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Predictors of Adolescents’ Interest in Stem Majors and Careers

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PREDICTORS OF ADOLESCENTS' INTEREST IN STEM MAJORS AND CAREERS

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Abstract

The United States currently faces a shortage of qualified workers in fields related to science, technology, engineering, and math (STEM). The first critical step in preventing the labor shortage in STEM is understanding the factors that guide adolescents toward STEM pursuits. Drawing on Eccles' expectancy-value theory (EVT), the current study aims to identify factors that are relevant to adolescents' interest in STEM majors and careers. Data were collected from 629 adolescents (M_{age} = 16.09). Participants attended a high school in northern California and predominantly identified as Asian American (82% of the sample). Preliminary analyses revealed that adolescent boys had higher STEM self-expectancies than did adolescent girls, whereas there was no gender difference in STEM values. Consistent with expectations, multiple regression demonstrated that STEM self-expectancies and values accounted for a significant amount of variance in participants' interest in STEM majors and careers. STEM value was an especially strong predictor; adolescents tended to be most interested in STEM pursuits when they were also high in STEM value. Moderation analyses showed that the association between STEM value and interest in STEM majors and careers was stronger for girls than for boys. As a whole, this study's findings suggest that valuing and enjoying STEM pursuits during high school could be an important antecedent of pursuing a STEM major and a STEM career later in life.

Introduction

With technological advancement over the past decade, science, technology, engineering and mathematics (STEM) have become critical to career growth and to the national economy. Between 2004 and 2008, the employment rate in STEM fields rose an average of 3.3% annually compared to an average 1.3% annual increase in employment in all occupations (NSF, 2010). However, there are not enough college graduates in STEM fields in the United States to meet the country's rapidly growing technological and industrial demands (Moakler Jr. & Kim, 2014). Given this increasing demand, it is crucial to promote students' interest and achievement in STEM fields.

Combatting the gender imbalance in STEM may help meet the increasing demand for STEM workers. Girls and women in the United States comprise the majority of students in almost all life and social sciences majors, but they continue to lag behind in math and math-intensive engineering and physical and computer sciences (Ceci & Williams, 2010; National Science Foundation, 2011; Schoon & Eccles, 2014; Watt & Eccles, 2006, 2008). The underrepresentation of women in math-intensive STEM fields is persistent in all educational levels. Girls are less likely than boys to take advanced placement exams in mathematics, physical and computer science; fewer women undergraduates attain math-intensive STEM degrees; and less than one-third of doctorates in math-intensive STEM fields are awarded to women (Hill, Corbett, & St. Rose, 2010).

However, the gender gap in STEM fields is relatively small compared to the gaps by ethnicity and socioeconomic status (SES; Hill, Corbett, & St. Rose, 2008). For both men and women, more than three-fourths of workers in engineering and computing in the United States are non-Hispanic European Americans (Hill et al., 2010). Among minorities, Asian Americans make up the largest proportion of the STEM workforce (Hill et al., 2010). Relatedly, Asian American youth on average tend to perform better in math and science (STEM) subjects than do students from other ethnic backgrounds (Hill et al., 2008, 2010). Regardless of these ethnic differences, men of all ethnic groups are better represented than women in the STEM workforce, with the exception of biological science fields (Hill et al., 2010). Research further suggests that the gender gap in the STEM workforce is larger among European Americans and Asian Americans than it is among members of other ethnic groups (Hill et al., 2010; O'Brien, Blodorn, Adams, Garcia, & Hammer, 2015). However, less is known about whether there are parallel trends in STEM self-expectancies and values among adolescents.

Relatedly, the majority of existing literature on student persistence and completion in the STEM pipeline is based on college-level experiences (Sass, 2015); comparatively few studies focus on the factors that shape entrance to postsecondary STEM disciplines and STEM careers (Wang, 2013). Research consistently reveals that high school is a critical time when individuals start developing their interest in STEM fields (Tai, Liu, Maltese, & Fan, 2006; Wang, 2013). Accordingly, identifying factors that are relevant to adolescents' interest in STEM college majors and careers may be a critical step in preventing the labor shortage in the STEM pipeline (Wang, 2013). Therefore, the goal of the current study is to examine factors at the high school level that predict adolescents' interest in pursuing STEM majors and careers. Many individual and social factors determine STEM educational and career choices (Eccles, 2005; Watt, 2006; Watt & Eccles, 2008). The current study focuses on the following individual and social factors while acknowledging that others may be important as well: gender, ethnicity, parent education, grades, perceived gender bias, and self-expectancies and values. More specifically, we used hierarchical linear regression to examine how powerful each predictor is relative to the others.

Literature Review

Asian American Educational and Occupations Choices

Our sample comprises a large number of Asian American participants (82% of the sample). Thus, it is essential to give a brief background about the culture of this ethnic group in regard to their educational and occupational choices. Asian/Asian American culture is collectivistic, and family values are often of paramount importance (Sandhu, 2015). For instance, the success/failure of one member of the family does not just reflect on the individual, but is a representation of the entire family (Stankov, 2010). In this sense, Asian Americans' educational and occupational choices are likely to be a family choice (Leong & Chou, 1994; Liu, 1998). Also, the majority of Asian American adolescents were raised to view educational success and prestigious STEM occupations as an opportunity for upward social mobility (Leong, 1991).

The role of parent expectations toward Asian/Asian Americans' education is well documented in the literature (Leong, 1991; Leung, Ivey, & Suzuki, 1994; Tang, Fouad, & Smith, 1999; Sandhu, 2011). For example, a longitudinal study found that more than 80% of Asian American parents expect their children to graduate with at least a Bachelor's degree (Peng & Wright, 1994). The common parent expectations among this ethnic group include successful school performance, obtaining good jobs, and financial security (Kao & Tienda, 1995; Kibria, 1993). The major influence of high parent expectations on Asian Americans is frequently explained by the "Immigrant Bargain," which describes how immigrant children are fully aware of their parents' sacrifices and feel obligated to fulfill their parents' expectations (Louie, 2004; Smith, 2006; Suárez-Orozco & Suárez-Orozco, 2001). Furthermore, Asian American children, in turn, internalize these expectations, which often drives them to live up to those standards to justify their parents' sacrifices (Goyette & Xie, 1999; Kao, 1995; Kao & Tienda 1998; Qian & Blair 1999; Sakamoto, Goyette, & Kim, 2009).

In addition to living up to the parents' expectations about excelling in school, Asian American students are often compelled to choose culturally sanctioned fields such as medicine, science, or business because the careers in these fields are perceived to be the most economically viable and socially rewarding (Yee, Su, Kim, & Yancura, 2009). Asian culture is orientated toward tangible evidence of academic ability, such as making good grades, being in the right major, or being in the right job. These achievements are often identified as indicators of success (Nguyen, 2015) and as enhancing the status and the honor of the family (Uba, 1994). Asian immigrant parents also often tend to push their children to pursue high-status, high-paying occupations related to STEM and medical fields (Min & Jang, 2015), which explains the overrepresentation of Asian Americans in STEM disciplines.

In addition to the family values and parent expectation variables, socialization and community networks in strengthening Asian American children's skills in mathematics and science subjects are likely to play a role in their preferences for STEM disciplines and occupations (Min & Jang, 2015). For example, Asian parents, more than parents from any other ethnic group, tend to exert a greater pressure on their children to excel in math since a very young age, and the children's proficiency in math may eventually lead them to pick math-intensive college majors and STEM fields. Given the influential role the parent expectation plays in this ethnic group, we conducted this as an exploratory analysis in our study.

