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

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ABSTRACT

The current investigation predicted ACT-tested grade 11 and 12 students' intentions to choose 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. A total of 1,958 students from grade 11 (48%) or grade 12 (52%) completed the measure and also indicated their intended college major and career. Results revealed that the 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 males and females, attitudes and interests were somewhat more predictive for females than for males. Intervention possibilities and implications for future research are discussed.
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Introduction

It is widely accepted that jobs in science, technology, engineering, and mathematics, so-called STEM jobs, are of key importance to the future of our economy (Rothwell, 2013). STEM jobs are responsible not only for a large percentage U.S. economic expansion, but also job growth in non-STEM fields (National Research Council, 2011). As such, it is imperative that the U.S. produce a sufficient number 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 U.S. is experiencing a shortage of STEM college graduates, and (b) many students who are academically capable of choosing STEM majors and careers are foregoing 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 U.S., they held only 24% of STEM jobs (Beebe, Julian, Langdon, McKittrick, Kohn, & Doms, 2011).

These facts underscore the importance of conducting research to predict who will choose STEM majors and STEM careers. The goal of this paper is to predict high school students' intention to major in STEM, and to have a STEM career, from a number of variables related to academic performance, achievement, socioeconomic status 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). The TPB will be reviewed below, followed by a brief review of other theories of educational and career choice.

Theory of Planned Behavior (TPB)

The Theory of Planned Behavior (TPB) is a theory that attempts to explain the determinants of behavior (Ajzen, 1991). The 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 looking at 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 the 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). Each of the components of the TPB will be discussed briefly below.

Attitudes

Attitudes are, simply put, evaluations (e.g., Eagly & Chaiken, 1993). These evaluations can then be separated into two dimensions (e.g., Fishbein & Ajzen, 2010). The first dimension, referred to as *experiential attitudes*, or 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 being 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 refer to 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 are using injunctive norms. The second dimension is *descriptive norms*, or what most people actually do. Descriptive norms can display 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 one believes he or she is capable of performing a behavior (Fishbein & Ajzen, 2010). In the TPB model, it is hypothesized 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 the TPB is the intention to perform a behavior. As stated above, the 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 in 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).

The TPB and STEM-Related Behaviors

The TPB model has been demonstrated to predict STEM-related academic behaviors, notably mathematics behaviors and outcomes. For instance, the 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 the 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, the 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 (Burrus & Moore, 2016). Finally, in a study of 220 12-15 year old students, mathematics grades and mathematics homework behavior were directly predicted by intentions and perceived behavioral control, while intentions were predicted by attitude and subjective norms (Hagger, Sultan, Hardcastle, & Chatzisarantis, 2015).

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

The Current Study

The purpose of the current study is 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 while simultaneously controlling for a number of important variables, 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 females tend to choose STEM majors and occupations less often than males, we also split the analysis by gender to examine whether the predictors of STEM participation are different for males and females.

We predict that the components of the TPB will predict both the intention to major in a STEM field and to later choose a career in STEM, controlling for the variables listed above. Furthermore, we specifically predict that attitude and intention will be the strongest predictors from the model. We predict that attitude will 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; Lipnevich et al., 2016). Second, attitudes can be thought of as more specific manifestations of interests (which has predicted STEM choice in the P-E fit literature), and the *principal of compatibility* (e.g., Ajzen, 1988) states that behavioral prediction will be improved to the extent that attitudes are measured at the similar level of specificity as the behavior. Thus, mathematics attitudes, with their compatibility to STEM, should be a better predictor of STEM choice than, say, 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; Lipnevich et al., 2016).

Method

Participants. A total of 1,958 students (65% female; 35% male) who took the ACT in December of 2014 participated. Students were in either their Junior (48%) or Senior (52%) year of high school with the following the most frequently self-reported race/ethnicities: White (60%), Black/African American (12%), Hispanic/Latino (12%), Asian (7%), and other/multi-race (8%). 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, 4% other/multi-race) (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 = .64) than 2014 ACT test takers (M = 3.04, SD = .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 two groups were the same in composition in terms of family income (*M ode*= $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 of 2014. A total of 9.4% 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 to participate in a survey about their attitudes and beliefs about mathematics. An invitation to participate in the survey was sent via email 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 two 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 which college major they plan to enter and which was 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 the mathematics classes taken. These grades were then converted to an overall mathematics GPA, which ranged from 0 to 4.00. Recently, Sanchez & 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 and Crede (2005) found that self-reported high school grades correlated at $r = .84$ 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 that is designed to assess students' mathematics skills that are generally learned before the 12th grade. It requires basic knowledge of formulas, computational skills, and requires the test-taker to use reasoning skills to solve practical mathematical problems. Median reliability for the test is $\alpha = .91$ (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 9 item conscientiousness scale of the Big Five Inventory (BFI; 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, Conway, Sederburg, 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 up 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).

