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Predicting STEM Major and Career Intentions With the Theory of Planned Behavior

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This investigation predicted ACT-tested 11th- and 12th-grade students' intentions to choose science, technology, engineering, and mathematics (STEM) college majors and STEM careers using a measure of mathematics beliefs and attitudes based on the theory of planned behavior (TPB; Ajzen, 1991). The TPB states that the best predictor of behavior is the intention to perform that behavior, and intention is influenced by attitudes, subjective norms, and perceived behavioral control. Students (N = 1,958) from 11th grade (48%) or 12th grade (52%) completed the measure and also indicated their intended college major and career. Results revealed that TPB predicted STEM major and career choice incrementally over a host of additional variables. More specifically, attitude and intention were the most predictive components. Although results were similar for male and female participants, attitudes and interests were somewhat more predictive for female than for male participants. Intervention possibilities and implications for future research were discussed.

Keywords: theory of planned behavior, STEM, gender, college choice, career choice

It is widely accepted that jobs in science, technology, engineering, and mathematics (STEM) are of key importance to the future of the U.S. economy (Rothwell, 2013). STEM jobs are responsible not only for a large percentage of U.S. economic expansion but also for job growth in non-STEM fields (National Research Council, 2011). As such, it is imperative that the United States produce a sufficient number of college graduates with STEM degrees to continue to spur this economic growth. Although there is some debate on the issue, much research has demonstrated that (a) the United States is experiencing a shortage of STEM college graduates and (b) many students who are academically capable of choosing STEM majors and careers are forgoing these options because they simply lack interest in STEM fields (Carnevale, Smith, & Melton, 2011). Furthermore, a gender gap exists in STEM employment. In 2009, whereas women held 48% of all of the jobs in the United States, they held only 24% of STEM jobs (Noonan, 2017).

These facts underscore the importance of conducting research to predict who will choose STEM majors and STEM careers. The goal of the research reported in this article was to predict high school students' intention to major in STEM, and to have a STEM career, from a number

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of variables related to academic performance, achievement, socioeconomic status (SES) and other demographic variables, course-taking patterns, and interests. Key to the current work is the inclusion of the *theory of planned behavior* (TPB), which has been used widely to predict various types of behaviors (Ajzen, 1991; Armitage & Conner, 2001; Fishbein & Ajzen, 2010). TPB will be reviewed below, followed by a brief review of other theories of educational and career choice.

TPB

TPB attempts to explain determinants of behavior (Ajzen, 1991). TPB states that the single best predictor of behavior is the intention to perform that behavior (Ajzen, 1991). Intention, in turn, is predicted by one's (a) attitude, (b) subjective norms, and (c) perceived behavioral control. A meta-analysis examining a variety of behavioral outcomes demonstrated that intention predicted behavior and that attitude, subjective norms, and perceived behavioral control all significantly predicted intention (Armitage & Conner, 2001). In relation to occupational choice, previous work has demonstrated that TPB predicts job search intentions in both U.S. and non-U.S. samples (Van Hooft, Born, Taris, & van der Flier, 2004; Zikic & Saks, 2009).

Attitudes

Attitudes are, simply put, evaluations (e.g., Eagly & Chaiken, 1993). These evaluations can be separated into two dimensions (e.g., Fishbein & Ajzen, 2010). The first dimension, referred to as *experiential attitudes*, indicates whether an object or behavior is considered pleasant, enjoyable, and so forth. The second dimension, referred to as *instrumental attitudes*, indicates whether a person believes some object or behavior has utility—whether it is useful, worthwhile, and so forth. In terms of attitudes toward STEM-related activities, a student's experiential attitudes toward, for example, math, might reflect the fact that the student feels that math is boring. Furthermore, his or her instrumental attitude toward math might reflect the fact that the student feels that math will not be worthwhile for his or her future career. The logical conclusion is that the student should have reduced intentions to engage in math in the future as a result of holding these two attitudinal stances.

Subjective Norms

Subjective norms have to do with perceived social pressure to perform an action. Like attitudes, subjective norms can be separated into two dimensions (Fishbein & Ajzen, 2010). First, *injunctive norms* refer to rules about what ought to be done. Parents who, for example, pressure their children to become doctors or engineers use injunctive norms. The second dimension is *descriptive norms*, or what most people actually do. Descriptive norms can exert powerful influences on behavior. One only needs to compare the average person's behavior in a church versus at a party to see descriptive norms in action. It follows, then, that students who have many friends interested in STEM fields should thus have greater intention to engage in STEM fields themselves.

Perceived Behavioral Control

Perceived behavioral control is the extent to which an individual believes he or she is capable of performing a behavior (Fishbein & Ajzen, 2010). TPB hypothesizes that perceived behavioral control can influence behavior indirectly, through intentions, and also directly. Perceived behavioral control can influence STEM-related behaviors via the belief that one can or cannot perform a behavior (e.g., “Math is too hard for me to do”) or via the belief that one simply has no control over the behavior (e.g., “My school does not offer calculus, so I am unable to take calculus”).

Intention

The final component of TPB is the intention to perform a behavior. As stated earlier, TPB claims that the best predictor of behavior is intentions. Thus, a student who intends to engage in STEM-related behaviors is more likely to do so than a student who has no intention to engage in STEM-related behaviors. A meta-analysis of 47 experimental studies on the relationship of intentions to behavior provided evidence that intentions do indeed seem to have some causal influence on behaviors; a “medium-to-large change in intention (d = .66) leads to a small-to-medium change in behavior (d = .36)” (Webb & Sheeran, 2006, p. 249).

