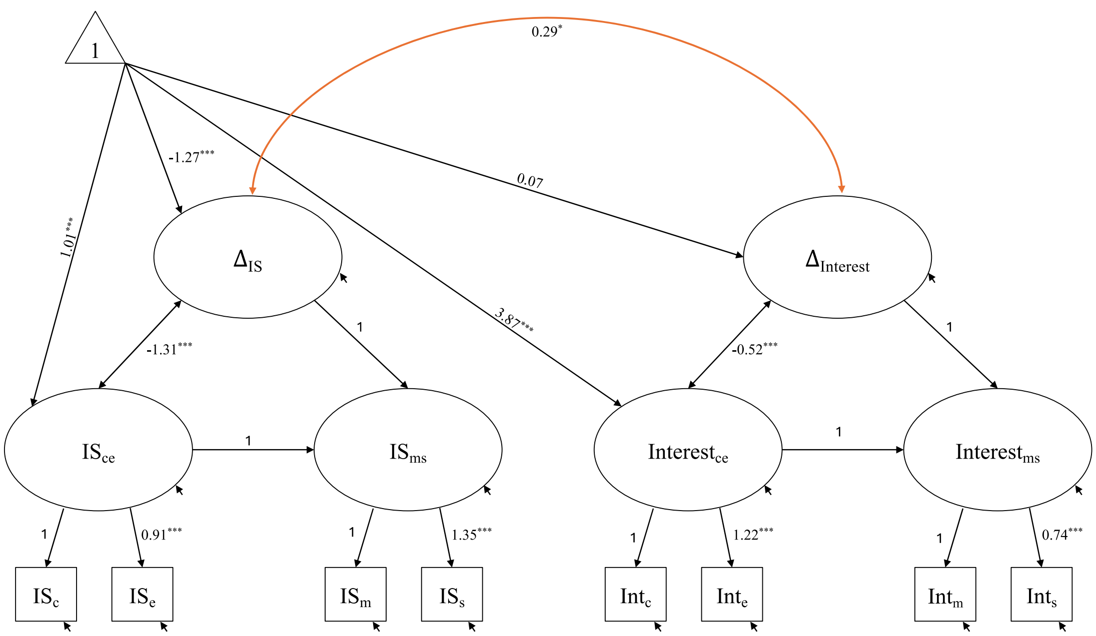
D


1
0.30***
-0.67***
-0.33***
0.59***
ΔIS
ΔInterest
4.44***
1
-0.40***
-0.43***
1
ISce
1
ISms
Interestce
1
Interestms
1
1.51***
1
2.12***
1
1.00***
1
1.11***
ISc
ISe
ISm
ISs
Intc
Inte
Intm
Ints

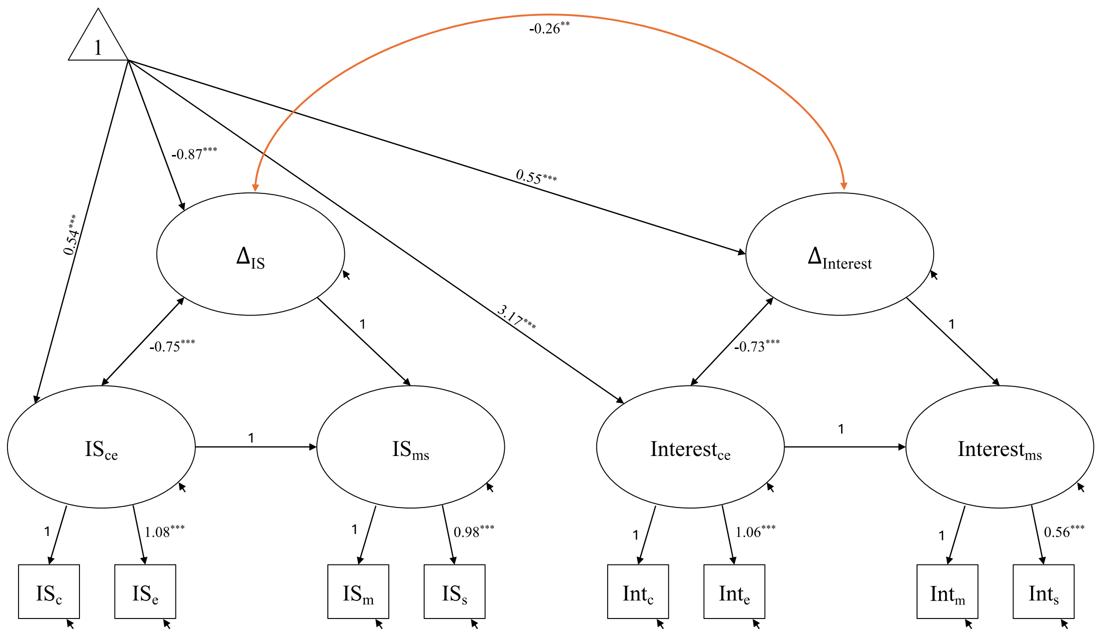
E


1
-0.53***
-1.02***
0.61***
0.86***
Δ_{IS}
$\Delta_{Interest}$
3.16***
1
-1.06***
-1.04***
1
IS_{ce}
1
IS_{ms}
$Interest_{ce}$
1
$Interest_{ms}$
1
0.94***
1
1.30***
1
1.07***
1
1.16***
IS_c
IS_e
IS_m
IS_s
Int_c
Int_e
Int_m
Int_s

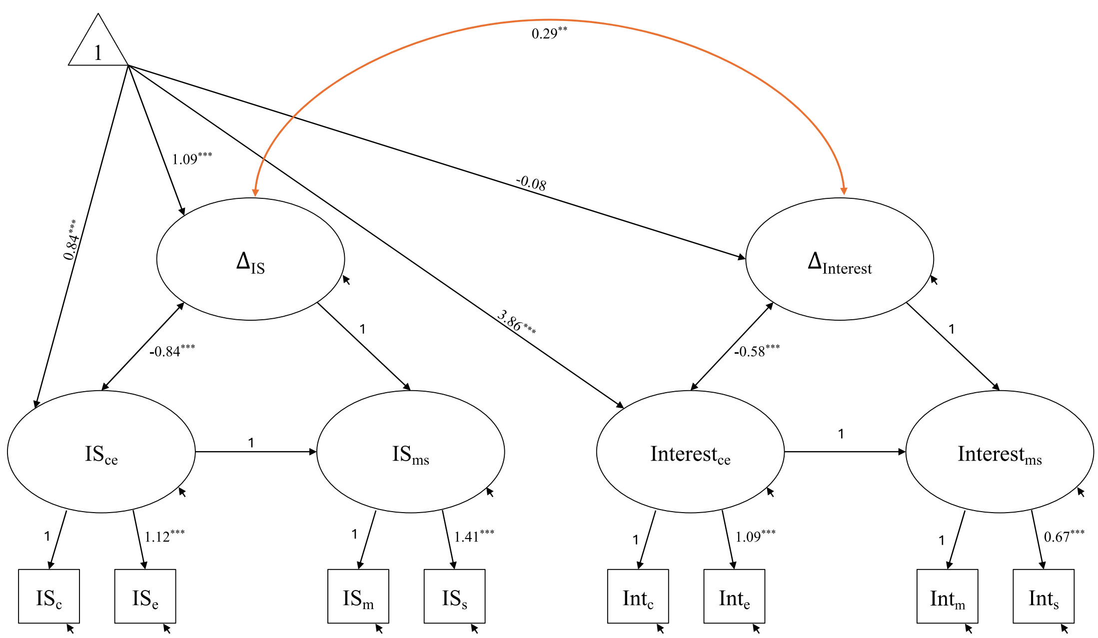
F


1
0.29*
-1.27***
0.07
1.01***
Δ_{IS}
$\Delta_{Interest}$
3.87***
1
-1.31***
-0.52***
1
IS_{ce}
1
IS_{ms}
$Interest_{ce}$
1
$Interest_{ms}$
1
0.91***
1
1.35***
1
1.22***
1
0.74***
IS_c
IS_e
IS_m
IS_s
Int_c
Int_e
Int_m
Int_s

G



H



Latent divergence score models for Study 1 interest stereotypes for girls (**A**) and boys (**B**), ability stereotypes for girls (**C**) and boys (**D**), and Study 2 interest stereotypes for girls (**E**) and boys (**F**), and ability stereotypes for girls (**G**) and boys (**H**). IS = interest stereotypes. AS = ability stereotypes. Int = personal interest. C = Computer Science. E = Engineering. M = Math. S = Science. ΔIS = latent divergence score for interest stereotypes between computer science/engineering and math/science. ΔAS = latent divergence score for ability stereotypes between computer science/engineering and math/science. ΔInterest = latent divergence score for personal interest between computer science/engineering and math/science. The correlation/covariance between the latent divergence scores is represented with the double-headed orange arrow from the stereotype latent divergence score to the personal interest latent divergence score. For ease of presentation, the residual variances, covariances of observed variables, and covariances of latent variables are not presented. Paths linked with the triangles present the constants of the latent variables. *$P \leq 0.05$, **$P \leq 0.01$, ***$P \leq 0.001$.

Table S1. Preregistered Hypotheses and Findings

Hypothesis	Prediction	Supported?
Study 1		
1	Correlations between ability stereotypes and interest will be significantly more negative for girls than for boys.	Yes
2A	Girls' ability stereotypes will be significantly stronger (i.e., more likely to report that boys are better than girls) for computer science/engineering than for math/science.	Yes
2B	Girls' ability stereotypes about computer science/engineering will be stronger than stereotypes about math/science by second grade.	Yes
3A	There will be a gender × field interaction on interest.	Yes
3B	For the interaction in Hypothesis #3A, in terms of simple effects, girls' interest will be significantly lower for computer science/engineering than for math/science. (The difference between boys' interest in the two sets of fields will be smaller or in the opposite direction than the difference for girls' interest.)	Yes
3C	For the interaction in Hypothesis #3A, in terms of simple effects, gender differences in math/science will be smaller than gender differences in computer science/engineering.	Yes
Study 2		
1	Stereotypes favoring boys are linked to lower motivation for girls, but not boys.	Yes
1A	In general, girls' stereotypes will be *negatively* correlated with their motivation, while boys' stereotypes will be *positively* correlated with their motivation. For girls, we expect to have adequate power to find significant correlations between interest stereotypes and interest in math, science, computer science, engineering; interest stereotypes and sense of belonging in math, science, computer science; interest stereotypes and ability self-concept in math, science, and computer science; ability stereotypes and interest in engineering; and ability stereotypes and ability self-concept in computer science. For boys, we expect to have adequate power to find significant correlations between interest stereotypes and interest in math; interest stereotypes and ability self-concept in math; ability stereotypes and interest in math; and ability stereotypes and ability self-concept in math.	Yes
1B	In general, correlations between stereotypes and motivation (identification, sense of belonging, ability self-concept, and interest) will be *more negative for girls* than for boys in five fields (math/science/computer science/engineering/ language arts). We expect to have adequate power to find significant differences between girls' and boys' correlations for interest stereotypes and interest in math, science, computer science; interest stereotypes and sense of belonging in math, computer science; interest stereotypes and ability self-concept in math, science, computer science; ability stereotypes and interest in math; and ability stereotypes and ability self-concept in math, science, computer science.	Yes
2	Students' interest stereotypes will significantly differ across five fields (math/science/computer science/engineering, and language arts).	Yes

2A	Students' interest stereotypes about computer science/engineering will be significantly higher (i.e., more likely to report boys are more interested than girls) than math/science.	Yes
2B	Students' interest stereotypes about language arts will be significantly lower (i.e., more likely to report that girls are more interested than boys) than math/science.	Yes
2C	Students' interest stereotypes about language arts will be significantly lower (i.e., more likely to report that girls are more interested than boys) than computer science/engineering.	Yes
3A	There will be a gender × field interaction for each motivational variable (identification, sense of belonging, ability self-concept, and interest).	Yes
3B	For the interaction in Hypothesis #3A, in terms of simple effects for girls**,** motivation will be significantly higher for language arts than for math/science.	Mixed
3C	For the interaction in Hypothesis #3A, in terms of simple effects for girls, motivation will be significantly higher for language arts than for computer science/engineering.	Yes
3D	For the interaction in Hypothesis #3A, in terms of simple effects for girls, motivation (identification, ability self-concept, and interest, but not sense of belonging) will be significantly higher for math/science than computer science/engineering.	Yes
3E	The differences in boys' motivation in the STEM fields will be smaller or in the opposite direction than the differences for girls' motivation (with boys' motivation higher for STEM fields than for language arts).	Yes
3F	For the interaction in Hypothesis #3A, in terms of simple effects, gender differences in math/science motivation will be smaller than gender differences in computer science/engineering (boys will be highest).	Yes
3G	For the interaction in Hypothesis #3A, in terms of simple effects, gender differences in math/science motivation will be smaller than gender differences in language arts (girls will be highest).	Yes

Note: For Hypothesis 3B, the mixed results showed no difference for interest and identification (No), but a significant difference for sense of belonging and ability self-concept (Yes).

Table S2. Stereotypes by Field

Group	*N*	Math *M* (*SD*)	Science *M* (*SD*)	Computer Science *M* (*SD*)	Engineering *M* (*SD*)	Language Arts *M* (*SD*)	Math/science vs. CS/ENG η_p^2
Study 1 – Interest Stereotypes							
All	1484	**-0.18 (1.62)**	-0.01 (1.38)	**0.67 (1.52)**	**1.13 (1.54)**		**0.32**
Girls	741	-0.18 (1.55)**	**-0.17 (1.35)**	**0.52 (1.53)**	**1.04 (1.56)**		**0.31**
Boys	742	-0.17 (1.70)**	**0.16 (1.39)**	**0.82 (1.50)**	**1.22 (1.52)**		**0.33**
White	549	**-0.27 (1.62)**	0.00 (1.31)	**0.70 (1.54)**	**1.10 (1.50)**		**0.35**
Girls	268	-0.18 (1.43)*	-0.15 (1.23)*	**0.51 (1.53)**	**0.95 (1.44)**		**0.32**
Boys	281	**-0.36 (1.77)**	0.14 (1.37)	**0.88 (1.52)**	**1.24 (1.54)**		**0.38**
Hisp/Latine	354	-0.11 (1.57)	-0.09 (1.30)	**0.63 (1.34)**	**1.17 (1.47)**		**0.32**
Girls	189	-0.10 (1.58)	-0.27 (1.34)**	**0.56 (1.27)**	**1.16 (1.52)**		**0.32**
Boys	165	-0.12 (1.56)	0.12 (1.22)	**0.72 (1.41)**	**1.18 (1.41)**		**0.33**
Asian	145	0.05 (1.36)	0.09 (1.33)	**0.77 (1.26)**	**1.16 (1.44)**		**0.33**
Girls	66	-0.11 (1.27)	0.00 (1.31)	**0.74 (1.29)**	**1.03 (1.16)**		**0.30**
Boys	79	0.18 (1.42)	0.16 (1.35)	**0.80 (1.24)**	**1.27 (1.64)**		**0.35**
Black	120	0.01 (1.76)	0.21 (1.36)	**0.90 (1.81)**	**1.31 (1.78)**		**0.28**
Girls	52	-0.02 (1.46)	0.15 (1.09)	0.60 (1.82)*	**1.15 (1.93)**		**0.26**
Boys	68	0.03 (1.97)	0.26 (1.54)	**1.13 (1.78)**	**1.43 (1.65)**		**0.32**
Multiracial	220	-0.25 (1.56)*	-0.09 (1.50)	**0.59 (1.55)**	**1.05 (1.63)**		**0.32**
Girls	115	-0.25 (1.67)	-0.25 (1.44)	0.45 (1.63)**	**0.93 (1.76)**		**0.32**
Boys	105	-0.25 (1.44)	0.09 (1.56)	**0.74 (1.46)**	**1.18 (1.47)**		**0.33**
Elementary	460	-0.20 (1.94)*	0.05 (1.71)	0.22 (1.77)**	**1.23 (1.89)**		**0.18**
Girls	227	**-0.40 (1.81)**	-0.27 (1.73)*	-0.11 (1.82)	**1.03 (1.96)**		**0.18**
Boys	231	0.00 (2.06)	**0.39 (1.63)**	**0.56 (1.64)**	**1.43 (1.80)**		**0.19**
Middle Sch.	485	**-0.28 (1.43)**	-0.08 (1.19)	**0.79 (1.34)**	**1.03 (1.34)**		**0.39**
Girls	250	-0.10 (1.36)	-0.18 (1.10)**	**0.64 (1.17)**	**0.92 (1.32)**		**0.35**
Boys	235	**-0.48 (1.49)**	0.02 (1.28)	**0.94 (1.50)**	**1.14 (1.36)**		**0.42**
High School	538	-0.07 (1.47)	0.02 (1.20)	**0.95 (1.35)**	**1.13 (1.36)**		**0.42**
Girls	262	-0.07 (1.45)	-0.07 (1.16)	**0.98 (1.33)**	**1.16 (1.34)**		**0.44**
Boys	276	-0.08 (1.49)	0.10 (1.23)	**0.93 (1.36)**	**1.11 (1.37)**		**0.41**
Study 2 – Interest Stereotypes							
All	1254	**-0.18 (1.51)**	**-0.14 (1.31)**	**0.93 (1.63)**	**0.93 (1.57)**	**-0.96 (1.42)**	**0.35**
Girls	663	-0.10 (1.47)	**-0.25 (1.33)**	**0.85 (1.58)**	**0.83 (1.50)**	**-0.95 (1.38)**	**0.33**
Boys	591	**-0.26 (1.54)**	-0.03 (1.28)	**1.02 (1.68)**	**1.04 (1.63)**	**-0.98 (1.47)**	**0.37**
White	426	-0.07 (1.52)	-0.10 (1.34)	**0.93 (1.66)**	**0.87 (1.56)**	**-0.93 (1.53)**	**0.30**
Girls	229	0.07 (1.41)	-0.22 (1.37)*	**0.74 (1.62)**	**0.72 (1.56)**	**-0.90 (1.45)**	**0.25**
Boys	197	-0.23 (1.63)*	0.04 (1.28)	**1.14 (1.67)**	**1.06 (1.55)**	**-0.97 (1.62)**	**0.35**
Hisp/Latine	375	-0.19 (1.48)*	-0.16 (1.21)**	**0.98 (1.60)**	**0.94 (1.47)**	**-0.88 (1.28)**	**0.38**
Girls	186	-0.04 (1.47)	-0.14 (1.14)	**0.92 (1.52)**	**0.84 (1.34)**	**-0.76 (1.24)**	**0.35**
Boys	189	-0.33 (1.48)**	-0.19 (1.27)*	**1.03 (1.68)**	**1.03 (1.59)**	**-0.99 (1.31)**	**0.40**
Asian	78	-0.10 (1.77)	-0.35 (1.54)	**0.71 (1.61)**	**0.81(1.56)**	**-1.21 (1.46)**	**0.34**
Girls	42	-0.21 (1.65)	-0.55 (1.55)*	0.74 (1.47)**	**0.81 (1.53)**	**-1.02 (1.54)**	**0.42**
Boys	36	0.03 (1.92)	-0.11 (1.53)	0.67 (1.79)*	0.81 (1.62)**	**-1.42 (1.36)**	**0.26**
Black	171	-0.23 (1.54)	-0.10 (1.48)	**0.91 (1.85)**	**1.18 (1.72)**	**-1.09 (1.60)**	**0.34**
Girls	94	-0.29 (1.47)	-0.34 (1.47)*	**0.87 (1.86)**	**0.98 (1.58)**	**-1.38 (1.35)**	**0.33**
Boys	77	-0.16 (1.62)	0.19 (1.44)	**0.95 (1.84)**	**1.42 (1.87)**	**-0.74 (1.79)**	**0.38**
Multiracial	185	**-0.34 (1.40)**	-0.12 (1.22)	**0.96 (1.42)**	**0.90 (1.59)**	**-0.95 (1.29)**	**0.40**
Girls	107	-0.30 (1.49)*	-0.27 (1.38)*	**1.01 (1.35)**	**0.92 (1.55)**	**-0.95 (1.38)**	**0.45**
Boys	78	-0.40 (1.26)**	0.09 (0.93)	**0.90 (1.52)**	**0.87 (1.65)**	**-0.94 (1.18)**	**0.37**
Middle Sch.	524	**-0.31 (1.55)**	-0.13 (1.32)*	**0.88 (1.72)**	**0.87 (1.67)**	**-0.90 (1.42)**	**0.32**
Girls	281	-0.23 (1.44)**	-0.23 (1.29)**	**0.79 (1.60)**	**0.75 (1.57)**	**-0.83 (1.32)**	**0.29**
Boys	243	**-0.41 (1.67)**	-0.02 (1.35)	**0.98 (1.85)**	**1.00 (1.89)**	**-0.97 (1.52)**	**0.33**
High School	729	-0.08 (1.47)	-0.15 (1.31)**	**0.97 (1.56)**	**0.97 (1.49)**	**-1.01 (1.43)**	**0.38**

