Leaning into STEM: Predicting STEM Major Choice Using Measures of Academic Tilt and Measured Interest Tilt

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This study examined the value of using measures of academic "tilt" and vocational interest "tilt" to predict whether students will declare a STEM major during their first term in college. Academic tilt looks at students' relative academic strengths by appropriately comparing their math and science achievement levels to their English, reading, and social studies achievement levels. Vocational interest tilt measures are based on students' People/Things and Data/Ideas work-task dimension scores that underlie the ACT World-of-Work map. Results suggested that having a relative strength in math and science achievement and having a tilt toward things and ideas on the People/Things and Data/Ideas dimensions are positively related to STEM major choice, after statistically controlling for mathematics and science academic achievement levels, high school coursework taken and grades earned, major intentions, certainty of major intentions, and gender.

As new initiatives and programs are implemented to promote STEM (Science, Technology, Engineering, and Mathematics) interest and participation among US students, it is important to gain a better understanding of what student characteristics are useful for identifying those who are likely to declare a STEM major during their first term in college. Prior research has found that having higher mathematics and science standardized test scores, taking higher-level mathematics and science coursework in high school, expressing interest in a STEM-related field, and having measured vocational interests in STEM are positively related to STEM major choice, persistence, and degree completion in college (Le, Robbins, & Westrick, 2014; Mattern & Radunzel, 2016; Mattern, Radunzel, & Westrick, 2015; Radunzel, Mattern, & Westrick, 2016).

It is also widely recognized that female students are underrepresented in math-intensive STEM fields, both in college and in the workforce (National Science Foundation, 2015). Researchers have examined this issue from multiple perspectives and provided alternative explanations for the difference in male/female participation rates. Some researchers have studied the gap by examining vocational interests. Using Holland's (1959; 1997) framework of vocational interests and Prediger's (1982) People/Things (PT) and

Data/Ideas (DI) work-task dimensions, there is strong evidence that males prefer occupations that are associated with working with things and females' interests are more aligned with occupations that emphasize working with people (Su, Rounds, & Armstrong, 2009). These studies also suggest that math-intensive STEM fields such as engineering tend to attract students with a stronger interest in working with things.

Other research suggests that students' perceptions of their relative strength, whether they are better (or worse) at math-intensive studies than they are at verbal-intensive studies, influences students' decisions on whether or not to enroll, persist, earn a degree, and eventually work in a STEM field (Coyle, Purcell, Snyder, & Richmond, 2014; Davison, Jew, & Davenport, 2014; Riegle-Crumb, King, Grodsky, & Muller, 2012). The literature also suggests that students with high mathematics ability also tend to have high verbal abilities, and this is especially true for female students, giving them a wide variety of academic majors from which to choose (Lubinski & Benbow, 2007). In contrast, male students with high mathematics ability are said to have a larger gap in their mathematics and verbal abilities and are thus more likely to see themselves as constrained to math-intensive STEM fields (e.g., Lubinski & Benbow, 2007).

An exploratory analysis from a recent study by Westrick (2018) provides some support for the notion that students tend to gravitate toward academic majors that match their relative academic strengths. The study examined the precollege academic and measured interest profiles of fourth-year undergraduate students and found that males generally showed greater strength in math and science on average among those in STEM majors and greater strength in English and reading among those in non-STEM majors. In comparison, females generally showed greater strength in English and reading on average across all the majors examined in the study, but the magnitude of the tilt toward higher verbal skills was found to be higher among verbal-intensive majors than among math-intensive majors with almost no tilt found in Engineering. These findings highlight the need for further research on this topic to better understand whether students' relative academic strengths help to explain why females tend to be underrepresented in math-intensive STEM fields.

Building on these previous studies, the study had three objectives. The objectives were to 1) develop measures of relative academic strength or "tilt" as related to differences in STEM and non-STEM achievement levels; 2) examine whether academic tilt and established vocational interest tilt measures on Prediger's People/Things and Data/Ideas dimensions are predictive of STEM major choice, after statistically controlling for mathematics and science achievement, high school coursework taken and grades earned, major intentions, certainty of major intentions, and gender; and 3) determine if the effects of the academic achievement and tilt measures on STEM major choice differ by gender.