TPB and STEM-Related Behaviors

TPB has been demonstrated to predict STEM-related academic behaviors, notably mathematics behaviors and outcomes. For instance, TPB strongly predicted middle school students’ mathematics grades in samples of U.S. and Belarusian students (controlling for mathematics achievement in the U.S. sample; Lipnevich, MacCann, Krumm, Burrus, & Roberts, 2011). Lipnevich and colleagues later found that TPB predicted mathematics grades, controlling for reasoning ability and Big Five personality traits (Lipnevich, Preckel, & Krumm, 2016). Furthermore, in a study of ACT-tested high school juniors and seniors, Burrus and Moore (2016) found that TPB predicted ACT Mathematics test scores after controlling for a host of variables, including grades in high school mathematics courses, SES, race/ethnicity, gender, and conscientiousness. Finally, in a study of 220 students ages 12 to 15 years old, mathematics grades and mathematics homework behavior were directly predicted by intentions and perceived behavioral control, whereas intentions were predicted by attitudes and subjective norms (Hagger, Sultan, Hardcastle, & Chatzisarantis, 2015).

Additionally, TPB has been used to predict intention to engage in STEM-related courses in both high school and college. For example, separate studies of high school students demonstrated that attitudes and perceived behavioral control predicted students’ intention to enroll in a high school physics course (Crawley & Black, 1992) and intention to enroll in a high school chemistry course (Crawley & Koballa, 1992). Furthermore, one study of college students found that subjective norms and attitudes both predicted minority students’ intention to pursue a health sciences degree (Boekeloo, Brooks, & Wang, 2017). Given the research evidence, we expected that TPB should be a valid predictor of choice to major in a STEM field and, later, to choose a career in STEM.

Purpose of the Study

The purpose of the current study was to use the TPB model to predict ACT-tested high school students' intentions to major in STEM fields and to later choose a career in a STEM field. A number of important variables were controlled for, including ACT Mathematics test score, conscientiousness, high school GPA in mathematics courses, SES, gender (in the initial analysis), race/ethnicity, mathematics courses taken, and realistic and investigative interests. Because there is a disparity in STEM participation such that female students tend to choose STEM majors and occupations less often than do male students, we also split the analysis by gender to examine whether the predictors of STEM participation are different for male and female students.

We expected that the components of TPB would predict intention both to major in a STEM field and to later choose a career in STEM, controlling for the aforementioned variables. Furthermore, we specifically predicted that attitude and intention would be the strongest predictors from the model. We expected that attitude would be a strong predictor for two reasons. First, of the TPB components, attitudes were the strongest predictor of mathematics grades and achievement in previous work (Burrus & Moore, 2016; Lipnevich et al., 2011, 2016). Second, attitudes can be thought of as more specific manifestations of interests (which have predicted STEM choice in the person–environment fit literature; Radunzel, Mattern, & Westrick, 2017), and the *principle of compatibility* (e.g., Ajzen, 1988) states that behavioral prediction will be improved to the extent that attitudes are measured at a level of specificity similar to that with which the behavior is measured. Thus, mathematics attitudes, with their compatibility to STEM, should be a better predictor of STEM choice than more general interests. Finally, intention should be a strong predictor because intention is posited to be the single best predictor of behavior in the TPB model. On the other hand, subjective norms and perceived behavioral control were not strong predictors of mathematics achievement and grades in previous work (Burrus & Moore, 2016; Lipnevich et al., 2011, 2016).

Method

Participants

Participants were 1,958 students (65% female, 35% male) who took the ACT in December 2014. Students were in either their junior (48%) or senior (52%) year of high school with the following most frequently self-reported race/ethnicities: White (60%), Black/African American (12%), Hispanic/Latino (12%), Asian (7%), and other/multirace (8%). (Percentages do not total 100 because of rounding.) This is close to the general U.S. ethnic composition of 2014 ACT test takers (56% White, 13% Black/African American, 15% Hispanic/Latino, 4% Asian, and 12% other/multirace; ACT, 2015) but statistically different in gender composition (57% female, 43% male). Likewise, survey respondents had a higher mathematics course GPA (M = 3.43, SD = 0.64) than did 2014 ACT test takers (M = 3.04, SD = 0.83); they had a higher ACT Mathematics test score (M = 22.89, SD = 5.56) than the national average (M = 19.72, SD = 5.05) and took one more mathematics course on average (M = 4.00, SD = 1.06) relative to the national average (M = 3.06, SD = 1.20). The survey respondents and the 2014 ACT test takers were the same in terms of family income (mode = \$80,000 to \$100,000) and parents' educational level (bachelor's degree) relative to the national average.

Procedure

An online survey was administered to a random sample of 37,000 test takers out of 390,985 who had completed the ACT in December 2014; 9.5% were randomly selected to participate in the survey, with a 5.3% response rate. Contact information (email addresses) was obtained from ACT's national database of registered test takers. This contact information was then used to send out an invitation for test takers to participate in a survey about their attitudes and beliefs about mathematics. An invitation to participate in the survey was sent via email in January 2015. The invitation described the purpose of the study, indicated that participation was completely voluntary and would in no way affect students' ACT scores, and stated that survey responses would not be provided to students' chosen universities. The invitation message included a survey link unique to the participant. The invitation message was vague in nature and made no reference to STEM interests, major, or careers. The survey stayed open for 2 weeks. No incentives were provided. Students took approximately 7 minutes to complete the survey. These survey responses were then matched back to the ACT database that includes students' ACT scores (e.g., composite score and subject-specific scores), self-reported demographic information (e.g., race, gender), and family background information (e.g., parent's income) provided at the time of test administration.

