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Gender Equity in College Majors: Looking Beyond the STEM/Non-STEM Dichotomy for Answers Regarding Female Participation

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Women are underrepresented in many science, technology, engineering, and mathematics (STEM) majors and in some non-STEM majors (e.g., philosophy). Combining newly gathered data on students' perceptions of college major traits with data from the Education Longitudinal Study of 2002 (ELS:2002), we find that perceived gender bias against women emerges as the dominant predictor of the gender balance in college majors. The perception of the major being math or science oriented is less important. We replicate these findings using a separate sample to measure college major traits. Results suggest the need to incorporate major-level traits in research on

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gender gaps in college major choices and the need to recognize the impact of perceptions of potential gender discrimination on college major choices.

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Women's continued underrepresentation in many science, technology, engineering, and mathematics (STEM) fields remains a concern for policymakers, educators, and researchers around the world (Blickenstaff, 2005; Ceci, Williams, & Barnett, 2009; Hill, Corbett, & St. Rose, 2010; National Science Board [NSB], 2010; National Strategic Review of Mathematical Sciences Research in Australia, 2006; Natural Sciences and Engineering Research Council of Canada, 2010). In certain STEM fields, the gender gap has closed or narrowed. For example, in 2012, women—who made up 56% of all college students that year (National Center for Education Statistics [NCES], 2014)—earned nearly 60% of bachelor's degrees in the biological sciences and 41% of bachelor's degrees in the physical sciences (National Science Foundation [NSF], 2014). In contrast, only 18% of bachelor's degrees in computer science and 19% of bachelor's degrees in engineering were awarded to women in 2012 (NSF, 2014). Researchers are still trying to understand the factors that steer women away from certain majors within STEM given the lack of improvement in gender balance in some STEM fields at the undergraduate level. With a gross gender imbalance still characterizing a number of STEM fields, public and private sectors continue to call for increased STEM degree production and participation by women (NSB, 2010). Despite decades of interventions and research, however, questions remain as to how to achieve gender equity in all STEM fields. Importantly, there is also variability in the representation of women within non-STEM fields (e.g., psychology has more women, economics has more men). These gender differences suggest that the gender imbalance is not strictly a STEM phenomenon, and thus, researchers should look beyond just STEM majors for the answers to differential major participation patterns.

Limitations of the STEM/Non-STEM Dichotomy

Much of the research and related policy literature dichotomizes STEM and non-STEM majors, implicitly assuming that the college majors constituting these two categories are inherently different and can be grouped together into two monolithic categories. A lack of consensus of what fields comprise "STEM" confounds the dichotomy further. For example, the Department of Homeland Security's Immigration and Customs Enforcement's definition of STEM, designed to regulate international students' optional practical training programs, does not include the social sciences, whereas the NSF does include them. Due to the stark differences in the representation of women and men in different STEM and non-STEM fields, the STEM/non-STEM distinction may no longer be informative to the examination of gender differences in college major (and subsequent career) choices—and in fact may be misleading efforts to understand, address, and close gender gaps (Ma, 2011; Turner & Bowen, 1999). Furthermore, Riegle-Crumb and King (2010) encourage additional research on the lack of women in specific STEM areas where we see some of the lowest numbers, such as computer science and engineering. Some studies have improved on this dichotomy by considering gender representation in different majors within STEM to better understand where the gender gaps lie (George-Jackson, 2011, 2014; Perez-Felker, McDonald, Schneider & Grogan, 2012; Riegle-Crumb & King, 2010; Riegle-Crumb, King, Grodsky, & Muller, 2012); however, even these more nuanced categorizations still may not get at the heart of the issue.

This reliance on a STEM/non-STEM dichotomy has multiple implications for the research conducted in this area as it leads to (a) an oversimplification of students' college majors by relying only on the first reported major in order to stay within the STEM/non-STEM distinction and (b) the exclusion of major-level characteristics that cut across STEM and non-STEM majors when examining factors related to gendered college major choices (as we will discuss in greater detail in the following section). The reliance on students' first-reported major does not accurately capture college students who simultaneously major in two or three different fields, which may also span multiple STEM and/or non-STEM disciplines. Likewise, many college majors are interdisciplinary in nature, with some straddling the STEM/non-STEM divide (e.g., math education). Without incorporating all of students' college major information and recognizing the uniqueness of a student's particular major and minor combination, examinations of gender differences in students' choice of majors may not allow us to see the entire picture, missing much of the complexity.

Predictors of Gender Differences in College Major Choices

The current body of research on individual-level factors that contribute to gender differences in STEM major choices has identified several important variables, including but not limited to math and science preparation and achievement (Blickenstaff, 2005; Dalton, Ingels, Downing, & Bozick, 2007; Elliott, Strenta, Adair, Matier, & Scott, 1996; Ethington, 2001; Watt et al., 2017), attitudinal factors (e.g., interest, confidence; Eccles, 2009, 2011; Köller, Baumert, & Schnabel, 2001; Moakler & Kim, 2014; Watt et al., 2012, 2017), and students' values (e.g., importance of family or of making money; Wiswall & Zafar, 2015). Other studies that have examined gender differences in choice of STEM majors have focused on parents' STEM occupation (Moakler & Kim, 2014), students' occupational plans when they are in high school (Maltese & Tai, 2011; S. L. Morgan, Gelbgiser, & Weeden, 2013), and the connections between majors and career preparation (Mann & DiPrete, 2013). Regarding program- and policy-specific influences, establishing STEM ambassadors for outreach and other recruitment events (Gartland, 2014), attending public high schools focused on STEM (Subotnik, Tai, Rickoff, & Almarode, 2009), and early exposure programs (DeJarnette, 2012) are documented ways to increase students' interest in and/or entrance into STEM majors. The policies, programs, and structures of educational opportunities may differ according to context. For instance, South Korean students are tracked into one of two types of high schools, which then in turn influences their choice of major (Paik & Shim, 2013).

A comparatively small body of work has examined students' perceptions of the characteristics of college majors and how these perceptions may shape men and women's college major decisions. Rather than making a rational choice of which college major to pursue, which assumes the individual has correct and full information to make an objective decision, students are likely making a choice from a limited set of options. These options are influenced by their perceptions, which are shaped by their knowledge, experiences, and observations. Therefore, it is critical to focus specifically on these perceptions because these perceptions are what students use to make decisions when full, accurate, and timely information on all possible options is not necessarily available to them.

Focusing on the characteristics of college majors allows for a method that can account for both the fact that the characteristics of majors that are considered "STEM" and "non-STEM" may overlap and that characteristics of majors are likely perceived on a continuum as opposed to a dichotomy. Furthermore, this approach connects research to practice and policy by focusing on the characteristics of disciplinary fields, including how these characteristics are communicated, as potential levers for increasing gender equity in STEM rather than attempting to "correct" women's and men's choice of major. Young men and women likely choose their college major(s) and minor(s) based on their perceptions of a range of characteristics of college majors, including the degree to which they perceive the major as math or science based. Students are also likely to consider college majors along other continua, such as how welcoming a major is or if a major may lead to a career that involves helping people (Eccles, 1994; C. Morgan, Isaac, & Sansone, 2001). Although researchers and policymakers have emphasized the dichotomous STEM versus non-STEM categories, a more accurate approach might be to consider a variety of traits of college majors and each of these characteristics along a continuum.

Recent research suggests a number of potential traits of majors that may factor into gendered student choices in college majors and careers other than whether the majors are math or science based. Our main focus in this study is on whether or not majors are perceived as gender biased and how likely women are to choose majors that are often perceived as biased against them. Of course, there are many other characteristics of majors that may predict the size and direction of gender differences in those fields and that are also likely correlated with the extent to which a major is perceived as biased against women, math oriented, or science oriented. Based on the literature, our analyses will also consider the following traits of majors: helpful orientation, money orientation, and creative orientation. These other traits are not the main focus of our analyses, but we interpret the results for these traits to present a full picture of the results.