ACT Interest Inventory. The Unisex Education 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 theory of careers (ACT, 2009), which include Arts, Social Service, Business Administration and Sales, and 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 uses these two scales to indicate a measured interest in STEM (e.g., Radunzel, Mattern, & Westrick, 2017). This study used the UNIACT edition that has 90 items with15 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 Questionnaire (MAQ; Lipnevich et al., 2011*).* The MAQ is a survey intended to measure the four components of the TPB – attitudes, subject norms, perceived control, and intentions (Lipnevich et al., 2011). Participants responded on six-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 α = .70 (perceived control) to α =.85 (attitudes). Some of the Lipnevich et al. items were modified for a high school population . Subscale scores were calculated by summing up the scores for each of the four TPB components. In the current study, the internal consistencies for these scales were α = .91 for attitudes, .87 for subjective norms, .86 for perceived control, and .94 for intentions.

Statistical Controls. In order to better isolate the effect of the above variables, we included additional student characteristics in our analysis. In this study, we statistically controlled for the impact of whether they took different types of mathematics courses (took less than Algebra II, took Algebra II, Took Trigonometry or other advanced mathematics course, beginning calculus. Algebra II was the reference group) , took honors mathematics (yes=1, no=0), was exposed to college preparatory high school curriculum (yes=1, no=0), parents' income (9-point scale ranging from $24,000 or less to $150,000 or more), parents' educational level (an 8-point scale where less than high school to Doctorate or professional degree), students' race (5 categories including, African American, Asian, Hispanic/Latino, Other, White) and gender (male =0, female =1). These student academic and demographic characteristics were collected at the time of registration.

Results

Missing data. Survey research is often plagued with the problem of missing data. This occurs when survey respondents choose to answer only a select number of items or when they break off before the survey is complete. Ignoring missing data can be problematic because it can reduce statistical power and it assumes that those people who answered all questions are similar to the people who broke off. Therefore, missing data were accounted for in the study using multiple imputation (Rubin, 1987). Here, the predicted values replace the missing values to create a full dataset with no missing data. Imputation is conducted multiple times, in the case here five times, to create estimates that pool across the multiple data sets. The predicted values were estimated using all the variables in the hierarchical linear logistic regression model since 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 person's response to a survey item; rather the intent is to analyze data that maintains 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 go into a STEM career, the two outcome variables. Missingness for the control and predictor variables was as follows: parent's educational level (15%); parent's income level (25%); high school GPA (8.6%); attitudes (7.8%); subjective norms (12.3%); perceived control (14.7%); 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 the TPB to predict students' STEM choices, two confirmatory factor analyses (CFAs) were fit. CFA was conducted to provide empirical justification for the use of mean scores in the regression models. The first model represents the one-factor CFA of conscientiousness, entered before the structural model of the 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 χ^2 (22) = 213.92, RMSEA = .067 (90% CI: .059 to .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 $p < .05$. The second was a five-factor CFA representing the four components of the TPB and conscientiousness. The fit indices were: Satorra-Bentler χ^2 (419) = 4647.67, RMSEA = .072 (90% CI: .070 to .074), normed fit index (NFI) = .86, comparative fit index (CFI) – .87. Standard estimates of the factor loadings ranged from .31 to .93 and were all significant at $p < .05$. Correlations between latent variables were .28 (attitude and subject norms), .65 (attitudes and perceived control), .63 (attitude and intentions), .29 (subject norms and perceived control), .30 (subjective norms and intentions), .53 (perceived control and intentions), .30 (conscientiousness and intentions), .09 (conscientiousness and subject norms), .14 (conscientiousness and attitude), and .16 (conscientiousness and perceived control).