Measures

STEM major and occupation intentions. At registration, students were asked to indicate the college major they planned to enter and their first choice of occupation (vocation). Approximately 200 college majors and occupational choices were provided. These choices were recoded into either having a STEM emphasis (1) or not (0). STEM college majors and occupations included environmental science, business/management quantitative methods, computer and information sciences, engineering, and the biological/physical sciences. Examples of non-STEM majors included liberal arts and general studies, arts: visual and performing, and English and foreign languages.

Mathematics course GPA. Students were also asked to self-report their course grades in mathematics classes taken. These grades were then converted to an overall mathematics GPA, which ranged from 0 to 4.00. Sanchez and Buddin (2015) investigated the level of agreement between self-reported and actual mathematics course grades for over 15,000 students from 286 high schools in one midwestern state. They found that for mathematics the percentage of students who were correct within one letter grade in reporting their grade ranged between 97% (e.g., trigonometry, calculus) and 94% (e.g., other advanced mathematics courses). Furthermore, a meta-analysis by Kuncel, Credé, and Thomas (2005) found that self-reported high school grades correlated (r = .84) with actual grades.

ACT Mathematics test. Students' scores on the ACT Mathematics test were gathered from their student record. The ACT Mathematics test is a 60-question, 60-minute test designed to assess students' mathematics skills that are generally learned before the 12th grade. It requires basic knowledge of formulas, requires computational skills, and requires the test taker to use reasoning skills to solve practical mathematical problems. Median reliability (Cronbach's alpha) for the test is .91 (ACT, 2018). It also has strong evidence for validity, as it predicts outcomes such as college enrollment and college GPA (ACT, 2018).

Conscientiousness. Conscientiousness was measured with the nine-item Conscientiousness scale of the Big Five Inventory (Benet-Martinez & John, 1998). It was included as a control for two reasons. First, of known personality dimensions, conscientiousness is the most consistent predictor of academic performance (Poropat, 2009). Second, research suggests that survey response is related to conscientiousness (Rogelberg et al., 2003). Participants responded on 6-point scales ranging from 1 (*strongly disagree*) to 6 (*strongly agree*). An example item includes "I stick to a task until it is finished." One subscale score was calculated by summing the scores across the nine conscientiousness items. The Conscientiousness scale demonstrated high internal consistency in a U.S. sample (α = .82; Benet-Martinez & John, 1998).

Vocational interests. The Unisex Edition of the ACT Interest Inventory (UNIACT) was used to ascertain two of the six basic types of vocational interests aligned to the six interest types on Holland's (1959) theory of careers (ACT, 2009), which include Arts, Social Service, Business Administration and Sales, Business Operations, Science and Technology, and Technical. The assessment has evidence for validity, as student interest profiles tend to correlate strongly with planned college major (ACT, 2009). Although students completed the entire assessment, only the latter two scales were used in the current analysis given their emphasis in STEM. The use of these two scales is consistent with previous research that used these two scales to indicate a measured interest in STEM (e.g., Radunzel et al., 2017). We used the UNIACT edition that has 90 items with 15 items per scale. Each item describes work-relevant activities that are easily observable. For each item, students indicate whether they would dislike doing the activity, are indifferent (do not care one way or the other), or would like doing the activity. Summed raw scores were transformed to standard scores with an approximate mean of 50 and a standard deviation of 10 (ACT, 2009). Past test–retest reliabilities for the UNIACT standard scores are .89 for Technical and .92 for Science and Technology.

Mathematics attitude. The Mathematics Attitude Questionnaire (Lipnevich et al., 2011) measured the four components of TPB: attitudes, subjective norms, perceived control, and intentions (Lipnevich et al., 2011). Participants responded on 6-point scales ranging from 1 (*strongly disagree*) to 6 (*strongly agree*). Six items measure attitudes (e.g., "I like subjects that require an understanding of math"), five items measure subjective norms (e.g., "My friends think math is an important subject"), five items measure perceived control (e.g., "How well I do in math is completely up to me"), and six items measure intentions (e.g., "I am determined to become good at math"). The items within each construct were presented in matrix form. Items within each matrix were randomly displayed. Lipnevich et al. reported internal consistencies for these scales ranging from a Cronbach's alpha of .70 (perceived control) to a Cronbach's alpha of .85 (attitudes). Some of the Lipnevich et al. items were modified for a high school population. Subscale scores were calculated by summing the scores for each of the four TPB components. In the current study, the internal consistencies for these scales were as follows: α = .91 for attitudes, α = .87 for subjective norms, α = .86 for perceived control, and α = .94 for intentions.

Statistical controls. To better isolate the effect of the aforementioned variables, we included additional student characteristics in our analysis. We statistically controlled for the impact of whether participants took different types of mathematics courses, including took less than Algebra II, took Algebra II, took trigonometry or other advanced mathematics course, or took beginning calculus. Algebra II was the reference group. We also controlled for whether participants took honors mathematics (yes = 1, no = 0) and whether they were exposed to a college preparatory high school curriculum (yes = 1, no = 0). Parent and student characteristics were also controlled for, including parents' income (measured on a 9-point scale ranging from $24,000 or less to $150,000 or more), parents' educational level (measured on an 8-point scale ranging from less than high school to doctorate or professional degree), students' race (five categories, including African American, Asian, Hispanic/Latino, other, and White), and students' gender (male = 0, female = 1). These academic and demographic characteristics were collected at the time of registration.