Expectancy-Value Theory and Academic Choices

Expectancy-value theory (EVT) consists of two constructs: (1) self-expectancies and (2) subjective task values. Both constructs are thought to have a direct influence on students' academic choices, persistence, and motivation. Specifically, EVT predicts that individuals select activities and choose occupations for which they have the highest expectations for success and attach the greatest subjective task values (Eccles, 1983). A large body of empirical work illustrates the importance of both self-expectancies and subjective task values on motivation, academic outcomes, and subsequent career choices (for a review, see Wang & Degol, 2013).

Self-expectancies. Self-expectancies are individuals' beliefs about how well they will perform on a task in the future (Wigfield & Cambria, 2010). Self-expectancies in EVT are similar to self-efficacy expectations in the sense that they are both predictive of performance and choice (Wigfield & Eccles, 2000). Among young children and adolescents, self-efficacy and expectancy constructs are highly correlated (Hulleman & Harackiewicz, 2009); hence, we will use both terms (i.e., *self-efficacy* and *self-expectancies*) when describing the research below. According to EVT, individuals' beliefs about their ability to succeed in a given domain are a critical determinant of their academic and career trajectories (Eccles & Wigfield, 2002). Prior research indicates that self-efficacy predicts academic outcomes even after ability indicators such as grades and test scores are controlled (Chemers, Hu, & Garcia, 2001). Likewise, individuals' STEM self-efficacy predicts achievement and career aspirations in STEM domains (DeBacker & Nelson, 1999; Robnett, Chemers, & Zurbriggen, 2015; Robnett & Leaper, 2013; Watt, 2006). For example, students with higher self-expectations of success in STEM are more likely to take advanced STEM courses in high school, pick STEM as their college majors, feel like they belong in STEM, and express interest in STEM fields (Chemers, Zurbriggen, Syed, Goza, & Bearman, 2011; Robnett et al., 2015; Watt et al., 2012).

Academic self-efficacy differs across academic domains. Gniewosz, Eccles, and Noack (2014) argue that there is a negative relationship between the grades in one subject area and one's self-efficacy in another subject area, although one's grades and self-efficacy are positively associated within the same subject area. That is, a student with high self-efficacy in math will not necessarily have high self-efficacy in English. Many studies have been consistent in their findings that high school boys express higher self-expectancies than girls in math, whereas the reverse is true for English (Pajares, 2005; Watt & Eccles, 2006, 2008). Self-efficacy in math ability predicts entering STEM fields for both males and females; on the other hand, females with higher English self-efficacy than math self-efficacy are less represented in STEM fields (Eccles & Wang, 2016).

Subjective task values. The second construct, subjective task values, refers to how much value individuals place on a particular task, which subsequently influences their motivation and persistence with the task (Wigfield, Tonks, & Klauda, 2009). The construct is deemed subjective because the value one places on a particular task can fluctuate from person to person (Wang & Degol, 2013). The subjective task values construct contains four sub-scales: attainment value (importance), intrinsic value (interest), utility value (usefulness), and cost (Eccles, 1983). Subjective task values play an influential role in attributing why someone picks a particular academic/career option over another. For example, high intrinsic value is positively associated with the number of math and science courses taken in high school and aspirations for STEM-related careers (Meece, Wigfield, & Eccles, 1990).

Gender Differences in EVT

Mathematics is considered to be one of the key reasons for the gender imbalance in STEM educational and occupational contexts (Meece et al., 1990; Shapka, Domene, & Keating, 2006). Several research findings indicate that it is girls' lower math self-efficacy, rather than their math competency, that prevents them from pursuing STEM majors. International studies on school achievement consistently reveal that gender differences in mathematics and science abilities are nonsignificant (Mullis, Martin, & Foy, 2008). Girls and women, on average, report lower mathematics self-efficacy than boys and men, regardless of their similar capabilities or past equivalent achievements in math (Hill et al., 2010). One explanation pertains to girls' higher standards for performance in mathematics compared to boys (i.e., girls tend to believe that they need to be exceptional at math in order to succeed in perceived male fields; Hill et al., 2010). The reported gender difference in STEM self-efficacy begins in middle school and continues to expand throughout high school and college (Pajares, 2005).

Girls' underrepresentation in STEM in educational contexts is also attributed to girls' lack of interest in STEM or lower STEM intrinsic values. Research over the past decades has shown that the average gender gap of math subjective task values is no longer significant; however, girls remain less interested in the physical sciences (Wigfield, Eccles, Schiefele, Roeser, & Davis-Kean, 2006). Girls express less interest in math or science careers than boys do starting in early adolescence (Lapan, Adams, Turner, & Hinkelman, 2000; Turner et al., 2008). Other findings suggest that girls' interest in math decreases as they move through adolescence, whereas boys' level of interest in math does not change (Eccles & Harold, 1991; Koller, Baumert, & Schnabel, 2001). Wang and Degol (2013) also argue that females tend to have lower utility values and expectancies about their STEM attainment value (STEM importance). In short, Eccles' EVT explains the gender gap in STEM such that fewer females pick STEM-related educational and occupational fields because they have lower math and science self-efficacy and because they place less subjective task values on STEM fields (Eccles, 2011).

Gender Bias in STEM

According to EVT, self-expectancies and values are shaped by the social context and social interactions. Thus, understanding social-contextual factors that have the potential to shape individuals' self-efficacy or achievement is imperative in understanding the dynamics leading individuals to make distinct educational choices. In the current study, we take into account the social context by examining adolescents' perceptions of gender bias in STEM.

Gender bias originates from stereotypes. That is, stereotypes often escalate into bias and thus do damage by fostering prejudice and discrimination. Negative stereotypes about girls' and women's mathematics and science abilities are common (Hill et al., 2010). Although gender stereotypes and biases are often subtle, many adolescent girls internalize these beliefs. This can unfavorably influence their academic outcomes (Leaper & Friedman, 2007). Girls' internalization of these lower expectations in turn affects their self-concepts, socioemotional adjustment, achievement, and academic and career choices (see Freedman-Doan et al., 2000; Hyde & Kling, 2001; Leaper & Friedman, 2007; Hill et al., 2010). Some adolescent girls also report overhearing negative comments about their STEM ability and often feel that they need to work harder than boys do in order to be taken seriously in STEM (Robnett, 2016).

Current Study

The current study is designed to identify individual and social predictors of adolescents' interest in STEM majors and careers and to explore how powerful each predictor is relative to the others. More specifically, we used hierarchical linear regression to test for predictors of three outcome variables: (1) interest in a STEM major, (2) the amount of math required for participants' preferred major, and (3) interest in a STEM career. Our hypotheses were grounded in Eccles' EVT, which suggests that self-expectancies and values play an important role in academic motivation and choices. Thus, our first hypothesis is as follows:

Hypothesis 1: *Self-expectancies and values will predict the adolescents' interest in STEM majors and careers above and beyond their grades and other control variables.*

Research consistently suggests that girls and women persist at lower rates in STEM fields across all educational levels (Hill et al., 2010). Hence, we also examined the moderation effects of gender in predicting the adolescents' STEM major and career interests. Despite the rich literature that connects self-expectancies and values to academic decision-making, little prior research focuses on whether these associations differ on the basis of gender. In addition, Leaper and Brown (2008) found that over half of the adolescent girls (52%) in their sample had reported their experiences with academic discouragement in math and science-related domains. Hence, the following moderation effects were included in our models: 1). The 2-way interaction between gender and self-expectancies/values, and 2). The 2-way interaction between gender and perceptions of gender bias in STEM. The corresponding hypotheses are as follows:

Hypothesis 2a: *The associations between STEM self-expectancies and values and interest in a STEM major and career will be moderated by participants' gender.* In other words, we expect that the association between STEM self-expectancies and values and interest in a STEM major and career will differ for girls and boys.