Predicting College Major and Career Intentions in STEM. 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 which 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 information – number of mathematics courses taken, high school curriculum, parental income, parent's educational level, race/ethnicity (African American as referent), and gender (female as referent) were treated as controls and therefore were entered at all three steps. This model allows us to test whether the TPB predicts students' ACT 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 Cronbach's alpha, means, standard deviations, and zero order correlation coefficients, from the imputed data sets, for the measures used to predict college major intentions in STEM (Model 1) and career intentions in STEM (Model 2). A total of 24% of the survey respondents reported an intention to major in STEM, whereas 20% intended to pursue a STEM career. The relationship between the two outcome measures and the key predictors were similar. Attitudes towards mathematics, perceived control, and intentions had small relationships with both college major intentions and career intention in STEM (ranging from .07 to .27), followed by technical interest (r = .10 for both outcome measures). Conscientiousness and interest in science and technology was not meaningfully correlated with both intention measures. Course work (e.g., calculus, and honors mathematics), academic performance (e.g., ACT mathematics score), and student demographics (e.g., gender, Asian) were correlated with both outcome measures ($.10 \leq r \leq .27$)

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 20.8% and 18.3% of the variation in college major intentions and career intentions, respectively, while conscientiousness, technical interest and science & technology interest accounted for approximately 1% in each model. Science & technology interest, however, did show a statistically significant relationship with the two STEM intention outcome variables; albeit in the opposite direction we had hoped. The TPB components accounted for an additional 4.1% and 4.5% 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. Further, 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 in career intentions in STEM. Thus, a one unit 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 controlling 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 (OR = 1.212) but not for career intentions in STEM. It is worth noting that females were less than half as likely to have intentions to major in STEM in college and intentions in a STEM career relative to their male counterparts. Therefore, we investigate this phenomenon in more detail next.

Predicting College Major Intentions and Career Intentions in STEM, by Gender.

Next, estimates were generated for male and female respondents separately to determine if 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.

Means, standard deviations, and zero order correlation coefficients, from the imputed data sets, for the measures used to predict college major intentions in STEM and career intentions in STEM by gender are presented in Table 3. Thirty-four percent of males and 12% of females reported an intention to major in STEM. Similar percentages reported an intention to pursue a STEM career (30% and 15%, respectively). This aligns to the predicted findings in Models 1 and 2, which indicated that the odds of males pursuing a college major and career in STEM were greater than those of females. For both males and females separately, the relationship between the two outcome measures and the key predictors were similar. However, the relationships between the predictors and two outcome measures were stronger for males relative to females. In addition, for males, attitudes towards mathematics and mathematics intentions had a small relationship with both college major intentions and career intention in STEM; only attitudes towards mathematics, but not mathematics intentions, was correlated with college and career intentions in STEM for females. Conscientiousness and interest in science and technology was not correlated with either intention measure for both males and females. Course work (e.g., calculus, and honors mathematics) and academic performance (e.g., ACT mathematics score), were correlated with both outcome measures more so for males than for females.

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 males and females separately. This model aids in determining whether variables in the model differentially predict intentions to major in STEM and pursue a STEM career for males and females. There are a few noteworthy trends. First, adding the components of the TPB statistically improved the model relative to when these indicators were omitted. This was true for both males and females in predicting college major intentions in STEM and intentions in a STEM career. Interestingly, adding conscientiousness, technical interest and science & technology interest statistically improved the percentage of variance explained for females, but not for males. 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 females (23% and 18% for college major and career intentions, respectively) than for males (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 towards mathematics. For females, statistically significant predictors also included the "other" and Asian racial categories, and the two interest measures. Science and Technology, however, was in the opposite predicted direction. For males, taking honors mathematics was statistically important. Fourth, the factors that predicted males' intentions to major in STEM and pursue a career in STEM was the same, but for females the predictors varied depending on the outcome variable under investigation. It appears that race and technical interest, while important predictors of intentions to major in STEM, are not as important in career intentions. Fifth, in each model, regardless of gender, attitudes towards mathematics was a statistically significant predictor of students' intentions. However, the magnitude of this effect was slightly stronger for females than for males in predicting college major intentions and approximately the same in predicting career intentions. Thus, a one unit increase in mathematical attitudes increased the odds of college major intentions by a factor of 1.39 or 49% for males and by a factor of 1.55 or 57% for females, after controlling for interest in STEM, academic performance, mathematics high school course work, and demographics.