Results

Missing data were accounted for using multiple imputation (Rubin, 1987). Here, the predicted values replaced the missing values to create a full data set with no missing data. Imputation was conducted multiple times, in the case here five times, to create estimates that pool across multiple data sets. The predicted values were estimated using all the variables in the hierarchical linear logistic regression model because it is important to include correlates of the dependent variable used in the primary analysis. It is worth noting that the intent of multiple imputation is not to guess an individual's response to a survey item; rather, the intent is to analyze data that maintain the variability and relationship of all the variables in the model. An analysis was conducted to determine whether there might be systematic differences on the outcome measure between those who had missing data versus those who did not. Results showed no meaningful differences. This suggests that missingness was not systematic. Calculations for multiple imputations were conducted in SPSS (Version 20).

There were no missing data for the proportion of students who intended to major in STEM or for the proportion of students who intended to enter a STEM career, the two outcome variables. Missingness for the control and predictor variables was as follows: parents' educational level, 15%; parents' income level, 25%; high school GPA, 8.6%; attitudes, 7.8%; subjective norms, 12.3%; perceived control, 14.7%; and conscientiousness, 19.7%. Missingness for the four components of the TPB and for conscientiousness was imputed at the item level with subscale scores calculated using the imputed values.

Measurement Models

Before running a hierarchical logistic regression model that examined the ability of TPB to predict students' STEM choices, we conducted two confirmatory factor analyses (CFAs). CFA provided empirical justification for use of mean scores in the regression models. The first model represents the one-factor CFA of conscientiousness, entered before the structural model of TPB. The second model represents the five-factor CFA of conscientiousness, attitudes, subjective norms, perceived control, and intentions. These variables were entered in the hierarchical logistic regression together at the third step.

Two measurement models were fitted to the data, with each showing at least acceptable fit. The first was a one-factor conscientiousness model. Fit indices were Satorra–Bentler $\chi^2(22) = 213.92$, root-mean-square error of approximation (RMSEA) = .067 (90% CI [.059, .075]), normed fit index (NFI) = .94, and comparative fit index (CFI) = .94. Standard estimates of the factor loadings ranged from .30 to .67 and were all significant at a probability level of less than .05. The second was a five-factor CFA representing the four components of TPB and conscientiousness. The fit indices were Satorra–Bentler $\chi^2(419) = 4{,}647.67$, RMSEA = .072 (90% CI [.070, .074]), NFI = .86, and CFI = .87. Standard estimates of the factor loadings ranged from .31 to .93 and were all significant at a probability level of less than .05. Correlations between latent variables were .28 (attitudes and subjective norms), .65 (attitudes and perceived control), .63 (attitudes and intentions), .29 (subjective norms and perceived control), .30 (subjective norms and intentions), .53 (perceived control and intentions), .30 (conscientiousness and intentions), .09 (conscientiousness and subjective norms), .14 (conscientiousness and attitudes), and .16 (conscientiousness and perceived control).

Predicting STEM College Major and Career Intentions

Two sets of hierarchical linear logistic regression models predicting students' STEM college major intentions (Model 1) and STEM career intentions (Model 2) were conducted. In each set, mathematics course GPA and ACT score were entered in Step 1; conscientiousness, science and technology interest, and technical interest were entered at Step 2; and the four TPB components were entered in Step 3. Students' background data—number of mathematics courses taken, high school curriculum, parents' income, parents' educational level, race/ethnicity (African American as referent), and gender (male as referent)—were treated as controls and therefore entered at all three steps. This allowed us to test whether TPB predicts students' STEM college major intentions and STEM career intentions independently of mathematics course taking, previous performance in mathematics classes (as measured by GPA), conscientiousness, and student demographics.

Table 1 presents descriptive statistics from the imputed data sets for the measures used to predict STEM college major intentions (Model 1) and STEM career intentions (Model 2). A total of 24% of the survey respondents reported an intention to major in STEM, whereas 20%

TABLE 1

Correlations, Descriptive Statistics, and Reliabilities for Select Study Variables Predicting College Major Intentions and Career Intentions in Science, Technology, Engineering, and Mathematics (STEM)

Variable	1	2	3	4	5	6	7	8	9	10
1. SCI	—									
2. SCMI	**.79**	—								
3. Female	**−.26**	**−.25**	—							
4. CON	−.04	−.02	**.06**	—						
5. Tech	**.10**	**.10**	.00	.03	—					
6. ST	**.05**	.02	−.02	.01	**.84**	—				
7. Attitudes	**.26**	**.27**	**−.18**	**.12**	**.10**	.04	—			
8. SN	**.07**	**.09**	**−.09**	**.05**	.02	.00	**.35**	—		
9. PC	**.13**	**.14**	**−.14**	**.11**	**.06**	.02	**.60**	**.30**	—	
10. Intentions	**.16**	**.17**	−.02	**.26**	**.11**	**.06**	**.62**	**.33**	**.47**	—
M	0.20	0.24	.65	4.49	48.00	43.33	4.18	4.07	4.96	4.66
SD	0.40	0.43	.48	0.70	21.26	19.09	1.27	1.09	1.00	1.08
R				.77	.89	.92	.91	.87	.86	.94

Note. *N* = 1,958. Covariates were removed from the table. To see the entire table, readers can contact the first author. Correlations in boldface are statistically significant at an alpha level of .05 or less. SCI = STEM career intention; SCMI = STEM college major intention; CON = conscientiousness; Tech = technical interest; ST = science and technology interest; SN = subjective norms; PC = perceived control.

intended to pursue a STEM career. The relationship between the two outcome measures and the key predictors were similar. Attitudes toward mathematics, perceived control, and intentions had small relationships with both college major intentions and career intention in STEM (ranging from .13 to .27), followed by technical interest (r = .10 for both outcome measures). Conscientiousness and interest in science and technology were not meaningfully correlated with both intention measures.