Hypothesis 2b: *The associations between perceived prevalence and severity of gender bias in STEM and interest in a STEM major and career will be moderated by participants' gender*. That is, the associations between perceived prevalence and severity of gender bias in STEM and interest in a STEM major and career will differ for girls and boys.

Lastly, we conducted exploratory analyses examining the effect of perceived parent expectations on the participants' interest in STEM majors and careers. As noted above, parent expectations have more influence on educational and career choices among Asian American ethnic group (Sandhu, 2015). Given that little prior research has examined the role of parental expectations within an expectancy-value framework, we did not have prior hypothesis about this construct. Thus, we advanced the following research question:

RQ 1: *To what extent does perceived parent expectation play a role in predicting the participants' interest in STEM majors and careers?*

Method

Participants

The current study used a cross-sectional design, meaning that data were collected at one time-point. A total of 629 adolescents from a high school in northern California participated during the 2012-2013 academic year. Students ranged from middle to high socioeconomic status (SES), which was reflected in the low percentage (4.2%) of students at the school who received free/reduced lunch. Relatedly, participants' parents had a high level of education: 540 (86%) reported that one or both of their parents had obtained at least a bachelor's degree. Participants themselves were fairly STEM oriented as 354 (56%) indicated that they planned to pursue a STEM college major.

Participants ranged in age from 13 to 19 (M = 16.09, SD = 1.21). Of the participants, 300 (48%) were girls and 321 (51%) were boys; 8 participants (1%) elected not to disclose their gender identity. With respect to ethnic backgrounds, 386 participants (61%) identified as East Asian, 134 (21%) identified as South Asian, 66 (11%) identified as European American, 16 (3%) identified as Multiracial, 11 (2%) identified as Middle Eastern, 8 (1%) identified as African

American, 6 (1%) identified as Latino/a, and 2 (.3%) identified as American Indian or Pacific Islander.

Procedure

Math and science teachers sent home parental consent forms with students. The consent forms explained that students were invited to participate in a study that focused on their academic interests. About one month after distributing the consent forms, the research team returned to the classrooms for survey administration. In addition to obtaining parental consent, the research team obtained written assent from all participants. Students completed the survey during their math or science classes, which lasted approximately one hour. Nearly all participants completed the full survey. Students who did not participate in the study worked on other schoolwork while their peers completed the survey.

Measures

Before administering the surveys, the research team asked each participant whether they were more interested in math or science. The survey the participants received had wording that was tailored to their preference. For instance, students who reported that they were more interested in science responded to questions about their science identity, whereas students who reported that they were more interested in math responded to questions about their math identity.

Control Variables

A key goal of the current study was to examine the predictive strength of STEM expectancies and values after controlling for other theoretically grounded variables. In addition to controlling for ethnicity and gender, we also included the following control variables in the regression models.

Parent education. Participants separately indicated their mother and father's level of education on the following scale: 1 = *elementary school*, 2 = *some high school*, 3 = *high school graduate*, 4 = *some college*, 5 = *bachelor's degree*, 6 = *some graduate school,* or 7 = *graduate degree*. When participants provided information about both parents, these values were averaged to create a composite parent education variable. Otherwise, the value for the one parent was used.

Perceived parent expectation. In addition to gender, ethnicity, and parent education, we included perceived parent expectation in our exploratory analyses. Perceived parent expectation in our study was assessed by asking, "When you consider your future occupational/educational goals, how important are your parents' expectations?" and was measured on the Likert scale ranging from *1 (Not Important)* to *5 (Extremely Important)*.

Self-reported grades. Kuncel, Crede and Thomas (2005)'s meta-analysis findings note that self-reported grades are generally considered a close index of students' actual grades and they both predict similar outcome measures. Accordingly, participants' self-reported grades were used as a reliable measurement in the current study. Given that the current study recognized math and science as two distinct domains, grades in math and science were used separately. Participants were asked to circle one of the grades they typically received on their report card for each subject: A+, A, A-, B+, B, B-, C+, C, C-, and below C-. These grades were converted to a 10-point scale (A+ = 10, below C- = 1).

Focal Predictors

Perceived gender bias. We examined the participants' perceived gender bias using two separate measures. First, we assessed students' perceived *prevalence and severity* of gender bias in STEM. Given that adolescents may not be familiar with the definition of gender bias, the research team provided participants with some brief introductory information before assessing their perceptions of the prevalence and severity of sexism in math [science] (see Leaper & Brown, 2008). Specifically, the research team provided a brief definition of sexism and explained that some people are concerned about sexism in STEM, whereas others are not, in the survey. In addition, the research team encouraged participants to provide their personal opinion and assured that there were no right or wrong answers. Participants responded to two closed-ended questions after reading the prompt. The first question assessed participants' perceived prevalence of gender bias: "In your opinion, how common is gender bias in the field of math [science]?" Participants responded on a scale ranging from 1 (*not common at all*) to 5 (*very common*). The second question assessed their perceived severity of gender bias: "In your opinion, how serious a problem is gender bias in the field of math [science]? Participants responded on a scale ranging from 1 (*not serious at all*) to 5 (*very serious*).

STEM expectancies and values. Participants' expectancies and values in math and science were individually measured using the items from Eccles' expectancy-value model of motivation (Eccles & Wigfield, 1995). The measure consisted of a total of 17 items, 10 items for expectancy scale and 7 items for value scale. All items were rated on a 4-point scale. Examples of expectancy scale are as follows: "In general, how difficult is math [science] for you?" (1 = *very difficult*, 2 = *somewhat difficult*, 3 = *somewhat easy*, and 4 = *very easy*) and "How well do you think you will do in your math [science] course this year?" (1 = *not at all well*, 2 = *fairly well*, 3 = *very well*, and 4 = *extremely well*). Examples of value scale are as follows: "In general, how interesting or fun do you find working on math [science] assignments? (1 = *very boring*, 2 = *somewhat boring*, 3 = *somewhat interesting*, and 4 = *very interesting*)." and "How important is it to you to get good grades in math [science]?" (1 = *not at all important*, 2 = *slightly important*, 3

= *somewhat important*, and 4 = *very important*). The internal reliability for the self-expectancy measure was excellent (α = .93); the internal reliability for the value measure was good (α = .81).

Outcome Variables

Interest in a STEM major. We provided a list of 46 college majors to assess participants' anticipated college majors. Participants were asked to put a checkmark next to the major they planned to pursue in college. Participants could skip this question if they did not plan to attend college; however, all participants responded. Only three participants (.5%) indicated that they were undecided about their major. The remaining 626 students were first grouped according to whether they anticipated pursuing a STEM major (e.g., biological sciences, computer engineering, mathematics) or a non-STEM major (e.g., art, history, literature, business). Given that women tend to be well represented in social sciences (e.g., psychology, anthropology; NSF, 2016), these majors were not included in the STEM category.

Amount of math required for major. We used the website O*NET OnLine (https://www.onetonline.org/) to determine the amount of required math for the listed 46 college majors. On a scale of 1-100, we entered a specific value for each college major, based on the closest prospective career on the website. For example, we entered 94 for physics major, which is the amount of math required for physicists according to the O*NET OnLine website. Similarly, we entered 36 for psychology major, which is the amount of math required for clinical psychologists.

Interest in a STEM career. To assess participants' interest in pursuing a STEM career in the future, we asked them to respond to the following question: "Please rate your likelihood of pursuing a career related to science someday." Response options ranged from 1 (*extremely unlikely*) to 7 (*extremely likely*).