Data

The data included nearly 80,000 students who took the ACT® test, enrolled as a first-time entering student in fall 2005 through 2009, and declared a major during their first fall term of enrollment. More than 40 four-year postsecondary institutions were represented in the sample. The institutions were diverse with regard to institutional control, selectivity, and size. Seventy percent were public institutions, 23% had highly selective admission policies, and more than one-half (56%) had a student body of fewer than 5,000 students. Institutions provided the six-digit Classification of Instruction Program (CIP) major codes; these codes were used to identify STEM and non-STEM majors. Students' demographic characteristics, high school coursework and grades, major plans and interests, and ACT Interest Inventory results were obtained from the ACT registration database; students provided this information at the time they registered to take the ACT. Official ACT test scores were also obtained. If students took the ACT more than once, only scores from the most recent ACT administration were used.

Methods

Defining STEM Major Choice

The study outcome was math-intensive STEM major choice during the first fall term of college enrollment and was coded as a binary outcome (STEM major (1) vs. non-STEM major (0)). Researchers have distinguished between math-intensive STEM fields, non-math-intensive STEM fields, and non-STEM fields (e.g., Ceci, Williams, & Barnett, 2009; Pennock-Roman, 1994). The math-intensive STEM programs included in this study were Engineering and Technology, Computer Science and Mathematics, and Natural Science majors.[1] Inclusion of these majors as being math-intensive is supported by the results from a catalog and course transcript review of the typical first-year mathematics course taken in college by STEM majors (overall and by cluster) and non-STEM majors (see Table 3 from Mattern et al. (2015) for more details). For the purposes of this study, Medical & Health majors, which are sometimes considered STEM majors (ACT, 2016), were not included. All other majors were classified as non-STEM.

Defining Academic Tilt

There are multiple ways that one might compare test scores to define a relative academic strength or "tilt" measure on differences in students' STEM and non-STEM achievement levels. Two methods include examining (1) the difference in scale scores and (2) the difference in score percentiles. Each approach has its weakness. For example, a student may have a higher scale score on Test A than on Test B, but the student may have a higher percentile rank on Test B than on Test A. The problem is that score distributions can differ across subject tests that use the same score scale. Based on these methods, the student's relative academic strength or "tilt" would depend on the approach used. Standardizing the scale scores for each measure eliminates this issue (Coyle et al., 2014; Shea, Lubinski, & Benbow, 2001). Therefore, in this study, relative academic strengths were determined by subtracting the z-scores of non-STEM achievement from the z-scores of STEM achievement. The means and standard deviations from a national reference group of ACT-tested students were used to convert the scale scores to z-scores. ACT examinees from fall 2003 through spring 2009 served as the reference group for this study. This approach accounted for differences in the score distributions across subject areas.

Two different relative academic strength variables that measured a tilt toward STEM-related subject areas were examined in this study. The first variable (labeled as ACT tilt) was based on ACT test scores. It was calculated as the difference in the standardized mean ACT mathematics and science score (or the ACT STEM score) minus the standardized mean ACT English and reading score. The second variable (referred to as high school grade point average (GPA) tilt) was based on students' grades earned in their high school courses. It was calculated as the difference in the standardized high school STEM GPA (that is, the mean high school mathematics and science GPA) minus the standardized mean high school English and social studies GPA.

Defining Vocational Interest Tilt

Students' ACT Interest Inventory scores were converted to Prediger's (1982) People/Things and Data/Ideas work-task dimension scores, which serve as ideal measures of vocational interest tilt. Students' ACT Interest Inventory scores are reported visually on the ACT World-of-Work Map (see Figure 1), which links individuals measured interests to career clusters. Underlying the map are the People/Things and Data/Ideas dimensions. Math-intensive STEM fields such as Engineering & Technologies, Natural Science & Technologies, and Computer & Information Specialties are located in the right of the map, oriented more toward Things than toward People on the People/Things dimension. Most STEM fields are located in the bottom half of the map, higher on Ideas than on Data on the Data/Ideas dimension, though Computer & Information Specialties are located near the middle of the map. Students' People/Things and Data/Ideas work-task dimension scores were converted to z-scores using the same national reference group of ACT-tested students that was used when standardizing students' ACT scores and subject area high school GPAs. The standardized z-scores served as the People/Things and Data/Ideas tilt measures in this study.