Table 2 shows the odds ratios obtained from the imputed data set for the hierarchical logistic regression predicting college major intentions in STEM (Model 1) and career intentions in STEM (Model 2). Mathematics course GPA, mathematics courses taken, and demographic variables accounted for 21% and 18% of the variation in college major intentions and career intentions, respectively, whereas conscientiousness, technical interest, and science and technology interest accounted for approximately 1% in each model. Science and technology interest, however, did show a statistically significant relationship with the two STEM intention outcome variables, albeit in the opposite direction of the direction we had expected. The TPB components accounted for an additional 4% and 5% of variance in college major intentions and career intentions, respectively, which was not accounted for by conscientiousness, interests, course GPA, type of mathematics courses taken, or student demographic information. Furthermore, adding the TPB indicators statistically improved the model fit relative to when these indicators were excluded.

Of the TPB components, attitudes most strongly predicted college major intentions in STEM and career intentions in STEM. Thus, a 1-unit

TABLE 2

Hierarchical Logistic Regression Predicting College Major Intentions (Model 1) and Career Intentions (Model 2) in STEM

	Model 1 College Major Intentions				Model 2 Career Intentions			
Predictor Variable	ΔR^2	*B*	*SE*	OR	ΔR^2	*B*	*SE*	OR
Step 1[a]	.21				.18			
ACT Mathematics		0.07*	0.02	1.08		0.06*	0.02	1.06
Math GPA		0.00	0.00	1.00		0.00	0.00	1.00
Parents' income		0.01	0.03	1.01		–0.01	0.04	0.99
Female		–1.09*	0.12	0.34		–1.20*	0.12	0.30
Parents' education		–0.01	0.04	0.99		–0.01	0.05	0.99
Other		0.11	0.27	1.12		–0.04	0.29	0.96
White		–0.08	0.22	0.92		–0.09	0.23	0.91
Hispanic		0.22	0.26	1.25		0.32	0.27	1.38
Asian		0.63*	0.28	1.88		0.47	0.29	1.59
CP		–0.11	0.15	0.90		–0.01	0.16	0.99
<Algebra II		1.68	1.12	5.34		1.22	1.11	3.39
Trig		–0.03	0.14	0.97		–0.04	0.15	0.97
Calculus		0.57*	0.14	1.76		0.44*	0.15	1.56
HM		0.50*	0.14	1.65		0.37*	0.15	1.44
Step 2[b]	.01				.01			
CON		–0.04	0.09	0.96		–0.10	0.10	0.91
Tech		0.02*	0.01	1.02		0.02	0.01	1.02
ST		–0.02*	0.01	0.98		–0.01*	0.01	0.99
Step 3[c]	.04				.05			
Attitudes		0.40*	0.09	1.49		0.45*	0.09	1.57
Subjective norms		–0.07	0.06	0.94		–0.11	0.07	0.90
Perceived control		–0.13	0.09	0.88		–0.12	0.09	0.89
Intentions		0.19*	0.09	1.21		0.18	0.09	1.19

Note. Parents' income was measured on a 9-point scale ranging from $24,000 or less to $150,000 or more. Gender was coded male = 0, female = 1. Parents' educational level (Parents' education) was measured on an 8-point scale ranging from less than high school to doctorate or professional degree. Students' race was measured on a 5-point categorical scale including African American, Asian, Hispanic/Latino, other race or ethnicity (Other), and White; African American was the reference category. College prep high school curriculum (CP) measured whether the student was exposed to college preparatory high school curriculum (yes = 1, no = 0). <Algebra II, Trig, and Calculus measured whether the student took various mathematics courses (took less than Algebra II, took Algebra II, took trigonometry [Trig] or other advanced mathematics course, took beginning calculus); Algebra II was the reference group. Honors mathematics (HM) measured whether the student took honors mathematics (yes = 1, no = 0). STEM = science, technology, engineering, and mathematics; OR = odds ratio; Math GPA = mathematics course grade point average; CON = conscientiousness; Tech = technical interest; ST = science and technology interest.

[a]Model 1: χ^2 = 292.50, df = 14, p < .001; Nagelkerke pseudo R^2 = 21%; and Hosmer and Lemeshow test = 5.11, df = 8, p = .421. Model 2: χ^2 = 238.28, df = 14, p < .001; Nagelkerke pseudo R^2 = 18%; and Hosmer and Lemeshow test = 5.93, df = 8, p = .653. [b]Model 1: χ^2 = 1,833.46, df = 3, p < .001; Nagelkerke pseudo R^2 = 22%; and Hosmer and Lemeshow test = 1.31, df = 8, p = .282. Model 2: χ^2 = 14.27, df = 3, p < .001; Nagelkerke pseudo R^2 = 19%; and Hosmer and Lemeshow test = 6.55, df = 8, p = .592. [c]Model 1: χ^2 = 65.86, df = 4, p < .001; Nagelkerke pseudo R^2 = 26%; and Hosmer and Lemeshow test = 12.77, df = 8, p = .168. Model 2: χ^2 = 63.88, df = 4, p < .001; Nagelkerke pseudo R^2 = 24%; and Hosmer and Lemeshow test = 5.06, df = 8, p = .738.

*p < .05.

increase in mathematical attitudes increased the odds of college major intentions by a factor of 1.49 or 49% and by a factor of 1.57 or 57% for STEM career intentions after we controlled for interest in STEM, academic performance, mathematics high school course work, and demographics. Mathematical intentions were a statistically significant predictor of STEM college major intentions (odds ratio = 1.21) but not of career intentions in STEM. It is worth noting that female participants were less than half as likely to have intentions to major in STEM in college and intentions to choose a STEM career relative to their male counterparts. Therefore, we investigate this phenomenon in more detail next.