Gender Bias in Education and Academic Disciplines

Boys and girls develop gendered perceptions of disciplines early in their education (Farenga & Joyce, 1999; Steffens, Jelenec, & Noack, 2010), and these perceptions persist throughout middle and high school (Adamson, Foster, Roark, & Reed, 1998; Hirsch, Berliner-Heyman, Cano, Kimmel, & Carpinelli, 2011), a time at which plans for college major choices are developing (e.g., Maltese & Tai, 2010). This stereotyping has negative consequences for women's science career aspirations (Cundiff, Vescio, Loken, & Lo, 2013) and can lead to discrimination and negative attitudes toward women in typically male-dominated professions (Heilman, Wallen, Fuchs, & Tamkins, 2004). This research suggests that real discrimination and perceptions of potential discrimination based on stereotypes may impact gender differences in major choices, steering men and women toward majors with less discrimination against their gender (Cheryan, 2012). Gender stereotypes and discrimination could help to explain why gender gaps only exist in some STEM fields as fields with larger gender differences tend to be the ones that are perceived as more stereotypically masculine (e.g., engineering, computer science) compared to those that are less stereotypically masculine (e.g., health sciences, biology; Cheryan, 2012). This same argument can be extended to non-STEM fields in which more stereotypically masculine fields (e.g., economics, business) tend to have gender gaps favoring men whereas more stereotypically feminine fields tend to have more women (e.g., social work, education). Thus, it is critical to gain an understanding of the extent to which gender bias predicts gender differences in major choice over and above whether the major is a STEM field (or more precisely for this study, whether it is more strongly math and/or science oriented) and other potentially important traits of majors.

Other Traits of Majors

Traits beyond the gender bias or math or science orientation of majors may also influence students' choices. First, research suggests that the perception of a major as helpful to people may influence students' major choices. Women tend to be more likely than men to pursue majors that they perceive as allowing them to help others (Charles, 2011; Eccles, 1994; Turner & Bowen, 1999) while avoiding majors perceived as less helpful to others, despite the fact that these fields can often lead to careers that have benefits to society (Bonous-Hammarth, 2000; Diekman, Brown, Johnston, & Clark, 2010). Second, students incorporate future career earnings expectations when choosing their college major (Arcidiacono, Hotz, & Kang, 2012), with men being more likely to do so (Montmarquette, Cannings, & Mahseredjian, 2002; Wiswall & Zafar, 2015; Zafar, 2013). For example, Zafar (2013) found that men's preference for high future earnings explained the gender gap in choice of major more so than did ability. Thus, men may choose careers based on earning potential and as a consequence may gravitate toward STEM majors, which tend to lead to higher paying careers (Ryan, 2012). Third, the level of creativity and innovation that one feels they can utilize in their job may be related to their choices. Specifically, a student's choice of major is guided in part by how much they value challenges and independence, which may be one manifestation of creativity (Balsamo, Lauriola, & Saggino, 2013). It is important to account for these potentially relevant factors when examining the role of gender bias in gender differences in college major choices. In this way, we can better understand whether these factors predict gender differences in majors or whether perceived gender bias predicts gender differences above and beyond these factors.

The Current Study

In this study, we attempt to move beyond the limitations of past research generated by a reliance on a STEM/non-STEM dichotomy and contribute a new approach to the literature by (a) disaggregating college majors into a set of specific traits and (b) matching students on individual characteristics to isolate the role of college major traits. To accomplish these goals, we focus on the underlying traits associated with common majors instead of using the majors themselves or groups of majors (e.g., STEM or non-STEM) as the variables of interest. Drawing on the existing literature reviewed previously, we classify a set of 20 popular college majors using six newly developed scales that measure the extent to which a major is perceived as being (a) math oriented, (b) science oriented, (c) gender biased (against women), (d) helpful oriented, (e) money oriented, and (f) creative oriented. These six scales will be hereafter referred to as "major-level traits" or "traits of majors." In this study, our main focus is to examine the role of perceived gender bias in college major choices after accounting for the math and science orientation as well as control variables, which include helpful orientation, money orientation, and creative orientation.

In addition to the perceived traits of majors predicting gender differences in college major choices, we conceptualize gender imbalances to be influenced by individual characteristics that vary by gender (e.g., prior achievement in math, attitudes toward math). To account for these individual differences, we match men and women in a large, nationally representative data set on individual characteristics that have been shown to predict major choices. In this way, we can examine how traits of majors themselves are related to gender differences for men and women who have *similar* individual characteristics.

In this study, we focus on two research questions:

Research Question 1: How do undergraduate students perceive different traits of college majors?

Research Question 2: Does perceived gender bias against women predict gender differences in college majors over and above individual differences between male and female students and a number of other traits of majors (i.e., whether or not the major is perceived as being math or science oriented, money oriented, helpful oriented, or creative oriented)?

Although various traits of majors have been found to predict gender differences in college major choice (e.g., women are less likely to be in math-oriented fields), we hypothesize that gender bias against women will be the strongest predictor of gender differences in major choices and that women will be no less likely to enter math- or science-oriented disciplines after accounting for other aspects of those disciplines often found to be related to gender.

Data and Methods

In this study, we combined two data sets: the Education Longitudinal Study of 2002 (ELS:2002) and newly gathered data from undergraduate students. Both samples are described in more detail in the following sections. We also gathered data from Amazon's Mechanical Turk that replicates the data from the undergraduate students as a robustness check. We do not discuss this sample or the results from this sample in the article, but patterns were very similar to those found with undergraduate students. Information about this sample and results within this sample are included in the Supplementary Materials in the online version of the journal.

Education Longitudinal Study of 2002

The ELS:2002 data set is a large, longitudinal, nationally representative sample of U.S. students, allowing us to generalize to the population of 10th-grade U.S. students in 2002. This study draws on ELS:2002 data gathered from students in 10th grade (base year), 12th grade (first follow-up), and 2 years later (second follow-up) as well as high school transcript data. Because we examined students' college major choices, we selected students who were both enrolled full-time in a four-year college and had chosen at least one major at the second follow-up. Remaining students who were missing 10th-grade math and reading scores (n = 45) or had college major information that could not be categorized into 1 (or a combination) of our 20 majors based on the information provided (n = 72) were removed from the data set prior to analysis. The remaining sample included approximately 4,850 participants.[1]

Over half (57%) of the students were female, which is similar to the overall undergraduate population in the United States (NCES, 2013). To reduce the effects of missing data on our findings, we included indicator variables for whether a student was missing on a particular variable and matched on that indicator when conducting the propensity score matching analysis (Reardon, Cheadle, & Robinson, 2009).

Individual characteristics used to match men and women were selected from the ELS data set in each of four categories: (a) demographics (e.g., student race, socioeconomic status), (b) academic preparation and achievement variables (e.g., prior math and science courses taken), (c) math attitudinal variables (e.g., agreement with "Most people can learn to be good at math"), and (d) values variables (e.g., agreement with "It is important for me to find a job close to my family"). A list of all matching variables is provided in Supplementary Table S1 in the online version of the journal.

College Major

To characterize students' college major choices, we coded information provided in two variables in the ELS data set in which students wrote their first and second major(s).[2] Rather than using the exact Classification of Instructional Programs (CIP) codes, which code fields of study, provided by NCES in the data set, we recoded verbatim responses into 1 or more of 20 majors that are based on combinations of CIP codes (see Table 1 for list of majors/major categories and a summary of the weighted proportion of men and women in each major). We coded verbatim responses because the NCES data codes are inaccurate for about 20% of responses (Ingels et al., 2007) and NCES coded only the first major and did not take into account other majors or any concentrations within a major. More than one code was assigned to some responses to better capture the fields the major represents (e.g., math education was coded to capture both math and education) or capture multiple majors and/or concentrations. Each student's major information was coded by two independent coders. We calculated interrater agreement counting any disagreements (i.e., different major coded, different concentration coded, disagreement on whether there were additional majors or concentrations) between the two raters and found interrater agreement to be 91%. Discrepancies were discussed as a research team until a consensus was reached. Responses from the overwhelming majority of students (98%) fit into the 20 major categories (or some combination of them), though a small percentage did not, and those students were excluded from the sample. Excluded majors include those in which we could not determine the actual field of study (e.g., bachelor of arts, bachelor of

Table 1
Gender Differences in Students' Majors in the Education Longitudinal Study of 2002 Sample Sorted From Highest Percentage Males to Lowest Percentage Males

	Representation in Sample (Unweighted n = 4,850) Percent	Male Students (Unweighted n = 2,100) Percent	Female Students (Unweighted n = 2,750) Percent
Across majors		43.23	56.77
Engineering	7.69	89.38	10.62
Computer science	2.70	78.59	21.41
Economics	1.16	70.87	29.13
Philosophy	0.86	65.90	34.10
Architecture	0.98	60.73	39.27
Criminal justice	3.28	58.18	41.82
Mathematics	1.08	57.03	42.97
Physical science (e.g., chemistry, physics)	1.93	56.23	43.77
Business	20.14	52.06	47.94
Political science	4.33	49.33	50.67
Agriculture	1.67	46.61	53.39
Biology	6.70	44.79	55.21
Humanities (e.g., English, history)	6.09	44.15	55.85
Arts	6.21	42.88	57.12
Communications	5.26	35.95	64.05
Sociology	1.53	21.25	78.75
Education	8.69	21.07	78.93
Psychology	6.23	20.70	79.30
Health and clinical sciences	12.44	17.65	82.35
Social work	1.04	12.69	87.31

Note. Sample sizes are rounded to the nearest 10. Proportions were assigned based on how many majors and concentrations were reported for each student. The proportions for each major were then weighted by F2BYWT.

science, applied science) or that were a field of study that is traditionally associated with a two-year degree (e.g., cosmetology, automotive technology).