Girls	381	-0.01 (1.49)	**-0.26 (1.37)**	**0.90 (1.57)**	**0.88 (1.45)**	**-1.04 (1.42)**	**0.36**
Boys	348	-0.16 (1.45)*	-0.03 (1.23)	**1.05 (1.56)**	**1.07 (1.52)**	**-0.98 (1.44)**	**0.40**
Study 1 – Ability Stereotypes							
All	1489	**-0.32 (1.42)**	**-0.21 (1.33)**	**0.41 (1.44)**	**0.71 (1.49)**		**0.27**
Girls	743	**-0.47 (1.33)**	**-0.40 (1.22)**	**0.18 (1.38)**	**0.54 (1.49)**		**0.27**
Boys	745	**-0.17 (1.48)**	-0.01 (1.40)	**0.63 (1.46)**	**0.89 (1.48)**		**0.27**
White	550	**-0.35 (1.35)**	-0.17 (1.28)**	**0.44 (1.41)**	**0.70 (1.42)**		**0.27**
Girls	268	**-0.39 (1.16)**	**-0.38 (1.12)**	0.19 (1.26)*	**0.49 (1.32)**		**0.23**
Boys	283	**-0.32 (1.50)**	0.03 (1.39)	**0.67 (1.51)**	**0.90 (1.48)**		**0.32**
Hisp/Latine	356	**-0.33 (1.38)**	**-0.29 (1.19)**	**0.40 (1.42)**	**0.66 (1.45)**		**0.30**
Girls	191	**-0.53 (1.30)**	**-0.46 (1.13)**	0.25 (1.36)*	**0.58 (1.42)**		**0.38**
Boys	164	-0.10 (1.43)	-0.10 (1.23)	**0.58 (1.48)**	**0.75 (1.48)**		**0.23**
Asian	144	-0.17 (1.40)	-0.20 (1.21)*	**0.60 (1.38)**	**0.88 (1.39)**		**0.31**
Girls	66	-0.35 (1.39)*	-0.21 (1.13)	0.41 (1.15)**	**0.70 (1.34)**		**0.26**
Boys	78	-0.03 (1.40)	-0.19 (1.28)	**0.76 (1.54)**	**1.04 (1.42)**		**0.35**
Black	122	-0.16 (1.55)	-0.07 (1.47)	**0.50 (1.45)**	**0.83 (1.61)**		**0.24**
Girls	52	-0.23 (1.63)	-0.19 (1.47)	0.44 (1.50)*	**0.96 (1.77)**		**0.26**
Boys	70	-0.10 (1.50)	0.03 (1.47)	0.54 (1.42)**	**0.73 (1.48)**		**0.21**
Multiracial	220	**-0.40 (1.39)**	**-0.34 (1.39)**	0.26 (1.35)**	**0.61 (1.50)**		**0.27**
Girls	115	**-0.57 (1.40)**	**-0.56 (1.33)**	0.02 (1.43)	0.39 (1.65)*		**0.27**
Boys	105	-0.22 (1.36)	-0.11 (1.42)	**0.52 (1.21)**	**0.86 (1.28)**		**0.26**
Elementary	460	-0.18 (1.71)*	-0.02 (1.72)	**0.30 (1.73)**	**0.97 (1.87)**		**0.18**
Girls	226	**-0.59 (1.60)**	**-0.44 (1.54)**	-0.19 (1.66)	**0.60 (1.90)**		**0.18**
Boys	228	0.20 (1.72)	**0.42 (1.77)**	**0.79 (1.68)**	**1.32 (1.74)**		**0.19**
Middle Sch.	490	**-0.42 (1.20)**	**-0.27 (1.12)**	**0.42 (1.19)**	**0.64 (1.26)**		**0.36**
Girls	252	**-0.41 (1.11)**	**-0.31 (1.06)**	0.21 (1.05)**	**0.50 (1.18)**		**0.33**
Boys	238	**-0.43 (1.29)**	-0.23 (1.17)**	**0.65 (1.28)**	**0.79 (1.32)**		**0.38**
High School	538	**-0.35 (1.31)**	**-0.31 (1.08)**	**0.48 (1.36)**	**0.57 (1.29)**		**0.30**
Girls	262	**-0.43 (1.28)**	**-0.44 (0.99)**	**0.48 (1.32)**	**0.53 (1.31)**		**0.33**
Boys	276	**-0.29 (1.34)**	-0.18 (1.14)**	**0.49 (1.41)**	**0.61 (1.27)**		**0.26**
Study 2 – Ability Stereotypes							
All	1249	**-0.35 (1.33)**	**-0.26 (1.14)**	**0.62 (1.47)**	**0.68 (1.46)**	**-0.81 (1.34)**	**0.33**
Girls	660	**-0.41 (1.29)**	**-0.39 (1.13)**	**0.44 (1.45)**	**0.49 (1.43)**	**-0.84 (1.27)**	**0.30**
Boys	589	**-0.29 (1.37)**	-0.12 (1.14)*	**0.81 (1.47)**	**0.88 (1.46)**	**-0.78 (1.41)**	**0.35**
White	423	**-0.33 (1.30)**	**-0.26 (1.11)**	**0.65 (1.46)**	**0.61 (1.46)**	**-0.81 (1.35)**	**0.32**
Girls	227	**-0.34 (1.34)**	**-0.39 (1.19)**	**0.41 (1.46)**	**0.43 (1.53)**	**-0.78 (1.34)**	**0.25**
Boys	196	**-0.31 (1.26)**	-0.12 (0.99)	**0.92 (1.43)**	**0.83 (1.34)**	**-0.86 (1.37)**	**0.39**
Hisp/Latine	374	**-0.32 (1.27)**	**-0.26 (1.11)**	**0.66 (1.51)**	**0.71 (1.37)**	**-0.74 (1.27)**	**0.33**
Girls	186	**-0.34 (1.20)**	**-0.35 (1.05)**	**0.45 (1.45)**	**0.47 (1.27)**	**-0.73 (1.21)**	**0.30**
Boys	188	-0.30 (1.35)**	-0.16 (1.16)	**0.88 (1.53)**	**0.96 (1.42)**	**-0.74 (1.32)**	**0.36**
Asian	78	-0.32 (1.57)	-0.32 (1.42)*	0.41 (1.67)*	0.54 (1.73)**	**-0.96 (1.43)**	**0.28**
Girls	42	-0.52 (1.49)*	-0.50 (1.38)*	0.17 (1.71)	0.29 (1.64)	**-0.88 (1.35)**	**0.26**
Boys	36	-0.08 (1.66)	-0.11 (1.45)	0.69 (1.60)*	0.83 (1.81)**	**-1.06 (1.53)**	**0.31**
Black	172	-0.30 (1.51)**	-0.22 (1.39)*	**0.70 (1.54)**	**0.92 (1.60)**	**-0.84 (1.53)**	**0.34**
Girls	95	**-0.52 (1.36)**	-0.40 (1.29)**	**0.53 (1.44)**	**0.67 (1.46)**	**-1.08 (1.32)**	**0.40**
Boys	77	-0.04 (1.64)	0.01 (1.48)	**0.92 (1.63)**	**1.23 (1.71)**	-0.55 (1.72)**	**0.29**
Multiracial	183	**-0.49 (1.20)**	**-0.23 (0.89)**	**0.47 (1.28)**	**0.60 (1.37)**	**-0.84 (1.22)**	**0.34**
Girls	105	**-0.51 (1.20)**	**-0.36 (0.89)**	**0.53 (1.36)**	**0.56 (1.39)**	**-0.91 (1.12)**	**0.37**
Boys	78	**-0.46 (1.20)**	-0.05 (0.87)	0.38 (1.18)**	**0.65 (1.36)**	**-0.74 (1.34)**	**0.34**
Middle Sch.	523	**-0.39 (1.32)**	**-0.24 (1.12)**	**0.60 (1.47)**	**0.73 (1.49)**	**-0.80 (1.32)**	**0.33**
Girls	282	**-0.36 (1.30)**	**-0.32 (1.09)**	**0.44 (1.34)**	**0.55 (1.41)**	**-0.83 (1.25)**	**0.29**
Boys	241	**-0.44 (1.34)**	-0.15 (1.15)*	**0.80 (1.59)**	**0.93 (1.56)**	**-0.77 (1.40)**	**0.37**
High School	725	**-0.32 (1.34)**	**-0.27 (1.16)**	**0.63 (1.48)**	**0.64 (1.43)**	**-0.82 (1.35)**	**0.33**
Girls	348	**-0.45 (1.28)**	**-0.45 (1.16)**	**0.45 (1.54)**	**0.44 (1.45)**	**-0.85 (1.28)**	**0.32**

Boys	377	-0.18 (1.39)*	-0.09 (1.13)	**0.82 (1.39)**	**0.85 (1.38)**	**-0.78 (1.41)**	**0.33**

Note: Stereotypes are difference scores for ratings about boys minus ratings about girls. Positive values indicate stereotypes favoring boys, and negative values indicate stereotypes favoring girls. Significance represents difference from neutral/egalitarian stereotypes. The strongest gender stereotypes were among computer science and engineering (favoring boys) and language arts (favoring girls). Effect sizes represent the contrast between math/science vs. computer science/engineering stereotypes. CS = Computer Science. ENG = Engineering. Hisp = Hispanic. Sch. = School. $P \leq 0.001$ is indicated **in bold**, $^{**}P \leq 0.01$, $^{*}P < 0.05$.

Table S3. Motivation as Personal Interest by Field, Participant Gender, Race/Ethnicity, and School Level

Group	*N*	Math *M* (*SD*)	Science *M* (*SD*)	Computer Science *M* (*SD*)	Engineering *M* (*SD*)	Language Arts *M* (*SD*)	Math/science vs. CS/ENG η_p^2
Study 1							
All	1492	4.07 (1.60)	4.50 (1.37)	4.17 (1.57)	4.07 (1.54)		**.02**
Girls	743	4.04 (1.62)	4.42 (1.43)	3.88 (1.63)	3.71 (1.57)		**.10**
Boys	749	4.11 (1.58)	4.58 (1.31)	4.45 (1.46)	4.42 (1.42)		.005*
White	554	3.98 (1.60)	4.54 (1.35)	4.12 (1.58)	4.07 (1.58)		.01**
Girls	269	4.01 (1.58)	4.52 (1.52)	3.85 (1.65)	3.77 (1.66)		**.10**
Boys	285	3.95 (1.61)	4.56 (1.29)	4.37 (1.46)	4.36 (1.44)		.007
Hisp/Latine	355	4.06 (1.62)	4.45 (1.45)	4.04 (1.61)	4.03 (1.56)		**.03**
Girls	190	3.84 (1.66)	4.19 (1.51)	3.73 (1.63)	3.53 (1.52)		**.09**
Boys	165	4.32 (1.54)	4.74 (1.34)	4.38 (1.53)	4.62 (1.39)		.001
Asian	145	4.38 (1.33)	4.52 (1.29)	4.50 (1.35)	4.18 (1.37)		.01
Girls	66	4.27 (1.28)	4.43 (1.20)	4.12 (1.37)	3.77 (1.28)		.11**
Boys	79	4.47 (1.38)	4.59 (1.37)	4.81 (1.26)	4.52 (1.36)		.02
Black	122	4.17 (1.49)	4.50 (1.30)	4.28 (1.61)	4.12 (1.43)		.01
Girls	52	4.25 (1.41)	4.55 (1.39)	3.89 (1.70)	3.83 (1.52)		.16**
Boys	70	4.11 (1.56)	4.47 (1.25)	4.57 (1.49)	4.34 (1.33)		.02
Multiracial	221	3.84 (1.71)	4.35 (1.36)	3.84 (1.53)	3.89 (1.51)		.02*
Girls	115	3.76 (1.82)	4.31 (1.48)	3.59 (1.62)	3.57 (1.56)		**.09**
Boys	106	3.92 (1.58)	4.39 (1.22)	4.11 (1.38)	4.23 (1.38)		.00
Elementary	462	4.66 (1.54)	4.79 (1.33)	4.94 (1.30)	4.30 (1.62)		.007
Girls	229	4.66 (1.57)	4.81 (1.34)	4.87 (1.38)	4.11 (1.69)		.04**
Boys	233	4.66 (1.52)	4.77 (1.33)	5.02 (1.22)	4.49 (1.52)		.001
Middle Sch.	491	3.70 (1.60)	4.52 (1.28)	4.08 (1.59)	4.17 (1.51)		.00
Girls	252	3.77 (1.57)	4.41 (1.36)	3.71 (1.54)	3.77 (1.50)		**.07**
Boys	239	3.62 (1.62)	4.63 (1.20)	4.48 (1.54)	4.60 (1.40)		**.08**
High School	539	3.91 (1.50)	4.23 (1.43)	3.58 (1.50)	3.77 (1.45)		**.09**
Girls	262	3.75 (1.56)	4.08 (1.50)	3.18 (1.50)	3.30 (1.44)		**.21**
Boys	277	4.06 (1.43)	4.38 (1.35)	3.95 (1.40)	4.21 (1.32)		.02*
Study 2							
All	1247	3.81 (1.63)	4.49 (1.33)	3.48 (1.66)	3.74 (1.63)	3.87 (1.43)	**.11**
Girls	660	3.71 (1.66)	4.44 (1.35)	3.14 (1.58)	3.33 (1.60)	4.05 (1.38)	**.25**
Boys	587	3.91 (1.58)	4.54 (1.31)	3.87 (1.67)	4.20 (1.55)	3.66 (1.46)	.02**
White	424	3.78 (1.64)	4.57 (1.29)	3.60 (1.66)	3.89 (1.62)	3.77 (1.44)	**.08**
Girls	228	3.64 (1.71)	4.52 (1.31)	3.25 (1.61)	3.50 (1.63)	3.95 (1.45)	**.19**
Boys	196	3.94 (1.55)	4.63 (1.26)	3.99 (1.64)	4.34 (1.48)	3.57 (1.41)	.007
Hisp/Latine	372	3.73 (1.64)	4.35 (1.35)	3.40 (1.63)	3.64 (1.59)	3.88 (1.40)	**.11**
Girls	187	3.70 (1.67)	4.36 (1.35)	3.04 (1.49)	3.19 (1.51)	4.15 (1.33)	**.32**
Boys	185	3.77 (1.62)	4.35 (1.35)	3.77 (1.67)	4.09 (1.55)	3.60 (1.43)	.007
Asian	78	4.23 (1.44)	4.80 (1.12)	3.67 (1.55)	4.06 (1.58)	3.74 (1.38)	**.20**
Girls	42	4.11 (1.58)	4.70 (1.18)	3.39 (1.57)	3.58 (1.46)	3.90 (1.30)	**.45**
Boys	36	4.37 (1.26)	4.92 (1.05)	3.99 (1.48)	4.63 (1.54)	3.54 (1.46)	.05
Black	168	3.82 (1.51)	4.49 (1.38)	3.28 (1.76)	3.54 (1.65)	4.01 (1.49)	**.17**
Girls	92	3.76 (1.45)	4.48 (1.40)	2.96 (1.63)	3.24 (1.60)	4.15 (1.41)	**.31**
Boys	76	3.88 (1.58)	4.49 (1.37)	3.66 (1.84)	3.90 (1.65)	3.85 (1.57)	.06*
Multiracial	186	3.76 (1.72)	4.44 (1.38)	3.46 (1.68)	3.65 (1.73)	3.93 (1.43)	**.11**
Girls	106	3.64 (1.76)	4.25 (1.44)	3.10 (1.65)	3.19 (1.71)	4.03 (1.34)	**.19**
Boys	80	3.93 (1.66)	4.69 (1.26)	3.93 (1.61)	4.26 (1.57)	3.81 (1.55)	.02
Middle Sch.	520	4.14 (1.57)	4.62 (1.30)	3.86 (1.66)	4.10 (1.61)	3.98 (1.47)	**.06**
Girls	280	4.03 (1.61)	4.53 (1.32)	3.55 (1.60)	3.79 (1.62)	4.06 (1.40)	**.13**
Boys	240	4.26 (1.52)	4.73 (1.28)	4.21 (1.66)	4.46 (1.52)	3.87 (1.55)	.01
High School	726	3.57 (1.62)	4.39 (1.25)	3.22 (1.61)	3.48 (1.60)	3.79 (1.40)	**.16**
Girls	379	3.48 (1.66)	4.37 (1.37)	2.85 (1.50)	2.99 (1.50)	4.04 (1.37)	**.36**