Predicting STEM College Major and Career Intentions by Gender

Estimates were generated for male and female respondents separately to determine whether the predictive power of the variables entered at all three steps had a differential impact by gender on STEM college major intentions (Female Model 3; Male Model 3) and STEM career intentions (Female Model 4; Male Model 4). Gender was removed as a control.

Descriptive statistics from the imputed data sets for the measures by gender appear in Table 3. Thirty-four percent of male participants and

TABLE 3

Correlations, Descriptive Statistics, and Reliabilities for Select Study Variables Predicting College Major Intentions and Career Intentions in Science, Technology, Engineering, and Mathematics (STEM) for Male and Female Participants

Variable	1	2	3	4	5	6	7	8	9
1. SCI	—	**.74**	–.01	**.14**	**.06**	**.21**	.05	**.10**	**.14**
2. SCMI	**.81**	—	.02	**.11**	.00	**.23**	**.06**	**.09**	**.16**
3. CON	–.04	**–.06**	—	.03	.00	**.14**	**.06**	**.14**	**.28**
4. Tech	**.08**	**.09**	.04	—	**.82**	**.10**	.04	**.06**	**.10**
5. ST	.05	.05	.02	**.86**	—	.02	.01	.03	.04
6. Attitudes	**.26**	**.28**	**.13**	**.11**	**.07**	—	**.32**	**.58**	**.59**
7. SN	**.06**	**.10**	.05	.00	–.03	**.40**	—	**.27**	**.31**
8. PC	**.12**	**.16**	**.08**	.05	.00	**.59**	**.33**	—	**.46**
9. Intentions	**.19**	**.20**	**.22**	**.13**	**.09**	**.70**	**.37**	**.50**	—
Male participants									
M	0.34	0.39	4.43	48.09	43.92	4.48	4.21	5.16	4.69
SD	0.47	0.49	0.70	23.21	21.17	1.18	1.08	0.92	1.08
R			.77	.88	.92	.90	.87	.87	.93
Female participants									
M	0.12	0.16	4.52	47.96	43.01	4.02	4.00	4.85	4.64
SD	0.32	0.36	0.70	2.14	17.87	1.29	1.09	1.03	1.09
R			.76	.89	.92	.91	.86	.88	.09

Note. *N* = 1,958. Correlation results for male participants (*n* = 684) are presented below the diagonal and for female participants (*n* = 1,274) above the diagonal. Correlations in boldface are statistically significant at an alpha level of .05 or less. Covariates were removed from the table. To see the entire table, readers can contact the first author. SCI = STEM career intention; SCMI = STEM college major intention; CON = conscientiousness; Tech = technical interest; ST = science and technology interest; SN = subjective norms; PC = perceived control.

12% of female participants reported an intention to pursue a STEM career. Similar percentages reported an intention to major in STEM (39% and 16%, respectively). This aligns with the predicted findings in Models 1 and 2, which indicated that the odds of male participants pursuing a college major and career in STEM were greater than those of female participants. For both male and female participants separately, the relationships between the two outcome measures and the key predictors were similar. However, the relationships between the predictors and two outcome measures were stronger for male participants relative to female participants. Conscientiousness and interest in science and technology were correlated with both intention measure for male participants, but for female participants only STEM career intention and science and technology interests were correlated, albeit a small correlation ($r = .06$).

Table 4 shows the odds ratios obtained from the imputed data set for the hierarchical logistic regression predicting college major intentions in STEM (Model 3) and career intentions in STEM (Model 4) for male and female participants separately. This model aids in determining whether variables in the model differentially predict intentions to major in STEM and pursue a STEM career for male and female participants.

There are a few noteworthy trends. First, adding the components of TPB statistically improved the model relative to when these indicators were omitted. This was true for both male and female participants in predicting college major intentions in STEM and career intentions in STEM. Of interest, adding conscientiousness, technical interest, and science and technology interest statistically improved the percentage of variance explained for female participants, but not for male participants. This was true for both models estimated. Second, the amount of variance explained, once all variables were entered into the model, was slightly higher for female participants (23% and 18% for college major and career intentions, respectively) than for male participants (21% and 16%). Third, the factors that significantly predicted college major intentions were different for male and female students with the exception of taking calculus and attitudes toward mathematics. For female participants, statistically significant predictors also included the "other" and Asian racial categories, as well as the two interest measures. Science and technology, however, was in the opposite of the predicted direction. For male participants, taking honors mathematics was statistically important. Fourth, the factors that predicted male participants' intentions to major in STEM and pursue a career in STEM were the same, but for female participants, the predictors varied depending on the outcome variable under investigation. It appears that race and technical interest, although important predictors of intentions to major in STEM, are not as important in career intentions. Fifth, in each model, regardless of gender, attitudes toward mathematics was a statistically significant predictor of students' intentions. However, the magnitude of this effect was slightly stronger for female than for male participants in predicting college major intentions and approximately the same in predicting career intentions. Thus, a 1-unit increase in mathematical attitudes increased the odds of college major intentions by a factor of 1.39 or 49% for male participants and by a factor of 1.55 or 57% for female participants, after we controlled for interest in

TABLE 4

Hierarchical Logistic Regression Predicting College Major Intentions (Model 3) and Career Intentions (Model 4) in STEM by Gender