College Major Traits

The ELS data set has many strengths, including its large nationally representative sample, the extensive pre-college individual-level variables available (information that is unavailable in most postsecondary data sets), and its inclusion of students' verbatim responses to a question about their major(s). However, our motivation for this study was to shed light on *why* men and women entered particular majors, which the ELS data set does not provide.

Therefore, we developed a scale assessing college major characteristics to act as a proxy for ELS students' perceptions of different college major traits to better understand why men and women might differentially select majors with different characteristics. We collected these new data from a sample of undergraduate students because they were a similar age to the students in the ELS:2002 data set when they participated in the second follow-up (approximately two years after high school graduation). Therefore, these students provide a reasonable approximation of how students in the ELS data set might have perceived these majors at the time of second follow-up.

We iteratively developed a survey of college major characteristics through a mixed-methods process, which included cognitive interviews with a small sample. More details about scale development are included in the Supplementary Materials available in the online version of the journal. We developed six new scales, each of which assessed one potentially important characteristic of college majors: (a) math orientation, (b) science orientation, (c) gender bias (against women), (d) helpful orientation, (e) money orientation, and (f) creative orientation. For example, the math orientation items included, "To be successful in this major, you should be comfortable using math," while the money orientation items included "If a student chooses this major, that student will make a lot of money." Respondents rated how much they agreed (on a Likert scale from 1 = *strongly disagree* to 7 = *strongly agree*) with the statements provided for each of the 20 majors. Table 2 displays the items used for each scale.

As gender bias against women is the focal construct of the article, we now discuss the gender bias scale (and its creation) in greater detail. To assess perceived gender bias, we asked respondents the extent to which they agreed with the following three statements: "Women in this major experience discrimination based on their gender," "Women have a hard time succeeding in this major," and "This major is more welcoming to men than women." Because respondents could agree with these statements for a given major simply because they observed (or perceived) more men to be in that given major, we needed to find a way to ensure that our measure of gender bias operated independently from how many females a respondent thought were in a major. To achieve this independence, respondents were also asked what percentage of students in each major they thought were women with the following choices: 0% to 25%, 26% to 35%, 36% to 45%, 46% to 55%, 56% to 75%, and 76% to 100%. When we constructed the latent variable for gender bias from the responses to the three Likert items in the scale, we conditioned out participants' responses to the item about female representation. This process ensured that our measure isolated gender bias from what a respondent thinks female representation in the field is, circumventing concerns about the "bias" simply reflecting a discipline's gender balance. This is a real strength of our approach.

Table 2
Items and Factor Loadings for the Six Traits of Majors Scales

Scale	Items	α	Range of Factor Loadings
Math oriented	People in this major use math on a regular basis.	.96	.89–.91
	A person who is not good at math will struggle to succeed in this major.		
	To be successful in this major, you should be comfortable using math.		
	If a student chooses this major, that student should have a strong math background.		
	If a student chooses this major, that student will take a lot of courses that use math.		
Science oriented	People in this major use science on a regular basis.	.94	.85–.88
	A person who is not good at science will struggle to succeed in this major.		
	To be successful in this major, you should be comfortable with scientific concepts.		
	If a student chooses this major, that student should have a strong science background.		
	If a student chooses this major, that student will take a lot of courses that involve science.		
Gender biased	Women in this major experience discrimination based on their gender.	.81	.59–.82
	Women have a hard time succeeding in this major.		
	This major is more welcoming to men than women.		
	What percentage of students in this major are women? (0%–25%, 26%–35%, 36%–45%, 46%–55%, 56%–75%, 76%–100%) (covaried out)		
Helpful oriented	People in this major use their skills and knowledge to help others.	.85	.71–.83
	If a student chooses this major, that student will likely have a direct impact on others.		
	People in this major are devoted to the welfare of others.		
	If a student chooses this major, that student will work to improve people's lives.		
Money oriented	If a student chooses this major, that student will make a lot of money.	.91	.74–.90
	If a student chooses this major, that student will struggle to make ends meet.[a]		
	If a student chooses this major, that student will live a comfortable lifestyle.		
	If a student chooses this major, that student is likely to earn a high future salary.		
Creative oriented	People in this major use their creativity on a regular basis.	.85	.66–.82
	If a student chooses this major, that student will express ideas creatively.		
	A person who chooses this major is expected to be highly creative.		
	People in this major have to think outside the box.		

Note. n = 330. Items were rated on a scale from 1 (*strongly disagree*) to 7 (*strongly agree*) unless otherwise noted.
[a]Reverse-coded item.

The survey was administered to a sample of 330 undergraduate students from a large Southeastern university who took the survey through the psychology department subject pool. These students were 76% female and had an average age of 19.7 years (for more sample information, see Supplementary Table S2 available in the online version of the journal). The initial sample was 524 students, but 4 part-time students were removed (to match the ELS:2002 inclusion criteria used for this study), as were students with missing data or who incorrectly answered "catch" items that were included.

With data from this sample, we conducted a confirmatory factor analysis in MPlus 7.1 (Muthén & Muthén, 1998–2012) with all six scales including covariances between each scale. In the model, we treated the gender-biased latent factor slightly differently, as discussed previously. This factor was made up of the ratings on the three bias-based items (see Table 2) with participants' estimates of the percentage of women in each major covaried out. To reiterate, our goal was to only include the variance that was based on perceptions of bias and not on perceptions of the size of the gender gap.

Fit indices indicated that this model fit the data well, χ^2 = 600.01, df = 276, $p < .001$; root mean square error of approximation (RMSEA) = .013 (90% CI [.012, .015]); Comparative Fit Index (CFI) = .987; Tucker-Lewis Index (TLI) = .985, based on the criteria offered by Brown (2006; RMSEA $< .05$, CFI and TLI $> .95$). Table 2 shows the factor loadings for the items in this model as well as reliability estimates for each scale. To extract data from this analysis that could be used in the ELS sample, we extracted factor scores for each major on each scale and found the mean of these factor scores for each major/scale combination. These mean factor scores are displayed in Table 3 for each major on each scale. Raw means are available in Table 4. We provide both the mean factors scores and the raw means of each major because factor scores were used in the analysis, whereas the means are informative as they are in the metric of the original scale (1–7).

