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Gender Differences in Motivational and Curricular Pathways Towards Postsecondary Computing Majors

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Abstract

Gender disparities persist in postsecondary computing fields, despite improvements in postsecondary equity overall and STEM fields as an aggregate. The entrenchment of this issue requires a comprehensive, longitudinal lens. Building on expectancy-value theory, the present study examines the relationships among students' gender-ability stereotypes, attainment values, course-taking, and major choices. Using data from the High School Longitudinal Study of 2009 (HSLS: 2009), we applied weighted t-tests and multiple-group structural equation modeling to investigate how motivational beliefs (i.e., gender-ability stereotypes, attainment values) and course-taking patterns in math and science may predict major choice in computing. Overall, we find gender differences in identity-based mathematics and science motivational beliefs have long-term effects. Gender-ability stereotypes in math and science shape attainment values in each domain, whereby stereotypes suppress girls' attainment values and enhance boys' attainment values ($p<0.001$), in turn shaping course-taking and major decisions. Math- and sciencerelated motivational and curricular factors affect "other" STEM more than computing major outcomes. Specifically, computer science course-taking is completed more by boys (d=0.21), but girls' chances of declaring computing majors are especially enhanced by completing these courses in high school. Advanced science course-taking and science attainment value positively predict boys' but not girls' likelihood of declaring computing majors. We discuss the implications of these findings for research, policy, and practice.

Keywords Computing · Course-Taking · Expectancy-Value Theory · Gender Stereotypes · Motivational Beliefs · STEM Education

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Despite women's overall advancements in postsecondary educational attainment, certain science, technology, engineering, and mathematics (STEM) fields continue to be characterized by gender segregation (Chen & Soldner, 2014; Snyder & Dillow, 2011). Gender gaps[1] in postsecondary education are particularly wide in computing fields, including high-demand and high-paying majors such as information technology, computer programming, and computer science. Indeed, the U.S. Bureau of Labor Statistics (2022) projects a 15% increase in computer and information technology employment opportunities over the next decade, with a median wage of $97,430. Importantly, the varying trends over the past few decades indicate potential change in response to evolving social norms. The share of women in computing professions increased between 1990 and 2013; it then declined from 35 to 26% (Corbett & Hill, 2015) and dropped further to 24% in 2019 (National Center for Science and Engineering Statistics, 2021). Gender disparities are even more pronounced at the beginning of college. Women constitute only 19.9% of first-year college students who intend to major in computer and information sciences (down from 27.0% to 1998), despite comprising 56.6% of undergraduates (NCSES, 2021). This is partially attributed to the limited exposure of women and girls to computing experiences prior to college (Beyer, 2014; Lehman et al., 2020). These acute and persistent postsecondary gender disparities require a comprehensive, longitudinal lens.

Therefore, this study aims to examine gender differences in computing pathways from secondary school through college relative to alternative STEM major pathways. Building upon expectancy-value theory, this study focuses on two explanatory factors: motivational beliefs and course-taking. We investigate two identity-based motivational beliefs—gender-ability stereotypes and perceived alignment of tasks with one's own identity (referred to as attainment value)—that are closely associated with one's gender identity (Eccles, 2009). We analyze high school course-taking specifically in advanced mathematics/science and in computer science. Computer and information science courses are now available in 53% of U.S. high schools (Roberts et al., 2022) but are regrettably understudied, even in research focused on postsecondary computing outcomes (e.g., Blaney and Wofford, 2021). It is important that we consider the motivational and curricular factors in both mathematics and science domains, as both domains play influential roles in students' achievement and pursuit of STEM-related fields (Robinson et al., 2022; Sadler et al., 2014; Sahin et al., 2017).

Despite well-documented gender disparities in computing fields, limited knowledge exists regarding the factors that uniquely contribute to students' choice of a computing major. Previous research too often aggregates STEM domains, which may have distinct motivational profiles; this tendency can hinder our understanding of why gender differences in postsecondary computing outcomes persist. Instead, this study delves into a more nuanced exploration of students' STEM motivation and choices, focusing on variables specifically related to computing.

This study leverages restricted-use data from the High School Longitudinal Study of 2009 (HSLS:09), the most recent nationally representative U.S. panel tracking students

[1] We recognize distinctions between gender and sex, whereby the latter typically refers to binary and biological notions of male/female in distinction to gender which is developed through socialization and realized via gendered behavior, performance, and identity. This manuscript is constrained by the binary nature of data procured by the federal government from U.S. high schools., Wherever possible, we refer to boys/girls and men/women and use the term "gender" because of our focus on gender stereotypes, gender-role identities, and other constraints from socialization into the gender system. See also Perez-Felkner et al. (2023) and Ridgeway and Smith-Lovin (1999).

from high school to college. Specifically, we examine the longitudinal relationship between two domain-specific exploratory factors, namely motivational beliefs and course-taking, and their effects on college students' decisions to major in computing, using structural equation modeling. Our findings suggest that students' subscription to gender stereotypes shapes the evaluation of their attainment values in these domains and indirectly shapes their high school course-taking through the mediation of their attainment values, ultimately influencing their major choice in college.

Theoretical Framing and Literature Review

Two major predictors of students' intention to enter STEM-related fields of study in college are: (1) students' motivational beliefs – specifically, mathematics/science gender-ability stereotypes and attainment values (e.g., Musu-Gillette et al., 2015; Wang and Degol, 2013) – and (2) secondary school course-taking in STEM-related subjects (Wang, 2013; Zhao and Perez-Felkner, 2022). Students' domain-specific motivational beliefs can further predict their major choices via the mediation of course-taking in corresponding domains (Jiang et al., 2020). Drawing on expectancy-value theory, we discuss these two major predictors in terms of identity-based motivational beliefs, course-taking (in mathematics, science, and computer science), and their gendered effects on computing majors. Empirical studies have identified gender gaps in students' motivational beliefs in math and science domains, while fewer gender differences are observed in students' math- and science course selection. To better understand the gender patterns within computing fields, we discuss variations in motivational and curricular paths associated with gender identity and unique to computing fields of study.