Other Predictors

Other predictors included intended academic major (categorized as STEM, medical and health, non-STEM, and undecided); certainty of major intentions (categorized as very sure, fairly sure, not sure); taking Calculus in high school (yes=1, no=0); taking Physics in high school (yes=1, no=0); and gender (male=1, female=0). Major sureness was relevant for students with an intended major only; it was not evaluated for undecided students. Consequently, when the major sureness variable was included as a predictor in the models, it was included in relation to intended major.[2]

Statistical Procedures

Due to the nested structure of the data, hierarchical logistic regression models with random slopes and random intercepts were used to estimate students' likelihood of declaring a math-intensive STEM major. Three models were compared. The first included measures of academic achievement, intended academic major, sureness of intended major, and gender. The second model added the four tilt measures of ACT-tilt, HSGPA-tilt, People/Things tilt, and Data/Ideas tilt to the first model, where the first two variables were the academic tilt measures and the last two were the vocational interest tilt measures. The third model added interactions between gender and six other predictors to the second model: ACT STEM score, STEM-HSGPA, ACT-tilt, HSGPA-tilt, People/Things tilt, and Data/Ideas tilt.

To assess model fit, we calculated the typical accuracy rate (AR) and logistic R across institutions. The AR estimates the proportion of students correctly identified as entering either a math-intensive STEM major or a non-STEM major. The logistic R – defined as the standard deviation of the estimated logit function (Allen & Le, 2008) – measures the overall predictive strength of the model. The higher the logistic R is, the stronger the relationship is between the predictors and the criterion. This measure is derived in a manner analogous to that for the multiple R in multiple linear regression, but it is appropriate for logistic regression models. Given that it is the standard deviation of the estimated logit function, it is not bounded between 0 and 1 as is the multiple R.

Results

Descriptive Statistics

Tables 1 and 2 contain descriptive statistics on student characteristics for the national population of ACT-tested students and the sample, respectively. The study sample tended to be better prepared academically than the national population, on average. For example, the means for ACT scores – ACT STEM and ACT English and reading – and high school GPAs – STEM HSGPA and English and Social Studies HSGPA – were higher in the sample than in the population. The directionality of the tilt measures by gender tended to be similar between the sample and the population. For instance, the mean ACT-tilt for male students was 0.18 nationally and 0.22 in the sample. For female students, the national mean was -0.14 compared to -0.33 in the sample. This indicated that male students had performed, on average, relatively stronger on ACT math and science tests than they had on the English and reading tests, and female students had performed, on average, relatively stronger on the ACT English and reading tests than they had on the math and science tests. A similar pattern held for HSGPA tilt where the standardized value was 0.07 for male students and -0.07 for female students, nationally, but the mean HSGPA-tilt in the sample was 0.05 and 0.03 for male and female students, respectively. For measured interests, the male average on the People/Things dimension was 0.29 nationally and 0.21 in the sample (tilted toward Things) whereas the female average was -0.23 nationally and -0.33 in the sample (tilted toward People). Gender differences on the Data/Ideas dimension in the sample and nationally were smaller, with means close to zero for both males and females.