Integrating Information About Major Traits With ELS Major Data

To connect the information from the undergraduate sample with data from students in the ELS data set, the mean factor scores from the undergraduate student survey were assigned to students in the ELS data set based on their reported majors. This approach allowed us to incorporate factor scores for each of the six traits according to each student's unique major (and concentration, if applicable) combination. Students who had more than one major code were assigned a weighted mean of factor scores such that a major was equivalent to 1 and a minor or concentration was equivalent to .5.[3] For example, to assign a score for the science orientation rating, a student with a music business major would get credit for business as a major (mean factor score = −0.94) and music as a concentration (mean factor score for arts =

Table 3
Mean Factor Scores of Traits of Majors

Major Category	Math Oriented	Science Oriented	Gender Biased[a]	Helpful Oriented	Money Oriented	Creative Oriented
Engineering	2.20	1.54	1.00	−0.02	1.77	0.37
Computer science	1.31	0.85	0.67	−0.60	0.98	−0.27
Economics	1.46	−0.50	0.54	−0.50	0.62	−0.77
Philosophy	−1.90	−1.25	−0.29	−0.78	−1.40	0.60
Architecture	1.43	0.14	0.52	−0.37	0.93	1.30
Criminal justice	−0.94	−0.48	0.34	0.71	−0.06	−0.31
Mathematics	2.15	0.03	0.60	−1.02	0.30	−1.13
Physical science (e.g., chemistry, physics)	1.87	2.27	0.57	0.00	1.13	−0.74
Business	1.21	−0.94	0.64	−0.48	1.01	0.00
Political science	−0.68	−0.42	0.46	−0.37	0.34	−0.49
Agriculture	−0.55	0.30	0.22	−0.21	−0.81	−0.58
Biology	1.17	2.24	0.24	0.33	1.04	−0.75
Humanities (e.g. English, history)	−2.01	−1.73	−0.73	−0.71	−1.42	0.34
Arts	−2.24	−2.00	−0.95	−0.82	−1.70	1.93
Communications	−1.43	−1.35	−0.55	−0.04	−0.41	0.32
Sociology	−1.45	−0.53	−0.61	0.25	−0.98	−0.26
Education	0.00	0.04	−1.02	1.21	−1.30	0.80
Psychology	−0.89	0.86	−0.62	0.99	−0.05	0.24
Health and clinical sciences	0.98	2.08	−0.10	1.27	1.23	−0.49
Social work	−1.69	−1.13	−0.91	1.16	−1.22	−0.11

Note. n = 330. Majors are sorted from highest percentage males to lowest percentage males.
[a]Higher factor scores for gender bias indicate bias against women.

Table 4
Raw Means of Traits of Majors

Major Category	Math Oriented	Science Oriented	Gender Biased[a]	Helpful Oriented	Money Oriented	Creative Oriented
Engineering	6.71	5.81	5.16	4.82	6.19	5.04
Computer science	5.75	5.12	4.64	4.11	5.40	4.30
Economics	6.10	3.46	4.40	4.37	5.01	3.69
Philosophy	2.34	3.00	3.40	3.91	2.97	5.25
Architecture	5.99	4.26	4.40	4.45	5.35	6.02
Criminal justice	3.32	3.64	4.41	5.95	4.38	4.20
Mathematics	6.89	4.08	4.48	3.68	4.56	3.30
Physical science (e.g., chemistry, physics)	6.35	6.74	4.47	4.74	5.47	3.79
Business	5.79	2.94	4.59	4.41	5.51	4.55
Political science	3.54	3.77	4.50	4.47	4.85	4.01
Agriculture	3.77	4.65	4.18	4.71	3.45	3.91
Biology	5.54	6.74	3.97	5.11	5.44	3.73
Humanities (e.g. English, history)	2.28	2.41	2.59	3.96	3.02	4.82
Arts	2.06	2.17	2.29	3.78	2.72	6.66
Communications	2.87	2.72	2.82	4.84	4.14	4.81
Sociology	2.85	3.71	2.81	5.19	3.42	4.21
Education	4.64	4.21	2.12	6.45	2.93	5.32
Psychology	3.35	5.26	2.71	6.00	4.43	4.80
Health and clinical sciences	5.36	6.48	3.35	6.36	5.70	3.98
Social work	2.68	2.93	2.38	6.46	3.17	4.30
Mean	4.41	4.21	3.68	4.89	4.40	4.53
Standard deviation	1.66	1.42	0.96	0.91	1.10	0.83

Note. n = 330. Items were rated on a scale from 1 to 7. Majors are sorted from highest percentage males to lowest percentage males.
[a]Higher scores for gender bias indicate bias against women.

–2.00) and would therefore be assigned $(-0.94 \times 2 - 2.00)/3 = -1.29$ to take into account both their major and their focus within that major.

Analytic Approach

Research Question 1

To examine the traits of each major and the relations between traits, we focused on the interpretation of descriptive information in the undergraduate student sample. We examined patterns in the mean factor scores for each scale for each major and examined the correlations between the ratings on each of the six scales.

Research Question 2

To examine whether perceived gender bias predicted the gender of the student choosing a major after accounting for other traits of majors, we used the ELS data set that included the new information about major traits from the undergraduate student sample. We ran two different sets of models: one with an unmatched sample and one with a matched sample.

We first examined this research question within an unmatched sample using a weighted linear probability regression analysis in Stata 12. The models predicted whether the student was male as a function of the major traits for the majors/minors of each student (e.g., science oriented, math oriented, gender biased). Note that our outcome of interest is the gender of the student. While this approach may appear unconventional at first, it is the most straightforward way to examine the relation between student gender and the major traits while both holding other traits constant and accounting for individual background characteristics. Thus, the results indicate the probability of a student being male given the student's values on each of the major traits relative to other majors. For example, a regression coefficient of 0.1 for math oriented would indicate that a major that is one point higher on the math-oriented factor scale than another major would, on average, have 10 percentage points more males in that major than the other major.

Note that in this first set of analyses, we did not match men and women on their individual characteristics. Thus, this approach gave us the estimated associated probability for each major characteristic in an unmatched sample of men and women who may differ on some critical individual characteristics (e.g., men in the sample may have higher math confidence and interest than do women). So that we may make claims that are generalizable, we used the ELS longitudinal weight (F2BYWT) in this analysis. We also conducted these same analyses including individual-level covariates (available on request), and the pattern of results was similar.

To account for gender differences in individual characteristics, we then conducted a set of parallel analyses with a sample that has been matched using propensity score matching (PSM; Rosenbaum & Rubin, 1983) in Stata 12. With this approach, we were able to adjust for observable differences in characteristics between men and women and then assess the strength of each of the six traits of college majors' ability to predict the probability of being a man.

Propensity score matching has advantages compared to ordinary least squares (OLS) regression that make it ideal for this study. It allows the modeling assumptions of OLS regression to be relaxed by not assuming a linear relation between each of the predictor variables and the outcome and not extrapolating beyond the data to regions where there are no similar men and women (i.e., where matched pairs cannot be identified). In our case, we do not use PSM to make causal inferences but rather as a technique to identify individuals in different groups—here, men and women—who share common individual-level pre-college characteristics, thereby making the comparisons more transparent and less reliant on statistical adjustment (similar approaches have been used by Crosnoe, 2005, Robinson & Espelage, 2012, and Robinson-Cimpian, Lubienski, Ganley, & Copur-Gencturk, 2014).

This propensity score matching analysis was conducted in three steps:

1. Matching: To create a sample of men and women with similar characteristics on our set of matching variables, we fitted a logit model predicting the probability of the student being a man from the set of matching variables. This model created a propensity score for each student, which is the predicted probability of the gender of the student—here, being a man—given the individual's values on each of the matching variables (for a list of variables included in the matching, see Supplementary Table S1 available in the online version of the journal). We used one-to-one, nearest neighbor matching with replacement and a caliper of 0.25 standard deviations.

   We then assigned each student a weight, combining the ELS base year to second follow-up longitudinal weight (F2BYWT) and the student's propensity score. This method of weighting allows us to generalize to the population and take into account students' propensity scores simultaneously (for a similar approach, see Reardon et al., 2009).
2. Balance checks: Next, we performed balance checks, including significance testing, to ensure there was no gender difference within the matched sample on each of the variables included in the matching and on the propensity score. We also checked for large absolute standardized differences and total bias reduction (Robinson-Cimpian et al., 2014).
3. Final model: The main analyses utilized a series of weighted linear probability models (Angrist & Pischke, 2008; Mood, 2010) predicting the outcome (male) from the six traits of majors using the matched sample and weighting by the combined weight. In the models reported, we also included the individual-level covariates as predictors to account for any remaining differences due to these characteristics, improve model precision, and ensure the results are doubly robust. Analyses were also conducted without the covariates, available on request, and results were similar.