Discussion

Decades of research have now shown that the Theory of Planned Behavior (TPB Ajzen, 1991) can powerfully predict a range of behaviors and choices (Armitage & Conner, 2001). This study represents an important extension of the recent work on the 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; Lipnevich et al., 2016). Despite its demonstrated predictive power, the 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% - 4.5% of the variance incrementally over these variables. Consistent with our hypotheses, of the TPB components, attitudes and intentions were the strongest predictors or 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 was a particularly strong predictor. In fact, attitudes was 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 males and females, the 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 males and females 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 males, technical interests did predict STEM major choice in females. Furthermore, although attitudes did predict STEM major and career choice in males, the effect was stronger for females, especially in the case of STEM major choice. Thus, interest in STEM, at varying level of specificity ranging from general (technical interest) to specific (mathematics attitudes), seems to be a more important consideration for female's STEM-related choices than male's 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 to consider in majors and careers, and thus males may be more likely to choose STEM careers based on these factors rather than on their interest in the work itself.

Limitations and Future Directions

One limitation of the current study is the low response rate with a non-random, slightly unrepresentative sample. Thus, participants may have had fundamentally different characteristics than typical 11^{th} and 12^{th} grade students. Our analysis did indeed suggest that participants were higher achieving than typical ACT-tested students. Fortunately, the results for the TPB held even after controlling for achievement. Nonetheless, future studies of this type can be strengthened by the use of a nationally representative sample of 11^{th} and 12^{th} 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: 1) interest inventory and STEM major and career intention measures at the time of ACT test registration, 2) ACT test taken, 3) 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 they 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 (Azjen 2006; Fishbein & Ajzen, 2010) states that attitudes can be changed by first addressing these beliefs. And, 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 field 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 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

As stated in the introduction, participation in STEM careers is essential to the health of the U.S. (and the world) economy. Given its essential nature, it is important to ensure that the STEM workforce is stocked with as many capable workers as possible. In order for this stockpiling 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 based on the 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 careers.

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Table 1.
Reliability, Descriptive Statistics, and Correlation Coefficients For All Study Variables Predicting College Major Intentions and Career Intentions in STEM (N = 1,958).