Expectancy-Value Theory: The Role of Identity-Based Motivational Beliefs

Our study is guided by a well-established social-cognitive theoretical framework. Expectancy-value theory views individual motivational beliefs as conditioned by social and cultural contexts, with a focus on two primary factors: expectancy of success and subjective task value—the value individuals attach to a task (Eccles et al., 1983). This theory has explained the relationships between motivational beliefs and academic outcomes such as performance, engagement, and persistence (e.g., Durik et al., 2006; Fielding-Wells et al., 2017; Lauermann et al., 2017), while subjective task values appear to be particularly predicative of students' educational and occupational choices (Eccles & Wigfield, 2020). Subjective task values include: intrinsic value (i.e., enjoyment), utility value (i.e., instrumental value) and attainment value (i.e., relevance to one's identity) (Eccles, 2009). Among these categories, attainment value is a crucial component of one's motivation that is associated with their gender-role identity and predicts their academic choices (Eccles, 2009; Eccles & Wigfield, 2020).

Attainment Value and Identity

Eccles (2005, 2009) has proposed that gender differences in the participation of certain activities are partially explained by the fact that girls and boys acquire different attainment values of these activities during social identity development, which informs their perceptions of who they are and what they would like to be, shaping their personal and social identities. These identities are posited to have the strongest effect on the attainment value an individual attaches to distinct educational and vocational activities. The concept of attainment value, inherently associated with identities, aligns with research on the relationship between girls' and young women's social identities and their disciplinary (STEM) identities (see Kim et al., 2018; Starr et al., 2020; Steinke, 2017).

Prior empirical studies on students' subjective task values is often focused on utility and intrinsic value (Andersen & Ward, 2014; Jiang et al., 2020) – research on attainment value is scarce. Recent research has provided insights about the development of students' attainment value in mathematics. For example, Musu-Gillette et al. (2015) grouped students' perceived importance/relevance of mathematics from 6th grade through the first year of college into three categories: those showing a slow decline (49% of the sample), those with relatively stable perceptions (39%), and those with a fast decline (13%). Regarding science attainment value, Robinson et al. (2022) observed that chemistry students' attainment value was stable over a 13-week semester. Accordingly, domain-specific attainment values may explain gender differences in students' achievement-related choices during their secondary and postsecondary pathways to careers, particularly in highly gender-segregated fields like computing.

Gender-Ability Stereotypes, Attainment Value, and Academic Choices

Applying expectancy-value theory, Eccles (2005, 2009) has explained that when individuals' perceived engagement in a task is consistent with their personal and/or social identities (i.e., high attainment value), their likelihood of choosing this task increases. Cvencek et al. (2014) found that the association between gender-ability stereotype (e.g., boy=math) and domain-specific self-concept or identity (e.g., me=math) based on gender identity (i.e., me=boy) remains stable across cultures, reflecting a culturally universal cognitive consistency where individuals tend to balance their personal and social identities. Similarly, Cech (2013) argues that stereotypic norms positing men and women excel in different fields of study are maintained in structural and cultural contexts; these in turn induce individuals to internalize the social identity embedded with gender-ability stereotypes as their *own* identity, resulting in gendered individualist self-expression being reflected in their career choices.

Gender-role identity is shaped by the attitudes, behaviors and norms associated with a gender category, which is socially and culturally constructed rather than an inherent trait (Butler, 2011; Risman, 2018). Empirical research suggests that internalized gender stereotypes about mathematics and science abilities biases students' evaluation of their own competence in these domains. Indeed, girls typically report lower self-ratings of math and science competence-related beliefs than boys, despite performing similarly or better in math and science classes and tests (Correll, 2001; Ertl et al., 2017; Robnett, 2016). Yet, little is known about how gender stereotypes shape subjective task values— especially attainment values that children attach to mathematics and science domains. Prior research suggests that students' stereotype endorsement favoring a certain gender group indirectly predicts their course grades and career intentions, and is mediated by their beliefs about expectancy of success and utility value (Plante et al., 2013). This knowledge gap leaves unresolved an important understanding about how gender stereotypes on subjective task values affect student's educational and vocational choices.

Expectancy-value theory suggests that group differences in STEM-related motivations and behaviors can arise during gender-role socialization, as students internalize gender stereotypes present in their immediate social contexts such as schools and families and the broader socio-cultural environments (Eccles, 2009; Wigfield et al., 2015). Differences in gender-role identity can lead to (a) mean-level differences across gender groups (i.e., girls and boys varying in their motivational beliefs and course completion), and (b) process-level differences, showing that the effect of certain motivational and curricular factors vary in strength by gender. In sum, expectancy-value theory states that the gender differences in students' educational and occupational choices can be explained by variation in girls' and boys' motivations towards STEM tasks, which are influenced by individuals' social environments. Our analyses thus focus on whether girls' and boys' gender stereotypes affect their math/science attainment values, whether these attainment values predict course-taking in math, science, and computer science and subsequent major declaration of computing, and whether these relationships vary by gender.

Gendered Relationships Between Course-Taking and Major Choice

Rigorous high school mathematics and science course completion strongly predicts STEM achievement as well as overall postsecondary academic success (Adelman, 2006; Wang, 2015). Indeed, completing these courses function as academic momentum that propels students toward pursuing degrees in STEM fields (Wang, 2015). Numerous studies have found associations between the rigor and number of high school math and/or science courses taken and students' college aspirations and subsequent achievements in STEM-related fields (Bozick & Ingels, 2008; Riegle-Crumb, 2006; Wang, 2013). Although gender gaps in secondary math and science course-taking and performance have largely decreased (Hyde et al., 2008; Riegle-Crumb et al., 2012; Tyson et al., 2007), additional evidence is needed to explain the gender differences in curricular preparation for some STEM fields such as computing. Thus, we examined gender patterns within advanced math and science course-taking and its effects on major choice using the most recent national dataset with a special focus on computing.