Results

Perceptions of College Major Traits

Examination of the mean factor scores and raw means in Tables 3 and 4 shows that patterns of college major ratings by undergraduate students were in expected directions. For example, engineering is perceived as highly math oriented, science oriented, gender biased, and money oriented. Conversely, engineering was perceived as average on the helpful orientation scale. Fields that are generally classified as STEM fields were rated highly on the math-oriented scale, science-oriented scale, or both. Interestingly, some typical STEM fields were rated very highly on both math and science orientation (engineering, physical sciences), whereas others had either a higher math rating than science rating (computer science, architecture, mathematics) or a higher science rating than math rating (biology, health and clinical sciences). Further, it seems as though the gender difference in the major was less likely to favor men when the science rating was higher than the math rating, even if both ratings were quite high. Education, health and clinical sciences, and social work were rated highest on the helpful orientation scale, while architecture and the arts were rated as highly creative oriented. With regard to perceptions of bias against women, majors such as education and social work were rated very low on this scale, whereas computer science and engineering had the highest ratings. Interestingly, majors such as agriculture and political science are ranked higher than average on the gender bias scale, but there is not a gender difference in these majors within the ELS sample. Overall, the findings fit with common perceptions of majors.[4]

Correlations between the factor scores for each pair of scales prior to merging the major trait data with the ELS data set are shown in Table 5. The highest correlations are between math orientation and (a) money orientation (r = .73), (b) science orientation (r = .66; see Figure 1), and (c) gender bias (r = .58; see Figure 2). These correlations show that majors that are believed to require a lot of math are also seen as (a) leading to higher paying careers, (b) requiring more science, and (c) biased against women. Additional high correlations were found between money orientation and the science orientation (r = .59) and gender bias scales (r = .58; see Figure 3). These correlations suggest that college majors that are perceived to lead to higher paying careers are also seen as more science oriented and more biased against women. Figures 1, 2, and 3 display the relations between different traits while also showing the size of the gender difference in each major in the ELS data set.

College Major Traits Predicting Gender

An examination of the mean gender differences in the individual covariates for the unmatched and matched samples (see Supplementary Table S3

Table 5
Correlations Between Traits of Majors Prior to Education Longitudinal Study of 2002 Merge

	Math Oriented	Science Oriented	Gender Biased	Helpful Oriented	Money Oriented	Creative Oriented
Math oriented	1					
Science oriented	.66**	1				
Gender biased	.58**	.31**	1			
Helpful oriented	.02	.36**	−.24*	1		
Money oriented	.73**	.59**	.58**	.17	1	
Creative oriented	−.14	−.13	−.21*	.15	−.10	1

Note. n = 330.
*p < .05. **p < .01.

available in the online version of the journal) shows that many student-level covariates differed between males and females in the unmatched sample, but all magnitudes were greatly reduced, and no significant differences in the matching variables remained after matching.

As a reminder, the analyses highlighted here are based on the combined ELS:2002 and undergraduate student perception data. Prior to running our main models, we examined zero-order correlations between each of the six major traits with student gender (see Table 6). These correlations show that men are more likely to enter fields that are perceived as more math oriented, more biased against women, less helpful, and where they will make more money. There were no significant relations with gender for science orientation and creative orientation.

We report on two sets of analyses, the first set (Models 1–6) is with the unmatched sample of students and does not include any individual-level covariates in the models. The second set of analyses (Models 7–12) is conducted with a sample of students who are matched on individual-level covariates (e.g., race, age, stated values) and also included these covariates as predictors in the model. Three participants could not be matched, resulting in a slight reduction of the sample for the matched analyses.[5]

Each model within a set represents a different combination of the college major traits as predictors. Table 7 shows those combinations and how the coefficients change across models.[6] We start out with the traditional "STEM" variables, first math orientation (Model 1), then science orientation (Model 2), and then both with their interaction (Model 3). Our rationale for including an interaction term between math orientation and science orientation is driven by the nature of some majors drawing heavily on both math and science skills (e.g., engineering, physical sciences), as evidenced in our earlier analysis, with others involving one of these more than the other

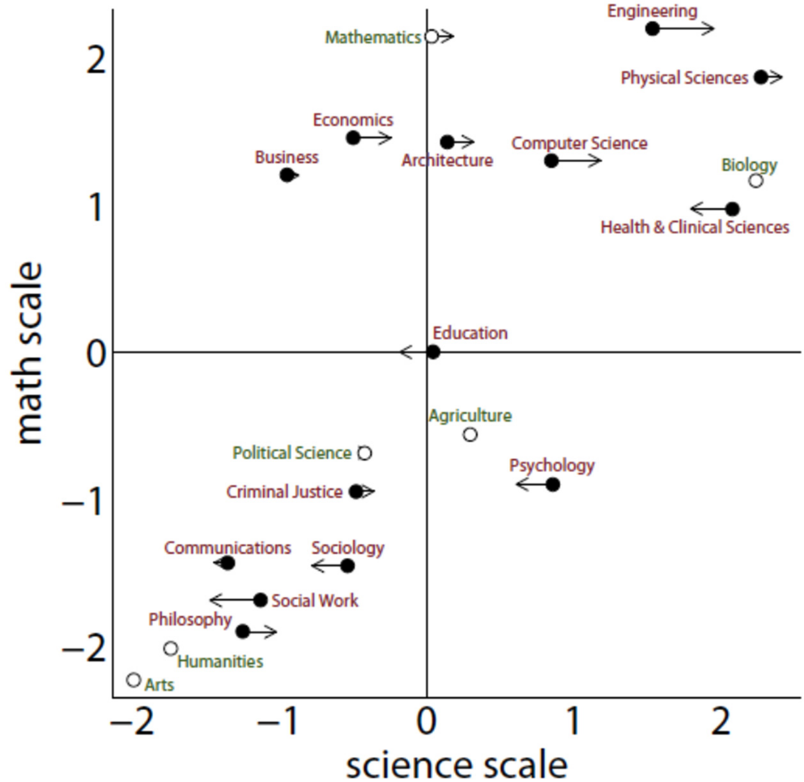

Figure 1. **Scatter plot with mean factor scores for the math-oriented and science-oriented scales. Higher numbers indicate a greater focus on math or science. The arrows display the size of the gender difference on each major in the Education Longitudinal Study of 2002 sample; filled circles indicate that this gender difference is significant.**

(e.g., biology). We then added the other covariates (helpful orientation, money orientation, creative orientation; Model 4). Next, to examine the predictive ability of gender bias over and above these other traits, we added the gender bias scale but removed the math-science orientation interaction term (Model 5). For the final model, we added back in the math-science orientation interaction term (Model 6). We will discuss results from multiple models, but we focus our main interpretations on the results of the final models within each set (i.e., Models 6 and 12). As a reminder, when interpreting these results, a regression coefficient of 0.1 for a particular major trait indicates that a one-point difference in a major's factor score on that scale corresponds with a 10% greater likelihood of that person being a man.

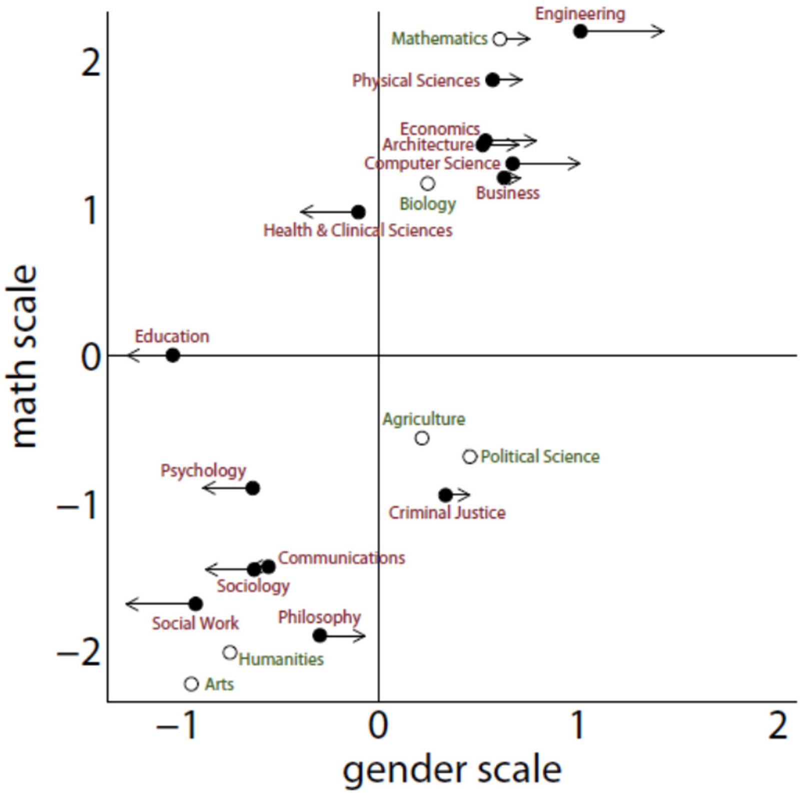

Figure 2. **Scatter plot with mean factor scores for the math-oriented and gender-biased scales. Higher numbers indicate a greater focus on math or higher perceived gender bias against women. The arrows display the size of the gender difference on each major in the Education Longitudinal Study of 2002 sample; filled circles indicate that this gender difference is significant.**