Results

Preliminary Analyses

Multivariate analyses of variance (MANOVAs) were used to test for mean ethnic and gender differences in the predictor variables. More specifically, we conducted separate MANOVAs to test for ethnic and gender variation in four sets of variables: mother/father education, STEM grades, perceived gender bias, and expectancy/value. Findings are detailed in Tables 1 and 2 and summarized below.

Ethnic differences. The first set of MANOVAs tested for differences across three ethnic groups, namely East Asian, South Asian, and European American because they make up the majority (93%) of the sample. The MANOVA testing for ethnic differences in *perceived gender bias* had a nonsignificant multivariate effect. This means that perceptions of the prevalence and severity of gender bias in STEM did not significantly differ as a function of participant ethnicity. In contrast, the other three MANOVAs testing for ethnic differences were significant. First, the MANOVA testing for ethnic differences in *parent education* showed a significant multivariate effect, Pillai's Trace = .04, $F(4, 1024) = 5.54$, $p < .001$, partial $\eta^2 = .02$. As detailed in Table 1, follow up univariate ANOVAs illustrated that the main effect of ethnicity was significant for both father education and mother education. Post-hoc pairwise comparisons using a Bonferroni correction showed the same pattern for both father education and mother education: Participants who identified as South Asians had fathers and mothers with significantly higher education than participants from East Asian and European American groups. However, participants from East Asian and European American groups did not significantly differ in their father education and mother education.

Second, the MANOVA testing for ethnic differences in *grades* showed a significant multivariate effect, Pillai's Trace = .02, $F(4, 1154) = 3.35$, $p = .01$, partial $\eta^2 = .01$. As detailed in Table 1, follow-up univariate ANOVAs illustrated that the main effect of ethnicity was significant for both math grades and science grades. Post-hoc pairwise comparisons using Bonferroni correction demonstrated that participants who identified as European American were significantly lower in math grades than participants from East Asian and South Asian groups, whereas participants from East Asian and South Asian groups did not significantly differ in their math grades. On the other hand, participants who identified as South Asians had significantly higher science grades than participants who identified as European Americans. Participants from the East Asian group, however, did not differ in science grades with the other two groups.

Third, the MANOVA testing for ethnic differences in STEM *expectancy/value* showed a significant multivariate effect, Pillai's Trace = .04, $F(4, 1164) = 6.13$, $p = .003$, partial $\eta^2 = .02$. As detailed in Table 1, follow-up univariate ANOVAs illustrated that the main effect of ethnicity was significant for values, but not for self-expectancies. Post-hoc pairwise comparisons using Bonferroni correction demonstrated that participants in the South Asian group reported significantly higher STEM values than participants in East Asian and European American groups. Participants from East Asian and European American groups, however, did not significantly differ in their values.

Gender differences. The MANOVA testing for gender differences in *parent education* had a nonsignificant multivariate effect. This finding means that parent education did not significantly differ as a function of participant gender. In contrast, the other three MANOVAs testing for gender differences were significant. First, the MANOVA testing for gender differences in *grades* showed a significant multivariate effect, Pillai's Trace = .01, $F(2, 611) =$

3.66, p = .03, partial η^2 = .01. As detailed in Table 2, follow-up univariate ANOVAs illustrated that the main effect of gender was significant for math grades, but nonsignificant for science grades. Investigation of the means demonstrated that boys were significantly higher in math grades compared to girls.

Second, the MANOVA testing for gender differences in *perceived gender bias* showed a significant multivariate effect, Pillai's Trace = .05, $F(2, 618)$ = 15.20, p = .00, η^2 = .05. As detailed in Table 2, follow-up univariate ANOVAs illustrated that the main effect of gender was significant for both perceived prevalence and severity of gender bias. Investigation of the means demonstrated that girls were significantly higher in both their perceived prevalence and severity of gender bias in STEM compared to boys.

Third, the MANOVA testing for gender differences in STEM *expectancy/value* showed a significant multivariate effect, Pillai's Trace = .102, $F(2, 616)$ = 34.80, p = .00, η^2 = .10. As detailed in Table 2, follow-up univariate ANOVAs illustrated that the main effect of gender was significant for self-expectancies, but not significant for values. Descriptive statistics demonstrated that boys were significantly higher in self-expectancies compared to girls.

Hierarchical Linear Regression

We began by conducting bivariate correlations and regression diagnostics to test for multicollinearity. Correlations among continuous predictor variables (and corresponding descriptive statistics) are presented in Table 3. Father education is positively correlated with the amount of math required for the major, which indicates that participants are more likely to pursue college majors that involve higher levels of math if their father education levels are higher. Participants' math and science grades as well as their self-expectancies and values are also positively correlated with the amount of math required for the major. In other words, participants are more likely to pursue math-intensive college majors if they have (a) higher grades in math and science and (b) higher self-expectancies and values in math and science. The same pattern of findings emerged when we examined correlations of participants' interest in a STEM career. In addition, the amount of math required for the major and interest in a STEM career had a moderate positive correlation with each other. Regression diagnostics illustrated that the variance inflation factors (VIF) at the significant step in each model were less than the threshold value of 2.5, with *one* exception of the math grades in predicting interest in a math career (VIF=2.61). These diagnostics indicate that multicollinearity was not a problem. All participants completed the surveys. We did not have any missing data per se because the means of each construct were computed based on the available data even in the case of accidentally skipped items for a construct.

Hierarchical regression was used to test our hypotheses.[1] As noted, we considered three outcome variables: interest in a STEM major, amount of math required for major, and interest in a STEM career. All models were tested separately for the math and science survey takers. In Step 1 of each regression, we included the following background variables: participants' gender, ethnicity, and parent education. Gender was dummy coded (0 = *girl,* 1 = *boy*). In addition, two categories of ethnicity were dummy coded such that European American participants were the reference category against which East Asian and South Asian participants were compared (0 = *European American,* 1 = *East/South Asian*). In Step 2 of each regression, we included STEM grades (both math and science grades). Perceived prevalence and severity of gender bias and self-expectancies and values were included in Step 3 and Step 4 of the regression models,

[1] Preliminary analyses demonstrated that the "parent expectation" predictor variable was nonsignificant in all models. Accordingly, it was dropped from the forthcoming analyses. One of the models is presented in the Appendix. Additional findings are available from the first-author upon request.

respectively. In Step 5 of each regression, we included the hypothesized 2-way interactions involving gender (i.e., moderation effects).

Math career interest. As seen in Table 4, results of hierarchical linear regression revealed that the model was significant at each of the five steps in predicting participants' interest in a math career. Furthermore, except for math and science grades entered in Step 2 and perceived gender bias entered in Step 3, each step of the regression added significantly to the model. Therefore, the model is interpreted at Step 5. At this step, the model accounted for 32.8% of the variance in participants' interest in a math career. Being a boy, perceiving a greater prevalence of gender bias in math, and being higher in math value each significantly predicted greater math career interest. Also, two interaction terms were significant: Gender x Perceived Prevalence of Gender Bias and Gender x Math Values.

The 2-way interaction between gender and math values is plotted in Figure 1. The simple slope for girls was significant ($b = .50$, $p < .001$), such that interest in a math career increased as girls' math values increased. The simple slope for boys was also significant ($b = .24$, $p = .01$), but it was less pronounced for boys than it was for girls. The 2-way interaction for gender and perceived prevalence of gender bias is plotted in Figure 2. However, the simple slopes for both girls and boys were nonsignificant. This interaction is therefore not discussed further.