Meanwhile, comparatively little is known about the gender differences in computer-science coursework and how it is associated with gender gaps in computing fields. Students' high school experiences with programing and/or computer science are shown to positively predict their performance in computer science courses in college (Bottia et al., 2015; Wilson & Shrock, 2001). These high school computing-related activities provide opportunities for students to develop personal connections to and direct knowledge about computing fields (President's Council of Advisors on Science and Technology (PCAST), 2010). Empirical findings suggest that pre-college computing experiences may have particular benefits for girls and help alleviate the gender gap in computing majors in college (Taylor & Mounfield, 1994; Weston et al., 2020). For example, Weston et al. (2020) found that students' involvement in high school programming and in computer science AP exams predicted girls' intention to major in computing. Thus, we particularly investigated computer science course-taking as a mediator of STEM-related motivations and as a predictor for students' interest in entering computing fields.

Current Study

Overall, our study aimed to examine the longitudinal relationships among students' motivational beliefs and course-taking during high school and how these experiences shaped their declaration of postsecondary majors in computing and other STEM fields. We were also interested in the direct relationship between students' motivational beliefs and their course-taking. Drawing from expectancy-value theory, we hypothesized that students' motivational beliefs shaped their decisions on course-taking and major declaration. Figure 1 shows the conceptual model which we describe below.

Our study incorporates mathematics and science motivational and curricular factors in an explanatory SEM model, with a theoretical emphasis on the role of identity-based motivational beliefs (i.e., gender-ability stereotypes and attainment values), and an application of mean- and process-level analyses on gendered differences in computing pathways with a nationally representative longitudinal database. Detailed hypotheses are presented below:

H1 Students' gender stereotypes about math and science abilities shape the evaluation of their attainment values of these subjects based on their gender identity. Gender stereotypes favoring males will enhance boys' attainment value and undermine girls' attainment value in the corresponding domain, and vice versa.

H2 Math attainment values have a positive effect on mathematics course-taking, and science attainment values on science course-taking [H2.1]. Math attainment values have a weak positive effect on science course-taking, and science attainment values on mathematics course-taking [H2.2]. Both math and science attainment values have a weak positive effect on course-taking in computer science subjects [H2.3].

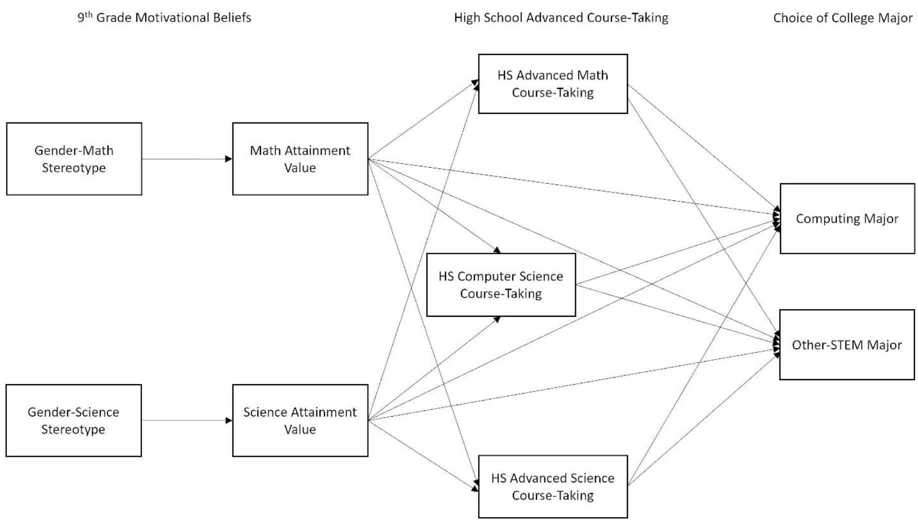

Fig. 1 The Hypothesized Model
Source. High School Longitudinal Study, Student Surveys, 2009 to 2016. N = 10,710.
Note. Totals are rounded to the nearest 10 to comply with IES restricted data restrictions

H3 Both students' attainment values and course-taking in high school positively predict their choices of computing as well as other STEM majors in college [H3.1]. Students' course-taking in computer science particularly predicts their choice of computing majors [H3.2].

H4 H4. Math and science attainment values fully mediates the effects of their gender stereotypes of math and science abilities on subsequent computing-related course-taking (i.e., advanced math and science course-taking and computer science course-taking) and major declaration in computing and other STEM fields.

Method

Data Sources and Sample

To investigate the above hypotheses, we used restricted-use data from the High School Longitudinal Study of 2009 (HSLS:09). Administered by the U.S. National Center for Education Statistics (NCES), HSLS:09 tracks a cohort of 9th grade students from 2009 through high school and transitions to and through college. This most recent nationally representative U.S. longitudinal study used a stratified, two-stage random sampling design. First, 940 schools were drawn into the sample from 10 states. Second, students were randomly selected from these schools. Study variables were drawn from the baseline-year (2009) through the second follow-up (2016) surveys. From the original sample of 25,210 participants, we excluded students who did not pursue a postsecondary education by February 2016 (n = 12,260), and those who did not indicate their gender – most of which had additional missing information on other relevant indicators (n = 980). Data missing from exogenous observed variables (i.e., variables that are not affected by any other variables in the model) were deleted listwise for structural equation modeling (n = 1,260). As a result, our final analytic sample included 10,710 students.

Measures

Gender Stereotyped Beliefs of Mathematics and Science Abilities

Gender math/science stereotypes were derived from 9th grade students' self-rating of the item, "how would you compare boys and girls in each of the following subjects." These items were on five-point Likert scales (1 = females are much better; 5 = males are much better; 3 = neutral stance).[2] Higher ratings indicated students' attitudes favored males in math/science, and lower ratings suggested students' attitudes favored females. Table 1 presents descriptive statistics for students' gender-stereotyped beliefs about math and science, by gender. For further information on all variables, see Supplemental Table S1.