The first model using the unmatched sample (Model 1) includes only math orientation and suggests that students who major in more math-oriented fields (e.g., engineering, mathematics) are not significantly more likely to be male (b = 0.06, SE = 0.03, p = .064). When we add in a second predictor, science orientation, as well as the interaction between these two variables (Model 3), we find that students enrolled in college majors with average science orientation but higher in math orientation (e.g., mathematics, architecture) are 15% (SE = .03, p < .001) more likely to be male, but students enrolled in college majors with average math orientation but higher in science orientation are 11% (SE = .03, p = .002) *less* likely to be male, and

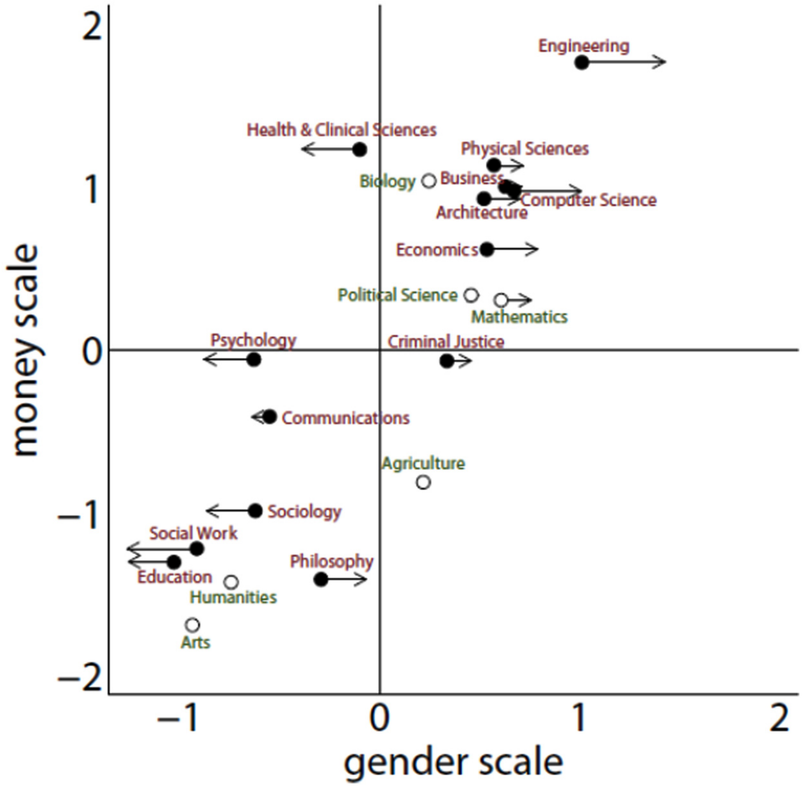

Figure 3. **Scatter plot with mean factor scores for the money-oriented and gender-biased scales. Higher numbers indicate a higher expected salary or higher perceived gender bias against women. The arrows display the size of the gender difference on each major in the Education Longitudinal Study of 2002 sample; filled circles indicate that this gender difference is significant.**

students in majors high on both math and science orientation (e.g., engineering, physical sciences) are 6% (SE = .02, p = .003) more likely to be male. Once the rest of the major characteristics are added in the final model (Model 6), math and science orientation are no longer significant predictors, but the interaction between them is (b = .03, SE = .01, p = .039), although its magnitude is reduced.

An examination of additional results from Model 6 for the major traits included as covariates show that students who major in more money-oriented fields (e.g., engineering, health and clinical sciences) are less likely to be male, and students who major in more creative fields (e.g., arts,

Table 6
Correlations Between Student Gender and Traits of Majors After Education Longitudinal Study of 2002 Merge

	Gender	Math Oriented	Science Oriented	Gender Biased	Helpful Oriented	Money Oriented	Creative Oriented
Gender	1						
Math oriented	.18**	1					
Science oriented	−.02	.61**	1				
Gender biased	.31**	.79**	.28**	1			
Helpful oriented	−.26**	.10**	.64**	−.33**	1		
Money oriented	.17**	.88**	.62**	.85**	.09**	1	
Creative oriented	.01	−.50**	−.54**	−.52**	−.23**	−.61**	1

Note. n = 4,850. Male is coded as 1, female as 0. Correlations are weighted by F2BYWT.
**$p < .01$.

architecture) are more likely to be male, but helpful orientation is not a significant predictor of gender. Turning to our main hypothesized relation in Model 6, we see that students who major in more gender-biased fields (e.g., engineering) are 50 percentage points (SE = .07, $p < .001$) more likely to be male, after taking into account other factors about the majors.

Note, however, that Models 1 through 6 do not account for student-level differences between males and females that may influence a student's choice of major. Thus, our preferred model is Model 12, which is identical to Model 6 with two exceptions: First, the analyses are estimated on the matched sample; second, to ensure the analyses were doubly robust, we included all student-level matching covariates as covariates in the estimation models as well, thereby statistically adjusting for any remaining, albeit small, student-level differences after matching.

The results for Model 12 are very similar to those for Model 6 with the exception that the interaction between math and science orientation is no longer statistically significant. Students who major in fields that are perceived as being biased against women are still 45 percentage points (SE = .07, $p < .001$) more likely to be male. Some of the coefficients in this model are slightly smaller once students are matched and covariates are included, but the coefficients are still quite similar.[7] Although some of the student-level covariates that were included do show gender differences, eliminating these gender differences generally does *not* change the relations between the major traits and the student's gender in any meaningful or substantial way. Thus, these student-level factors appear to operate largely independently from the relations of the more macro-level major traits and student gender.

Table 7

Regression Results for Predicting Student Gender in Unmatched and Matched Samples

	Raw Model (No Covariates)						Matched (With Covariates)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Math oriented	0.06		0.15***	0.05*	−0.02	0.00	0.04		0.12***	0.02	−0.03	−0.01
	(0.03)		(0.03)	(0.02)	(0.02)	(0.02)	(0.03)		(0.03)	(0.03)	(0.02)	(0.03)
Science oriented		−0.01	−0.11**	0.03	0.08***	0.03		−0.02	−0.10**	0.03	0.07***	0.03
		(0.04)	(0.03)	(0.04)	(0.02)	(0.03)		(0.03)	(0.03)	(0.04)	(0.02)	(0.03)
Gender biased					0.48***	0.50***					0.43***	0.45***
					(0.09)	(0.07)					(0.09)	(0.07)
Helpful oriented				−0.22**	−0.09*	−0.03				−0.22***	−0.10*	−0.05
				(0.07)	(0.04)	(0.04)				(0.06)	(0.04)	(0.03)
Money oriented				0.03	−0.15**	−0.16***				0.04	−0.13**	−0.14**
				(0.05)	(0.05)	(0.04)				(0.05)	(0.04)	(0.04)
Creative oriented				0.05	0.13***	0.10**				0.04	0.11*	0.09*
				(0.05)	(0.04)	(0.03)				(0.05)	(0.04)	(0.04)
Science × Math			0.06**	0.01		0.03*			0.05*	0.01		0.02
			(0.02)	(0.02)		(0.01)			(0.02)	(0.02)		(0.02)
Constant	0.42*	0.44***	0.35	0.42	0.47	0.43	0.55	0.61*	0.61*	0.64*	0.74**	0.73**
	(0.05)	(0.05)	(0.04)	(0.02)	(0.02)	(0.02)	(0.32)	(0.32)	(0.30)	(0.29)	(0.28)	(0.27)
R^2	0.03	0.00	0.09	0.12	0.15	0.16	0.02	0.01	0.07	0.09	0.12	0.12
N	4,850	4,850	4,850	4,850	4,850	4,850	4,840	4,840	4,840	4,840	4,840	4,840

Note. Samples sizes are rounded to the nearest 10. Clustered on students' unique major. Unmatched regression results are weighted by F2BYWT. Three students were not matched in Models 7 through 12. The covariates that were matched on and included in the model are those listed in Supplementary Table S3 (available in the online version of the journal).
$^*p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Discussion

The findings of this study advance current understandings of gendered choices of college majors and provide insight into traits that characterize college majors. The results suggest that gender bias (perceived and/or real) predicts why we see gender differences in certain fields over and above a math or science focus or any other trait of major included in the analysis. Disaggregating college major traits revealed gendered choices of majors in new ways, and—although not a panacea for resolving gender inequities in STEM—the findings have implications for postsecondary institutions to (re)examine field-specific environments. This kind of examination might then lead to changing the environments and the degree to which different genders feel welcome.