Science career interest. As seen in Table 5, results of hierarchical linear regression revealed that the model was significant at all steps except at Step 1. Furthermore, the variables in Step 2 and Step 4 added significantly to the model. Step 5, however, did not add to the model, which indicates that were no significant interaction effects. Hence, the model is interpreted at Step 4. At this step, the model accounted for 43.4% of the variance in participants' science career interest. Higher math grades, higher science self-expectancies, and higher science values each predicted greater interest in pursuing a science career.[2]

Amount of math required for major. As seen in Table 6, results of hierarchical linear regression revealed that the model was significant at each of the five steps in predicting the amount of math required for the major for *math survey takers.* Furthermore, except for the perceived prevalence and severity of gender bias in Step 3 and the 2-way interaction terms in Step 5, each step of the regression added significantly to the model. Therefore, the model is interpreted at Step 4. At this step, the model accounted for 17.7% of the variance in predicting the amount of math required for the major. Gender and higher math values were significant predictors of the amount of math required for the major.

As seen in Table 7, results of hierarchical linear regression revealed that the model was significant at each of the five steps in predicting the amount of math required for the major for *science survey takers.* Furthermore, each step of the regression added significantly to the model, except for perceived gender bias in Step 3 and the 2-way interaction terms in Step 5. Therefore, the model is interpreted at Step 4. At this step, the model accounted for 18.3% of the variance in predicting the amount of math required for the major. Gender, higher father education, and higher science values were significant predictors of the amount of math required for the major.

Discussion

The present study examined the factors that predict adolescents' interest in STEM majors and careers. Predictions were guided by expectancy-value theory, which emphasizes the influence of individuals' self-expectancies and values on their academic and career choices

[2] We also conducted binary logistic regressions to identify predictors of participants' STEM major interest (i.e., STEM vs. non-STEM). The results of these analyses were nearly identical to those examining STEM career interest. Those analyses are therefore not reported here; however, a write-up is available from the first-author upon request.

(Eccles, 1983). Although STEM self-expectancies were not strongly associated with participants' interest in STEM majors and careers, STEM values consistently emerged as a significant predictor across the hierarchical regressions. Moderation analyses indicated that this association differed in strength for girls and boys. Below, further details and implications of these findings are discussed.

Self-Expectancies and Values

EVT suggests that individuals' expectancies and values play an important role in predicting academic outcomes, even after ability indicators, such as grades, are controlled (Chemers et al., 2001). Hence, we hypothesized that adolescents' STEM self-expectancies and values would be significant predictors of their interest in STEM majors and careers after controlling for gender, ethnicity, parent education, grades, and perceived gender bias. Consistent with expectations, our findings demonstrated that self-expectancies and values accounted for a significant amount of variance in predicting the interest in a STEM major and career in all four models, which is consistent with prior research (e.g., Wang & Degol, 2013). However, in the current study, *only* STEM values consistently emerged as a significant predictor of interest in a STEM major and career.

Contrary to our expectations and prior research (e.g., Eccles & Wigfield, 2002; Watt, 2006; Watt et al., 2012), self-expectancies in both math and science domains were nonsignificant in most of the regression models. (Self-expectancies were only significant at the .05 significant level in predicting interest in a science career.) It is not clear why self-expectancy was not a stronger predictor. One possible explanation pertains to the majority presence of Asian American participants in our sample. Specifically, Wang's (2013) findings indicate that math self-expectancies, influenced by early math achievements, had a much less positive influence on

STEM intent among European American and Asian students compared to the underrepresented minority students. However, it is noteworthy as well as anticipated that adolescent boys in our sample still indicated higher STEM self-expectancies than adolescent girls. The finding is similar to prior research with other samples, which revealed that girls and women were, on average, lower in STEM self-expectancies than were boys and men (Wang & Degol, 2013; Watt, 2006), and extends prior research such that this gender difference was documented in a sample that predominantly included Asian American adolescents.

On the other hand, we did find partial support for Hypothesis 1 such that STEM values predicted the adolescents' STEM major and career interests above and beyond other control variables. These results are consistent with work showing that attitudes toward math and science (e.g., being interested in the subject and recognizing its importance) at an early age have a positive influence on fostering the intent to choose STEM disciplines in college (Wang, 2013).

Demographic Variation

Although Asian Americans are overrepresented in STEM fields, a gender imbalance in the STEM workforce still exists within this ethnic group (Hill et al., 2010). Our findings reveal the same pattern such that *gender* was consistently a significant predictor in most of the regression models. In particular, our findings suggest that boys were more likely than girls to express an interest in STEM pursuits, and imply that educators and policymakers need to find the means to promote girls and women's interest in STEM fields. The inclusion of girls and women in STEM fields not only helps create a more diverse workforce, but also maximizes innovation, creativity, and competitiveness in developing better designed scientific and technological products, services, and solutions that represent all users (Hill et al., 2010).

In addition, father education was significant in predicting the amount of math required for the major for science survey takers. It is not as clear why father education was significant in one model, but not in the others. However, literature reveals the important role family plays in Asian American populations (see Archer et al., 2013; Lee, Min, & Mamerow, 2015; Ma, 2001). For instance, Asian American students are more likely than European American students to be influenced by their families in their career choices (Tang, 2002). In particular, Sandhu's (2015) study found that relationships with fathers had a significant influence on the Asian American young adults' career choices. Similarly, Sandhu's (2011) study results showed that both Asian American and Chinese groups viewed their father as the most influential person in their career choices. A study that examined the factors related to women's degree attainment and career goals in STEM also found that science majors had fathers who were more educated (Nitopi, 2010).

Math and Science Grades

Math and science grades were included in Step 2 of each of the four regression models. Our results indicated that *only* math grades were significant in predicting participants' interest in pursuing a science career. This result is not surprising. Math is often a gateway course for STEM majors and careers (Hyde, Fennema, & Lamon, 1990; Watt & Eccles, 2008). However, neither math nor science grades were significant in other regression models. Interestingly, science grades were initially significant in Step 2 of the models that predicted interest in science careers, but the significance of science grades vanished once science self-expectancies and values were included in the models; there was not enough leftover variance in science grades to function as a significant predictor. This result is consistent with EVT, which explains that one's self-expectancies and values are a much more important predictor of academic motivation than ability indicators such as grades (Chemers et al., 2001). A few studies' findings also suggest that high school math coursework preparation is indeed a more important predictor of entering STEM disciplines than the grades (Goyette & Mullen, 2006; Ma, 2009).

The Interaction Effect of Gender and Math Values

Our MANOVA findings suggest that there are no gender differences in STEM values. However, the moderation effects indicated that the association between STEM values and interest in a STEM major and career varied on the basis of gender. Specifically, the simple slope for math values indicated that interest in a math career increased as a girl's math values increased. The corresponding simple slope was also significant for boys, but was much less pronounced than it was for girls. This finding suggests that despite the fact that girls and boys in our sample both value math to the same degree, math values operate differently as a predictor. In particular, girls are much more likely to express an interest in STEM careers as their math values increase.

Perceived Gender Bias

Gender bias in STEM fields is still very much present (Leaper & Brown, 2008; Moss-Racusin, Dovidio, Brescoll, Graham, & Handelsman, 2012). Despite its prevalence, the perceptions of gender bias in STEM may not be consistent across individuals or ethnic groups. Our findings indicate that the adolescents' perceived prevalence and severity of gender bias did not significantly predict their interest in STEM majors or careers. Because our study comprised a majority of Asian American participants, it is possible that a positive math ability stereotype associated with Asian ethnic groups helps protect Asian American female adolescents from gender stereotype threats (Shih, Pittinsky, & Ambady, 1999). Robnett's (2016) findings also suggest that gender bias becomes more serious once girls and women join male-dominated math-intensive majors in college, so our sample of high school students might not understand the extent of the problem. Moreover, average ratings of perceived prevalence and severity of gender bias in STEM are likely to vary across regions and the globe. Thus, it is possible that our pattern of findings might not replicate in other regions of the United States.