Boys	347	3.67 (1.58)	4.40 (1.32)	3.63 (1.63)	4.02 (1.55)	3.51 (1.38)	.02**

Note: The range of personal interest is from 1 (*really not interested*) to 6 (*really interested*). Effect sizes represent the contrast between math/science vs. computer science/engineering. Across both studies, divergent patterns of motivation (personal interest) were strongest for girls, white and Hispanic/Latine students, and high school students. CS = Computer Science. ENG = Engineering. Hisp = Hispanic. Sch. = School. $P \leq 0.001$ is indicated **in bold**, $^{**}P \leq 0.01$, $^{*}P < 0.05$.

Table S4. Study 2 Ability Self-Concepts by Field, Participant Gender, Race/Ethnicity, and School Level

Group	*N*	Math	Science	Computer Science	Engineering	Language Arts	Math/science vs. CS/ENG
		M (*SD*)	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)	η_p^2
All	1239	4.26 (1.40)	4.75 (1.04)	3.43 (1.49)	3.67 (1.48)	4.55 (1.13)	**.33**
Girls	652	4.13 (1.43)	4.69 (1.07)	3.20 (1.45)	3.37 (1.46)	4.66 (1.10)	**.40**
Boys	587	4.42 (1.34)	4.81 (0.99)	3.68 (1.50)	4.00 (1.42)	4.43 (1.14)	**.25**
White	423	4.31 (1.42)	4.87 (1.01)	3.58 (1.47)	3.87 (1.46)	4.60 (1.14)	**.29**
Girls	225	4.18 (1.53)	4.79 (1.08)	3.37 (1.50)	3.57 (1.52)	4.70 (1.22)	**.34**
Boys	198	4.45 (1.27)	4.96 (0.92)	3.82 (1.41)	4.20 (1.32)	4.49 (1.03)	**.23**
Hisp/Latine	372	4.13 (1.43)	4.54 (1.09)	3.27 (1.44)	3.52 (1.40)	4.40 (1.12)	**.34**
Girls	187	4.01 (1.40)	4.52 (1.12)	3.13 (1.38)	3.28 (1.38)	4.53 (1.07)	**.43**
Boys	185	4.25 (1.44)	4.56 (1.06)	3.42 (1.48)	3.76 (1.38)	4.27 (1.16)	**.26**
Asian	76	4.70 (0.96)	4.94 (0.73)	3.60 (1.49)	3.89 (1.46)	4.36 (1.14)	**.43**
Girls	41	4.52 (1.03)	4.84 (0.77)	3.28 (1.36)	3.50 (1.41)	4.52 (0.89)	**.61**
Boys	35	4.90 (0.85)	5.06 (0.67)	3.97 (1.55)	4.34 (1.41)	4.17 (1.37)	**.26**
Black	164	4.27 (1.32)	4.83 (1.02)	3.34 (1.63)	3.43 (1.56)	4.71 (1.11)	**.37**
Girls	88	4.11 (1.33)	4.77 (1.09)	3.01 (1.52)	3.12 (1.46)	4.82 (1.06)	**.49**
Boys	76	4.45 (1.29)	4.89 (0.93)	3.73 (1.68)	3.80 (1.60)	4.58 (1.16)	**.24**
Multiracial	185	4.22 (1.44)	4.74 (1.00)	3.38 (1.46)	3.61 (1.52)	4.65 (1.06)	**.32**
Girls	106	4.03 (1.46)	4.64 (1.05)	3.11 (1.44)	3.24 (1.49)	4.71 (1.01)	**.38**
Boys	79	4.47 (1.37)	4.88 (0.91)	3.75 (1.42)	4.11 (1.44)	4.57 (1.13)	**.25**
Middle Sch.	515	4.44 (1.34)	4.79 (1.06)	3.72 (1.47)	3.95 (1.45)	4.49 (1.17)	**.25**
Girls	277	4.28 (1.41)	4.68 (1.14)	3.52 (1.46)	3.70 (1.45)	4.50 (1.19)	**.28**
Boys	238	4.63 (1.24)	4.92 (0.96)	3.95 (1.44)	4.23 (1.41)	4.47 (1.16)	**.21**
High School	723	4.14 (1.42)	4.71 (1.02)	3.22 (1.47)	3.47 (1.46)	4.59 (1.09)	**.38**
Girls	374	4.01 (1.44)	4.69 (1.02)	2.97 (1.39)	3.11 (1.42)	4.77 (1.02)	**.50**
Boys	349	4.28 (1.39)	4.73 (1.01)	3.50 (1.51)	3.85 (1.41)	4.39 (1.13)	**.27**

Note: The range of ability self-concepts is from 1 (*really not good*) to 6 (*really good*). Effect sizes represent the contrast between math/science vs. computer science/engineering. Data is from Study 2; ability self-concepts in engineering were not measured in Study 1. Divergent patterns of ability self-concepts were strongest for girls, Asian students, and high school students. CS = Computer Science. ENG = Engineering. Hisp = Hispanic. Sch. = School. $P \leq 0.001$ is indicated **in bold**, $^{**}P \leq 0.01$, $^{*}P < 0.05$.

Table S5. Study 1 Comparison of Boys' and Girls' Correlations Between Gender Stereotypes and Personal Interest in STEM

Field	Boys		Girls		
	r	*N*	*r*	*N*	*Z*
Interest Stereotypes					
Math	**0.21**	743	**-0.26**	738	**9.20**
Science	**0.17**	743	**-0.17**	740	**6.60**
Computer Science	0.09*	743	**-0.25**	739	**6.64**
Engineering	0.08*	741	**-0.32**	738	**7.90**
Ability Stereotypes					
Math	**0.26**	745	-0.07	740	**6.47**
Science	0.11**	745	-0.06	743	3.28**
Computer Science	0.05	745	**-0.14**	741	**3.67**
Engineering	0.08*	744	**-0.19**	742	**5.24**

Note: Gender stereotypes (coded so that positive numbers indicate stereotypes favoring boys) were more negatively correlated with girls' personal interest than boys' personal interest. *Z*-scores were calculated using the Fisher r-to-Z transformation to calculate a value of Z that assesses the difference between correlation coefficients found in independent samples. **P* ≤ 0.05, ***P* ≤ 0.01, *P* ≤ 0.001 is indicated **in bold**.

Table S6. Study 2 Correlations Between Stereotypes and Motivation Variables

Variable	1	2	3	4	5	6
Math						
1. Interest stereotypes	-	**0.43**	**-0.27**	**-0.29**	**-0.31**	**-0.28**
2. Ability stereotypes	**0.41**	-	-0.05	-0.06	-0.12**	-0.07
3. Identification	**0.17**	**0.22**	-	**0.73**	**0.75**	**0.84**
4. Sense of belonging	**0.19**	**0.21**	**0.73**	-	**0.79**	**0.75**
5. Ability self-concept	**0.22**	**0.29**	**0.76**	**0.76**	-	**0.77**
6. Personal interest	**0.22**	**0.24**	**0.81**	**0.73**	**0.75**	-
Science						
1. Interest stereotypes	-	**0.37**	-0.13**	**-0.17**	**-0.20**	**-0.16**
2. Ability stereotypes	**0.39**	-	-0.03	-0.10**	**-0.14**	-0.07
3. Identification	**0.16**	0.07	-	**0.68**	**0.65**	**0.81**
4. Sense of belonging	0.11**	0.05	0.66**	-	**0.74**	**0.70**
5. Ability self-concept	**0.21**	**0.15**	0.64**	**0.70**	-	**0.73**
6. Personal interest	**0.18**	0.05	0.76**	**0.67**	**0.69**	-
Computer Science						
1. Interest stereotypes	-	**0.50**	**-0.24**	**-0.25**	**-0.27**	**-0.23**
2. Ability stereotypes	**0.44**	-	-0.11**	**-0.14**	**-0.18**	-0.10**
3. Identification	0.01	0.06	-	**0.74**	**0.79**	**0.84**
4. Sense of belonging	0.01	0.06	**0.76**	-	**0.75**	**0.72**
5. Ability self-concept	0.01	0.09*	**0.80**	**0.75**	-	**0.79**
6. Personal interest	0.07	0.08*	**0.83**	**0.76**	**0.74**	-
Engineering						
1. Interest stereotypes	-	**0.52**	**-0.16**	**-0.19**	**-0.23**	**-0.18**
2. Ability stereotypes	**0.45**	-	-0.12**	**-0.18**	**-0.20**	-0.13**
3. Identification	-0.03	-0.01	-	**0.63**	**0.67**	**0.73**
4. Sense of belonging	-0.004	0.004	**0.66**	-	**0.76**	**0.74**
5. Ability self-concept	-0.05	0.02	**0.70**	**0.74**	-	**0.78**
6. Personal interest	-0.01	0.01	**0.74**	**0.78**	**0.76**	-
Language Arts						
1. Interest stereotypes	-	**0.48**	**-0.17**	**-0.19**	**-0.24**	**-0.16**
2. Ability stereotypes	**0.45**	-	-0.04	-0.12**	**-0.15**	-0.06
3. Identification	**0.22**	**0.25**	-	**0.69**	**0.64**	**0.80**
4. Sense of belonging	**0.22**	**0.28**	**0.65**	-	**0.72**	**0.68**
5. Ability self-concept	**0.19**	**0.26**	**0.60**	**0.69**	-	**0.64**
6. Personal interest	**0.24**	**0.24**	**0.75**	**0.68**	**0.62**	-

Note: Girls (N = 644 – 667) are above the diagonals, and boys (N = 578 – 595) are below the diagonal. Stereotypes are difference scores for ratings about boys minus ratings about girls. All data reported here are from students who passed an attention check question in the survey. **$P \leq 0.01$, $P \leq 0.001$ is indicated **in bold**.

Table S7. Study 2 Comparison of Boys' and Girls' Correlations Between Stereotypes and Motivation in Five Fields

	Interest Stereotypes					Ability Stereotypes				
	Boys		Girls			Boys		Girls		
Correlation	*r*	*N*	*r*	*N*	*Z*	*r*	*N*	*r*	*N*	*Z*
Identification										
Math	**0.17**	590	**-0.27**	660	**7.90**	**0.22**	588	-0.05	658	**4.81**
Science	**0.16**	589	-0.13**	660	**5.14**	0.07	587	-0.03	658	1.76
Comp. Sci.	0.01	583	**-0.24***	655	**4.46**	0.06	581	**-0.11**	653	2.98**
Engineering	-0.03	583	**-0.16**	652	2.30*	-0.01	581	-0.12**	649	1.93
Lang. Arts	**0.22**	590	**-0.17**	660	**6.96**	**0.25**	588	-0.04	658	**5.19**
Sense of belonging										
Math	**0.19**	590	**-0.29**	663	**8.65**	**0.22**	588	-0.06	661	**4.99**
Science	**0.11**	590	**-0.17**	663	**4.97**	0.05	588	-0.10*	661	2.65**
Comp. Sci.	0.02	589	**-0.25**	660	**4.85**	0.06	587	**-0.14**	658	**3.53**
Engineering	-0.004	589	**-0.19**	660	**3.31**	0.004	587	**-0.18**	657	3.27**
Lang. Arts	**0.22**	590	**-0.20**	663	**7.52**	**0.28**	588	-0.12**	661	**7.18**
Ability self-concept										
Math	**0.22**	585	**-0.31**	661	**9.56**	**0.29**	583	-0.12**	659	**7.35**
Science	**0.21**	585	**-0.20**	661	**7.31**	**0.15**	583	-0.14**	659	**5.12**
Comp. Sci.	0.01	580	**-0.27**	650	**5.01**	0.10*	578	**-0.18**	648	**4.92**
Engineering	-0.05	582	**-0.23**	647	3.22**	0.02	580	**-0.20**	644	**3.88**
Lang. Arts	**0.19**	585	**-0.24**	661	**7.68**	**0.26**	583	**-0.15**	659	**7.32**
Personal interest										
Math	0.22**	588	**-0.28**	662	**9.00**	**0.24**	586	-0.07	660	**5.53**
Science	**0.18**	587	**-0.16**	662	**6.04**	0.05	585	-0.07	660	2.11*
Comp. Sci.	0.07	582	**-0.23**	656	**5.33**	0.09*	580	**-0.10**	654	**3.33**
Engineering	-0.01	584	**-0.19**	654	3.19**	0.01	582	-0.13**	651	2.46*
Lang. Arts	**0.24**	588	**-0.16**	662	**7.15**	**0.24**	586	-0.06	660	**5.36**

Note: This table provides results for whether girls' gender stereotypes (coded so that positive numbers indicate stereotypes favoring boys) are more negatively correlated with their motivation than boys' stereotypes. *Z*-scores were calculated using the Fisher *r*-to-*Z* transformation to calculate a value of *Z* that assesses the difference between correlation coefficients found in independent samples. **P* ≤ 0.05, ***P* ≤ 0.01, *P* ≤ 0.001 is indicated in **bold**.