Predicting STEM Major Choice

Overall, 34% of the students in the sample declared a math-intensive STEM major during their first term in college; however, this rate varied across institutions (median = 30%, 10th percentile = 17%, 90th percentile = 39%). Additionally, the likelihood of declaring a math-intensive STEM degree was found to be significantly related to all of the student characteristics included in the first model (see Table 3). Specifically, students who entered college better prepared academically in mathematics and science had a greater likelihood of declaring a math-intensive STEM major during their first semester. This is evidenced by all of the academic measures – ACT STEM score, STEM HSGPA, taking a Calculus course, and taking a Physics course in high school – being positively related to the likelihood of declaring a math-intensive STEM major. Additionally, students who had expressed interest in a math-intensive STEM major or a Medical & Health STEM major, or who were undecided about their major intentions were more likely to declare a math-intensive STEM major during their first semester than those who had planned to major in a non-STEM field. Moreover, the likelihood of declaring a STEM major increased as a student's certainty about their STEM major intentions increased. The effect for gender was positive, indicating that male students were more likely to declare a math-intensive STEM major than were female students (adjusted odds ratio = 1.39), after statistically controlling for the other variables in the model. The median logistic R was 1.448, and the median AR was .809, indicating that approximately 81% of the students were correctly classified by the model as having declared a math-intensive STEM major.

Results for Model 2 are presented in Table 4. As in the first model, all of the student characteristics were significantly related to STEM major choice. Having a tilt toward math and science on the ACT-tilt and HSGPA-tilt measures and having a tilt toward Things and Ideas on the People/Things and Data/Ideas dimensions were each associated with an increased likelihood of declaring a STEM major. As these measures increased, the likelihood that a student would declare a math-intensive STEM major increased. Additionally, as was indicated in Model 1, results from Model 2 suggested that male students were more likely than female students to declare a STEM major (adjusted odds ratio = 1.21). However, the gender effect in Model 2 was somewhat smaller than it was in Model 1. This finding suggests that statistically controlling for the tilt measures helped to reduce but did not eliminate the gender gaps in STEM major choice. Adding the tilt measures slightly increased the model fit statistics: The median logistic R increased from 1.448 to 1.515 and the median AR increased from .809 to .812.

Table 5 contains the results for the third model. Only one of the six interactions tested, Gender x STEM-HSGPA, was statistically significant. This finding suggests that the effect of the ACT STEM score and the four tilt measures on STEM major choice did not differ between males and females. For STEM-HSGPA, the interaction estimate was negative, indicating that the slope for STEM-HSGPA was steeper for female students than for male students. That is, the odds of declaring a STEM major that is associated with a one standardized unit increase in STEM-HSGPA was greater for females (adjusted odds ratio = 1.36) than for males (adjusted odds ratio = 1.24). Moreover, the significant Gender x STEM-HSGPA interaction indicated that the effect of gender on STEM major choice depended about students' high school math and science GPAs. More specifically, the results suggested that the gender effect decreased as STEM-HSGPA increased when holding all other predictors constant.[3] The median logistic R and median AR for Model 3 were essentially unchanged, 1.518 and .812, respectively, from those in Model 2.

Conclusion

In conclusion, the results from this study demonstrate the value of considering measures of academic tilt and vocational interest tilt when identifying whether a student is likely to enter a STEM major. Two measures for relative academic strength or tilt were explored that were derived by taking the differences in a student's standardized STEM and non-STEM achievement levels. The first measure was based on ACT test scores and the second measure was based on subject area high school GPAs. The approach taken to obtain these tilt measures accounted for differences in the score distributions between STEM and non-STEM areas; this was done by first converting STEM and non-STEM achievement levels to standardized z-scores based on summary statistics obtained from a national reference group of ACT-tested students, and then subtracting the two z-scores to obtain the academic tilt measures. Likewise, two measures of vocational interest tilt were examined using Prediger's (1982) People/Things and Data/Ideas work-task dimension scores; these measures were standardized using summary statistics from the same national reference group.

The two academic tilt measures were positively related to STEM major choice, meaning that students with greater tilt toward math and science according to their test scores or their subject area high school GPAs had a greater likelihood of declaring a math-intensive STEM major. Additionally, as a student's work-task dimension scores tilted more toward Things and Ideas on the People/Things and Data/Ideas dimensions, the more likely they were to declare a STEM major. These results held even after statistically controlling for mathematics and science academic achievement levels, high school coursework taken and grades earned, major intentions, certainty of major intentions, and gender. The findings lend support to previous research that has found a positive relationship between having a tilt toward math and science and choosing a STEM major (Coyle et al., 2014; Davison et al., 2014). This research adds to our understanding of which students are likely to declare a math-intensive STEM major as compared to a non-STEM major.