[2] While we generally avoid using male/female in this manuscript (see also footnote 1), we do here and in the corresponding results discussion use "males" and "females" when it refers to the language used in the gender stereotype items described here.

Table 1 describes focal variables, including weighted and unweighted means, standard deviations, weighted t-tests, and effect sizes. Overall, boys had higher gender-math and gender-science stereotypes favoring boys over girls. Boys also had significantly higher ratings of math and science attainment values than girls (d=0.12 and d=0.18, respectively) when they entered high school. There were no significant gender differences in the number of credits earned in AP/IB math and science courses, yet boys earned considerably more credits in computer science courses than girls during high school (d=0.21)

Variables	Analytic Sample				Analytic Sample by Gender					
					Girls		Boys			
	M (SD)	Wtd M (WtdSD)	Min	Max	M (SD)	Wtd M (WtdSD)	M (SD)	Wtd M (WtdSD)	T-Test	Effect Size
Stereotype Beliefs										
Gender stereotype: Math	3.01 (0.84)	2.98 (0.85)	1	5	2.88 (0.79)	2.85 (0.81)	3.16 (0.87)	3.12 (0.86)	-7.71***	-0.32
Gender stereotype: Science	3.06 (0.77)	3.05 (0.77)	1	5	2.98 (0.72)	2.98 (0.75)	3.17 (0.81)	3.13 (0.78)	-5.57***	-0.20
Self-Concept Beliefs										
Math attainment value	2.68 (0.83)	2.65 (0.84)	1	4	2.62 (0.84)	2.59 (0.85)	2.74 (0.83)	2.72 (0.84)	-4.24***	-0.12
Science attainment value	2.43 (0.80)	2.38 (0.79)	1	4	2.36 (0.78)	2.31 (0.78)	2.51 (0.81)	2.45 (0.81)	-5.73***	-0.18
High School Course-Taking										
Credits earned in AP math classes	0.31 (0.61)	0.26 (0.55)	0	4	0.28 (0.58)	0.24 (0.51)	0.33 (0.64)	0.28 (0.59)	-1.84	-0.07
Credits earned in AP science classes	0.35 (0.74)	0.28 (0.63)	0	7	0.35 (0.72)	0.27 (0.60)	0.35 (0.75)	0.29 (0.66)	-0.59	-0.03
Credits earned in computing classes	0.50 (0.73)	0.52 (0.75)	0	9	0.42 (0.60)	0.45 (0.62)	0.60 (0.85)	0.61 (0.87)	-5.21**	-0.21

Source. High School Longitudinal Study, Student Surveys, 2009 to 2016. N=10,710

Note. Numbers reported here result from unweighted and weighted data. Wtd=weighted. T-test and effect size calculation are based on weighted statistics. Effect sizes are Cohen's d: small effect 0.10, moderate effect 0.30, large effect 0.80. Totals are rounded to the nearest 10 to comply with IES data restrictions. *** $p<0.001$, ** $p<0.01$, * $p<0.05$

Mathematics and Science Attainment Values

Students' math and science attainment values were represented by the mean score of two items that measured students' perceived relevancy of math and science domains to their own identity. These two items were on a four-point Likert scale, which asked about students' endorsement of the statements, "you see yourself as a math/science person" and "other people see you as a math/science person" (1 = strongly agree; 4 = strongly disagree). Items were reverse-coded so that the higher ratings indicate higher levels of attainment value. The Cronbach's alpha for both math and science attainment value measures were 0.84.

High School Course-Taking in Mathematics, Science and Computer Science

Drawn from 2013 high school transcripts, we used total credits earned in AP and IB Mathematics/Science courses as indicators of students' advanced math/science course-taking. Advanced mathematics courses include AP Calculus, AP Statistics and IB Mathematics courses. Advanced science courses include AP/IB Biology, AP/IB Chemistry, AP/IB Physics, AP Environmental Science, IB Physical Science, IB Design Technology, and IB Environmental Systems. Credits earned in Computer and Information Sciences were used to operationalize students' computer science course-taking. A credit is equivalent to a one-year academic course taken one period a day, five days a week.

College Major Declaration

Major declaration was coded from the NCES-generated indicator of the primary major or field of study that students declared, designated as their reference degree field as of the second follow-up interview wave (2016). Majors were classified using the U.S. Department of Education's Classification of Instructional Programs, 2010 edition (CIP 2010) and then classified as STEM using the definition used by the SMART grant. We first used the collapsed variable of STEM majors, X4RFDGMJSTEM, which only indicated whether one's choice of major was STEM or non-STEM. Then we used X4RFDGMJ12 to specify computing majors with all other majors within the STEM category of X4RFDGMJSTEM being coded as other-STEM majors. Therefore, we recoded computing major declarations into three categories: 0 = Non-STEM, 1 = Other-STEM, 2 = Computing.

Analytic Methods

The analyses leveraged weighted t-tests to examine the mean-level group differences in motivational and curricular factors, and multiple-group structural equation modeling to examine the longitudinal effects of motivational and curricular factors on pursuit of computing major (i.e., process-level group differences) with gender as a moderator. We used Stata 16 to produce unweighted and weighted descriptive statistics, and to conduct independent sample weighted t-tests on the mean-level comparisons of motivational and curricular variables. The t-test scores and effect sizes are reported in Table 1.