Table S8. List of Complete Measures in each Study

Measure	# of scale items	Relevant counterbalancing	Sample item
Study 1			
School ID	1		*Please enter your 5 digit school ID number.*
Grade level	1		*What grade are you in right now?*
Teacher name	1		*Please choose your teacher's name from the list below* [elementary school only].
Practice questions	3 (middle and high school) or 6 (elementary school)		*I like to eat ice cream.*
Stereotypes about interest	16 (1 item for each of 4 fields and 4 groups: girls, boys, women, men)	Order of 4 STEM fields (math, science, engineering, computer coding); order of interest or ability stereotype block first	*How much do most girls like math?*
Stereotypes about ability	16 (1 item for each of 4 fields and 4 groups: girls, boys, women, men)	Order of 4 STEM fields (math, science, engineering, computer coding); order of interest or ability stereotype block first	*How good are most girls at math?*
Awareness of stereotypes about interest	12 (1 item for each of 3 fields and 4 groups: girls, boys, women, men)	Order of 3 STEM fields (math, science, computer coding); order of interest or ability stereotype block first	*How much do most people think that girls like math?*
Awareness of stereotypes about ability	12 (1 item for each of 3 fields and 4 groups: girls, boys, women, men)	Order of 3 STEM fields (math, science, computer coding); order of interest or ability stereotype block first	*How good do most people think that girls are at math?*
Belonging	9 (3 items for each of 3 fields)	Order of 3 STEM fields (math, science, computer coding)	*I feel like I belong in my math class.*
Attention check	1		*Please choose "slightly disagree" to show that you read this question.*
Ability self-concepts	6 (2 items for each of 3 fields)	Order of 3 STEM fields (math, science, computer coding)	*I am good at math activities.*
Interest	8 (2 items for each of 4 fields)	Order of 4 STEM fields (math, science, engineering, computer coding)	*I like to do math activities.*

Interest mindsets	9 (3 items for each of 3 fields)	Order of 3 STEM fields (math, science, computer coding)	*People can't change whether they like math or not.*
Ability mindsets	9 (3 items for each of 3 fields)	Order of 3 STEM fields (math, science, computer coding)	*You can learn new things, but you can't really change how good you are at math.*
Questions about computer sci.	2		*What do you think computer science is?*
Self-reported grades	3 (1 item for each of 3 fields)		*What type of overall grades do you usually get in your math classes?*
Computer sci. classes taken	1 (high school only)		*Are you currently taking or have you already taken any Technology Education or Computer Science classes in high school? If so, which ones?*
Computer sci. classes planning to take	1 (high school only)		*Are you planning on taking any more Technology Education or Computer Science classes in high school? If so, which ones?*
Birthdate	1		*When is your birthday?*
Gender	1		*What is your gender?*
Race/ethnicity	1		*What race/ethnicity do you identify as? Please check all that apply.*
Parental education	2 (father's ed for middle/high school only)		*What is your mother's (or other primary caregiver's) highest level of education?*
Feedback	1		*Was anything about these questions confusing? If yes, what?*
Study 2			
Grade level	1		*What grade are you in right now?*
Stereotypes about interest	10 (1 item for each of 5 fields and 2 groups: girls, boys)	Order of interest or ability stereotype block first; order of 5 fields (math, science, engineering, computer coding, language arts)	*How much do you think that most girls like these subjects? [Math]*
Stereotypes about ability	10 (1 item for each of 5 fields and 2 groups: girls, boys)	Order of interest or ability stereotype block first; order of 5 fields (math, science, engineering, computer coding, language arts)	*How good do you think that most girls are at these subjects? [Math]*

Belonging	15 (3 items for each of 5 fields)	Order of 5 fields (math, science, engineering, computer coding, language arts)	*How much do you feel like you belong when you do these classes and activities at school? [Math]*
Attention check	1		*Please choose the face marked "slightly disagree" to show that you read this question.*
Ability self-concepts	10 (2 items for each of 5 fields)	Order of 5 fields (math, science, engineering, computer coding, language arts)	*How good are you at these classes and activities? [Math]*
Identification	10 (2 items for each of 5 fields)	Order of 5 fields (math, science, engineering, computer coding, language arts)	*How important are these classes and activities to you? [Math]*
Interest	10 (2 items for each of 5 fields)	Order of 5 fields (math, science, engineering, computer coding, language arts)	*How much do you like to do these activities? [Math]*
Questions about computer sci.	2		*What do you think computer science is?*
Gender	1		*What is your gender?*
Race/ethnicity	1		*What race/ethnicity do you identify as? Please check all that apply.*
Self-reported grades	4 (1 item for each of 4 fields)		*What type of overall grades do you usually get in your math classes?*
Experiences with coding and engineering	6		*Please tell us about any coding or engineering classes or activities you have done.*
Science subfield	1		*What kind of science were you thinking about? Were there any science classes or activities that you thought a lot about?*
Feedback	1		*Was anything about these questions confusing? If yes, what?*

Note: Sci. = Science.

Table S9. Study 1 Size of Differences Between Pairs of Stereotypes about Fields

		Interest Stereotypes			Ability Stereotypes		
Group	*N*	Science	Computer Science	Engineering	Science	Computer Science	Engineering
		M	*M*	*M*	*M*	*M*	*M*
Math							
All	1481	**-0.18**	**-0.86**	**-1.31**	-0.12**	**-0.74**	**-1.04**
Girls	739	-0.01	**-0.71**	**-1.22**	-0.08	**-0.66**	**-1.01**
Boys	742	**-0.34**	**-1.00**	**-1.39**	-0.17**	**-0.82**	**-1.07**
White	549	**-0.27**	**-0.97**	**-1.37**	-0.18*	**-0.78**	**-1.05**
Girls	268	-0.04	**-0.70**	**-1.13**	-0.02	**-0.58**	**-0.88**
Boys	281	**-0.50**	**-1.24**	**-1.60**	**-0.35**	**-0.99**	**-1.22**
Hisp/Latine	354	-0.03	**-0.75**	**-1.27**	-0.06	**-0.74**	**-0.99**
Girls	189	0.18	**-0.65**	**-1.24**	-0.09	**-0.78**	**-1.13**
Boys	165	-0.24	**-0.84**	**-1.30**	-0.03	**-0.71**	**-0.85**
Asian	145	-0.05	**-0.73**	**-1.11**	0.00	**-0.78**	**-1.07**
Girls	66	-0.11	**-0.85**	**-1.14**	-0.14	**-0.76**	**-1.05**
Boys	79	0.01	**-0.62**	**-1.09**	0.14	**-0.79**	**-1.09**
Black	120	-0.21	**-0.88**	**-1.30**	-0.08	-0.66**	**-1.01**
Girls	52	-0.17	-0.62*	**-1.17**	-0.04	-0.67*	**-1.19**
Boys	68	-0.25	**-1.15**	**-1.43**	-0.13	-0.64**	**-0.83**
Multiracial	220	-0.18	**-0.84**	**-1.31**	-0.06	**-0.67**	**-1.03**
Girls	115	0.00	**-0.70**	**-1.18**	-0.02	**-0.59**	**-0.97**
Boys	105	-0.36*	**-0.98**	**-1.44**	-0.10	**-0.75**	**-1.09**
Elementary	458	-0.26	**-0.42**	**-1.43**	-0.18	**-0.49**	**-1.16**
Girls	227	-0.13	-0.29	**-1.43**	-0.15	**-0.40****	**-1.19**
Boys	231	-0.38**	**-0.56**	**-1.42**	-0.22	**-0.59**	**-1.13**
Middle Sch	485	-0.21**	**-1.08**	**-1.32**	-0.15*	**-0.85**	**-1.07**
Girls	250	0.08	**-0.74**	**-1.03**	-0.10	**-0.62**	**-0.91**
Boys	235	**-0.50**	**-1.42**	**-1.61**	-0.20*	**-1.08**	**-1.22**
High School	538	-0.09	**-1.03**	**-1.21**	-0.05	**-0.84**	**-0.92**
Girls	262	-0.00	**-1.05**	**-1.23**	0.01	**-0.91**	**-0.96**
Boys	276	-0.17	**-1.01**	**-1.18**	-0.10	**-0.77**	**-0.89**
Science							
All	1481		**-0.68**	**-1.13**		**-0.61**	**-0.92**
Girls	739		**-0.70**	**-1.21**		**-0.58**	**-0.94**
Boys	742		**-0.66**	**-1.05**		**-0.65**	**-0.90**
White	549		**-0.70**	**-1.09**		**-0.60**	**-0.87**
Girls	268		**-0.66**	**-1.09**		**-0.56**	**-0.87**
Boys	281		**-0.74**	**-1.10**		**-0.64**	**-0.87**
Hisp/Latine	354		**-0.72**	**-1.24**		**-0.68**	**-0.93**
Girls	189		**-0.83**	**-1.42**		**-0.69**	**-1.04**
Boys	165		**-0.61**	**-1.06**		**-0.67**	**-0.82**
Asian	145		**-0.69**	**-1.07**		**-0.78**	**-1.07**
Girls	66		**-0.74**	**-1.03**		-0.62**	**-0.91**
Boys	79		**-0.63**	**-1.10**		**-0.94**	**-1.23**
Black	120		-0.67**	**-1.09**		-0.57**	**-0.93**
Girls	52		-0.44	**-1.00**		-0.63**	**-1.15**
Boys	68		**-0.90**	**-1.18**		-0.51*	-0.70**
Multiracial	220		**-0.66**	**-1.13**		**-0.61**	**-0.96**
Girls	115		**-0.70**	**-1.18**		**-0.57**	**-0.95**
Boys	105		**-0.62**	**-1.08**		**-0.65**	**-0.98**
Elementary	458		-0.17	**-1.17**		-0.31**	**-0.98**
Girls	227		-0.15	**-1.30**		-0.25*	**-1.04**

Boys	231		-0.18	**-1.04**		-0.37**	**-0.91**
Middle Sch	485		**-0.87**	**-1.11**		**-0.70**	**-0.91**
Girls	250		**-0.82**	**-1.11**		**-0.52**	**-0.81**
Boys	235		**-0.92**	**-1.11**		**-0.88**	**-1.02**
High School	538		**-0.94**	**-1.12**		**-0.79**	**-0.88**
Girls	262		**-1.05**	**-1.23**		**-0.92**	**-0.97**
Boys	276		**-0.83**	**-1.01**		**-0.67**	**-0.79**
Computer Science							
All	1481			**-0.45**			**-0.31**
Girls	739			**-0.51**			**-0.36**
Boys	742			**-0.40**			**-0.25**
White	549			**-0.39**			**-0.27**
Girls	268			**-0.43**			**-0.30**
Boys	281			**-0.36**			-0.23*
Hisp/Latine	354			**-0.52**			-0.25*
Girls	189			**-0.59**			-0.35**
Boys	165			**-0.45**			-0.15
Asian	145			-0.38*			-0.29
Girls	66			-0.29			-0.29
Boys	79			-0.47**			-0.29
Black	120			-0.42			-0.35
Girls	52			-0.56*			-0.52*
Boys	68			-0.28			-0.19
Multiracial	220			**-0.47**			**-0.35**
Girls	115			-0.48**			-0.37**
Boys	105			-0.46**			-0.33*
Elementary	458			**-1.00**			**-0.67**
Girls	227			**-1.14**			**-0.79**
Boys	231			**-0.87**			**-0.54**
Middle Sch	485			**-0.24**			**-0.21**
Girls	250			**-0.28**			**-0.29**
Boys	235			-0.19*			-0.13
High School	538			-0.18*			-0.08
Girls	262			-0.18*			-0.05
Boys	276			-0.18*			-0.12

Note: Interest stereotypes are in the left columns and ability stereotypes are in the right columns. Values represent the difference between stereotypes about each set of fields. Positive values indicate that the field in that row favors boys more strongly than the field in that column; negative values indicate that the field in that column favors boys more strongly than the field in that row. The largest differences were: math vs. computer science, math vs. engineering, science vs. computer science, and science vs. engineering, which is evidence of the divergence between math/science and computer science/engineering. Hisp = Hispanic. Sch = School. $P \leq 0.001$ is indicated **in bold,** $^{**}P \leq 0.01$, $^{*}P < 0.05$.

Table S10. Study 2 Size of Differences Between Pairs of Stereotypes about Fields

		Interest Stereotypes				Ability Stereotypes			
Group	*N*	Science	Computer Science	Eng.	Lang. Arts	Science	Computer Science	Eng.	Lang. Arts
		M	*M*	*M*	*M*	*M*	*M*	*M*	*M*
Math									
All	1254	-0.05	**-1.12**	**-1.12**	**0.78**	-0.10**	**-0.98**	**-1.03**	**0.46**
Girls	663	0.14*	**-0.96**	**-0.93**	**0.85**	-0.02	**-0.85**	**-0.90**	**0.43**
Boys	591	**-0.23**	**-1.28**	**-1.30**	**0.71**	**-0.17**	**-1.10**	**-1.17**	**0.49**
White	426	0.01	**-1.03**	**-0.97**	**0.85**	-0.07	**-0.99**	**-0.95**	**0.49**
Girls	229	0.29**	**-0.68**	**-0.65**	**0.96**	0.04	**-0.75**	**-0.78**	**0.43**
Boys	197	-0.27*	**-1.38**	**-1.29**	**0.74**	-0.19*	**-1.22**	**-1.13**	**0.55**
Hisp/Latine	375	-0.03	**-1.17**	**-1.12**	**0.69**	-0.07	**-0.98**	**-1.03**	**0.42**
Girls	186	0.10	**-0.97**	**-0.88**	**0.72**	0.01	**-0.78**	**-0.81**	**0.39**
Boys	189	-0.15	**-1.37**	**-1.36**	**0.66**	-0.14	**-1.18**	**-1.26**	**0.44**
Asian	78	0.24	**-0.80**	**-0.90**	**1.13**	0.00	**-0.73**	**-0.86**	0.66**
Girls	42	0.33	**-0.95**	**-1.02**	0.81*	-0.02	-0.69**	**-0.81**	0.36
Boys	36	0.14	-0.64*	-0.78*	**1.44**	0.03	-0.78**	**-0.92**	0.97**
Black	171	-0.15	**-1.13**	**-1.42**	**0.84**	-0.08	**-1.00**	**-1.23**	**0.54**
Girls	94	0.05	**-1.16**	**-1.27**	**1.10**	-0.12	**-1.04**	**-1.19**	**0.57**
Boys	77	-0.35	**-1.10**	**-1.57**	0.58**	-0.05	**-0.96**	**-1.27**	0.51**
Multiracial	185	-0.26*	**-1.30**	**-1.24**	**0.60**	**-0.28**	**-0.95**	**-1.10**	**0.34**
Girls	107	-0.03	**-1.31**	**-1.21**	0.65**	-0.15	**-1.05**	**-1.08**	**0.40**
Boys	78	-0.49**	**-1.29**	**-1.27**	0.54**	**-0.41**	**-0.85**	**-1.12**	0.28
Middle Sch.	524	-0.19*	**-1.20**	**-1.20**	**0.58**	-0.16**	**-1.02**	**-1.14**	**0.40**
High School	729	0.06	**-1.06**	**-1.06**	**0.93**	-0.05	**-0.95**	**-0.96**	**0.50**
Science									
All	1254		**-1.07**	**-1.07**	**0.83**		**-0.88**	**-0.94**	**0.56**
Girls	663		**-1.10**	**-1.07**	**0.70**		**-0.83**	**-0.88**	**0.45**
Boys	591		**-1.05**	**-1.07**	**0.95**		**-0.93**	**-1.00**	**0.66**
White	426		**-1.04**	**-0.98**	**0.84**		**-0.92**	**-0.88**	**0.56**
Girls	229		**-0.97**	**-0.94**	**0.67**		**-0.80**	**-0.82**	**0.39**
Boys	197		**-1.11**	**-1.02**	**1.01**		**-1.04**	**-0.94**	**0.74**
Hisp/Latine	375		**-1.14**	**-1.10**	**0.71**		**-0.92**	**-0.97**	**0.48**
Girls	186		**-1.06**	**-0.98**	**0.62**		**-0.80**	**-0.82**	**0.38**
Boys	189		**-1.22**	**-1.21**	**0.81**		**-1.04**	**-1.12**	**0.59**
Asian	78		**-1.03**	**-1.14**	**0.89**		**-0.74**	**-0.87**	**0.66**
Girls	42		**-1.29**	**-1.36**	0.48		-0.67**	**-0.79**	0.38
Boys	36		-0.78**	-0.92**	**1.31**		-0.81**	**-0.94**	**0.94**
Black	171		**-0.98**	**-1.27**	**0.99**		**-0.92**	**-1.15**	**0.62**
Girls	94		**-1.21**	**-1.32**	**1.04**		**-0.93**	**-1.07**	**0.68**
Boys	77		**-0.75**	**-1.22**	**0.94**		**-0.91**	**-1.22**	0.56**
Multiracial	185		**-1.04**	**-0.98**	**0.85**		**-0.67**	**-0.81**	**0.62**
Girls	107		**-1.28**	**-1.19**	**0.68**		**-0.90**	**-0.92**	**0.55**
Boys	78		**-0.81**	**-0.78**	**1.03**		-0.44**	**-0.71**	**0.69**
Middle Sch.	524		**-1.01**	**-1.00**	**0.77**		**-0.85**	**-0.98**	**0.57**
High School	729		**-1.12**	**-1.12**	**0.86**		**-0.90**	**-0.91**	**0.55**
Computer Science									
All	1254			0.00	**1.90**			-0.06	**1.44**
Girls	663			0.02	**1.80**			-0.05	**1.28**
Boys	591			-0.02	**2.00**			-0.07	**1.59**
White	426			0.06	**1.88**			0.03	**1.48**
Girls	229			0.03	**1.64**			-0.02	**1.19**
Boys	197			0.09	**2.11**			0.09	**1.78**
Hisp/Latine	375			0.04	**1.86**			-0.05	**1.40**
Girls	186			0.08	**1.68**			-0.02	**1.18**

Boys	189				0.01	**2.03**				-0.08	**1.62**
Asian	78				-0.11	**1.92**				-0.13	**1.40**
Girls	42				-0.07	**1.76**				-0.12	**1.05**
Boys	36				-0.14	**2.08**				-0.14	**1.75**
Black	171				-0.29*	**1.97**				-0.23*	**1.54**
Girls	94				-0.11	**2.26**				-0.15	**1.61**
Boys	77				-0.47*	**1.69**				-0.31*	**1.47**
Multiracial	185				0.06	**1.90**				-0.15	**1.29**
Girls	107				0.09	**1.96**				-0.03	**1.45**
Boys	78				0.03	**1.83**				-0.27*	**1.13**
Middle Sch.	524				0.01	**1.78**				-0.12*	**1.42**
High School	729				0.00	**1.98**				-0.01	**1.45**
Engineering											
All	1254					**1.90**					**1.50**
Girls	663					**1.78**					**1.33**
Boys	591					**2.02**					**1.66**
White	426					**1.82**					**1.45**
Girls	229					**1.61**					**1.21**
Boys	197					**2.03**					**1.68**
Hisp/Latine	375					**1.81**					**1.45**
Girls	186					**1.60**					**1.20**
Boys	189					**2.02**					**1.70**
Asian	78					**2.03**					**1.53**
Girls	42					**1.83**					**1.17**
Boys	36					**2.22**					**1.89**
Black	171					**2.26**					**1.77**
Girls	94					**2.36**					**1.76**
Boys	77					**2.16**					**1.78**
Multiracial	185					**1.84**					**1.44**
Girls	107					**1.87**					**1.48**
Boys	78					**1.81**					**1.40**
Middle Sch.	524					**1.78**					**1.54**
High School	729					**1.99**					**1.46**

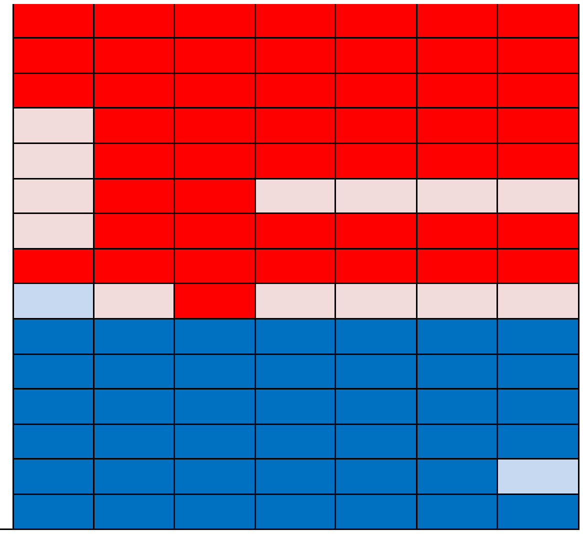
Note: Interest stereotypes are in the left columns and Ability stereotypes are in the right columns. Values represent the difference between stereotypes about each set of fields. Positive values indicate that the field in that row favors boys more strongly than the field in that column; negative values indicate that the field in that column favors boys more strongly than the field in that row. The largest differences were math vs. computer science, math vs. engineering, science vs. computer science, science vs. engineering, language arts vs. computer science, and language arts vs. engineering, which is evidence of the divergence between math/science and computer science/engineering. Eng = Engineering. Lang = Language. Hisp = Hispanic. Sch = School. $P \leq 0.001$ is indicated **in bold,** $^{**}P \leq 0.01$, $^{*}P < 0.05$.