Limitations and Future Directions

Our study has some limitations, which will be highlighted along with corresponding future research directions. The first limitation of the study relates to generalizability. Our sample was predominantly composed of Asian American and European American participants, who are highly represented in STEM-related fields. Also, participants were recruited from a school in a middle-to-high SES neighborhood. Hence, it is not clear whether our findings would generalize to other ethnic minorities in STEM or to adolescents who originate from a different SES background. Another limitation pertains to the measurement of some variables such as self-reported grades. Despite the prevalent use of self-reported measures in many STEM-related studies (Gottfried & Williams, 2013; Lee et al., 2015), the use of such measures is still regarded as a concern due to the possible large measurement error with self-reporting items (Bertrand & Mullainathan, 2001).

In addition, the number of variables were limited in our study in order to prevent multicollinearity. For example, our research did not examine the impact of other meaningful variables, such as high school GPA (e.g., Lent, Brown, & Gore, 1997; Sax, 1994), peer support (e.g., Riegle-Crumb, Farkas, & Muller, 2006; Stake & Nickens, 2005), the influence of teachers (e.g., Heaverlo, 2011), parental occupation (e.g., Sahin, Ekmekci, & Waxman, 2017), math coursework preparation (e.g., Moakler Jr. & Kim, 2014), or being placed into higher-ability mathematics courses (e.g., DeThomas, 2017), on the adolescents' STEM major and career interests.

Another limitation pertains to the measurement of the perceived parent expectation variable. While conducting the analyses, we realized that perceived parent expectation is perhaps one of the most, if not the most, critical variables in predicting Asian American adolescents' college major choices in STEM fields. Research suggests that parent expectations exert strong influence on occupational choices among the Asian American population and these expectations are consistently a significant predictor of the adolescents' expected career choices (Sandhu, 2015). Thus, we included *perceived parent expectation* as one of the control variables in our study as an exploratory analysis, but did not obtain any significant results. This finding was contrary to our expectations and literature on Asian American ethnic groups, which consistently show that parent expectations greatly influence students' college major and career choices (Archer et al., 2013; Lee et al., 2015; Ma, 2001).

We conclude that this null result might be due to the weak measure of the variable in the survey. Perceived parent expectation in our study was measured on a Likert scale ranging from *1 (Not Important)* to *5 (Extremely Important)* with a single questionnaire. We reasoned that we did not obtain reliable results as the measure was just a single item, which had some vague wording. It is possible that we would have found significant effects of perceived parent expectation if we had constructed the survey item differently by including multiple questionnaires that were better-phrased. For example, in Fukuoka's (2016) study, the author established a total of 18 items to measure the perceived parent expectations about humanity and academic achievement/career using a five-point scale. Previous studies that have shown the significant impact of perceived parent expectations on STEM major choices and STEM persistence have also used open-ended questions and then employed thematic analysis (e.g., Nguyen, 2015). It is important for future similar studies that focus on the predictive associations of the participants' perceived parent expectations and their STEM major and career interests to utilize previously validated measures of the perceived parent expectations construct.

Another limitation is that our study focused only on whether or not participants *intend* to major in STEM in college. Hence, addressing issues such as STEM degree persistence, STEM degree completion, and STEM career choice upon graduation is beyond the scope of our current study (Moakler Jr. & Kim, 2014). Longitudinal data would be advantageous to track whether the participants who indicated STEM major interests actually picked STEM majors, and whether those who chose a STEM major persisted in or dropped out of STEM fields, as well as the possible factors shaping their decisions. Such data would provide a well-rounded understanding about what we should do if we want to attract more students and workers into STEM-related fields.

One of the key findings from our current study shows the associations between gender and STEM major and career interests. Although the hierarchical regressions provide predictive associations, examining the mechanisms (i.e., mediators) underlying these associations would be a worthwhile direction for future research. For example, research shows that adolescent girls report receiving less peer support of their STEM major and career pursuits relative to adolescent boys (Kessels, 2005; Robnett & Leaper, 2013; Stake & Nickens, 2005). Because gender was consistently a significant predictor of adolescents' STEM major and career interests, a future direction would be to test whether peer support mediates the associations between gender and STEM major and career interests. That is, the mediation analysis will allow us to examine whether being a boy is associated with greater peer support of STEM, which is in turn associated with greater STEM major and career interests, and vice versa for girls.

In addition, STEM values were significant predictors of potential STEM career interests in all models. Identifying and understanding what factors influence adolescents' STEM values is beyond the scope of the current study. Robnett's (2013) study found STEM identification, which is the extent to which students view themselves as members of STEM-related fields (Aschbacher, Li, & Roth, 2010), mediated the association between peer support and the intent to pursue a STEM career among high school students. Recent research also shows that STEM identification is predictive of expected and actual persistence in the STEM pipeline (Aschbacher et al., 2010; Chemers et al., 2011; Estrada, Woodcock, Hernandez, & Schultz, 2010). Moreover, girls and women find it more challenging to identify with STEM than boys and men (e.g., London, Rosenthal, Levy, & Lobel, 2011; Settles, Jellison, & Pratt-Hyatt, 2009). In this sense, it is also suggested to test whether STEM identification mediates the associations between values and STEM major and career interests as a future direction.

Conclusion

Given the increasing demand for STEM workers in the United States, attracting a bigger population to the STEM workforce is essential to compete in the global economy (Sahin et al., 2017). With a better understanding of precollege factors that influence students to pursue STEM disciplines, educators and policymakers can help expand the future STEM workforce. Overall, our findings build on prior research showing that STEM values from EVT predict STEM major and career interests, but add important new information showing that high math values appear to be especially important for adolescent girls. In light of these findings, schools may need to focus on developing interventions to increase students' STEM values. These interventions may include promoting STEM-related activities in classrooms and schools, early mathematics preparation, and support from parents, peers, and teachers. Future research is needed to understand what influences the adolescents' STEM values. Doing so will not only promote STEM entrance into postsecondary education but also will bring a diverse population into STEM as our findings highlight the importance of helping adolescent girls attain higher math values. From an economic and policy-maker standpoint, greater diversity in STEM helps advance STEM innovation and progress (Handelsmann, Briggs, Sullivan, & Towler, 2005; Zakaria, 2011). Lastly, a well-rounded understanding of the important contributing factors on the population who is highly represented in STEM disciplines can help researchers develop ideas about what might or might not work with attracting less represented groups into STEM fields.

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Table 1

MANOVA Showing Mean Ethnic Differences in Parent Education, Grades and Expectancy/Value

	East Asian	South Asian	European American	ANOVA Test Statistics		
	M (*SD*)	*M* (*SD*)	*M* (*SD*)	*F*	*p*	η_p^2
Parent Education						
Father education	6.15_a (1.37)	6.61_b (.79)	5.81_a (1.29)	9.84	<.001	.04
Mother education	5.51_a (1.38)	5.59_b (1.23)	5.44_a (1.17)	5.73	.003	.02
Grades						
Math grades	8.24_a (1.42)	8.20_a (1.50)	7.64_b (1.84)	4.58	.01	.02
Science grades	7.62_{ab} (1.68)	7.86_a (1.47)	7.19_b (1.74)	3.64	.03	.01
Expectancy/Value						
Self-expectancies	2.59_a (.62)	2.56_a (.65)	2.63_a (.70)	.28	.75	.00
Values	2.85_a (.53)	3.06_b (.54)	2.74_a (.65)	9.58	<.001	.03

Means in the same row with different subscripts are different at the .05 level.