Another key finding was that gender remained an important predictor of STEM major choice after statistically controlling for the other variables in the model. At the outset of the study, we had hypothesized that the gender effect would disappear once the academic tilt and vocational interest tilt measures were taken into account. This did not occur, though there was a reduction in the gender effect after the tilt measures were added to the model. Additionally, results from the third model that included interactions with gender indicated that the magnitude of the gender effect on STEM major choice decreased as students' high school mathematics and science GPA increased. Future research is needed to better understand this relationship, as well as to identify other factors, such as spatial ability (Andersen, 2014; Lubinski, 2010; Shea et al., 2001; Snow, 1999; Super & Bachrach, 1957; Wai, Lubinski, & Benbow, 2009; Wood & Lebold, 1968) and academic climate (Flam, 1991; Gayles & Ampaw, 2014; Walton, Logel, Peach, Spencer, & Zanna, 2014), that may explain the gender gaps among students declaring a math-intensive STEM major in the first term of college.

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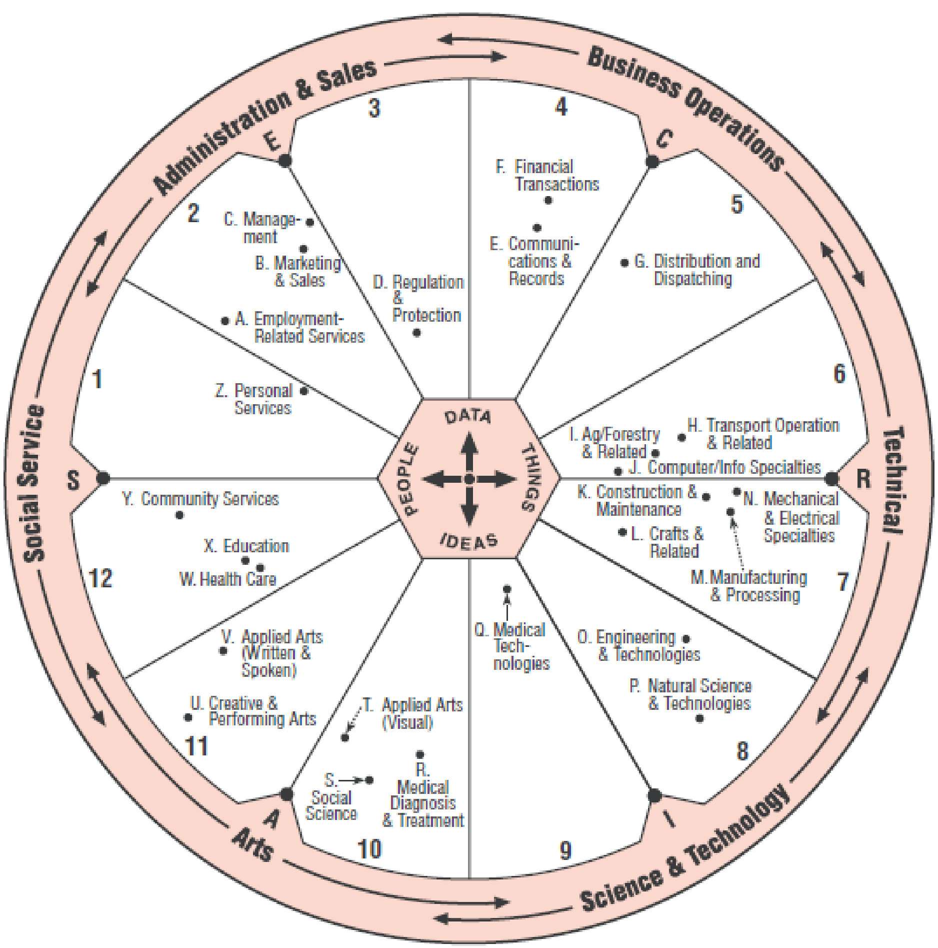
Notes