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
1. STEM Career Intention																								
2. STEM College Major Intentions	**.79**																							
3. ACT Mathematics	**.23**	**.27**																						
4. Mathematics Course GPA	**.12**	**.12**	**.54**																					
5. Parental Income	**.07**	**.09**	**.39**	**.24**																				
6. Female	**-.26**	**-.25**	**-.16**	-.02	**-.09**																			
7. Parents' Educational Level	**.06**	**.08**	**.36**	**.20**	**.54**	**-.07**																		
8. African American	**-.05**	**-.06**	**-.30**	**-.21**	**-.23**	**.02**	**-.11**																	
9. Hispanic	.03	.01	**-.13**	**-.10**	**-.17**	**-.04**	**-.25**	**-.14**																
1. White	-.03	-.03	**.23**	**.19**	**.32**	.03	**.28**	**-.54**	**-.52**															
11. Asian	**.10**	**.13**	**.18**	**.08**	-.01	-.03	-.01	**-.12**	**-.11**	**-.40**														
12. Other race/ethnicity	-.01	.01	-.01	-.03	-.02	.01	-.01	**-.12**	**-.12**	**-.11**	-.02													
13. College Prep High School Curriculum	**.05**	**.05**	**.23**	**.21**	**.21**	-.03	**.25**	**-.10**	**-.08**	**.15**	-.01	-.04												
14. < Algebra II	.02	.03	.01	.01	**.05**	-.03	**.05**	.01	-.01	**.06**	**-.12**	.03	.06											
15. Trig+	**.09**	**.11**	**.39**	**.24**	**.12**	-.02	**.14**	**-.07**	-.04	.04	**.09**	-.02	**.16**	**.08**										
16. Calculus	**.19**	**.23**	**.41**	**.20**	**.11**	**-.14**	**.14**	**-.05**	.00	-.03	**.14**	-.01	**.14**	-.02	**.26**									
17. Honors Mathematics	**.16**	**.19**	**.47**	**.35**	**.18**	-.04	**.17**	**-.11**	.00	.04	.07	.02	**.25**	**.06**	**.30**	**.30**								
18. Conscientiousness	-.04	-.02	.02	**.16**	-.01	**.06**	.01	-.02	-.04	**.09**	**-.10**	-.01	**.06**	.02	**.08**	-.01	.05							
19. Technical	**.10**	**.10**	**.07**	**.10**	**-.08**	.00	-.05	-.02	.03	-.02	.02	-.03	.03	**.06**	**.06**	**.05**	**.18**	.03						
2. Science and Technology	**.05**	.02	**-.04**	.02	**-.15**	-.02	**-.11**	.01	.04	-.03	-.01	-.02	-.03	**.05**	.00	-.01	**.10**	.01	**.84**					
21. Attitudes	**.26**	**.27**	**.39**	**.36**	**.08**	**-.18**	**.04**	-.03	.01	-.05	**.13**	-.02	**.06**	-.03	**.18**	**.22**	**.26**	**.12**	**.10**	.04				
22. Subjective Norms	**.07**	**.09**	**.19**	**.13**	**.14**	**-.09**	**.11**	**-.07**	-.02	.03	**.08**	-.03	**.09**	-.04	**.10**	**.09**	**.14**	**.05**	.02	.00	**.35**			
23. Perceived Control	**.13**	**.14**	**.25**	**.26**	**.05**	**-.14**	.01	.01	.01	-.03	.05	.00	.03	-.04	**.11**	**.12**	**.20**	**.11**	**.06**	.02	**.60**	**.30**		
24. Intentions	**.16**	**.17**	**.14**	**.20**	.01	-.02	.01	**.06**	.00	**-.07**	.05	.01	.05	-.02	**.07**	**.12**	**.15**	**.26**	**.11**	**.06**	**.62**	**.33**	**.47**	
Mean	.20	.24	22.90	3.44	4.81	.65	5.22	.12	.12	.65	.08	.09	.73	.99	.66	.21	.50	4.49	48.00	43.33	4.18	4.07	4.96	4.66
S.D.	.40	.43	5.56	.64	2.51	.48	1.96	.33	.32	.48	.27	.29	.45	.08	.47	.40	.50	.70	21.26	19.09	1.27	1.09	1.00	1.08
Reliability																		.77	.89	.92	.91	.87	.86	.94

Bold coefficients are statistically significant at alpha .05 or less.

Note. Parents’ income was measured on a9-point scale ranging from $24,000 or less to $150,000 or more; gender (male =0, female =1); parents’ educational level was measured on a 8-point scale where 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, White. African American was used at the reference category ; College Prep High School Curriculum measured whether the student was exposed to college preparatory high school curriculum (yes=1, no=0),:< Algebra II, Trig+ and Calculus measures whether the students took various mathematics courses (took less than Algebra II, took Algebra II, Took Trigonometry or other advanced mathematics course, beginning calculus). Algebra II was the reference group. Honors Mathematics indicates whether the student took honors mathematics (yes=1, no=0).

Table 2.

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

	Model 1 College Major Intentions				Model 2 Career Intentions			
Predictor	ΔR^2	B	S.E.	OR	ΔR^2	B	S.E.	OR
Step 1	.208				.183			
ACT Mathematics		.072*	.016	1.075		.062*	.017	1.064
Mathematics Course GPA		.000	.001	1.000		.001	.001	1.001
Parental Income		.005	.032	1.005		-.007	.035	.993
Female		-1.086*	.118	.338		-1.197*	.124	.302
Parent's Educational Level		-.009	.043	.991		-.009	.045	.991
Other race/ethnicity		.114	.272	1.121		-.037	.293	.963
White		-.082	.217	.921		-.094	.230	.910
Hispanic		.222	.255	1.249		.319	.266	1.376
Asian		.633*	.278	1.883		.466	.293	1.594
College Prep High School Curriculum		-.111	.153	.895		-.012	.159	.988
< Algebra II		1.675	1.123	5.340		1.222	1.111	3.393
Trigonometry		-.027	.143	.973		-.036	.152	.965
Calculus		.566*	.143	1.761		.442*	.150	1.556
Honors Mathematics		.499*	.138	1.647		.366*	.146	1.441
Step 2	.013				.010			
Conscientiousness		-.037	.091	.963		-.095	.097	.909
Technical Interest		.021*	.005	1.021		.016	.005	1.016
Science & Technology Interest		-.017*	.006	.983		-.007*	.006	.993
Step 3	.041				.045			
Attitudes		.399*	.085	1.490		.451*	.089	1.570
Subject Norms		-.067	.062	.935		-.106	.068	.900
Perceived Control		-.131	.086	.877		-.120	.093	.887
Intentions		.192*	.087	1.212		.175	.092	1.191
Step 1 Chi-Squared		292.500, df = 14, p.<.001				238.280, df = 14, p.<.001		
Nagelkerke pseudo R^2		21%				18%		
Hosmer & Lemeshow test		5.11, df = 8, p. = .421				5.930, df=8, p. = .653		
Step 2 Chi-Squared		1833.460, df = 3, p.<.001				14.273, df = 3, p.<.001		
Nagelkerke pseudo R^2		22%				19%		
Hosmer & Lemeshow test		1.306, df = 8, p. = .282				6.554, df=8, p. = .592		
Step 3 Chi-Squared		65.856, df = 4, p. <.001				63.878,, df = 4, p. <.001		
Nagelkerke pseudo R^2		26%				24%		
Hosmer & Lemeshow test		12.77, df = 8, p. = .168				5.059, df=8, p. = .738		