We then used MPlus 8.4 to conduct structural equation modeling on the conceptual model (Muthén & Muthén, 2012). We tested the relationships among motivational beliefs (i.e., math and science gender stereotype beliefs and attainment values), course-taking factors (i.e., math and science advanced course-taking and computer science course-taking), and major declaration (computing vs., other STEM, and the non-STEM reference category). Students' race/ethnicity, family socioeconomic status (SES), 9th grade math achievement and institution type they first attended were included as individual-characteristic controls. Urbanicity and type of high school were used as school-context controls for the variables shown in Fig. 1. To evaluate the validity of the structural model, we used log-likelihood ratio test (i.e., chi-square difference test) and compared the hypothesized model and saturated model (Jamshidian & Mata, 2007). A Satorra-Bentler (2001) scaled chi-square difference test was computed for the model comparison. Due to the large sample size, we set the significance level at $\alpha = 0.01$ to increase the bounds on type I error.

After finalizing the structural equation model, we then conducted a multiple-group analysis to determine if the relationships among motivational variables, course-taking and major declaration varied by gender. Further, we used the forward method to test whether the parameter estimates were equivalent across gender groups (Jung & Yoon, 2016). The forward method used one data analysis phase for the multiple-group analysis where the difference between each set of corresponding parameters were tested against zero. Lastly, we used Z-tests to identify significant differences in parameter estimates across gender.

Estimator, Missing Data, and Weights

To analyze the conceptual model, we used a robust maximum likelihood (MLR) estimator. MLR yields robust estimates when data is non-normally distributed (Curran et al., 1996), which was the case with all three course-taking variables. MPlus removes missing information in exogenous variables listwise before estimation and employs Full Information Maximum Likelihood (FIML) to adjust for other missingness. We did not observe significant distribution differences in key variables before and after these missing data adjustments. To correct for the standard errors from the stratified design of this study, we used the stratification ID and primary sampling unit (i.e., schools) variables, and specified TYPE = COMPLEX command for model estimation. The panel weight W4W1STU was selected to adjust for differential selection probability and nonresponse patterns from the base year wave (2009) up to the second follow-up interview (2016). Bootstrap replicate weights (W4W1STU001-W4W1STU200) were applied with Balanced Repeated Replication method to adjust for standard errors of the descriptive statistics for focal variables.

Results

Descriptive Analyses

Table 2 displays statistics describing all variables by major declared. The proportion of girls who declared any STEM major was small (37.5%) compared with that of boys (62.5%). The gender ratio was even wider with respect to declaring a computing major, with only 21.46% for girls and 78.54% for boys. Students who declared a computing major had gender-math and gender-science stereotypes favoring boys at a higher level than students who declared other STEM and non-STEM majors. Students who declared any non-computing STEM major had the highest math and science attainment values; they also had the most credits earned in AP/IB math and science classes. Students who declared a computing major earned the most credits in computer science classes. Correlations among all variables are presented in supplemental Table S2.

SEM and Multiple-Group Analysis

The chi-square difference test suggests that the hypothesized model fit the data as well as the saturated model ($\Delta\chi2(12)=22.15$, $p=0.04$). We then proceeded with the more parsimonious model (i.e., the original hypothesized model) and conducted multiple-group analysis. We identified three sets of parameters that varied significantly by gender: the relationships between gender-math stereotype and math attainment value ($\Delta\beta$ = -0.42, $p<0.001$), gender-science stereotype and science attainment value ($\Delta\beta$ = -0.31, $p<0.001$), science attainment value and computer science course-taking ($\Delta\beta$ = -0.10, $p=0.003$). The parameter estimates of the multiple-group SEM and group-equivalence test (Z-test) results were shown in Table 3.

The multiple-group SEM results confirmed that students' gender stereotypes about math and science abilities biased their perceived math and science attainment values [H1 supported; see Table 3]. Boys who agreed with the statement that males perform better than females in mathematics had higher math attainment values ($\beta=0.20$, $p<0.001$), whereas girls who held this stereotype belief had lower math attainment values (β = -0.22, $p<0.001$). Similarly, stereotypes that favored males in science were positively associated with boys' science attainment values ($\beta=0.13$, $p<0.001$), and negatively associated with girls' science attainment values (β = -0.18, $p<0.001$).

Regarding the relationships between attainment values and course-taking (Table 3 shows the path coefficient for both girls and boys), math attainment value positively predicted advanced math course-taking ($\beta=0.05$, $p<0.001$ for both girls and boys), and science attainment value positively predicted advanced science course-taking, similarly for girls ($\beta=0.08$, $p<0.001$) and boys ($\beta=0.07$, $p<0.001$) [H2.1 supported]. Additionally, science attainment value had a positive but weak prediction on course-taking in advanced mathematics ($\beta_{\text{girls}}=0.04$, $p<0.001$; $\beta_{\text{boys}}=0.02$, $p=0.10$); Math attainment value did not predict course-taking in advanced science [H2.2 partially confirmed]. Importantly, science-attainment value was a significant predictor of computer science course-taking, and only for boys ($\beta=0.05$, $p=0.01$) [H2.3 partially confirmed].

Regarding the predictions of attainment values and course-taking on major declaration, the parameter estimates were based on multinomial logistic regression. Table 3 shows both the path coefficients and relative risk ratios by gender. Having higher levels of math attainment values increased the likelihood of declaring a non-computing STEM major (RRR = 1.36, p < 0.001 for both girls and boys), but not a computing major; Science attainment values also showed the same pattern, with girls (RRR = 1.79, p < 0.001) and boys (RRR = 1.46, p < 0.001) experiencing an increased likelihood of choosing a non-computing STEM major rather than a computing major [H3.1 partially confirmed]. Taking more advanced math courses did *not* increase the chances of choosing any STEM major in college, while taking more advanced science classes enhanced the likelihood of declaring a non-computing STEM major rather than declaring a computing major ($\text{RRR}_{\text{girls}}= 1.83$, $p<0.001$; $\text{RRR}_{\text{boys}} = 1.59$, $p<0.001$) [H3.1 partially confirmed]. Computer science course-taking was a predictor for computing major declaration, such that for each credit that students earned in a computer science