1. See Table A1 from Radunzel et al. (2016) for a list of the individual Classification of Instruction codes included for each cluster.
2. In the models, the major certainty variable was multiplied by a dichotomous variable denoting whether the student had an intended major (coded as 1) compared to undecided students (coded as 0) to ensure the inclusion of the undecided students in the STEM major choice models.
3. For example, the gender coefficient was estimated to be 0.209 for students with a STEM HSGPA of 3.15 (adjusted odds ratio = 1.23), 0.171 for a student with a STEM HSGPA of 3.41 (adjusted odds ratio = 1.19), and 0.091 for a student with a STEM HSGPA of 3.98 (adjusted odds ratio = 1.09), holding all other predictors constant at their sample mean values.

Figure 1. Third edition of the ACT World-of-Work Map (ACT, 2009)



Tables

Table 1. Descriptive Statistics for the 2003-2009 National ACT-Tested Population

	Overall			Male			Female		
Observed	N	Mean	SD	N	Mean	SD	N	Mean	SD
ACT STEM Score	7,767,175	20.9	4.7	3,380,370	21.4	4.9	4,207,731	20.4	4.4
ACT English and Reading Score	7,767,175	21.0	5.7	3,380,370	20.6	5.8	4,207,731	21.2	5.7
STEM HSGPA	5,975,818	3.15	0.68	2,536,262	3.09	0.71	3,361,215	3.19	0.66
English and Social Studies HSGPA	6,030,699	3.30	0.64	2,559,982	3.20	0.67	3,391,648	3.38	0.60
People-Things	6,485,296	-0.07	32.35	2,781,554	9.44	31.32	3,610,212	-7.36	31.23
Data-Ideas	6,485,296	-3.48	33.75	2,781,554	-2.84	32.56	3,610,212	-3.97	34.64
High School Calculus*	5,954,481	0.13	0.34	2,527,008	0.14	0.35	3,349,426	0.12	0.32
High School Physics*	6,192,666	0.33	0.47	2,647,893	0.37	0.48	3,458,229	0.31	0.46
Standardized									
ACT STEM Score	7,767,175	0.00	1.00	3,380,370	0.12	1.06	4,207,731	-0.10	0.94
ACT English and Reading Score	7,767,175	0.00	1.00	3,380,370	-0.06	1.01	4,207,731	0.04	0.99
STEM HSGPA	5,975,818	0.00	1.00	2,536,262	-0.09	1.03	3,361,215	0.06	0.97
English and Social Studies HSGPA	6,030,699	0.00	1.00	2,559,982	-0.17	1.06	3,391,648	0.12	0.94
People/Things	6,485,296	0.00	1.00	2,781,554	0.29	0.97	3,610,212	-0.23	0.97
Data/Ideas	6,485,296	0.00	1.00	2,781,554	0.02	0.96	3,610,212	-0.01	1.03
ACT-Tilt**	7,767,175	0.00	0.63	3,380,370	0.18	0.62	4,207,731	-0.14	0.60
HSGPA-Tilt**	5,897,831	0.00	0.69	2,500,348	0.07	0.70	3,320,751	-0.07	0.67

Notes. *The mean is the proportion of students who reported taking the course. **Calculated using the standardized measures, hence the SDs do not necessarily equal 1.

SD = Standard deviation.