* $p < .05$.

Note. Parents' income was measured on a9-point scale ranging from $24,000 or less to $150,000 or more; gender (male =0, female =1); parents' educational level was measured on a 8-point scale where 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, White. African American was used at the reference category ; College Prep High School Curriculum measured whether the student was exposed to college preparatory high school curriculum (yes=1, no=0),:< Algebra II, Trig+ and Calculus measures whether the students took various mathematics courses (took less than Algebra II, took Algebra II, Took Trigonometry or other advanced mathematics course, beginning calculus). Algebra II was the reference group. Honors Mathematics indicates whether the student took honors mathematics (yes=1, no=0).

Table 3.
Reliability, Descriptive Statistics, and Correlation Coefficients for All Study Variables Predicting College Major Intentions and Career Intentions in STEM for Males (bottom, left) and Females (top, right).

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1. STEM Career Intention	1.00	**.74**	**.20**	**.10**	.05	**.08**	**-.07**	.00	-.01	**.11**	.01	.03	**.07**	**.15**	**.13**	-.01	**.14**	**.06**	**.21**	.05	**.10**	**.14**
2. STEM College Major Intentions	**.81**	1.00	**.26**	**.10**	**.08**	**.09**	**-.09**	-.03	.00	**.15**	**.06**	.05	**.12**	**.18**	**.16**	.02	**.11**	.00	**.23**	**.06**	**.09**	**.16**
3. ACT Mathematics	**.20**	**.22**	1.00	**.54**	**.39**	**.36**	**-.30**	**-.15**	**.22**	**.22**	.00	**.22**	**.40**	**.38**	**.46**	.04	.03	**-.09**	**.38**	**.18**	**.23**	**.14**
4. Mathematics Course GPA	**.16**	**.17**	**.57**	1.00	**.25**	**.21**	**-.23**	**-.11**	**.22**	**.09**	-.05	**.22**	**.23**	**.19**	**.35**	**.18**	**.10**	-.01	**.37**	**.16**	**.27**	**.19**
5. Parental Income	.05	**.06**	**.39**	**.24**	1.00	**.55**	**-.25**	**-.15**	**.30**	.01	-.03	**.20**	**.14**	**.09**	**.19**	.00	**-.10**	**-.17**	**.08**	**.12**	.04	.00
6. Parents' Educational Level	.01	.04	**.38**	**.20**	**.54**	1.00	**-.13**	**-.22**	**.24**	.02	.00	**.24**	**.17**	**.13**	**.17**	.02	-.05	**-.11**	.05	**.11**	.04	.01
7. African American	-.03	-.03	**-.33**	**-.18**	**-.22**	**-.09**	1.00	**-.13**	**-.57**	**-.12**	**-.12**	**-.08**	-.03	-.04	**-.10**	-.01	.01	.03	-.03	**-.08**	.02	**.07**
8. Hispanic	.05	.05	**-.14**	-.09	**-.23**	**-.32**	**-.14**	1.00	**-.51**	**-.10**	**-.11**	**-.08**	-.03	-.02	-.01	-.04	.01	.03	-.01	-.03	.01	-.02
9. White	**-.06**	**-.07**	**.28**	**.15**	**.36**	**.35**	**-.49**	**-.54**	1.00	**-.39**	**-.11**	**.16**	.01	-.03	.05	**.10**	-.05	**-.06**	-.05	.03	-.04	**-.09**