Table 2 Descriptive Statistics of All Covariates and Control Variables by Major Declaration

			Major Declaration					
	Total		Declared a Computing major		Declared another STEM major		Declared a non-STEM major	
	N	%	N	%	N	%	N	%
Background Characteristics								
Gender								
Girls	5,800	54.15	90	21.46	780	40.73	4,430	60.24
Boys	4,910	45.85	310	78.54	1,140	59.27	2,920	39.76
Race								
White	6,240	58.32	220	55.05	1,060	54.81	4,430	60.26
Latina/o/x	1,460	13.64	40	10.86	230	11.84	1,010	13.73
Black	890	8.31	30	7.07	110	5.56	660	9.03
Asian	1,090	10.19	80	19.44	360	18.55	570	7.78
Other race	1,020	9.53	30	7.58	180	9.25	680	9.20
School Type								
Public	8,140	76.07	320	80.56	1,430	74.18	5,500	74.86
Catholic	1,630	15.23	50	12.37	340	17.56	1,160	15.78
Other Private	930	8.69	30	7.07	160	8.26	690	9.36
School Urbanicity								
City	3,260	30.44	110	28.03	610	31.90	2,220	30.26
Suburban	5,130	47.90	220	54.29	930	48.31	3,500	47.62
Rural	2,320	21.66	70	17.68	380	19.79	1,630	22.12
Type of First Institution								
Four-year	7,450	69.56	280	71.46	1,620	84.31	5,140	69.97
Two-year	3,260	30.44	110	28.54	300	15.69	2,210	30.03
	N		Mean	SD	Mean	SD	Mean	SD
Stereotype Beliefs								
Gender stereotype: Math	10,710		3.18	0.82	3.11	0.81	2.98	0.85
Gender stereotype: Science	10,710		3.10	0.70	3.09	0.76	3.07	0.77
Attainment Values								
Math attainment value	10,640		2.88	0.81	3.03	0.76	2.59	0.83

Table 2 (continued)

		Major Declaration					
Science attainment value	10,620	2.61	0.79	2.77	0.77	2.35	0.78
<u>HS Advanced Course-Taking</u>							
Credits earned in AP math classes	10,250	0.41	0.71	0.65	0.80	0.24	0.53
Credits earned in AP science classes	10,250	0.45	0.87	0.81	1.06	0.25	0.59
Credits earned in computing classes	10,250	1.09	1.26	0.50	0.74	0.46	0.66
<u>Other Continuous Covariates</u>							
Socioeconomic status	10,710	2.99	0.76	0.54	0.84	0.27	0.77
Prior math achievement	10,710	0.71	0.86	0.90	0.82	0.39	0.73

Source. High School Longitudinal Study, Student Surveys, 2009 to 2016. N = 10,710

Note. Totals are rounded to the nearest 10 to comply with IES data restrictions

Table 3 Parameter Estimates of Final Multiple-Group SEM

	Girls			Boys			Z-Test Score
Model and Effect	Unstd.	SE	Std.	Unstd.	SE	Std.	
Math attainment value ON							
Gender stereotype: Math	-0.22***	0.03	-0.21	0.20***	0.02	0.21	-11.44***
Science attainment value ON							
Gender stereotype: Science	-0.18***	0.02	-0.17	0.13***	0.02	0.13	-11.00***
Advanced math course-taking ON							
Math attainment value	0.05***	0.01	0.09	0.05***	0.01	0.07	0.38
science attainment value	0.04***	0.01	0.06	0.02	0.01	0.03	1.17
Advanced science course-taking ON							
Math attainment value	0.01	0.01	0.01	0.02	0.01	0.03	-0.66
Science attainment value	0.08***	0.02	0.10	0.07***	0.02	0.09	0.47
Computer science course-taking ON							
Math attainment value	0.05	0.03	0.06	0.01	0.02	0.01	1.12
Science attainment value	-0.05	0.04	-0.05	0.05*	0.02	0.06	-2.93**
	Girls			Boys			Z-Test Score
	Unstd.	SE	RRR.	Unstd.	SE	RRR.	
<u>*Computing major ON*</u>							
Advanced math course-taking	0.18	0.29	1.20	-0.08	0.19	0.92	0.75
Advanced science course-taking	0.15	0.26	1.17	0.41**	0.15	1.51	-0.85
Computer science course-taking	0.77***	0.17	2.16	0.65***	0.09	1.92	0.60
Math attainment value	0.22	0.25	1.25	0.21	0.12	1.23	0.05
Science attainment value	0.54	0.31	1.71	0.28*	0.12	1.32	0.78
<u>*Other STEM major ON*</u>							
Advanced math course-taking	0.27*	0.13	1.31	0.10	0.11	1.11	0.92
Advanced science course-taking	0.61***	0.09	1.83	0.46***	0.10	1.59	1.27
Computer science course-taking	0.02	0.12	1.02	0.18	0.09	1.19	-0.94
Math attainment value	0.31***	0.09	1.36	0.31***	0.08	1.36	0.01
Science attainment value	0.58***	0.09	1.79	0.38***	0.10	1.46	1.49

Source. High School Longitudinal Study, Student Surveys, 2009 to 2016. N = 10,710.

Note. Totals are rounded to the nearest 10 to comply with IES restricted data procedures. The reference group for the outcome variable is non-STEM major. The unstandardized parameter estimates for paths towards major declaration are logits, which are not as intuitive as suggesting liner relationships. Relative risk ratios are used for interpretations. Unstd. = unstandardized coefficients. SE = standard error. Std. standardized coefficient. RRR. = relative risk ratio. Estimates of the correlations between math and science attainment values are 0.19 for girls and 0.24 for boys. Estimates of the correlations between advanced math and science course-taking are 0.36 for girls and 0.42 for boys. Z-test scores are used to identify gender differences between parameter estimates. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

course, their chances of declaring a computing major would increase two-fold (RRR = 2.16, $p < 0.001$ for girls; RRR = 1.92, $p < 0.001$ for boys) [H3.2 confirmed].