Table S11. Categorization of Stereotypes by Study, Type, Field, and Gender

	Grade Level											
	1	2	3	4	5	6	7	8	9	10	11	12
Study 1												
Interest Ster.												
Math: Overall												
Girls												
Boys												
Science: Overall												
Girls												
Boys												
Comp. Sci.: Overall												
Girls												
Boys												
Engin.: Overall												
Girls												
Boys												
Ability Ster.												
Math: Overall												
Girls												
Boys												
Science: Overall												
Girls												
Boys												
Comp. Sci.: Overall												
Girls												
Boys												
Engin.: Overall												
Girls												
Boys												
Study 2												
Interest Ster.												
Lang.: Overall												
Girls												
Boys												
Math: Overall												
Girls												
Boys												
Science: Overall												
Girls												
Boys												
Comp. Sci.: Overall												
Girls												
Boys												
Engin.: Overall												
Girls												
Boys												

Ability Ster.

Lang.: Overall
Girls
Boys
Math: Overall
Girls
Boys
Science: Overall
Girls
Boys
Comp. Sci.: Overall
Girls
Boys
Engin.: Overall
Girls
Boys



Note: Red = significantly favors girls (two-tailed *P* < .05); pink = non-significantly favors girls (two-tailed *P* > .05); dark blue = significantly favors boys (two-tailed *P* < .05); light blue = non-significantly favors boys (two-tailed *P* > .05); white = did not favor girls or boys. Comp. Sci. indicates computer science; Engin. indicates engineering; Lang. indicates language arts.

Table S12. Stereotype Prevalence: Percent of Students Whose Stereotypes Favored Girls, Boys, or Neither by Field and Specific Group

	Math			Science			Comp. Sci.			Engineering			Language Arts		
Group	G	B	N	G	B	N	G	B	N	G	B	N	G	B	N
Study 1 – Interest Stereotypes															
All	35	26	39	28	28	44	15	51	34	9	63	28			
Girls	34	42	24	32	23	45	17	48	35	10	62	28			
Boys	36	27	37	24	32	44	13	54	33	7	64	29			
White	37	24	39	27	25	48	14	53	33	9	62	29			
Girls	34	23	43	31	21	48	17	49	34	12	61	27			
Boys	39	25	36	23	29	48	10	57	33	6	63	31			
Hisp/Latine	33	27	40	32	26	42	13	50	37	8	66	26			
Girls	31	28	41	36	24	40	11	46	43	9	67	24			
Boys	35	26	39	27	29	44	13	56	31	7	65	28			
Asian	28	29	43	26	32	42	9	49	42	6	64	30			
Girls	30	23	47	29	27	44	11	47	42	4	61	35			
Boys	25	34	41	24	35	41	7	51	42	6	67	27			
Black	38	32	30	23	33	44	18	54	28	13	64	23			
Girls	33	33	34	23	27	50	25	52	23	17	56	27			
Boys	42	32	26	23	38	39	13	55	32	9	71	20			
Multiracial	35	25	40	30	29	41	18	52	30	9	64	27			
Girls	35	23	42	34	23	43	18	50	32	11	62	27			
Boys	36	25	39	26	36	38	18	55	27	7	66	27			
Elementary	37	29	34	30	33	37	24	37	39	13	61	26			
Girls	41	21	36	38	25	37	33	31	36	18	58	24			
Boys	34	35	31	22	40	38	15	43	42	8	64	28			
Middle Sch.	37	22	41	27	24	49	11	55	34	7	63	30			
Girls	31	25	44	29	20	51	11	53	36	8	61	31			
Boys	44	19	37	25	27	48	12	57	31	6	65	29			
High School	30	27	43	27	28	45	10	60	30	7	64	29			
Girls	30	26	44	30	25	45	8	58	34	6	66	28			
Boys	31	27	42	24	30	46	11	62	27	7	63	30			
Study 2 – Interest Stereotypes															
All	31	23	46	30	23	47	11	56	33	10	57	33	58	8	34
Girls	29	24	47	34	20	46	11	55	34	11	55	34	58	7	35
Boys	34	21	45	26	26	48	10	57	33	10	58	32	59	8	33
White	30	23	47	29	24	47	11	55	34	11	56	33	56	8	36
Girls	26	26	48	33	21	46	14	51	35	12	53	35	56	8	36
Boys	35	21	44	25	26	49	9	58	33	10	59	31	55	8	37
Hisp/Latine	31	21	48	31	21	48	9	58	33	9	58	33	56	8	36
Girls	27	24	49	31	21	48	9	57	34	7	59	34	52	9	39
Boys	35	18	47	32	22	46	10	58	32	10	58	32	59	7	34
Asian	30	28	42	35	20	45	8	47	45	8	47	45	69	3	28
Girls	33	26	41	40	19	41	7	52	41	7	52	41	67	5	28
Boys	25	31	44	28	22	50	8	42	50	8	42	50	72	0	28
Black	34	27	39	31	29	40	15	59	26	12	63	25	63	10	27
Girls	36	27	37	40	25	35	17	57	26	14	60	26	73	5	22
Boys	31	27	42	21	34	45	13	61	26	9	68	23	52	16	32
Multiracial	33	19	48	26	22	52	8	55	37	11	52	37	57	8	35
Girls	31	20	49	32	17	51	6	58	36	9	51	40	52	8	40
Boys	36	17	47	18	28	54	11	50	39	14	53	33	64	8	28
Middle Sch.	36	23	41	32	26	42	14	54	32	13	56	31	57	10	33
Girls	34	22	44	35	23	42	15	55	30	14	57	29	56	9	35
Boys	38	23	39	28	30	42	13	54	33	12	56	32	59	10	31

High School	28	23	49	29	20	51	8	57	35	8	57	35	59	6	35
Girls	26	25	49	33	18	49	9	55	36	8	54	38	59	6	35
Boys	31	19	50	25	22	53	8	59	33	9	59	32	59	6	35
Study 1 – Ability Stereotypes															
All	35	17	48	34	18	48	16	46	38	11	41	48			
Girls	37	13	50	39	13	48	18	34	48	14	43	43			
Boys	33	20	47	29	23	48	13	43	44	8	53	39			
White	34	15	51	32	18	50	14	37	49	10	46	44			
Girls	33	13	54	37	12	51	16	33	51	13	40	47			
Boys	34	17	49	28	23	49	12	41	47	8	51	41			
Hisp/Latine	36	19	45	36	16	48	17	41	42	13	47	40			
Girls	40	15	45	40	15	45	18	37	45	14	44	42			
Boys	32	24	44	30	19	51	15	46	39	10	52	38			
Asian	34	18	48	32	13	55	10	41	49	5	53	42			
Girls	35	12	53	30	11	59	11	33	56	6	48	46			
Boys	33	23	44	34	15	51	10	48	42	4	57	39			
Black	36	21	43	31	25	44	20	45	35	14	53	33			
Girls	39	17	44	39	19	42	25	48	27	15	50	35			
Boys	34	23	43	26	30	44	16	43	41	13	56	31			
Multiracial	36	14	50	35	18	47	16	33	51	10	45	45			
Girls	42	10	48	40	13	47	21	29	50	15	39	46			
Boys	30	18	52	29	23	48	10	37	53	5	50	45			
Elementary	32	23	45	32	27	41	21	35	44	14	57	29			
Girls	40	16	44	42	18	40	30	26	44	21	51	28			
Boys	24	30	46	22	36	42	13	44	43	7	63	30			
Middle Sch.	38	13	49	34	15	51	13	39	48	8	45	47			
Girls	35	11	54	34	12	54	15	32	53	8	39	53			
Boys	41	14	45	35	18	47	11	45	44	8	52	40			
High School	35	15	50	34	14	52	13	41	46	12	42	46			
Girls	38	12	50	39	11	50	12	42	46	14	40	46			
Boys	33	17	50	30	16	54	14	40	46	9	44	47			
Study 2 – Ability Stereotypes															
All	34	15	51	30	13	57	12	44	44	11	45	44	51	7	42
Girls	36	14	50	32	10	58	13	40	47	12	41	47	52	5	43
Boys	32	17	51	28	17	55	11	48	41	9	50	41	51	8	41
White	34	15	51	29	12	59	12	44	44	12	44	44	51	7	42
Girls	34	15	51	31	9	60	15	39	46	15	39	46	50	6	44
Boys	34	16	50	26	16	58	9	50	41	9	50	41	53	8	39
Hisp/Latine	31	15	54	30	12	58	11	44	45	9	45	46	49	7	44
Girls	32	13	55	29	9	62	13	38	49	10	37	53	47	7	46
Boys	31	16	53	30	16	54	10	50	40	9	52	39	51	8	41
Asian	24	17	59	27	13	60	10	37	53	9	41	50	48	5	47
Girls	31	12	57	26	12	62	14	33	53	12	40	48	45	5	50
Boys	17	22	61	28	14	58	5	42	53	5	42	53	50	6	44
Black	39	20	41	36	21	43	13	50	37	9	54	37	57	7	36
Girls	45	17	38	38	19	43	14	45	41	13	50	37	64	5	31
Boys	33	23	44	34	23	43	12	56	32	5	59	36	48	8	44
Multiracial	38	12	50	26	11	63	13	41	46	12	42	46	50	6	44
Girls	37	11	52	31	8	61	10	42	48	10	43	47	54	2	44
Boys	39	14	47	18	17	65	17	38	45	13	41	46	45	10	45
Middle Sch.	37	16	47	31	16	53	16	45	39	13	48	39	51	9	40
Girls	37	15	48	30	13	57	15	40	45	13	44	43	52	6	42
Boys	37	17	46	33	20	47	16	52	32	12	53	35	51	11	38
High School	32	15	53	29	12	59	10	42	48	9	43	48	51	5	44

Girls	35	12	53	34	8	58	12	40	48	12	38	50	51	5	44
Boys	28	18	54	25	15	60	7	46	47	7	48	45	50	6	44

Note: Values represent the percent of students within each group who reported stereotypes that favored girls (G), boys (B), or were neutral/egalitarian with equal ratings for girls and boys (N). Statistical significance was not calculated for this table. Rows of “Girls” and “Boys” refer to participant gender; columns of G and B refer to stereotypes favoring that group. Percents for each group were rounded so that they would add up to 100%. For example, for Study 1 math interest stereotypes, overall, 35% of students reported stereotypes that favored girls, 26% reported stereotypes that favored boys, and 39% reported neutral/egalitarian stereotypes that did not favor either gender group. The most prevalent gender stereotypes were among computer science and engineering (favoring boys) and language arts (favoring girls), but many students (20-65%) did not report stereotypes favoring either group. Hisp = Hispanic. Sch. = School. Comp. Sci. = Computer science.

Table S13. Study 1 Comparison of Gender Differences in Motivation (Personal Interest) across Fields

Group	Effect size of gender gap (η_p^2)	vs. Science	vs. Computer Science	vs. Engineering
Math				
All	0.00	0.001	**0.02**	**0.03**
White	0.00	0.001	**0.02**	**0.03**
Hispanic/Latine	0.02**	0.00	0.003	**0.03**
Asian	0.006	0.00	0.02	0.03*
Black	0.002	0.00	0.05*	0.04*
Multiracial	0.002	0.001	0.009	0.02*
Elementary School	0.00	0.00	0.002	0.01*
Middle School	0.002	0.01**	**0.05**	**0.07**
High School	0.01*	0.00	**0.02**	**0.04**
Science				
All	0.003*		**0.02**	**0.03**
White	0.00		**0.02**	**0.03**
Hispanic/Latine	**0.04**		0.001	**0.03**
Asian	0.004		0.04*	0.04*
Black	0.001		0.05*	0.03*
Multiracial	0.001		0.02*	0.03*
Elementary School	0.00		0.004	0.01*
Middle School	0.007		**0.03**	**0.05**
High School	0.01*		**0.02**	**0.04**
Computer Science				
All	**0.03**			0.003*
White	**0.03**			0.00
Hispanic/Latine	**0.04**			0.02**
Asian	0.07**			0.001
Black	0.04*			0.004
Multiracial	0.03*			0.002
Elementary School	0.003			0.005
Middle School	**0.06**			0.001
High School	**0.07**			0.004
Engineering				
All	**0.05**			
White	**0.04**			
Hispanic/Latine	**0.12**			
Asian	**0.08**			
Black	0.03			
Multiracial	**0.05**			
Elementary School	0.01*			
Middle School	**0.08**			
High School	**0.10**			

Note: Gender differences were largest in computer science and engineering. Gender gaps in engineering (and computer science to a lesser extent) were larger than gender gaps in math and science motivation. All values represent η_p^2. $P \leq 0.001$ is indicated **in bold,** $^{**}P \leq 0.01$, $^{*}P < 0.05$.

Table S14. Study 2 Comparison of Gender Differences in Motivation (Personal Interest) across Fields

Group	Effect size of gender gap (η_p^2)	vs. Science	vs. Computer Science	vs. Engineering	vs. Language Arts
Math					
All	0.004*	0.001	**0.02**	**0.03**	**0.02**
White	0.008	0.004	0.01*	0.02**	**0.03**
Hispanic/Latine	0.001	0.000	**0.03**	**0.05**	**0.03**
Asian	0.009	0.000	0.01	0.07*	0.03
Black	0.002	0.000	0.02*	0.02	0.01
Multiracial	0.007	0.002	0.02	0.04**	0.02
Middle School	0.005	0.000	0.01*	0.01**	0.01*
High School	0.004	0.002	**0.03**	**0.06**	**0.04**
Science					
All	0.001		**0.03**	**0.05**	**0.03**
White	0.002		**0.03**	**0.05**	0.02**
Hispanic/Latine	0.000		**0.04**	**0.07**	**0.04**
Asian	0.009		0.01	0.07*	0.03
Black	0.00		0.03*	0.03*	0.01
Multiracial	0.03*		0.01	0.03*	0.05**
Middle School	0.006		0.01**	0.02**	0.03**
High School	0.00		**0.04**	**0.08**	**0.03**
Computer Science					
All	**0.05**			0.003	**0.07**
White	**0.05**			0.001	**0.07**
Hispanic/Latine	**0.05**			0.004	**0.11**
Asian	0.04			0.04	0.06*
Black	0.04**			0.00	0.05**
Multiracial	**0.06**			0.009	**0.06**
Middle School	**0.04**			0.00	**0.04**
High School	**0.06**			0.01**	**0.10**
Engineering					
All	**0.07**				**0.09**
White	**0.07**				**0.08**
Hispanic/Latine	**0.08**				**0.14**
Asian	0.11**				0.13**
Black	0.04**				0.05**
Multiracial	**0.09**				**0.09**
Middle School	**0.04**				**0.04**
High School	**0.10**				**0.14**
Language Arts					
All	**0.02**				
White	0.02**				
Hispanic/Latine	**0.04**				
Asian	0.02				
Black	0.01				
Multiracial	0.006				
Middle School	0.004				
High School	**0.04**				

Note: Gender differences were largest in computer science and engineering, then language arts. Gender gaps in engineering (and computer science and language arts to a lesser extent) were larger than gender gaps in math and science motivation. All values represent η_p^2. $P \leq 0.001$ indicated **in bold,** $^{**}P \leq 0.01$, $^{*}P < 0.05$.