1. Asian	**.08**	**.10**	**.12**	**.08**	**-.06**	**-.08**	**-.12**	**-.13**	**-.42**	1.00	-.02	-.04	**.08**	**.16**	**.08**	**-.11**	.03	.01	**.16**	**.11**	.05	**.08**
11. Other race/ethnicity	-.03	-.05	.00	.01	.00	.00	-.11	**-.12**	**-.11**	-.03	1.00	-.03	-.05	-.02	.00	-.03	.01	.02	-.02	-.02	-.01	.02
12. College Prep High School Curriculum	**.08**	.04	**.26**	**.22**	**.25**	**.27**	**-.12**	**-.08**	**.14**	.04	-.05	1.00	**.17**	**.14**	**.26**	**.06**	.02	-.03	.06	**.09**	.03	.03
13. Trig+	**.12**	**.11**	**.41**	**.26**	**.09**	**.11**	**-.14**	**-.06**	**.08**	**.11**	**.06**	**.14**	1.00	**.22**	**.32**	**.06**	**.06**	.01	**.16**	**.09**	**.09**	.05
14. Calculus	**.19**	**.25**	**.43**	**.24**	**.12**	**.16**	**-.06**	.01	-.02	**.11**	.00	**.14**	**.33**	1.00	**.25**	.02	.03	-.03	**.18**	**.08**	**.10**	**.11**
15. Honors Mathematics	**.20**	**.25**	**.50**	**.38**	**.18**	**.19**	**-.11**	.01	.04	.03	.04	**.23**	**.26**	**.38**	1.00	**.07**	**.16**	**.07**	**.24**	**.13**	**.18**	**.13**
16. Conscientiousness	-.04	**-.06**	.02	**.13**	-.02	.02	-.04	-.03	**.08**	**-.07**	.03	**.06**	**.12**	-.04	.01	1.00	.03	.00	**.14**	**.06**	**.14**	**.28**
17. Technical	**.08**	**.09**	**.13**	**.12**	**-.05**	**-.06**	**-.08**	**.06**	.03	-.01	**-.08**	.05	**.06**	**.08**	**.21**	.04	1.00	**.82**	**.10**	.04	**.06**	**.10**
18. Science and Technology	.05	.05	.00	**.06**	**-.14**	**-.12**	-.03	**.06**	.01	-.04	**-.09**	-.03	.00	.01	**.13**	.02	**.86**	1.00	.02	.01	.03	.04
19. Attitudes	**.26**	**.28**	**.37**	**.35**	.05	.01	-.02	.03	-.04	**.06**	-.02	.05	**.22**	**.25**	**.29**	**.13**	**.11**	**.07**	1.00	**.32**	**.58**	**.59**
2. Subjective Norms	**.06**	**.10**	**.20**	**.08**	**.16**	**.12**	-.05	-.01	.03	.04	-.03	**.06**	**.11**	**.09**	**.16**	.05	.00	-.03	**.40**	1.00	**.27**	**.31**
21. Perceived Control	**.12**	**.16**	**.24**	**.26**	.05	.02	-.01	.01	.00	.02	.02	.02	**.14**	**.11**	**.23**	**.08**	.05	.00	**.59**	**.33**	1.00	**.46**
22. Intentions	**.19**	**.20**	**.16**	**.22**	.01	-.02	.04	.03	-.03	-.01	-.02	.08	**.11**	**.13**	**.18**	**.22**	**.13**	**.09**	**.70**	**.37**	**.50**	1.00
Male Mean	.34	.39	24.14	345.40	5.13	5.41	.11	.13	.63	.09	.09	.75	.68	.28	.52	4.43	48.09	43.92	4.48	4.21	5.16	4.69
(n=684) S.D.	.47	.49	5.84	61.72	2.50	1.93	.32	.34	.48	.29	.28	.44	.47	.45	.50	.70	23.21	21.17	1.18	1.08	.92	1.08
Reliability																.77	.88	.92	.90	.87	.87	.93
Female Mean	.12	.16	22.23	342.62	4.64	5.12	.13	.11	.66	.07	.09	.72	.66	.16	.48	4.52	47.96	43.01	4.02	4.00	4.85	4.64
(n=1,274) S.D.	.32	.36	5.28	65.19	2.50	1.97	.34	.31	.47	.26	.29	.45	.48	.37	.50	.70	2.14	17.87	1.29	1.09	1.03	1.09
Reliability																.76	.89	.92	.91	.86	.88	.094