Table 2. Descriptive Statistics for the Overall Sample

	Overall			Male			Female		
Observed	N	Mean	SD	N	Mean	SD	N	Mean	SD
ACT STEM Score	79,464	22.7	4.6	35,684	23.5	4.8	43,780	22.1	4.2
ACT English and Reading Score	79,464	23.2	5.5	35,684	22.9	5.6	43,780	23.4	5.3
STEM HSGPA	79,464	3.41	0.57	35,684	3.37	0.59	43,780	3.45	0.54
English and Social Studies HSGPA	78,854	3.56	0.49	35,373	3.48	0.52	43,481	3.62	0.45
People/Things	75,510	-2.84	33.79	33,622	6.87	32.56	41,888	-10.63	32.72
Data/Ideas	75,510	-2.69	35.77	33,622	-3.01	34.18	41,888	-2.43	36.99
High School Calculus*	79,464	0.20	0.40	35,684	0.22	0.42	43,780	0.18	0.38
High School Physics*	79,464	0.39	0.49	35,684	0.42	0.49	43,780	0.36	0.48
Standardized									
ACT STEM Score	79,464	0.40	0.98	35,684	0.56	1.04	43,780	0.27	0.91
ACT English and Reading Score	79,464	0.38	0.95	35,684	0.34	0.97	43,780	0.42	0.93
STEM HSGPA	79,464	0.39	0.83	35,684	0.33	0.87	43,780	0.44	0.79
English and Social Studies HSGPA	78,854	0.40	0.77	35,373	0.28	0.82	43,481	0.49	0.70
People/Things	75,510	-0.09	1.04	33,622	0.21	1.01	41,888	-0.33	1.01
Data/Ideas	75,510	0.02	1.06	33,622	0.01	1.01	41,888	0.03	1.10
ACT-Tilt	79,464	0.02	0.66	35,684	0.22	0.64	41,888	-0.33	1.01
HSGPA-Tilt	78,854	-0.01	0.57	35,373	0.05	0.58	41,888	0.03	1.10

Note. *The mean is the proportion of students who reported taking the course.

SD = Standard deviation.

Table 3. Predicting Math-Intensive STEM Major Choice, Model 1

Solutions for Fixed Effects	Estimate	SE	DF	*t* Value	*p* Value
Intercept	-2.412	0.110	42	-21.87	<.0001
Intended Major					
Math-Intensive STEM Major	1.608	0.103	42	15.61	<.0001
Medical & Health STEM Major	1.438	0.122	42	11.75	<.0001
Undecided	0.745	0.061	42	12.17	<.0001
Sureness of Intended Major*					
Very Sure	-0.469	0.052	42	-9.03	<.0001
Fairly Sure	-0.249	0.047	42	-5.32	<.0001
Intended Major x Major Sureness Interaction					
Math-Intensive STEM x Very Sure	1.621	0.080	42	20.36	<.0001
Medical & Health STEM x Very Sure	1.326	0.099	42	13.33	<.0001
Math-Intensive STEM x Fairly Sure	0.881	0.068	42	13.02	<.0001
Medical & Health STEM x Fairly Sure	0.555	0.083	42	6.72	<.0001
ACT STEM Score	0.359	0.027	42	13.35	<.0001
STEM-HSGPA	0.277	0.029	42	9.68	<.0001
High School Calculus	0.337	0.026	42	13.16	<.0001
High School Physics	0.149	0.029	42	5.17	<.0001
Gender (male=1; female=0)	0.331	0.054	42	6.12	<.0001
Model Fit, Institutional (N=43) Medians					
Logistic R	1.448				
Accuracy Rate	0.809				

Note. *Major sureness was examined for students with an intended major only; it was not evaluated for undecided students. An additional indicator for whether the student had an intended major (coded as 1) compared to undecided students (coded as 0) was multiplied by the major sureness main effect and intended major/major sureness interaction terms to ensure the inclusion of the undecided students in the sample used to estimate the STEM major choice models.

SE = standard error.

DF = degrees of freedom.