Table S15. Study 2 Comparison of Gender Differences in Ability Self-Concepts across Fields

Group	Effect size of gender gap (η_p^2)	vs. Science	vs. Computer Science	vs. Engineering	vs. Language Arts
Math					
All	**0.01**	0.003*	0.003	**0.01**	**0.02**
White	0.009*	0.001	0.003	0.01*	0.02**
Hispanic/Latine	0.007	0.004	0.000	0.005	0.02**
Asian	0.04	0.008	0.01	0.03	0.06*
Black	0.02	0.006	0.01	0.009	0.03*
Multiracial	0.02*	0.003	0.003	0.02	0.03*
Middle School	0.02**	0.001	0.001	0.003	0.01*
High School	0.01**	0.01*	0.006*	**0.02**	**0.04**
Science					
All	0.003*		**0.01**	**0.03**	**0.02**
White	0.007		0.007	0.02**	**0.02**
Hispanic/Latine	0.00		0.006	0.02**	0.02**
Asian	0.02		0.03	0.05*	0.05
Black	0.004		0.03*	0.03*	0.03*
Multiracial	0.015		0.01	0.04**	0.03*
Middle School	0.01**		0.003	0.008*	0.01**
High School	0.00		**0.02**	**0.05**	**0.03**
Computer Science					
All	**0.03**			0.005*	**0.04**
White	0.02**			0.006	**0.03**
Hispanic/Latine	0.01*			0.01	0.03**
Asian	0.05*			0.01	0.08*
Black	0.05**			0.00	0.06**
Multiracial	0.05**			0.01	0.05**
Middle School	**0.02**			0.002	0.02**
High School	**0.03**			0.01**	**0.06**
Engineering					
All	**0.05**				**0.06**
White	**0.05**				**0.06**
Hispanic/Latine	**0.03**				**0.05**
Asian	0.08*				0.09**
Black	0.05**				0.06**
Multiracial	**0.08**				**0.08**
Middle School	**0.03**				**0.03**
High School	**0.06**				**0.10**
Language Arts					
All	**0.01**				
White	0.009				
Hispanic/Latine	0.01*				
Asian	0.02				
Black	0.01				
Multiracial	0.004				
Middle School	0.00				
High School	**0.03**				

Note: Gender differences were largest in computer science and engineering, followed by language arts and math. Gender gaps in engineering ability self-concepts were larger than gender gaps in math and science ability self-concepts, while gender gaps in computer science were larger than math and science only for high school students. All values represent η_p^2. $P \leq 0.001$ indicated **in bold,** $^{**}P \leq 0.01$, $^{*}P < 0.05$.

Table S16. Comparisons of Final Analytic and Original Samples for Stereotypes and Personal Interest

	Analytic Sample		Original Sample				
Variable	*M*	*SD*	*M*	*SD*	*t*	*df*	*P*
Study 1							
Interest Stereotypes							
Math	-0.18	1.62	-0.16	1.65	0.35	3416	.72
Science	-0.01	1.38	-0.02	1.44	0.21	3419	.84
Computer Science	0.67	1.52	0.59	1.59	1.49	3413	.14
Engineering	1.13	1.54	1.08	1.61	0.92	3413	.36
Ability Stereotypes							
Math	-0.32	1.42	-0.31	1.48	0.20	3421	.84
Science	-0.21	1.33	-0.17	1.38	0.85	3425	.39
Computer Science	0.41	1.44	0.36	1.55	0.96	3420	.34
Engineering	0.71	1.49	0.72	1.60	0.19	3422	.85
Interest							
Math	4.07	1.60	4.11	1.60	0.72	3408	.47
Science	4.50	1.37	4.51	1.39	0.21	3408	.83
Computer Science	4.17	1.57	4.22	1.58	0.93	3472	.36
Engineering	4.07	1.54	4.12	1.55	0.94	3403	.35
Study 2							
Interest Stereotypes							
Math	-0.18	1.51	-0.18	1.53	0.00	2826	1.00
Science	-0.14	1.31	-0.15	1.34	0.20	2827	.84
Computer Science	0.93	1.63	0.87	1.67	0.96	2827	.34
Engineering	0.93	1.57	0.92	1.61	0.17	2824	.87
Ability Stereotypes							
Math	-0.35	1.33	-0.31	1.35	0.79	2818	.43
Science	-0.26	1.14	-0.24	1.20	0.39	2818	.70
Computer Science	0.62	1.47	0.59	1.51	0.53	2817	.60
Engineering	0.68	1.46	0.65	1.52	0.53	2815	.60
Interest							
Math	3.80	1.62	3.83	1.62	0.49	2788	.63
Science	4.48	1.34	4.45	1.37	0.58	2788	.56
Computer Science	3.49	1.66	3.53	1.66	0.64	2764	.52
Engineering	3.74	1.63	3.75	1.64	0.16	2764	.87

Note: Sample sizes for the *t*-tests range from *n* = 1484-1490 for the final analytic sample and *n* = 1913-1935 for the original sample in Study 1 due to skipped items. Sample sizes for the *t*-test range from *n* = 1249-1262 for final analytic sample and *n* = 1516-1574 for the original sample in Study 2 due to skipped items.

Table S17. *Uniqueness Analysis of Three Papers*

	Current paper	Master et al. (2021)	Tang et al. (2024)
Research questions	Do stereotypes and motivation about math/science diverge from computer science/ engineering? Do students endorse gender stereotypes favoring boys more strongly for computer science/ engineering than for math/science? Are gender gaps in motivation in computer science, engineering, and language arts larger than gender gaps in motivation in math and science?	Do students endorse gender-interest stereotypes about computer science and engineering? Do gender-interest stereotypes predict interest in computer science and engineering more strongly than gender-ability stereotypes?	What is the developmental change in gender-interest and gender-ability stereotypes in four STEM fields across a single calendar year?
Theoretical framework	Divergences in gender differences in motivation for math/science vs. computer science/engineering are linked to divergence in stereotypes favoring boys across those fields	Gender-interest stereotypes favoring boys reduce girls' interest and sense of belonging in computer science and engineering	Developmental intergroup theory and related models describing the formation of and change over time in stereotypes
Independent variables	Gender-interest and gender-ability stereotypes in math, science, computer science, engineering, and language arts	Gender-interest stereotypes in computer science and engineering, with gender-ability stereotypes as comparison	Gender, grade level, and timepoint
Dependent variables	Personal interest, identification, ability self-concepts, and sense of belonging in math, science, computer science, engineering, and language arts	Personal interest and sense of belonging in computer science and engineering	Gender-interest and gender-ability stereotypes in math, science, computer science, and engineering
Any other differences	Current paper includes a Study 2 which replicates current Study 1 for STEM fields and additionally compares stereotypes and motivation in STEM directly to language arts	Paper includes two additional studies manipulating gender-interest stereotypes	STEM fields considered individually, rather than as divergent pairs; smaller set of grade levels

Note: The current paper makes important advances beyond the Tang et al. (2024) paper, which did not make any statistical comparisons between the different STEM fields (each STEM field was analyzed individually). The current manuscript presents a comprehensive examination of the quantitative extent to which stereotypes vary across different STEM fields, particularly in terms of math/science vs. computer science/engineering, and links that divergence in stereotypes to divergence in motivation for these STEM fields. While Tang et al. (2024) reported stereotypes for multiple STEM fields, they did not statistically analyze or quantify differences in stereotypes between fields. A second major contribution of the current paper lies in the examination of how stereotypes are linked to academic motivation to pursue STEM pathways. Tang et al. (2024) did not report measures of student motivation. Another contribution is that the focus and implications of this paper differ from Tang et al. (2024), which focused on change in stereotypes within a given calendar year for individual students.

Table S18. Study 2 Results Comparing Girls' Motivation across Fields

Measure	M	SD	Language Arts vs. Math/Science F	Language Arts vs. Math/Science η_p^2	Language Arts vs. Comp. Science/ Engineering F	Language Arts vs. Comp. Science/ Engineering η_p^2	Math/Science vs. Comp. Science/ Engineering F	Math/Science vs. Comp. Science/ Engineering η_p^2
Identification			1.42	0.002	**304.30**	0.32	**409.37**	0.38
Language Arts	4.46	1.17						
Math	4.23	1.34						
Science	4.57	1.16						
Computer Sci.	3.09	1.45						
Engineering	3.57	1.63						
Sense of belonging			**11.68**	0.02	**317.47**	0.32	**355.66**	0.35
Language Arts	4.42	1.03						
Math	4.10	1.27						
Science	4.47	1.06						
Computer Sci.	3.39	1.30						
Engineering	3.50	1.33						
Ability self-concept			**25.86**	0.04	**446.96**	0.41	**442.05**	0.40
Language Arts	4.66	1.10						
Math	4.13	1.43						
Science	4.69	1.07						
Computer Sci.	3.20	1.45						
Engineering	3.37	1.46						
Interest			0.17	0.00	**127.83**	0.16	**220.05**	0.25
Language Arts	4.05	1.38						
Math	3.71	1.66						
Science	4.44	1.35						
Computer Sci.	3.14	1.58						
Engineering	3.33	1.60						

Note: Sci. = Science. *$P \leq 0.05$, **$P \leq 0.01$, $P \leq 0.001$ is indicated in **bold**.

Table S19. Study 2 Results Comparing Boys' Motivation across Fields

Measure	M	SD	Language Arts vs. Math/Science		Language Arts vs. Comp. Science/ Engineering		Math/Science vs. Comp. Science/ Engineering	
			F	η_p^2	F	η_p^2	F	η_p^2
Identification			**57.11**	0.09	4.11*	0.01	**86.79**	0.13
Language Arts	4.10	1.29						
Math	4.41	1.35						
Science	4.60	1.21						
Computer Sci.	3.70	1.57						
Engineering	4.21	1.62						
Sense of belonging			**21.41**	0.03	**11.40**	0.02	**72.59**	0.11
Language Arts	4.23	1.11						
Math	4.30	1.19						
Science	4.58	1.00						
Computer Sci.	3.94	1.33						
Engineering	4.14	1.25						
Ability self-concept			**13.10**	0.02	**76.31**	0.12	**190.29**	0.25
Language Arts	4.43	1.14						
Math	4.42	1.34						
Science	4.81	0.99						
Computer Sci.	3.68	1.50						
Engineering	4.00	1.42						
Interest			**81.71**	0.12	**23.09**	0.04	9.77**	0.02
Language Arts	3.66	1.46						
Math	3.91	1.58						
Science	4.54	1.31						
Computer Sci.	3.87	1.67						
Engineering	4.20	1.55						

Note: Sci. = Science. *$P \leq 0.05$, **$P \leq 0.01$, $P \leq 0.001$ is indicated in **bold**.

Table S20. Comparison of Study 1 Results from Final Analytic Sample (*N* = 1497) with Multiple Imputation

	Final Analytic Sample (*N* = 1497)				Multiple Imputation		
Analysis	*F/t*	*df*	*P*	n_p^2/d	*F/t*	*P*	n_p^2/d
Ster. Divergence							
Interest Ster.	696.57	1, 1479	< 0.001	0.32	696.10 to 711.35	< 0.001	0.32
Ability Ster.	548.57	1, 1480	< 0.001	0.27	545.29 to 554.73	< 0.001	0.27
Difference from Neutral							
Interest Ster.							
CS	17.04	1485	< 0.001	0.44	16.94 to 17.20	< 0.001	0.44
Engin.	28.22	1483	< 0.001	0.73	28.27 to 28.52	< 0.001	0.73
Math	-4.22	1484	< 0.001	-0.11	-4.40 to -4.19	< 0.001	-0.11
Science	-0.15	1486	0.88	-0.004	-0.24 to -0.04	0.81 to 0.97	-0.01 to 0.00
Ability Ster.							
CS	10.93	1489	< 0.001	0.28	10.89 to 11.05	< 0.001	0.28 to 0.29
Engin.	18.46	1489	< 0.001	0.48	18.46 to 18.58	< 0.001	0.48
Math	-8.81	1488	< 0.001	-0.23	-8.71 to -8.64	< 0.001	-0.23 to -0.22
Science	-6.04	1491	< 0.001	-0.16	-0.60 to -5.91	< 0.001	-0.16 to -0.15
Div. x Gender Interaction							
Interest Ster.	0.77	1, 1479	0.38	0.001	0.58 to 0.95	0.33 to 0.45	0.000 to 0.001
Ability Ster.	0.75	1, 1480	0.39	0.001	0.38 to 0.60	0.44 to 0.54	0.00
Personal Interest Div.	61.02	1, 1490	< 0.001	0.04	60.03 to 62.59	< 0.001	0.039 to 0.040
Effect of Gender on Personal Interest							
CS	50.33	1, 1490	< 0.001	0.03	49.46 to 51.18	< 0.001	0.03
Engin.	85.36	1, 1490	< 0.001	0.05	84.24 to 87.88	< 0.001	0.05 to 0.06
Math	0.67	1, 1490	0.41	0.000	0.51 to 0.70	0.40 to 0.48	0.00
Science	5.15	1, 1490	0.02	0.003	4.63 to 5.44	0.02 to 0.03	0.003 to 0.004
Girls' Personal Interest							
CS/E. vs. Math/Science	78.99	1, 659	< 0.001	0.096	77.67 to 81.29	< 0.001	0.09 to 0.10

Note: Multiple imputation was conducted with 10 datasets using SPSS; degrees of freedom corresponded to the full sample size. Ster. = stereotypes. CS = Computer science. E. = Engin. = Engineering. Int. = Interest. Abil. = Ability. Div. = Divergence. Sch. = School.

Table S21. Comparison of Study 1 Results from Full Sample (*N* = 1954) with Multiple Imputation

	Full Sample (*N* = 1954)				Multiple Imputation		
Analysis	*F/t*	*df*	*P*	n_p^2/d	*F/t*	*P*	n_p^2/d
Ster. Divergence							
Interest Ster.	85.99	1, 1917	< 0.001	0.043	81.86 to 88.11	< 0.001	0.04
Ability Ster.	55.19	1, 1914	< 0.001	0.028	51.61 to 55.59	< 0.001	0.03
Difference from Neutral							
Interest Ster.							
CS	16.41	1928	< 0.001	0.37	16.28 to 16.58	< 0.001	0.37 to 0.38
Engin.	29.59	1930	< 0.001	0.67	29.51 to 29.93	< 0.001	0.67 to 0.68
Math	-4.17	1932	< 0.001	-0.10	-4.36 to -4.07	< 0.001	-0.10 to -0.09
Science	-0.60	1933	0.55	-0.01	-0.69 to -0.42	0.25 to 0.67	-0.02 to -0.01
Ability Ster.							
CS	10.11	1931	< 0.001	0.23	10.00 to 10.22	< 0.001	0.23
Engin.	19.79	1933	< 0.001	0.45	19.67 to 20.02	< 0.001	0.45
Math	-9.19	1933	< 0.001	-0.21	-9.31 to -8.92	< 0.001	-0.21 to -0.20
Science	-5.35	1934	< 0.001	-0.12	-5.56 to -5.30	< 0.001	-0.12
Div. x Gender Interaction							
Interest Ster.	1.08	3, 1917	0.35	0.002	1.11 to 1.83	0.14 to 0.35	0.002 to 0.003
Ability Ster.	1.18	3, 1913	0.32	0.002	1.30 to 2.21	0.09 to 0.27	0.002 to 0.003
Personal Int. Div.	21.78	3, 1908	< 0.001	0.033	21.74 to 23.24	< 0.001	0.03 to 0.04
Effect of Gender on Personal Interest							
CS	20.11	3, 1908	< 0.001	0.031	17.81 to 20.08	< 0.001	0.03
Engin.	35.38	3, 1908	< 0.001	0.053	33.54 to 36.46	< 0.001	0.05
Math	3.37	3, 1908	0.018	0.005	2.18 to 2.95	0.03 to 0.09	0.003 to 0.005
Science	2.85	3, 1908	0.036	0.004	1.91 to 2.33	0.07 to 0.13	0.003 to 0.004
Girls' Personal Interest							
CS/E. vs. Math/Science	77.84	1, 890	< 0.001	0.080	78.33 to 84.39	< 0.001	0.08 to 0.09

Note: Multiple imputation was conducted with 10 datasets using SPSS; degrees of freedom corresponded to the full sample size. Ster. = stereotypes. CS = Computer science. E. = Engin. = Engineering. Int. = Interest. Abil. = Ability. Div. = Divergence. Sch. = School. The gender variable includes *n* = 19 students who self-identified as gender fluid/nonbinary, *n* = 22 who gave an irrelevant response, and *n* = 65 whose gender was missing.