Hypothesis 4 was also confirmed: the full mediation model (i.e., gender-ability stereotypes indirectly predicted course-taking and major declaration via attainment values) fit the data better than the partial mediation model ($\Delta\chi2(10) = 22.16, p = 0.01$). Specifically, mathematics attainment values fully mediated gender stereotypes of math abilities and subsequent computing-related course-taking, while science attainment values fully mediated gender stereotypes of science abilities and subsequent course-taking. When taking into account the effect of math and science attainment values, students' gender stereotype of math and science abilities no longer significantly predicted their computing-related course-taking (β ranged from 0 to 0.02, p value ranged from 0.99 to 0.07) and major declaration (relative risk ratios were close to one).

Gender Differences in Predictions on Computing Outcomes

We identified a significant gender pattern in terms of the association between students' science attainment value and computer science course-taking (Z = -2.93). Boys' science attainment value was positively associated with their computer science course-taking ($\beta=0.05$, $p=0.01$), while girls' science attainment value had no association with their computer science course-taking ($\beta = -0.05$, $p=0.17$). Boys' advanced science course-taking (RRR = 1.51, $p=0.01$) and science attainment value (RRR = 1.32, $p=0.02$) positively affects their choice to major in computing, but the same is not true for girls. Girls' advanced science course-taking and science attainment value had no effect on their choice to major in computing. In sum, we found evidence of process-level gender effects on students' academic choices within computing pathway.

Discussion

The gender pattern of the computing major selection aligns with national workforce trends: women are acutely underrepresented in computing as compared to other STEM fields (Cheryan et al., 2015); indeed, only 26% of professional computing occupations in 2021 and 22% of all computer and information sciences degrees in 2020 are held by women (National Center for Women & Information Technology (NCWIT), 2022). The present study revealed mixed findings on the motivational and curricular factors that might contribute to such gender differences within computing pathway. The mean-level results suggest that gender differences exist in students' motivational beliefs in math and science and course-taking in computer science but not in students' advanced math and science course-taking. The process-level results show that the relationships between motivational beliefs, course-taking and major declaration do not vary by gender, except for the relationship between science attainment value and computer science course-taking. Gender gaps in entry to computing fields are particularly associated with gender differences in computer science course-taking results we observe. Still, gender disparities in math and science motivational beliefs carry long-term effects, including on students' postsecondary major selection.

Gender Patterns in Motivational Beliefs

Gender stereotypes are salient in students' views towards competence of gender groups in math and science. Consistent with Heymand and Legare's (2004) findings, we found that both girls and boys held ingroup preferences for math and science competence. This suggests that endorsement of gender-ability stereotypes might not be the major cause for the gendered motivation to study math and science and to persist within STEM pathways.

Recent research suggests that gender-interest stereotypes presented in children's school environments as early as elementary education may contribute to the growing gender disparities in computing pathways (Cheryan et al., 2015). Their experimental follow-up study indicated that the presence of gender-interest stereotypes decreased girls' interest in participating in computer science activities, while boys' field interest remained intact (Master et al., 2021). Additionally, the slightly higher gender stereotype favoring males in math and science in the computing major group might suggest potential direction of self-selection. Past research did not find significant gender stereotypes regarding job opportunities in computing among major and non-major students (Beyer et al., 2003). However, there is a scarcity of literature exploring the appealing factors for computing-major students in relation to gender stereotypes.

The findings also suggest that gender disparities in math- and science-related motivations exist before high school – we found that boys perceived tasks in math and science domains as more aligned with their personal identity than girls did when they entered high school. While gender differences in the perceived math and science attainment values might not be as strong at the beginning of high school, students' gender stereotypes of math and science abilities indeed biased their math and science attainment values. This study support prior studies in highlighting the importance of students' identity-based motivations in fostering college students' long-term commitment to pursuing STEM and computing (Estrada et al., 2018; Wofford et al., 2022). Therefore, it is important to consider the gender differences within these STEM-domain-specific motivational beliefs in order to understand the factors that contribute to the reproduction and reinforcement of the gender gap in students' computing and other STEM pathways.

Gender Differences in Prediction of Motivational Beliefs

Consistent with prior findings (Else-Quest et al., 2013; Perez-Felkner et al., 2019; Jiang et al., 2020), the relationship between math attainment value and math-related choices and achievement did not vary by gender. On the other hand, science attainment value positively predicted computer science course-taking for boys but showed no effect for girls. While girls hold similarly high values of science attainment as boys, these motivations may show weaker associations with course-taking decisions for girls in computing and subsequently affect their pathways into college computing. These differences extend to postsecondary pursuits and may be attributed to classroom experiences within male-dominated majors where women have more difficulty connecting with peers and professors when compared to men or find less enjoyment or comfort within these spaces (Lawson, 2021).

Another explanation for the differential predictions of science attainment value on major declaration may be attributed to the distinctiveness of each STEM subfield. Students could hold differing perceptions of their personal values in physics, chemistry, biology as well as other technology-related science fields. Prior research has suggested that there may be nuanced gender differences in motivational beliefs by STEM subfield. For example, Jansen et al. (2014) measured high school students' science self-concept multi-dimensionally in terms of physics, chemistry, and biology. They found that girls tended to have lower physics and chemistry self-concepts which did not correspond to their actual achievement when compared to boys. Further, Sáinz and Eccles (2012) found that computing-specific self-concept rather than math self-concept mediated the relationship between gender and intention to pursue computing careers. Future research focusing on field-specific motivational beliefs should further examine gender patterns within distinct STEM fields.