Table 4. Predicting Math-Intensive STEM Major Choice, Model 2

Solutions for Fixed Effects	Estimate	SE	DF	*t* Value	*p* Value
Intercept	-2.240	0.108	42	-20.79	<.0001
Intended Major					
Math-Intensive STEM Major	1.410	0.098	42	14.33	<.0001
Medical & Health STEM Major	1.370	0.125	42	10.96	<.0001
Undecided	0.669	0.061	42	10.90	<.0001
Sureness of Intended Major*					
Very Sure	-0.431	0.054	42	-8.03	<.0001
Fairly Sure	-0.210	0.049	42	-4.28	0.0001
Intended Major x Major Sureness Interaction					
Math-Intensive STEM x Very Sure	1.568	0.083	42	18.92	<.0001
Medical & Health STEM x Very Sure	1.220	0.102	42	11.94	<.0001
Math-Intensive STEM x Fairly Sure	0.831	0.071	42	11.69	<.0001
Medical & Health STEM x Fairly Sure	0.474	0.087	42	5.47	<.0001
ACT STEM Score	0.285	0.028	42	10.32	<.0001
STEM-HSGPA	0.256	0.028	42	8.99	<.0001
High School Calculus	0.351	0.026	42	13.29	<.0001
High School Physics	0.146	0.030	42	4.88	<.0001
Gender (male=1; female=0)	0.190	0.054	42	3.54	0.0010
ACT-Tilt	0.175	0.028	42	6.17	<.0001
HSGPA-Tilt	0.056	0.026	42	2.15	0.0370
People/Things Tilt	0.270	0.022	42	12.52	<.0001
Data/Ideas Tilt	-0.201	0.021	42	-9.79	<.0001
Model Fit, Institutional (N=43) Medians					
Logistic R	1.515				
Accuracy Rate	0.812				

Note. *Major sureness was examined for students with an intended major only; it was not evaluated for undecided students. An additional indicator for whether the student had an intended major (coded as 1) compared to undecided students (coded as 0) was multiplied by the major sureness main effect and intended major/major sureness interaction terms to ensure the inclusion of the undecided students in the sample used to estimate the STEM major choice models.

SE = standard error.

DF = degrees of freedom.

Table 5. Predicting Math-Intensive STEM Major Choice, Model 3

Solutions for Fixed Effects	Estimate	SE	DF	*t* Value	*p* Value
Intercept	-2.253	0.108	42	-20.92	<.0001
Intended Major					
Math-Intensive STEM Major	1.407	0.098	42	14.30	<.0001
Medical & Health STEM Major	1.370	0.125	42	10.98	<.0001
Undecided	0.668	0.061	42	10.91	<.0001
Sureness of Intended Major*					
Very Sure	-0.430	0.054	42	-8.02	<.0001
Fairly Sure	-0.209	0.049	42	-4.25	0.0001
Intended Major x Major Sureness Interaction					
Math-Intensive STEM x Very Sure	1.572	0.083	42	18.98	<.0001
Medical & Health STEM x Very Sure	1.222	0.103	42	11.92	<.0001
Math-Intensive STEM x Fairly Sure	0.833	0.071	42	11.72	<.0001
Medical & Health STEM x Fairly Sure	0.473	0.087	42	5.46	<.0001
ACT STEM Score	0.252	0.031	42	8.24	<.0001
STEM-HSGPA	0.309	0.034	42	9.21	<.0001
High School Calculus	0.353	0.026	42	13.31	<.0001
High School Physics	0.146	0.030	42	4.89	<.0001
Gender (male=1; female=0)	0.188	0.055	42	3.40	0.0015
ACT-Tilt	0.181	0.033	42	5.54	<.0001
HSGPA-Tilt	0.025	0.034	42	0.75	0.4574
People/Things Tilt	0.253	0.024	42	10.50	<.0001
Data/Ideas Tilt	-0.183	0.022	42	-8.43	<.0001
Gender x ACT STEM Score	0.065	0.037	42	1.78	0.0829
Gender x STEM HSGPA	-0.097	0.038	42	-2.57	0.0140
Gender x ACT-Tilt	-0.014	0.038	42	-0.35	0.7244
Gender x HSGPA-Tilt	0.051	0.044	42	1.17	0.2488
Gender x People/Things Tilt	0.039	0.025	42	1.55	0.1277
Gender x Data/Ideas Tilt	-0.043	0.023	42	-1.88	0.0665
Model Fit, Institutional (N=43) Medians					
Logistic R	1.518				
Accuracy Rate	0.812				

Note. *Major sureness was examined for students with an intended major only; it was not evaluated for undecided students. An additional indicator for whether the student had an intended major (coded as 1) compared to undecided students (coded as 0) was multiplied by the major sureness main effect and intended major/major sureness interaction terms to ensure the inclusion of the undecided students in the sample used to estimate the STEM major choice models.

SE = standard error.

DF = degrees of freedom.

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