Table S22. Comparison of Study 2 Results from Final Analytic Sample (*N* = 1268) with Multiple Imputation

	Final Analytic Sample (*N* = 1268)				Multiple Imputation		
Analysis	*F/t*	*df*	*P*	n_p^2/d	*F/t*	*P*	n_p^2/d
Ster. Divergence							
Interest Ster.	667.82	1, 1252	< 0.001	0.35	666.96 to 686.69	< 0.001	0.35
Ability Ster.	604.48	1, 1247	< 0.001	0.33	596.41 to 616.91	< 0.001	0.32 to 0.33
Difference from Neutral							
Interest Ster.							
CS	20.24	1253	< 0.001	0.57	20.10 to 20.51	< 0.001	0.57 to 0.58
Eng.	20.97	1253	< 0.001	0.59	20.75 to 21.17	< 0.001	0.58 to 0.59
Math	-4.20	1253	< 0.001	-0.12	-4.36 to -4.05	< 0.001	-0.12 to -0.11
Science	-3.89	1253	< 0.001	-0.11	-4.03 to -3.71	< 0.001	-0.11 to -0.10
Lang. Arts	-23.95	1253	< 0.001	-0.68	-24.06 to -23.81	< 0.001	-0.68 to -0.67
Ability Ster.							
CS	14.85	1249	< 0.001	0.42	14.83 to 15.19	< 0.001	0.42 to 0.43
Eng.	16.38	1248	< 0.001	0.46	16.16 to 16.64	< 0.001	0.45 to 0.47
Math	-9.36	1249	< 0.001	-0.27	-9.52 to -9.29	< 0.001	-0.27 to -0.26
Science	-8.05	1249	< 0.001	-0.23	-8.25 to -7.88	< 0.001	-0.23 to -0.22
Lang. Arts	-21.46	1249	< 0.001	-0.61	-21.72 to -21.27	< 0.001	-0.61 to -0.60
Div. x Gender Interaction							
Interest Ster.	3.64	1, 1252	0.057	0.003	3.05 to 4.18	0.04 to 0.08	0.002 to 0.003
Ability Ster.	5.54	1, 1247	0.019	0.004	3.98 to 5.72	0.02 to 0.05	0.003 to 0.004
Personal Int. Div.	60.72	1, 1245	< 0.001	0.05	58.18 to 61.32	< 0.001	0.04 to 0.05
Effect of Gender on Personal Interest							
CS	61.76	1, 1245	< 0.001	0.047	60.11 to 63.41	< 0.001	0.05
Eng.	94.68	1, 1245	< 0.001	0.07	90.90 to 95.67	< 0.001	0.07
Math	4.71	1, 1245	0.03	0.004	4.33 to 4.82	0.03 to 0.04	0.003 to 0.004
Science	1.77	1, 1245	0.18	0.001	1.71 to 2.06	0.15 to 0.19	0.001 to 0.002
Lang. Arts	23.61	1, 1245	< 0.001	0.019	23.78 to 25.18	< 0.001	0.018 to 0.020
Girls' Personal Interest							
CS/E. vs. Math/Sci.	220.05	1, 659	< 0.001	0.25	217.60 to 225.24	< 0.001	0.25
CS/E. vs. Lang. Arts	127.83	1, 659	< 0.001	0.16	125.41 to 130.88	< 0.001	0.16
Abil. Self-Concept Div.	20.72	1, 1237	< 0.001	0.016	19.72 to 21.61	< 0.001	0.02
Effect of Gender on Ability Self-Concept							
CS	32.59	1, 1237	< 0.001	0.026	31.56 to 34.90	< 0.001	0.02 to 0.03
Eng.	60.44	1, 1237	< 0.001	0.047	59.38 to 63.25	< 0.001	0.05
Math	13.52	1, 1237	< 0.001	0.011	13.30 to 14.12	< 0.001	0.01
Science	4.20	1, 1237	0.04	0.003	4.56 to 5.24	0.02 to 0.03	0.003 to 0.004
Lang. Arts	13.15	1, 1237	< 0.001	0.011	13.42 to 14.84	< 0.001	0.01
Girls' Ability Self-Concept							
CS/E. vs. Math/Sci.	442.05	1, 651	< 0.001	0.40	449.48 to 463.62	< 0.001	0.40 to 0.41
CS/E. vs. Lang. Arts	446.96	1, 651	< 0.001	0.41	460.15 to 470.77	< 0.001	0.41

Note: Multiple imputation was conducted with 10 datasets using SPSS; degrees of freedom corresponded to the full sample size. Ster. = stereotypes. CS = Computer science. E. = Eng. = Engineering. Sci. = Science. Lang. Arts = Language arts. Int. = Interest. Abil. = Ability. Div. = Divergence. Sch. = School.

Table S23. Comparison of Study 2 Results from Full Sample (N = 1629) with Multiple Imputation

	Full Sample (N = 1629)				Multiple Imputation		
Analysis	*F/t*	*df*	*P*	n_p^2/d	*F/t*	*P*	n_p^2/d
Ster. Divergence							
Interest Ster.	105.12	1, 1569	< 0.001	0.06	102.80 to 117.86	< 0.001	0.06 to 0.07
Ability Ster.	54.03	1, 1563	< 0.001	0.03	55.26 to 63.63	< 0.001	0.03 to 0.04
Difference from Neutral							
Interest Ster.							
CS	20.55	1574	< 0.001	0.52	20.22 to 20.67	< 0.001	0.50 to 0.51
Engin.	22.63	1572	< 0.001	0.57	22.33 to 23.06	< 0.001	0.55 to 0.57
Math	-4.60	1573	< 0.001	-0.12	-5.35 to -4.70	< 0.001	-0.13 to -0.12
Science	-4.51	1574	< 0.001	-0.11	-5.13 to -4.51	< 0.001	-0.13 to -0.11
Lang. Arts	-24.55	1572	< 0.001	-0.62	-25.08 to -24.32	< 0.001	-0.60 to -0.62
Ability Ster.							
CS	15.37	1568	< 0.001	0.39	15.16 to 15.50	< 0.001	0.38
Engin.	16.90	1567	< 0.001	0.43	16.72 to 17.16	< 0.001	0.41 to 0.43
Math	-9.18	1569	< 0.001	-0.23	-9.69 to –9.12	< 0.001	-0.24 to -0.23
Science	-7.79	1569	< 0.001	-0.20	-8.04 to -7.70	< 0.001	-0.20 to -0.19
Lang. Arts	-21.72	1569	< 0.001	-0.55	-21.22 to -21.47	< 0.001	-0.55 to -0.53
Div. x Gender Interaction							
Interest Ster.	0.45	3, 1569	0.72	0.001	0.32 to 1.03	0.38 to 0.81	0.001 to 0.002
Ability Ster.	2.85	3, 1563	0.04	0.01	2.54 to 4.49	0.004 to 0.055	0.01
Personal Int. Div.	23.67	3, 1509	< 0.001	0.05	23.09 to 27.28	< 0.001	0.04 to 0.05
Effect of Gender on Personal Interest							
CS	23.35	3, 1509	< 0.001	0.04	23.53 to 25.09	< 0.001	0.04
Engin.	39.69	3, 1509	< 0.001	0.07	40.41 to 43.06	< 0.001	0.07
Math	9.31	3, 1509	< 0.001	0.02	9.18 to 12.23	< 0.001	0.02
Science	5.46	3, 1509	< 0.001	0.10	3.42 to 7.55	0.00 to 0.02	0.01
Lang. Arts	7.41	3, 1509	< 0.001	0.02	7.51 to 12.38	< 0.001	0.01 to 0.02
Girls' Personal Interest							
CS/E. vs. Math/Sci.	238.10	1, 763	< 0.001	0.24	235.49 to 240.68	< 0.001	0.23 to 0.24
CS/E. vs. Lang. Arts	136.94	1, 763	< 0.001	0.15	135.21 to 139.92	< 0.001	0.15
Abil. Self-Concept Div.	49.24	1, 1519	< 0.001	0.03	60.53 to 73.57	< 0.001	0.04
Effect of Gender on Ability Self-Concept							
CS	11.85	3, 1519	< 0.001	0.03	14.63 to 16.31	< 0.001	0.03
Engin.	22.36	3, 1519	< 0.001	0.06	28.67 to 30.08	< 0.001	0.05
Math	13.44	3, 1519	< 0.001	0.03	12.38 to 19.03	< 0.001	0.02 to 0.03
Science	4.77	3, 1519	0.003	0.01	4.85 to 11.73	0.00 to 0.002	0.01 to 0.02
Lang. Arts	3.58	3, 1519	0.014	0.01	4.16 to 9.31	0.00 to 0.01	0.01 to 0.02
Girls' Ability Self-Concept							
CS/E. vs. Math/Sci.	494.93	1, 753	< 0.001	0.40	492.93 to 511.49	< 0.001	0.39 to 0.40
CS/E. vs. Lang. Arts	497.41	1, 753	< 0.001	0.40	506.94 to 521.51	< 0.01	0.40

Note: Multiple imputation was conducted with 10 datasets using SPSS; degrees of freedom corresponded to the full sample size. Ster. = stereotypes. CS = Computer science. E. = Engin. = Engineering. Sci. = Science. Lang. Arts = Language arts. Int. = Interest. Abil. = Ability. Div. = Divergence. Sch. = School. The gender variable includes n = 20 students who self-identified as gender fluid/nonbinary, n = 12 who gave an irrelevant response, and n = 70 whose gender was missing.

Dataset S1. (separate file) Missing values are left blank unless otherwise indicated. Race/ethnicity information was removed from the public dataset to exclude potentially identifying information.

Dataset S1. (separate file) Missing values are left blank unless otherwise indicated. Race/ethnicity information was removed from the public dataset to exclude potentially identifying information.

ResponseID	Participant identification number
Att_Check	Please choose "slightly disagree" to show that you read this question. (1 = Strongly disagree, 2 = Disagree, 3 = Slightly disagree, 4 = Slightly agree, 5 = Agree, 6 = Strongly agree) Participants who chose "3 = Slightly disagree" were included in analyses.
age_yr	Age in years
Gender_final	Self-identified gender (1 = boy, 2 = girl, 3 = gender fluid/non-binary, 4 = N/A, 5 = unknown).
grade	Grade levels 1-12
schl	School level (1 = Elementary, Grades 1–5; 2 = Middle, Grades 6–8; 3 = High, Grades 9–12)
order	Which order the four academic fields were displayed in (M = math; S = science; C = computer science; E = engineering): Order 1: MSCE Order 2: SMCE Order 3: CMSE Order 4: MCSE Order 5: SCME Order 6: CSME Order 7: CSEM Order 8: SCEM Order 9: ECSM Order 10: CESM Order 11: SECM Order 12: ESCM Order 13: EMCS Order 14: MECS Order 15: CEMS Order 16: ECMS Order 17: MCES Order 18: CMES Order 19: SMEC Order 20: MSEC Order 21: ESMC Order 22: SEMC Order 23: MESC Order 24: EMSC
mothersed	Mother's education level (1 = Didn't finish high school, 2 = Graduated from high school, 3 = Some college classes, 4 = Graduated from college, 5 = Some graduate school classes, 6 = Graduate degree)
lmeG	How much do most girls like math? (1 = Really do not like, 2 = Do not like, 3 = Slightly do not like, 4 = Slightly like, 5 = Do like, 6 = Really like); l represents like, m represents math, e represents endorsement (in contrast to awareness), and G represents girls
lseG	How much do most girls like science? (1 = Really do not like, 2 = Do not like, 3 = Slightly do not like, 4 = Slightly like, 5 = Do like, 6 = Really like); l represents like, s represents science, e represents endorsement, and G represents girls

lceG	How much do most girls like computer coding? (1 = Really do not like, 2 = Do not like, 3 = Slightly do not like, 4 = Slightly like, 5 = Do like, 6 = Really like); l represents like, c represents computer science, e represents endorsement, and G represents girls
leeG	How much do most girls like engineering? (1 = Really do not like, 2 = Do not like, 3 = Slightly do not like, 4 = Slightly like, 5 = Do like, 6 = Really like); l represents like, e represents engineering, e represents endorsement, and G represents girls
lmeB	How much do most boys like math? (1 = Really do not like, 2 = Do not like, 3 = Slightly do not like, 4 = Slightly like, 5 = Do like, 6 = Really like); l represents like, m represents math, e represents endorsement, and B represents boys
lseB	How much do most boys like science? (1 = Really do not like, 2 = Do not like, 3 = Slightly do not like, 4 = Slightly like, 5 = Do like, 6 = Really like); l represents like, s represents science, e represents endorsement, and B represents boys
lceB	How much do most boys like computer coding? (1 = Really do not like, 2 = Do not like, 3 = Slightly do not like, 4 = Slightly like, 5 = Do like, 6 = Really like); l represents like, c represents computer science, e represents endorsement, and B represents boys
leeB	How much do most boys like engineering? (1 = Really do not like, 2 = Do not like, 3 = Slightly do not like, 4 = Slightly like, 5 = Do like, 6 = Really like); l represents like, e represents engineering, e represents endorsement, and B represents boys
gmeG	How good are most girls at math? (1 = Really not good, 2 = Not good, 3 = Slightly not good, 4 = Slightly good, 5 = Good, 6 = Really good); g represents good at, m represents math, e represents endorsement, and G represents girls
gseG	How good are most girls at science? (1 = Really not good, 2 = Not good, 3 = Slightly not good, 4 = Slightly good, 5 = Good, 6 = Really good); g represents good at, s represents science, e represents endorsement, and G represents girls
gceG	How good are most girls at computer coding? (1 = Really not good, 2 = Not good, 3 = Slightly not good, 4 = Slightly good, 5 = Good, 6 = Really good); g represents good at, c represents computer science, e represents endorsement, and G represents girls
geeG	How good are most girls at engineering? (1 = Really not good, 2 = Not good, 3 = Slightly not good, 4 = Slightly good, 5 = Good, 6 = Really good); g represents good at, e represents engineering, e represents endorsement, and G represents girls
gmeB	How good are most boys at math? (1 = Really not good, 2 = Not good, 3 = Slightly not good, 4 = Slightly good, 5 = Good, 6 = Really good); g represents good at, m represents math, e represents endorsement, and B represents boys
gseB	How good are most boys at science? (1 = Really not good, 2 = Not good, 3 = Slightly not good, 4 = Slightly good, 5 = Good, 6 = Really good); g represents good at, s represents science, e represents endorsement, and B represents boys
gceB	How good are most boys at computer coding? (1 = Really not good, 2 = Not good, 3 = Slightly not good, 4 = Slightly good, 5 = Good, 6 = Really good); g represents good at, c represents computer science, e represents endorsement, and B represents boys

geeB	How good are most boys at engineering? (1 = Really not good, 2 = Not good, 3 = Slightly not good, 4 = Slightly good, 5 = Good, 6 = Really good); g represents good at, e represents engineering, e represents endorsement, and B represents boys
int1m	I like to do math activities. (1 = Strongly disagree, 2 = Disagree, 3 = Slightly disagree, 4 = Slightly agree, 5 = Agree, 6 = Strongly agree)
int1s	I like to do science activities. (1 = Strongly disagree, 2 = Disagree, 3 = Slightly disagree, 4 = Slightly agree, 5 = Agree, 6 = Strongly agree)
int1c	I like to do computer coding activities. (1 = Strongly disagree, 2 = Disagree, 3 = Slightly disagree, 4 = Slightly agree, 5 = Agree, 6 = Strongly agree)
int1e	I like to do engineering activities. (1 = Strongly disagree, 2 = Disagree, 3 = Slightly disagree, 4 = Slightly agree, 5 = Agree, 6 = Strongly agree)
int2m	I am interested in math activities. (1 = Strongly disagree, 2 = Disagree, 3 = Slightly disagree, 4 = Slightly agree, 5 = Agree, 6 = Strongly agree)
int2s	I am interested in science activities. (1 = Strongly disagree, 2 = Disagree, 3 = Slightly disagree, 4 = Slightly agree, 5 = Agree, 6 = Strongly agree)
int2c	I am interested in computer coding activities. (1 = Strongly disagree, 2 = Disagree, 3 = Slightly disagree, 4 = Slightly agree, 5 = Agree, 6 = Strongly agree)
int2e	I am interested in engineering activities. (1 = Strongly disagree, 2 = Disagree, 3 = Slightly disagree, 4 = Slightly agree, 5 = Agree, 6 = Strongly agree)
BirthYear_error	Identifies students who may have incorrectly entered their birth year (3 years from median age for that grade). These students were not included in mean age calculations.
intsterm	Difference score for math interest stereotypes (ImeB – ImeG); range -5 to 5
intsters	Difference score for science interest stereotypes (IseB – IseG); range -5 to 5
intsterc	Difference score for computer science interest stereotypes (IceB – IceG); range -5 to 5
intstere	Difference score for engineering interest stereotypes (IeeB – IeeG); range -5 to 5
gme	Difference score for math ability stereotypes (gmeB – gmeG); range -5 to 5
gse	Difference score for science ability stereotypes (gseB – gseG); range -5 to 5
gce	Difference score for computer science ability stereotypes (gceB – gceG); range -5 to 5
gee	Difference score for engineering ability stereotypes (geeB – geeG); range -5 to 5
intm	Scale interest in math (2 items); range 1–6
ints	Scale interest in science (2 items); range 1–6
intc	Scale interest in computer coding (2 items); range 1–6
inte	Scale interest in engineering (2 items); range 1–6
avintstms	Average of interest stereotypes about math and science

avintstce	Average of interest stereotypes about computer science and engineering
avablstms	Average of ability stereotypes about math and science
avablstce	Average of ability stereotypes about computer science and engineering
avintms	Average of personal interest in math and science
avintce	Average of personal interest in computer science and engineering
diverintster	Divergence between math/science and computer science/engineering interest stereotypes (avintstce – avintstms)
diverablster	Divergence between math/science and computer science/engineering ability stereotypes (avablstce – avablstms)
diverint	Divergence between math/science and computer science/engineering interest (avintce – avintms)

Dataset S2. (separate file) Missing values are left blank unless otherwise indicated. Race/ethnicity information was removed from the public dataset to exclude potentially identifying information.

Dataset S2. (separate file) Missing values are left blank unless otherwise indicated. Race/ethnicity information was removed from the public dataset to exclude potentially identifying information.