Gendered Motivational and Curricular Pathways Towards Computing Majors

This study found distinct motivational and curricular paths towards declaring a computing major when compared to other STEM majors. Neither motivational beliefs nor high school course-taking in math and science domains predicts students' decision to major in computing during college. On the contrary, both motivational beliefs and course-taking significantly predicted students' declaration of non-computing STEM majors—except for advanced math course-taking. The insignificant effect of AP math course-taking on interest in both computing and these other STEM majors aligns with previous research, where taking AP mathematics courses (other than AP Calculus) were insufficient to increase students' interest in entering STEM-related fields (Sadler et al., 2014; Warne et al., 2019).

In contrast, the present study shows that students' computer science course-taking in high school increased their probability of selecting a computing major in college. Johnson and Muse (2017) found that women who passed high school calculus tended to pursue a "realistic" field of study (such as computing) but tended to choose such fields less than their otherwise similar men. Notably, women enrolled in postsecondary computing courses are more likely to continue to pursue more computing courses when they perceive themselves to be skilled and challenged in these courses (Milesi et al., 2017). Finally, given that girls took fewer computer science courses than boys in high school, but these courses enhanced computing major declaration, gender disparities in college computing might be alleviated by promoting girls' participation in high school computer science curriculum.

Limitations

Our study has several limitations. Firstly, the longitudinal nationally representative data used does not include computing-related motivational beliefs (i.e., gender-ability stereotypes and attainment values) that might be more important for postsecondary computing outcomes; observable data existed only for mathematics and science beliefs. Related, we can only assess how gender shapes high school students' postsecondary pathways for those identifying as boys or girls, yet students identifying outside this binary do engage in computing education and careers (Casper et al., 2022). Finally, this quantitative study investigates the consequences of stereotypes which can preclude girls' and women's motivation to pursue computing careers (see Cheryan and Plaut, 2010); the environments which perpetuate those stereotypes—and the effects of gender-computing stereotypes—are beyond the scope of this study because of data limitations.

Future Directions

The present study suggests that domain—i.e., computing vs. mathematics—matters in how students associate their mathematical, science, and computing-related motivational beliefs with their behaviors. Scholars should attend to how gendered ability-related stereotypes and motivational patterns in a specific domain may shape gender disparities within a male-dominated STEM field like computing (Ehrlinger et al., 2018; Friend, 2015). Interventions developed to enhance students' science-related motivational beliefs might not be as effective in reducing gender disparities in these fields if they do not tap into students' motivations for and associations with computing specifically. For example, students' motivations may be less tied to mathematics versus creativity, as computing continues to evolve as a field (Sax et al., 2015, 2017). Indeed, future research may investigate the influence of computing-specific motivational beliefs, along with other dimensions associated with computing motivation, as well as the role of high school computing course-taking, on students' subsequent decision to major in computing.

Theoretical and Methodological Directions

While this study contributes to our understanding of how identity-based motivational beliefs during high school relate to college students' declared majors, future research could elucidate the extent to which these associations persist throughout college and shape degree completion. Additionally, future studies could investigate the factors that shape these beliefs and values during the gender-role socialization process prior to high school. One-third of our nationally representative analytic sample initially enrolled in two-year colleges, which are increasingly a focus in postsecondary research on STEM but less so on specific fields like computing nor to gender equity in these fields[3]. Emerging work on the experiences of upward transfer computing students suggests promising directions for future research (Blaney & Barrett, 2022; Blaney & Wofford, 2021). Accordingly, subsequent studies may also attend to outcomes including associates' degree field, completion, and upward transfer (Park et al., 2021; Wang et al., 2018).

Intersectionality

We recognize that gender does not function in isolation but rather intersectionally with other social identities which may experience at times multiple and compounding forms of marginalization in STEM fields (see Ireland et al., 2018; Perez-Felkner et al., 2019). For example, Chan et al. (2020) observed that students' experiences of race and social class together affect their engagement in out-of-school STEM programs and STEM aspirations. Moreover, African American women interested in STEM fields navigate stereotyped computing environments in middle school (e.g., Thomas et al., 2017) and continue to encounter challenges in postsecondary curricular environments (e.g., Rankin et al., 2019; Ross et al., 2020). McGee and Martin (2011) found that while Black mathematics and engineering students may be motivated to counter negative stereotypes, stereotype management can shift towards more intrinsic motivations to continue their career pathways. Future research may examine the effects of stereotypes and role identities on postsecondary STEM major choice—and computing major choice specifically—while considering the multiple intersections between gender and race/ethnicity, socioeconomic status, and other social characteristics and identities (see Lehman et al., 2017; Rodriguez and Lehman, 2017).

[3] Perez-Felkner et al. (2019) investigated the relationship between gender, institutional type, and STEM clusters but not distinct conceptual framing, data, and methodology.

Policy and Practice

Reducing postsecondary gender disparities in computing is not possible without first attending to pre-college experiences and specifically the structural issues that drive gender-ability stereotypes within these fields prior to college (see e.g., Flores et al., 2017 on the explanatory power of pre-college factors on postsecondary racial disparities). Within secondary schools, enhancing gender-inclusive computer science learning may involve capacity building for computer science educators and engagement of students' teachers, counselors, and parents/guardians. Postsecondary institutions—via their faculty, STEM teacher training programs, and community partnerships—may be well positioned to leverage outreach and recruitment resources by implementing and/or supporting programs that support development of computing skills and encourage computer science course-taking, to alleviate gender disparities in computing fields across student demographic backgrounds (e.g., COMPUGIRLS, etc. (Scott & White, 2013) (see Perez-Felkner et al., under review). Breaking down gender barriers at the secondary level may support women's computing-related identity development and motivations to pursue postsecondary computing degrees.

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Availability of Data and Materials Public use access to these data is available through the National Center for Education Statistics website, as is the application for restricted use data, such as we used for these analyses: https://nces.ed.gov/surveys/hsls09/hsls09_data.asp. Our restricted-use license number is 12100041. Statistical code generated to analyze supporting the findings of this study are available from the corresponding author upon request.

Declarations

Competing Interest The authors report there are no competing interests to declare.

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