Perceptions of College Major Traits

To examine our main research question about whether perceptions of gender bias of college majors predicts gender differences in major choice, we developed a survey for a set of college major traits, which includes our main variable of interest (gender bias), two "STEM" variables (math and science orientation), and three covariates (helpful orientation, money orientation, creative orientation). This helped us to move beyond the restrictions of using the STEM versus non-STEM distinction often used in this type of research. Perhaps not surprisingly, we found fairly strong relations between some of the six different major traits. Key among these was the relation between math and money orientations and gender bias and money orientation. The majors that were perceived as having the greatest potential for future income were more likely to be highly math focused and also had the highest levels of perceived gender bias (e.g., engineering, physical sciences, computer science). This suggests that women have fewer options for making a high salary if they would like to avoid college majors in which they perceive the potential for discrimination. The perception that these majors are gender-biased fields may contribute to women's decisions to not choose those majors despite the fact that they perceive these fields as having a potential for high salary. Figure 3 shows that health and clinical sciences and arguably psychology appear to be the only exceptions to this pattern. In addition, the fact that math-oriented fields are also those that are likely to come with a high income reinforces the idea that encouraging women to enter fields that are higher in math orientation may help address the pay gap (Dey & Hill, 2007).

College Major Traits Predicting Gender

Considering perceptions of gender bias alongside multiple other traits of majors, including math and science orientation, to predict gender differences in college majors proved fruitful as it allowed us to examine the unique contribution of gender bias. This led to the finding, consistent with our hypothesis, that whether a major is "STEM" (in our terms, has a high math or science orientation) is not the most important determiner of gender differences in college majors. The results suggest that perceived gender discrimination, above and beyond perceived gender representation, is an important factor to consider when determining the roots of gender differences in college majors. In other words, the perception that a college major may be unwelcoming to women is related to gender differences in students' choice of major and may contribute to the lower proportions of women in certain math- and science-based fields and not in others. Interestingly, both men and women in our data perceived this gender bias, though women rated some fields as more biased against women than did men. This suggests that perceptions of potential discrimination on the basis of gender may color both men and women's decisions about which college major to pursue above and beyond perceptions that a major is oriented toward math, science, creativity, making money, or helping people.

It is important to note that this scale specifically measured the discrimination aspect of a major *after accounting for* perceptions of the actual magnitude of gender differences. The fact that there were some majors that had no gender difference in representation but were rated as biased against women (e.g., mathematics, political science) suggests that we successfully teased apart these two constructs. While some researchers have suggested that gender discrimination is no longer an explanation for women's underrepresentation in scientific careers (e.g., Ceci & Williams, 2011), this work suggests that at least perceived discrimination, potentially based on stereotypes and/or actual discrimination, relates to students' differential choices of majors, which fits with the findings of other past research (DiDonato & Strough, 2013; Heilman et al., 2004).

Surprisingly, math orientation was only a significant predictor of gender when science orientation and the interaction between math and science orientations were included in the model but before gender bias was introduced into the models. In these models, math, science, and the interaction between the two variables were all statistically significant, yet science orientation actually decreased the likelihood that the student was male. This finding may be affected by varying levels of perceived math and science orientations, such as biology and health and clinical sciences being rated highly on science orientation but relatively lower on math orientation and having more equal gender distribution or a gender imbalance favoring women. Once gender bias was included in the final model, neither a major's math nor science orientation was significant, and neither was their interaction.

It is also worth pointing out the relations between covariates and gender differences in major choices, especially to the extent that these relations were affected by the inclusion of gender bias in the model. Specifically, we found that majors that are more helpful oriented have fewer male students, similar to past work (e.g., Charles, 2011; Eccles, 1994; Turner & Bowen, 1999), but this relation weakened when gender bias was taken into account and was not statistically significant in the final model, which included both gender bias and the interaction of science and math orientation. We also found interesting results for money orientation, which showed that when considered on its own, males were more likely to pursue majors that were rated as more money oriented, as was found in past research (Montmarquette et al., 2002; Wiswall & Zafar, 2015; Zafar, 2013). However, we found no relation when the other traits were included. Further, once gender bias was taken into account, men were less likely to enter money-oriented majors. Thus, our results suggest that once women are restricted to considering majors that they do not perceive to discriminate against them, they may in fact choose majors that lead to higher paying careers.

Implications

The fact that the perception of gender bias against women was the strongest predictor of gender differences in college majors suggests that this is a critical factor to consider in efforts to improve the representation of women and men in fields in which they are underrepresented. Gender discrimination (perceived or real), as detected by both men and women, points to the importance of context within postsecondary institutions and within specific disciplines. Although other pre-college factors are also known to affect students' choice of major, broadly speaking, fields should work to both identify and improve their gender climate (actual gender bias) as well as attempt to address how their field is understood (perceived gender bias). For example, multiple fields have made efforts to increase the representation of the underrepresented gender (e.g., nursing: Cottingham, 2014; engineering: National Academy of Engineering, 2008), and other fields may wish to engage in marketing efforts to change perceptions held by people about what individuals in those majors do and what career opportunities will be available to students who pursue those majors and critically, the perceptions of their field as gender biased.

To help identify fields with gender bias within campus contexts, postsecondary institutions can implement climate surveys and other data gathering mechanisms such as focus groups to assess the gender climate and inform interventions to improve the gender climate. We recommend that investigations of climate focus not only at the campus level but also at the *departmental* level, where students' experiences are shaped by the interactions with faculty and peers within their disciplinary home (Rincon & George-Jackson, 2016). Furthermore, gender-based climate investigations could occur across all disciplines for comparative purposes as well as to understand possible discriminatory experiences even in disciplines where gender parity has been achieved. Alongside these efforts should be assessments of implicit gender biases held by faculty, staff, and students to not only bring attention to individual's own perceptions but to also inform larger institutional efforts. This is particularly important given research that suggests that men are less likely to believe gender bias against women exists in STEM fields even after being presented with research findings that document its existence (Handley, Brown, Moss-Racusin, & Smith, 2015). Department chairs, college deans, and upper-level administrators should commit (and in some instances, recommit) to reducing instances of gender discrimination on their campus. Postsecondary institutions should focus on identifying structures that allow for and perpetuate gender discrimination within the academy and systematically work to reduce barriers that affect women (and likely men) on their respective campuses.

While colleges and universities work to reduce actual gender discrimination, targeted efforts can simultaneously work to change women and men's perceptions of gender discrimination. The ratings data from this study can help professors, administrators, and professional organizations understand how their discipline is perceived and inform recruitment and retention strategies aimed at increasing the participation of women or men.

Importantly, we do not just need to understand issues of gender bias for college majors that are pursued less frequently by women but also those majors that have an underrepresentation of men. Much attention has focused on why women pursue certain types of majors less frequently, but similar questions could be asked of men. For example, why are men less likely to pursue majors that are perceived as being helpful, and do men avoid majors where they might be discriminated against (e.g., education, social work)? Actual and potential gender bias as well as perceptions of each do not only hurt women and limit their career options but also do so for men. Future research should address the extent to which gender discrimination has an impact on both men and women's choice of major. The present study cannot tease apart whether only women, only men, or both men and women might be making decisions based on perceived gender discrimination.

In regard to implications for other researchers, our study provided an attempt to consider gender bias among multiple other traits of majors and advance understandings of nuanced differences between college majors, which pushes the field to move beyond the STEM/non-STEM dichotomy. We encourage researchers to not only use and refine these six traits to explore college major choices but also to *expand* the list of traits to incorporate dimensions not explored in the current study, including those that may account for some of the relation between gender bias and gender differences in major choices. The present study may serve as a template for how researchers of gender inequities in choice of college major may investigate college majors using methods that move beyond a binary classification system. Although the focus in the current study was on understanding gender differences in college major choices, these scales could be applied to research on major choices by other key demographic variables such as socioeconomic status and race or ethnicity by rewording the gender bias survey items to include these other demographic variables.