ResponseID	Participant identification number
grade	Grade levels 6–12
lmeG	How much do you think that most girls like these subjects? - Math (1 = Really do not like, 2 = Do not like, 3 = Slightly do not like, 4 = Slightly like, 5 = Do like, 6 = Really like); l represents like, m represents math, e represents endorsement (in contrast to awareness), and G represents girls
lseG	How much do you think that most girls like these subjects? - Science (1 = Really do not like, 2 = Do not like, 3 = Slightly do not like, 4 = Slightly like, 5 = Do like, 6 = Really like); l represents like, s represents science, e represents endorsement, and G represents girls
lceG	How much do you think that most girls like these subjects? - Computer coding (1 = Really do not like, 2 = Do not like, 3 = Slightly do not like, 4 = Slightly like, 5 = Do like, 6 = Really like); l represents like, c represents computer science, e represents endorsement, and G represents girls
leeG	How much do you think that most girls like these subjects? - Engineering (1 = Really do not like, 2 = Do not like, 3 = Slightly do not like, 4 = Slightly like, 5 = Do like, 6 = Really like); l represents like, e represents engineering, e represents endorsement, and G represents girls
lleG	How much do you think that most girls like these subjects? – English/Language Arts (1 = Really do not like, 2 = Do not like, 3 = Slightly do not like, 4 = Slightly like, 5 = Do like, 6 = Really like); l represents like, l represents language arts, e represents endorsement, and G represents girls
lmeB	How much do you think that most boys like these subjects? – Math (1 = Really do not like, 2 = Do not like, 3 = Slightly do not like, 4 = Slightly like, 5 = Do like, 6 = Really like); l represents like, m represents math, e represents endorsement, and B represents boys
lseB	How much do you think that most boys like these subjects? – Science (1 = Really do not like, 2 = Do not like, 3 = Slightly do not like, 4 = Slightly like, 5 = Do like, 6 = Really like); l represents like, s represents science, e represents endorsement, and B represents boys
lceB	How much do you think that most boys like these subjects? – Computer coding (1 = Really do not like, 2 = Do not like, 3 = Slightly do not like, 4 = Slightly like, 5 = Do like, 6 = Really like); l represents like, c represents computer science, e represents endorsement, and B represents boys
leeB	How much do you think that most boys like these subjects? – Engineering (1 = Really do not like, 2 = Do not like, 3 = Slightly do not like, 4 = Slightly like, 5 = Do like, 6 = Really like); l represents like, e represents engineering, e represents endorsement, and B represents boys
lleb	How much do you think that most boys like these subjects? – English/Language Arts (1 = Really do not like, 2 = Do not like, 3 = Slightly do not like, 4 = Slightly like, 5 = Do like, 6 = Really like); l represents like, l represents language arts, e represents endorsement, and B represents boys
gmeG	How good do you think that most girls are at these subjects? – Math (1 = Really not good, 2 = Not good, 3 = Slightly not good, 4 = Slightly good, 5 = Good, 6 = Really good); g represents good at, m represents math, e represents endorsement, and G represents girls

gseG	How good do you think that most girls are at these subjects? – Science (1 = Really not good, 2 = Not good, 3 = Slightly not good, 4 = Slightly good, 5 = Good, 6 = Really good); g represents good at, s represents science, e represents endorsement, and G represents girls
gceG	How good do you think that most girls are at these subjects? – Computer coding (1 = Really not good, 2 = Not good, 3 = Slightly not good, 4 = Slightly good, 5 = Good, 6 = Really good); g represents good at, c represents computer science, e represents endorsement, and G represents girls
geeG	How good do you think that most girls are at these subjects? – Engineering (1 = Really not good, 2 = Not good, 3 = Slightly not good, 4 = Slightly good, 5 = Good, 6 = Really good); g represents good at, e represents engineering, e represents endorsement, and G represents girls
gleG	How good do you think that most girls are at these subjects? – English/Language Arts (1 = Really not good, 2 = Not good, 3 = Slightly not good, 4 = Slightly good, 5 = Good, 6 = Really good); g represents good at, l represents language arts, e represents endorsement, and G represents girls
gmeB	How good do you think that most boys are at these subjects? – Math (1 = Really not good, 2 = Not good, 3 = Slightly not good, 4 = Slightly good, 5 = Good, 6 = Really good); g represents good at, m represents math, e represents endorsement, and B represents boys
gseB	How good do you think that most boys are at these subjects? – Science (1 = Really not good, 2 = Not good, 3 = Slightly not good, 4 = Slightly good, 5 = Good, 6 = Really good); g represents good at, s represents science, e represents endorsement, and B represents boys
gceB	How good do you think that most boys are at these subjects? – Computer coding (1 = Really not good, 2 = Not good, 3 = Slightly not good, 4 = Slightly good, 5 = Good, 6 = Really good); g represents good at, c represents computer science, e represents endorsement, and B represents boys
geeB	How good do you think that most boys are at these subjects? – Engineering (1 = Really not good, 2 = Not good, 3 = Slightly not good, 4 = Slightly good, 5 = Good, 6 = Really good); g represents good at, e represents engineering, e represents endorsement, and B represents boys
gleB	How good do you think that most boys are at these subjects? – English/Language Arts (1 = Really not good, 2 = Not good, 3 = Slightly not good, 4 = Slightly good, 5 = Good, 6 = Really good); g represents good at, l represents language arts, e represents endorsement, and B represents boys
bel1m	How much do you feel like you belong when you do these classes and activities at school? – Math (1 = Really do not belong, 2 = Do not belong, 3 = Slightly do not belong, 4 = Slightly belong, 5 = Belong, 6 = Really belong)
bel1s	How much do you feel like you belong when you do these classes and activities at school? – Science (1 = Really do not belong, 2 = Do not belong, 3 = Slightly do not belong, 4 = Slightly belong, 5 = Belong, 6 = Really belong)
bel1c	How much do you feel like you belong when you do these classes and activities at school? – Computer coding (1 = Really do not belong, 2 = Do not belong, 3 = Slightly do not belong, 4 = Slightly belong, 5 = Belong, 6 = Really belong)
bel1e	How much do you feel like you belong when you do these classes and activities at school? – Engineering (1 = Really do not belong, 2 = Do not belong, 3 = Slightly do not belong, 4 = Slightly belong, 5 = Belong, 6 = Really belong)
bel1l	How much do you feel like you belong when you do these classes and activities at school? – English/Language Arts (1 = Really do not belong, 2 = Do not belong, 3 = Slightly do not belong, 4 = Slightly belong, 5 = Belong, 6 = Really belong)

bel2m	How comfortable do you feel when you do these classes and activities at school? – Math (1 = Really not comfortable, 2 = Not comfortable, 3 = Slightly not comfortable, 4 = Slightly comfortable, 5 = Comfortable, 6 = Really comfortable)
bel2s	How comfortable do you feel when you do these classes and activities at school? – Science (1 = Really not comfortable, 2 = Not comfortable, 3 = Slightly not comfortable, 4 = Slightly comfortable, 5 = Comfortable, 6 = Really comfortable)
bel2c	How comfortable do you feel when you do these classes and activities at school? – Computer coding (1 = Really not comfortable, 2 = Not comfortable, 3 = Slightly not comfortable, 4 = Slightly comfortable, 5 = Comfortable, 6 = Really comfortable)
bel2e	How comfortable do you feel when you do these classes and activities at school? – Engineering (1 = Really not comfortable, 2 = Not comfortable, 3 = Slightly not comfortable, 4 = Slightly comfortable, 5 = Comfortable, 6 = Really comfortable)
bel2l	How comfortable do you feel when you do these classes and activities at school? – English/Language Arts (1 = Really not comfortable, 2 = Not comfortable, 3 = Slightly not comfortable, 4 = Slightly comfortable, 5 = Comfortable, 6 = Really comfortable)
bel3m	How much do you feel like people in these classes and activities are similar to you? – Math (1 = Really not similar, 2 = Not similar, 3 = Slightly not similar, 4 = Slightly similar, 5 = Similar, 6 = Really similar)
bel3s	How much do you feel like people in these classes and activities are similar to you? – Science (1 = Really not similar, 2 = Not similar, 3 = Slightly not similar, 4 = Slightly similar, 5 = Similar, 6 = Really similar)
bel3c	How much do you feel like people in these classes and activities are similar to you? – Computer coding (1 = Really not similar, 2 = Not similar, 3 = Slightly not similar, 4 = Slightly similar, 5 = Similar, 6 = Really similar)
bel3e	How much do you feel like people in these classes and activities are similar to you? – Engineering (1 = Really not similar, 2 = Not similar, 3 = Slightly not similar, 4 = Slightly similar, 5 = Similar, 6 = Really similar)
bel3l	How much do you feel like people in these classes and activities are similar to you? – English/Language Arts (1 = Really not similar, 2 = Not similar, 3 = Slightly not similar, 4 = Slightly similar, 5 = Similar, 6 = Really similar)
Att_Check	Please choose the face marked “slightly disagree” to show that you read this question. (1 = Strongly disagree, 2 = Disagree, 3 = Slightly disagree, 4 = Slightly agree, 5 = Agree, 6 = Strongly agree) Participants who chose “3 = Slightly disagree” were included in analyses.
eff1m	How good are you at these classes and activities? – Math (1 = Really not good, 2 = Not good, 3 = Slightly not good, 4 = Slightly good, 5 = Good, 6 = Really good)
eff1s	How good are you at these classes and activities? – Science (1 = Really not good, 2 = Not good, 3 = Slightly not good, 4 = Slightly good, 5 = Good, 6 = Really good)
eff1c	How good are you at these classes and activities? – Computer coding (1 = Really not good, 2 = Not good, 3 = Slightly not good, 4 = Slightly good, 5 = Good, 6 = Really good)
eff1e	How good are you at these classes and activities? – Engineering (1 = Really not good, 2 = Not good, 3 = Slightly not good, 4 = Slightly good, 5 = Good, 6 = Really good)
eff1l	How good are you at these classes and activities? – English/Language Arts (1 = Really not good, 2 = Not good, 3 = Slightly not good, 4 = Slightly good, 5 = Good, 6 = Really good)
eff2m	How well do you feel like you understand these classes and activities? – Math (1 = Really not understand, 2 = Not understand, 3 = Slightly not understand, 4 = Slightly understand, 5 = Understand, 6 = Really understand)

eff2s	How well do you feel like you understand these classes and activities? – Science (1 = Really not understand, 2 = Not understand, 3 = Slightly not understand, 4 = Slightly understand, 5 = Understand, 6 = Really understand)
eff2c	How well do you feel like you understand these classes and activities? – Computer coding (1 = Really not understand, 2 = Not understand, 3 = Slightly not understand, 4 = Slightly understand, 5 = Understand, 6 = Really understand)
eff2e	How well do you feel like you understand these classes and activities? – Engineering (1 = Really not understand, 2 = Not understand, 3 = Slightly not understand, 4 = Slightly understand, 5 = Understand, 6 = Really understand)
eff2l	How well do you feel like you understand these classes and activities? – English/Language Arts (1 = Really not understand, 2 = Not understand, 3 = Slightly not understand, 4 = Slightly understand, 5 = Understand, 6 = Really understand)
id1m	How much do you feel like you are a _____ person? – Math (1 = Strongly disagree, 2 = Disagree, 3 = Slightly disagree, 4 = Slightly agree, 5 = Agree, 6 = Strongly agree)
id1s	How much do you feel like you are a _____ person? – Science (1 = Strongly disagree, 2 = Disagree, 3 = Slightly disagree, 4 = Slightly agree, 5 = Agree, 6 = Strongly agree)
id1c	How much do you feel like you are a _____ person? – Computer coding (1 = Strongly disagree, 2 = Disagree, 3 = Slightly disagree, 4 = Slightly agree, 5 = Agree, 6 = Strongly agree)
id1e	How much do you feel like you are a _____ person? – Engineering (1 = Strongly disagree, 2 = Disagree, 3 = Slightly disagree, 4 = Slightly agree, 5 = Agree, 6 = Strongly agree)
id1l	How much do you feel like you are a _____ person? – English/Language Arts (1 = Strongly disagree, 2 = Disagree, 3 = Slightly disagree, 4 = Slightly agree, 5 = Agree, 6 = Strongly agree)
id2m	How important are these classes and activities to you? – Math (1 = Really not important, 2 = Not important, 3 = Slightly not important, 4 = Slightly important, 5 = Important, 6 = Really important)
id2s	How important are these classes and activities to you? – Science (1 = Really not important, 2 = Not important, 3 = Slightly not important, 4 = Slightly important, 5 = Important, 6 = Really important)
id2c	How important are these classes and activities to you? – Computer coding (1 = Really not important, 2 = Not important, 3 = Slightly not important, 4 = Slightly important, 5 = Important, 6 = Really important)
id2e	How important are these classes and activities to you? – Engineering (1 = Really not important, 2 = Not important, 3 = Slightly not important, 4 = Slightly important, 5 = Important, 6 = Really important)
id2l	How important are these classes and activities to you? – English/Language Arts (1 = Really not important, 2 = Not important, 3 = Slightly not important, 4 = Slightly important, 5 = Important, 6 = Really important)
int1m	How much do you like to do these activities? – Math (1 = Really do not like, 2 = Do not like, 3 = Slightly do not like, 4 = Slightly like, 5 = Like, 6 = Really like)
int1s	How much do you like to do these activities? – Science (1 = Really do not like, 2 = Do not like, 3 = Slightly do not like, 4 = Slightly like, 5 = Like, 6 = Really like)
int1c	How much do you like to do these activities? – Computer coding (1 = Really do not like, 2 = Do not like, 3 = Slightly do not like, 4 = Slightly like, 5 = Like, 6 = Really like)
int1e	How much do you like to do these activities? – Engineering (1 = Really do not like, 2 = Do not like, 3 = Slightly do not like, 4 = Slightly like, 5 = Like, 6 = Really like)

int1l	How much do you like to do these activities? – English/Language Arts (1 = Really do not like, 2 = Do not like, 3 = Slightly do not like, 4 = Slightly like, 5 = Like, 6 = Really like)
int2m	How interested are you in these activities? – Math (1 = Really not interested, 2 = Not interested, 3 = Slightly not interested, 4 = Slightly interested, 5 = Interested, 6 = Really interested)
int2s	How interested are you in these activities? – Science (1 = Really not interested, 2 = Not interested, 3 = Slightly not interested, 4 = Slightly interested, 5 = Interested, 6 = Really interested)
int2c	How interested are you in these activities? – Computer coding (1 = Really not interested, 2 = Not interested, 3 = Slightly not interested, 4 = Slightly interested, 5 = Interested, 6 = Really interested)
int2e	How interested are you in these activities? – Engineering (1 = Really not interested, 2 = Not interested, 3 = Slightly not interested, 4 = Slightly interested, 5 = Interested, 6 = Really interested)
int2l	How interested are you in these activities? – English/Language Arts (1 = Really not interested, 2 = Not interested, 3 = Slightly not interested, 4 = Slightly interested, 5 = Interested, 6 = Really interested)
Survey_order	1 = Interest stereotype questions first; 2 = Ability stereotype questions first
Gender	1 = Boy, 2 = Girl, 3 = Gender fluid/Non-binary, 4 = Unknown/Non-relevant answer
Age_CLRN	Age information from CLRN
Grade_CLRN	Grade information from CLRN
insterm	Difference score for math interest stereotypes (ImeB – ImeG); range -5 to 5
insters	Difference score for science interest stereotypes (IseB – IseG); range -5 to 5
insterc	Difference score for computer science interest stereotypes (IceB – IceG); range -5 to 5
instere	Difference score for engineering interest stereotypes (IeeB – IeeG); range -5 to 5
insterl	Difference score for language arts interest stereotypes (IleB – IleG); range -5 to 5
gme	Difference score for math ability stereotypes (gmeB – gmeG); range -5 to 5
gse	Difference score for science ability stereotypes (gseB – gseG); range -5 to 5
gce	Difference score for computer science ability stereotypes (gceB – gceG); range -5 to 5
gee	Difference score for engineering ability stereotypes (geeB – geeG); range -5 to 5
gle	Difference score for language arts ability stereotypes (gleB – gleG); range -5 to 5
belm	Scale sense of belonging in math (3 items); range 1–6
bels	Scale sense of belonging in science (3 items); range 1–6
belc	Scale sense of belonging in computer science (3 items); range 1–6
bele	Scale sense of belonging in engineering (3 items); range 1–6
bell	Scale sense of belonging in language arts (3 items); range 1–6
effm	Scale ability self-concepts in math (2 items); range 1–6
effs	Scale ability self-concepts in science (2 items); range 1–6
effc	Scale ability self-concepts in computer science (2 items); range 1–6

effe	Scale ability self-concepts in engineering (2 items); range 1–6
effl	Scale ability self-concepts in language arts (2 items); range 1–6
idm	Scale identification with math (2 items); range 1–6
ids	Scale identification with science (2 items); range 1–6
idc	Scale identification with computer science (2 items); range 1–6
ide	Scale identification with engineering (2 items); range 1–6
idl	Scale identification with language arts (2 items); range 1–6
intm	Scale interest in math (2 items); range 1–6
ints	Scale interest in science (2 items); range 1–6
intc	Scale interest in computer coding (2 items); range 1–6
inte	Scale interest in engineering (2 items); range 1–6
intl	Scale interest in language arts (2 items); range 1–6
schl	School level (0 = Middle, Grades 6–8; 1 = High, Grades 9–12)
avintstms	Average of interest stereotypes about math and science
avintstce	Average of interest stereotypes about computer science and engineering
avablstms	Average of ability stereotypes about math and science
avablstce	Average of ability stereotypes about computer science and engineering
avintms	Average of personal interest in math and science
avintce	Average of personal interest in computer science and engineering
diverintster	Divergence between math/science and computer science/engineering interest stereotypes (avintstce – avintstms)
diverablster	Divergence between math/science and computer science/engineering ability stereotypes (avablstce – avablstms)
diverint	Divergence between math/science and computer science/engineering interest (avintce – avintms)

SI References

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