	Model 3: College Major Intentions						Model 4: Career Intentions					
	Male Participants			Female Participants			Male Participants			Female Participants		
PV	*B*	*SE*	OR	*B*	*SE*	OR	*B*	*SE*	OR	*B*	*SE*	OR
Step 1[a]												
ACT	0.03	0.02	1.03	0.11	0.02	1.12	0.04	0.02	1.04	0.09*	0.03	1.10
Math	0.00	0.00	1.00	–0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
PI	0.03	0.05	1.03	–0.02	0.05	0.98	0.03	0.05	1.03	–0.05	0.05	0.95
PE	–0.04	0.06	0.96	0.02	0.06	1.02	–0.09	0.06	0.92	0.07	0.07	1.07
Other	–0.68	0.40	0.51	0.83*	0.39	2.30	–0.49	0.41	0.61	0.44	0.44	1.55
White	–0.33	0.30	0.72	0.31	0.34	1.36	–0.32	0.31	0.73	0.24	0.37	1.27
Hisp	0.09	0.35	1.10	0.37	0.41	1.44	0.05	0.36	1.06	0.62	0.43	1.85
Asian	0.36	0.40	1.44	0.97*	0.42	2.64	0.16	0.40	1.17	0.75	0.46	2.11
CP	–0.19	0.24	0.83	–0.03	0.22	0.97	0.16	0.24	1.18	–0.19	0.23	0.83
Trig	–0.07	0.20	0.93	0.07	0.21	1.08	0.06	0.21	1.07	–0.14	0.23	0.87
Calc	0.69*	0.21	2.00	0.44*	0.20	1.56	0.47*	0.21	1.59	0.42	0.22	1.52
HM	0.69*	0.20	1.99	0.35	0.19	1.42	0.43*	0.20	1.54	0.35	0.21	1.42
Step 2[b]												
CON	–0.17	0.14	0.85	0.10	0.12	1.11	–0.13	0.13	0.88	–0.05	0.14	0.96
Tech	0.00	0.01	1.00	0.04*	0.01	1.04	0.00	0.01	1.00	0.03	0.01	1.03
ST	0.00	0.01	1.00	–0.04*	0.01	0.96	0.00	0.01	1.00	–0.02*	0.01	0.98
Step 3[c]												
Att	0.33*	0.13	1.39	0.44*	0.12	1.55	0.44*	0.14	1.55	0.46*	0.13	1.58
SN	–0.07	0.10	0.94	–0.06	0.09	0.94	–0.13	0.10	0.88	–0.07	0.10	0.93
PC	–0.02	0.14	0.98	–0.19	0.12	0.82	–0.15	0.15	0.86	–0.07	0.13	0.93
Intent	0.20	0.13	1.22	0.17	0.12	1.19	0.18	0.13	1.19	0.16	0.15	1.18

Note. Parents' income (PI) was measured on a 9-point scale ranging from \$24,000 or less to \$150,000 or more. Parents' educational level (PE) was measured on an 8-point scale ranging from less than high school to doctorate or professional degree. Students' race was measured on a 5-point categorical scale including African American, Asian, Hispanic/Latino (Hisp), other race or ethnicity (Other), and White; African American was the reference category. College prep high school curriculum (CP) measured whether the student was exposed to college preparatory high school curriculum (yes = 1, no = 0). Trig and Calc measured whether the student took various mathematics courses (took trigonometry [Trig] or other advanced mathematics course, took beginning calculus [Calc]). Honors mathematics (HM) measured whether the student took honors mathematics (yes = 1, no = 0). STEM = science, technology, engineering, and mathematics; OR = odds ratio; PV = predictor variable; ACT = ACT Mathematics; Math = mathematics course grade point average; CON = conscientiousness; Tech = technical interest; ST = science and technology interest; Att = attitudes; SN = subjective norms; PC = perceived control; Intent = intentions.

[a]Model 3, males: $\chi^2 = 81.63$, $df = 12$, $p < .001$; Nagelkerke pseudo $R^2 = 15\%$; and Hosmer and Lemeshow test = 9.13, $df = 8$, $p = .440$. Model 3, females: $\chi^2 = 107.94$, $df = 12$, $p < .001$; Nagelkerke pseudo $R^2 = 14\%$; and Hosmer and Lemeshow test = 4.63, $df = 8$, $p = .771$. Model 4, males: $\chi^2 = 55.55$, $df = 12$, $p < .001$; Nagelkerke pseudo $R^2 = 11\%$; and Hosmer and Lemeshow test = 5.60, $df = 8$, $p = .709$. Model 4, females: $\chi^2 = 67.19$, $df = 12$, $p < .001$; Nagelkerke pseudo $R^2 = 10\%$; and Hosmer and Lemeshow test = 4.51, $df = 8$, $p = .773$. [b]Model 3, males: $\chi^2 = 2.80$, $df = 3$, $p = .424$; Nagelkerke pseudo $R^2 = 16\%$; and Hosmer and Lemeshow test = 4.57, $df = 8$, $p = .765$. Model 3, females: $\chi^2 = 36.59$, $df = 3$, $p < .001$; Nagelkerke pseudo $R^2 = 19\%$; and Hosmer and Lemeshow test = 5.45, $df = 8$, $p = .702$. Model 4, males: $\chi^2 = 2.29$, $df = 3$, $p = .515$; Nagelkerke pseudo $R^2 = 11\%$; and Hosmer and Lemeshow test = 6.21, $df = 8$, $p = .621$. Model 4, females: $\chi^2 = 25.54$, $df = 3$, $p < .001$; Nagelkerke pseudo $R^2 = 14\%$; and Hosmer and Lemeshow test = 4.75, $df = 8$, $p = .776$. [c]Model 3, males: $\chi^2 = 27.33$, $df = 4$, $p < .001$; Nagelkerke pseudo $R^2 = 21\%$; and Hosmer and Lemeshow test = 11.43, $df = 8$, $p = .287$. Model 3, females: $\chi^2 = 33.65$, $df = 4$, $p < .001$; Nagelkerke pseudo $R^2 = 23\%$; and Hosmer and Lemeshow test = 9.43, $df = 8$, $p = .336$. Model 4, males: $\chi^2 = 28.51$, $df = 4$, $p < .001$; Nagelkerke pseudo $R^2 = 16\%$; and Hosmer and Lemeshow test = 3.44, $df = 8$, $p = .888$. Model 4, females: $\chi^2 = 34.44$, $df = 4$, $p < .001$; Nagelkerke pseudo $R^2 = 18\%$; and Hosmer and Lemeshow test = 8.30, $df = 8$, $p = .426$.