Table 2

MANOVA Showing Mean Gender Differences in Grades, Perceived Gender Bias, and Expectancy/Value

	Boys	**Girls**	**ANOVA Test Statistics**		
	***M* (*SD*)**	***M* (*SD*)**	F	p	η_p^2
Grades					
Math grades	8.27_a (1.44)	7.94_b (1.61)	7.10	.01	.01
Science grades	7.69_a (1.60)	7.43_a (1.77)	3.63	.06	.01
Perceived Gender Bias					
Prevalence of gender bias	1.95_a (1.02)	2.39_b (1.08)	26.85	<.001	.04
Severity of gender bias	2.62_a (1.40)	3.04_b (1.29)	15.30	<.001	.02
Expectancy/Value					
Self-expectancies	2.77_a (.62)	2.39_b (.59)	60.97	<.001	.09
Values	2.86_a (.58)	2.86_a (.55)	.01	.93	.00

Means in the same row with different subscripts are different at the .05 level.

Table 3

Descriptive Statistics and Correlation Matrix for Continuous Variables

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
1. Father Education	--									
2. Mother Education	.564***	--								
3. Math Grade	.176***	.168***	--							
4. Science Grade	.256***	.214***	.533***	--						
5. Sexism Prevalence	.015	.055	.031	.071	--					
6. Sexism Severity	.01	.032	.049	.068	.434***	--				
7. STEM Self-expectancy	.064	.101*	.402***	.481***	-.018	-.006	--			
8. STEM Value	.027	.046	.227***	.319***	.088*	.130**	.327***	--		
9. Amount of Math Required for Major	.123**	.006	.201***	.201**	-.059	-.048	.246***	.263***	--	
10. STEM career interest	.100*	.06	.234***	.277***	.076	.069	.347***	.529***	.387***	--
Mean	6.18	5.58	8.1	7.56	2.17	2.82	2.59	2.86	64.3	5.02
Standard Deviation	1.31	1.36	1.56	1.71	1.07	1.36	0.63	0.56	16.7	1.78
Range	1-7	1-7	1-10	1-10	1-5	1-5	1-4	1.29-4	16-100	1-7

$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

Table 4

Hierarchical Regression Predicting Adolescents' Math Career Interest

	Step 1 β	Step 2 β	Step 3 β	Step 4 β	Step 5 β
Step 1: Background variables					
Gender	.026***	.26***	.28***	.24**	1.45**
Ethnicity	.09	.05	.07	.04	.07
Father Education	.09	.06	.05	.09	.06
Mother Education	.08	.07	.06	.05	.05
Step 2: Grades					
Math Grades		.08	.08	-.06	-.03
Science Grades		.11	.1	.1	.1
Step 3: Perceived Gender Bias					
Prevalence of gender bias			.07	.04	.26*
Severity of gender bias			.07	.02	-.14
Step 4: Expectancies and values					
Math Self-Expectancies				.1	.1
Math Values				.36***	.58***
Step 5: 2-way interactions					
Gender x Prevalence of gender bias					-.39*
Gender x Severity of gender bias					.26
Gender x Math Self-expectancies					-.08
Gender x Math Values					-1.08**
F_{model}	5.12**	4.23**	3.47**	6.15***	5.67***
R^2_{change}	.11	.02	.01	.13	.06
F_{change}	5.12**	2.3	1.16	14.63***	3.55**

$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

Table 5

Hierarchical Regression Predicting Adolescents' Science Career Interest

	Step 1 β	Step 2 β	Step 3 β	Step 4 β	Step 5 β
Step 1: Background variables					
Gender	.06	.02	.03	-.02	.42
Ethnicity	.1	.09	.08	.05	.06
Father Education	.93	.02	.02	.04	.03
Mother Education	-.34	-.07	-.07	-.04	-.04
Step 2: Grades					
Math Grades		.13	.13*	.11*	.11*
Science Grades		.23***	.23***	-.05	-.04
Step 3: Perceived Gender Bias					
Prevalence of gender bias			.05	.05	.01
Severity of gender bias			.05	.01	.04
Step 4: Expectancies and values					
Science Self-expectancies				.16*	.13
Science Values				.56***	.60***
Step 5: 2-way interactions					
Gender x Prevalence of gender bias					-.17
Gender x Severity of gender bias					-.08
Gender x Science Self-expectancies					.11
Gender x Science Values					-.33
F_{model}	1.35	6.66***	5.26***	23.59***	17.32***
R^2_{change}	.02	.1	.01	.32	.01
F_{change}	1.35	17***	1.07	85.38***	1.37

*$p < .05$; **$p < .01$; ***$p < .001$.

Table 6

Hierarchical Regression Predicting the Amount of Math Required for Adolescents' Preferred Majors (Math Survey-Takers)

	Step 1 β	Step 2 β	Step 3 β	Step 4 β	Step 5 β
Step 1: Background variables					
Gender	.23**	.22**	.25**	.21**	1.08*
Ethnicity	.07	.03	.05	.03	.05
Father Education	-.00	-.05	-.06	-.03	-.03
Mother Education	-.03	-.04	-.04	-.06	-.06
Step 2: Grades					
Math Grades		.06	.06	-.08	-.09
Science Grades		.18	.17	.18	.20*
Step 3: Perceived Gender Bias					
Prevalence of gender bias			.05	.04	.08
Severity of gender bias			.09	.06	.02
Step 4: Expectancies and values					
Math Self-expectancies				.12	.22
Math Values				.25**	.35**
Step 5: 2-way interactions					
Gender x Prevalence of gender bias					-.07
Gender x Severity of gender bias					.07
Gender x Math Self-expectancies					-.45
Gender x Math Values					-.49
F_{model}	2.54*	3.04**	2.60*	3.51***	2.73**
R^2_{change}	.06	.04	.01	.07	.02
F_{change}	2.54*	3.88*	1.23	6.50**	.8

$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

Table 7

Hierarchical Regression Predicting the Amount of Math Needed for Adolescents' Preferred Majors (Science Survey-Takers)

	Step 1 β	Step 2 β	Step 3 β	Step 4 β	Step 5 β
Step 1: Background variables					
Gender	.22***	.19**	.17**	.16**	.23
Ethnicity	.1	.1	.1	.08	.07
Father Education	.14*	.12	.11	.12*	.12
Mother Education	-.05	-.09	-.08	-.07	-.08
Step 2: Grades					
Math Grades		.1	.1	.09	.09
Science Grades		.14*	.14*	.04	.05
Step 3: Perceived Gender Bias					
Prevalence of gender bias			-.05	-.06	-.05
Severity of gender bias			-.04	-.05	-.04
Step 4: Expectancies and values					
Science Self-expectancies				.04	-.06
Science Values				.25***	.33***
Step 5: 2-way interactions					
Gender x Prevalence of gender bias					-.02
Gender x Severity of gender bias					-.02
Gender x Science Self-expectancies					.46
Gender x Science Values					-.46
F_{model}	6.55***	7***	5.50***	6.83***	5.14***
R^2_{change}	.08	.04	.01	.06	.01
F_{change}	6.55***	7.36**	.88	10.88***	.94

*$p < .05$; **$p < .01$; ***$p < .001$.