Limitations and Future Directions

As stated earlier, we view this study as an important first attempt to consider the perceptions of traits associated with college majors, and particularly the perception of gender biases, in research on gender stratification. It will be critical for future research to explore additional factors that may not currently be represented in our scales. In addition, within the major traits scales, we asked respondents to rank 20 majors because we felt that adding any more would be burdensome for our participants. These 20 majors were purposefully chosen yet fail to capture nuanced differences between subfields or areas of specialty within each major category (e.g., subfields of engineering or health sciences are likely to be ranked differently). Future research should examine additional college majors or perhaps focus on a particular subset of majors with more subcategories within those majors (e.g., aerospace engineering, chemical engineering, civil engineering, industrial engineering, mechanical engineering).

Although we focus on perceptions of academic disciplines around the time when students choose a college major, we do not yet know when these perceptions are formed—that is, they are likely formed well in advance of attending college. Of particular interest is when students form perceptions of potential gender bias and how such perceptions may lead to and explain long-term differences between men and women's participation in certain fields. Perceptions of gender bias in disciplines may reflect a history beginning early in development of receiving and internalizing discriminatory messages (e.g., young boys are more apt to be skilled at computer science than young girls). In the future, research should examine whether middle and high school students' perceptions of majors differ from those of the current samples. This is critical because academic prerequisites required for college majors and careers occur during middle and high school (e.g., Maltese & Tai, 2010). It would also be of interest to examine the sources of information used to shape perceptions (e.g., parents, teachers, older siblings) and how they are related to actual characteristics of college majors. In addition, our study does not include data for the ELS sample on their own perceptions of major traits, nor does it include how they may have considered these major traits or other information in their college major selection process. Because of this, we were unable to capture the *processes* by which students choose a college major, and for some students this process occurs over a long period of time, during which perceptions of majors in and of themselves may change (Stinebrickner & Stinebrickner, 2011).

There are some limitations to our strategy of assessing students' perceptions of college majors that can be addressed in future research. One issue is that it is possible that there is heterogeneity in these perceptions across institutions based on particular institutional characteristics (e.g., support programs for women in STEM, more balanced gender distributions in STEM fields). Fortunately, using the perception data from a Mechanical Turk sample who would have attended school at many institutions (see Supplementary Materials available in the online version of the journal), we find consistent patterns of results for this sample and the undergraduate sample for both of our research questions. This consistency suggests that between-institution heterogeneity in perceptions is unlikely to alter the patterns of findings in a meaningful way. Future research could, however, explore if there are institutional characteristics that relate to higher or lower ratings on particular perceptions to assess if there are any issues of generalizability and help identify potential points of intervention. It is also possible that views have changed over the course of the 12 years between when the ELS data collection occurred and when we collected data. Having similar results for the undergraduate sample and the Mechanical Turk sample suggests we have a reasonable approximation, but it is still possible that perceptions held by college students and the general population have changed over time.

Our work suggests that the degree of gender bias in an academic discipline is predictive of the proportion of females in the field after accounting for a number of factors about the majors and the students themselves. However, our study does not explain why this phenomenon occurs. A recent study (Leslie, Cimpian, Meyer, & Freeland, 2015) may provide some insights for future explorations. That study surveyed professors and graduate students in a variety of disciplines at several prestigious universities and found that the more members of a discipline endorsed the belief that one needed a natural "brilliance" to be successful in the field, the fewer women and African Americans pursued PhDs in the field. Leslie et al. (2015) proposed that stereotypes against women (and African Americans) that imply they are not naturally brilliant combine with the brilliance-required attitudes in some fields to create barriers to entry and success at the highest levels. Although we focus on students beginning undergraduate studies (rather than at the doctoral level) and the disciplines examined by Leslie and colleagues do not capture the full range of majors in the ELS sample, it is possible that some of the relations we observe reflect variation across fields in their endorsement of the belief that brilliance is required for success. Future research, then, could incorporate the major-traits approach of the present study with the brilliance-required theory of Leslie et al. to both more fully capture other characteristics of disciplines and explore mechanisms of bias. However, Leslie et al. examine a specific set of disciplines, and while their approach shows strong links between a field's brilliance-required attitudes and female participation, it is unclear how their approach could explain gender gaps in applied fields like criminal justice or business, where a different form of gender bias may operate (perhaps other masculinity stereotypes such as in Cheryan, 2012). Thus, future research will likely need to incorporate recent theories (e.g., Leslie et al., 2015) but also look for additional explanations that explain how gender bias manifests itself in the various realms of academia.

Conclusion

The present study contributes to our understanding of gender gaps in higher education by combining a novel approach to quantifying continua of traits possessed by disciplines with a large, nationally representative, longitudinal data set tracking the college major choices of recent students. By moving past the traditional STEM/non-STEM dichotomy and examining the role of gender bias while also considering other traits of majors, we offer a more nuanced understanding of gender differences in major choices as they relate to perceived college major traits that cut across STEM and non-STEM fields. This approach encourages researchers to think in terms of the multidimensionality of majors, and we recommend that future research explore the more complex and nuanced traits that constitute and cut across various majors. We were able to see through this disaggregation, that it is not that a major is considered “STEM” or “not STEM” that likely drives gender differences in major choices, but other characteristics, most strongly whether or not one perceives that a field will discriminate against their gender. Our results and those of other recent studies (e.g., Leslie et al., 2015) suggest fields should consider the detrimental role that gender bias may continue to play in accessing some fields. To improve gender equity in some fields, it may be critical for these disciplines to evaluate their practices and the messages—overt and subtle—that are being sent to students of both genders. Addressing sources of discrimination and perceived discrimination may impact perceptions and improve efforts to attract women to particular fields, which can benefit both women and the fields themselves.

Notes

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[1]In accordance with disclosure requirements of the Institute of Education Sciences, all sample sizes reported here are rounded to the nearest 10.

[2]The survey instructed students to not provide their minor; however, some students provided information regarding a concentration or focus within their major (e.g., music business was coded as a major in business with a concentration in music).

[3]We chose .5 as a more liberal estimate of the ratio of the coursework required for a focus or concentration compared to a major. We also ran analyses using .33, a more conservative estimate of this ratio. Results were similar when using .33 and are available on request.

[4]It is difficult to assess the accuracy of these perceptions given that it is difficult to collect data on many of these, but we found that money-oriented perceptions correlated strongly (r = .86) with actual data available for income by college major (Ryan, 2012). Please note, however, that majors did not map identically onto the data from Ryan (2012), so we made the best approximations possible.

[5]As mentioned previously, we also conducted analyses (a) with the unmatched sample with individual-level covariates included in the models and (b) with the matched sample without individual-level covariates included; the results were very similar to those reported in Models 7 through 12. We chose to report the results of the two sets of analyses that differ the most to show consistency across analytic decisions.

[6]Recall that some of the correlations in Tables 5 and 6 are rather high. Readers may be concerned that these correlations might strongly influence our results. We address these concerns in a couple of different ways. First, we present zero-order correlations (Tables 5 and 6) and a variety of more complex models (Table 7), all of which demonstrate that our focal construct (gender bias) is consistently highly predictive of the gender balance in the field. Second, we tested if the high correlations affect the estimates using the variance-inflation factor (VIF), which should generally be lower than 10 to indicate that collinearity is not a major concern. No variables have VIFs above the cutoff except for gender bias and money orientation in Models 5 and 6 of Table 7 (VIFs are just above cutoff in the 10–11 range). Fortunately, Model 4 provides us with coefficients for money orientation when gender bias is not included, so we can interpret this coefficient as well. The coefficient for money orientation when gender bias is not included is not significant, suggesting that there is likely a suppression effect when both gender bias and money orientation are included. The results in Models 5 and 6 show that when the variance in money orientation that is unrelated to gender bias is considered, what remains is negatively related to a student being male.

[7]We also conducted analyses using women's ratings of the major traits separately from men's ratings. We did so because we found gender differences in the gender bias ratings in 6 of the 20 majors (engineering, computer science, economics, architecture, criminal justice, health and clinical sciences), with women rating them as more gender biased (against women) than men. In these supplemental analyses, we found similar patterns, with only a few coefficients being subtly different in Model 12, yet different enough for some to move across the $p < .05$ significance threshold. We detail these differences here; however, it is important to keep in mind that these analyses are marked by similarities much more than they are by differences: When using women's ratings, the helpful orientation of a major became statistically significant. When using men's ratings, the significant relation for creative orientation was no longer significant, but the interaction between math and science orientation was significant.

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