* $p < .05$.

STEM, academic performance, mathematics high school course work, and demographics.

Discussion

Decades of research have now shown that TPB (Ajzen, 1991) can powerfully predict a range of behaviors and choices (Armitage & Conner, 2001). Our study represents an important extension of the recent work on TPB and mathematics-related outcomes, extending it to mathematics-related, and specifically STEM-related, choices (Burrus & Moore, 2016; Hagger et al., 2015; Lipnevich et al., 2011, 2016). Despite its demonstrated predictive power, TPB has yet to be used to predict students' choice to enter STEM majors in college, and later, to choose careers in STEM. The current study represents the first attempt to do so. A TPB-based measure predicted STEM-related choices above and beyond a host of variables, including ACT Mathematics test scores, high school mathematics course GPA, SES, race/ethnicity, courses taken, conscientiousness, and career interests. The TPB measure accounted for an additional 4% to 5% of the variance incrementally over these variables. Consistent with our hypotheses, of the TPB components, attitudes and intentions were the strongest predictors of STEM major and STEM occupation choice. Subjective norms and perceived behavioral control were not predictive of STEM choice. Of the variables entered into the model, attitudes were a particularly strong predictor. In fact, attitudes were one of the strongest predictors of all the variables entered into the model.

The results were largely similar when the analyses were split by gender. For both male and female participants, TPB added incremental prediction to STEM choices. Once again, attitudes were a particularly strong predictor for both genders. One notable difference in the predictors of STEM choice between male and female participants was in the predictive power of interest and attitudes. Although technology and science interests and technical interests were not significant predictors of STEM choice in male participants, technical interests did predict STEM major choice in female participants. Furthermore, although attitudes did predict STEM major and career choice in male participants, the effect was stronger for female participants, especially in the case of STEM major choice. Thus, interest in STEM, at varying levels of specificity ranging from general (technical interest) to specific (mathematics attitudes), seems to be a more important consideration for female participants' STEM-related choices than for male participants' choices. At present, it is not possible to discern the cause of this difference. To speculate, these findings could be a by-product of other factors not measured in the current study. For example, job prestige and salary may be factors that males are more likely than females to consider in choosing majors and careers, and thus males may be more likely than females to choose STEM careers on the basis of these factors rather than on the basis of their interest in the work itself.

Limitations and Future Directions

One limitation of the current study is the low response rate with a nonrandom, slightly unrepresentative sample. Thus, participants may have had fundamentally different characteristics than those of typical 11th- and 12th-grade students. Our analysis did indeed suggest that participants were higher achieving than typical ACT-tested students. Fortunately, the results for TPB held even after we controlled for achievement. Nonetheless, future studies of this type can be strengthened by the use of a nationally representative sample of 11th- and 12th-grade students.

Another limitation of this study concerns the temporal ordering of the completed measures. Students completed the measures in approximately this order with a time lag in between each step: (a) interest inventory and STEM major and career intention measures at the time of ACT test registration, (b) ACT test taken, and (c) TPB survey completed. Thus, it is impossible to infer causation from this design. It might be possible that mathematics attitudes cause STEM choice; however, it might also be possible that choosing a STEM major and STEM career might influence one's mathematics attitudes. Future work should order the completion of these measures so that the predictors are completed prior to the choice of major and career.

Interventions to Increase STEM Participation

A key advantage to the TPB model is its ability to speak to the creation of interventions that might encourage those students who are "on the fence" about entering into STEM fields to follow through in choosing STEM majors and careers. Because attitudes are among the best predictors of STEM choice, initial interventions should focus on influencing attitudes. In the TPB model, attitudes are determined by behavioral beliefs, and, as such, Ajzen (2006; Fishbein & Ajzen, 2010) stated that attitudes can be changed by first addressing these beliefs. Several interventions have been developed in fields outside of education that have successfully changed behavior by first changing beliefs (Fishbein & Ajzen, 2010). In the example of STEM choice, students might possess false beliefs about STEM that lead to negative attitudes toward STEM and, eventually, to the choice not to enter a STEM field. For example, students might falsely believe that it is too difficult to succeed in a STEM field, that STEM fields are boring, that STEM fields are not important, or that people in STEM careers do not earn sufficient salaries. In theory, each of these beliefs can be corrected with simple informational, experiential, or writing exercises. This possible approach to correcting false beliefs is also consistent with the utility-value interventions of Hulleman and colleagues, who have found improved school performance when students perform writing exercises that influence beliefs about school subjects (Hulleman, Godes, Hendricks, & Harackiewicz, 2010).

Conclusion

Participation in STEM careers is essential to the health of the U.S. (and the world) economy. Therefore, it is important to ensure that the STEM workforce includes as many capable workers as possible. In order for this to occur, we need to know who is most likely to intend to major in a STEM field in college and, later, to choose a career in STEM. The findings from the current work suggest that measures developed on the basis of TPB can be useful in predicting who is most likely to enter these fields. This work can, and should, be extended to further improve our ability to predict who will participate in these important occupations.

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