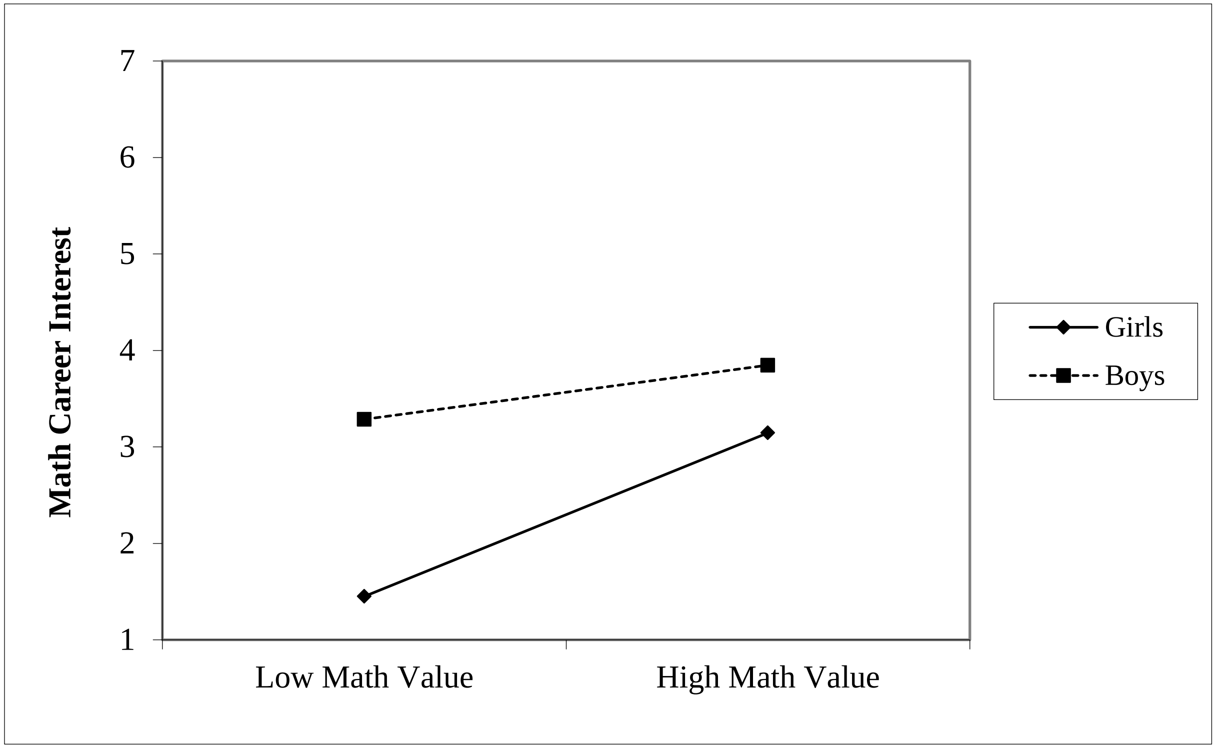

FIGURE 1. Gender x Math Value with Math Career Interest

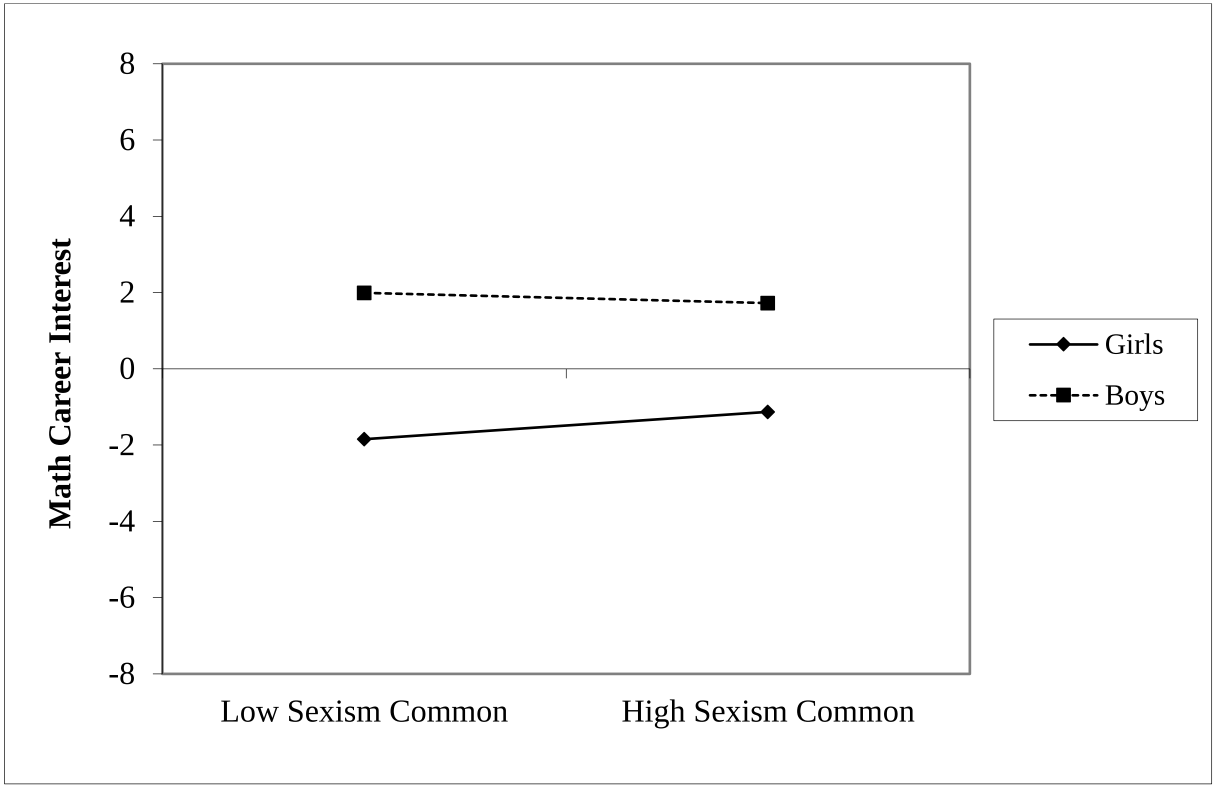

FIGURE 2. Gender x Perceived Prevalence of Gender Bias in STEM with Math Career Interest

Appendix

Table 8

Hierarchical Regression Predicting Adolescents' Math Career Interest (Parent Expectation Variable Included)

	Step 1 β	Step 2 β	Step 3 β	Step 4 β	Step 5 β
Step 1: Background variables					
Gender	.26**	.27**	.30***	.26**	1.6**
Ethnicity	-.12	-.06	-.08	-.09	-.10
Father Education	.02	-.04	-.05	.01	.02
Mother Education	-.02	-.03	-.05	-.08	.09
Parent Expectations	-.04	-.03	-.07	-.11	-.08
Step 2: Grades					
Math Grades		.07	.07	-.09	-.10
Science Grades		.17	.17	.17	.19
Step 3: Perceived Gender Bias					
Prevalence of gender bias			.08	.10	.24
Severity of gender bias			.13	.10	.07
Step 4: Expectancies and values					
Math Self-Expectancies				.12	.28
Math Values				.29***	.45**
Step 5: 2-way interactions					
Gender x Prevalence of gender bias					-.60
Gender x Severity of gender bias					-.65
Gender x Math Self-expectancies					-.24
Gender x Math Values					.02
F_{model}	2.72*	3.00**	2.90**	3.95***	3.43***
R^2_{change}	0.08	0.04	0.03	0.08	0.04
F_{change}	2.72*	3.47*	2.34	7.55**	1.76

*$p < .05$; **$p < .01$; ***$p < .001$.