Bold coefficients are statistically significant at alpha .05 or less.
Note: No male students had taken less than an algebra course while in high school. Therefore, this variable was removed from the model.
Note2. Parents’ income was measured on a9-point scale ranging from $24,000 or less to $150,000 or more; gender (male =0, female =1); parents’ educational level was measured on a 8-point scale where 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, White. African American was used at the reference category ; College Prep High School Curriculum measured whether the student was exposed to college preparatory high school curriculum (yes=1, no=0),:< Algebra II, Trig+ and

Calculus measures whether the students took various mathematics courses (took less than Algebra II, took Algebra II, Took Trigonometry or other advanced mathematics course, beginning calculus). Algebra II was the reference group. Honors Mathematics indicates whether the student took honors mathematics (yes=1, no=0).

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					
		Males			Females			Males			Females		
		B	**S.E.**	**OR**	**B**	**S.E.**	**OR**	**B**	**S.E.**	**OR**	**B**	**S.E.**	**OR**
Step 1	ACT Mathematics	.032	.023	1.033	.110	.023	1.116	.036	.023	1.037	.093*	.025	1.098
	Mathematics Course GPA	.002	.002	1.002	-.002	.002	.998	.002	.002	1.002	.000	.002	1.000
	Parental Income	.029	.047	1.030	-.016	.046	.984	.026	.045	1.026	-.047	.050	.954
	Parent's Educational Level	-.044	.059	.957	.015	.058	1.015	-.089	.059	.915	.070	.065	1.073
	Other race/ethnicity	-.676	.404	.509	.831*	.394	2.296	-.493	.408	.611	.440	.444	1.552
	White	-.334	.303	.716	.307	.342	1.359	-.319	.310	.727	.236	.372	1.266
	Hispanic	.094	.349	1.098	.365	.410	1.440	.053	.355	1.055	.617	.429	1.853
	Asian	.362	.401	1.436	.971*	.418	2.640	.156	.402	1.169	.746	.455	2.109
	College Prep High School Curriculum	-.188	.238	.829	-.028	.217	.972	.164	.239	1.179	-.188	.230	.829
	Trigonometry	-.071	.204	.931	.074	.211	1.077	.063	.208	1.065	-.142	.228	.867
	Calculus	.693*	.207	1.999	.444*	.202	1.560	.465*	.208	1.593	.416	.222	1.517
	Honors Mathematics	.689*	.201	1.991	.349	.193	1.418	.434*	.204	1.544	.349	.214	1.418
Step 2	Conscientiousness	-.166	.136	.847	.103	.121	1.109	-.131	.133	.877	-.045	.137	.956
	Technical Interest	.003	.007	1.003	.042*	.007	1.043	.002	.007	1.002	.033	.008	1.034
	Science & Technology Interest	.000	.008	1.000	-.039*	.009	.962	.001	.008	1.001	-.016*	.009	.984
Step 3	Attitudes	.331*	.133	1.393	.440*	.118	1.552	.438*	.135	1.550	.456*	.134	1.577
	Subject Norms	-.067	.096	.936	-.062	.086	.940	-.130	.098	.878	-.069	.097	.933
	Perceived Control	-.017	.140	.983	-.193	.118	.824	-.152	.148	.859	-.074	.132	.929
	Intentions	.202	.131	1.224	.171	.122	1.186	.177	.134	1.194	.162	.152	1.176
Step 1	Chi Squared	81.631, df = 12, p. <.001			107.939, df = 12, p. <.001			55.553, df = 12, p. <.001			67.194, df = 12, p. <.001		
	Nagelkerke pseudo R^2	15%			14%			11%			10%		
	Hosmer & Lemeshow test	9.125, df = 8, p. = .440			4.629, df = 8, p. = .771			5.595, df = 8, p. = .709			4.508, df = 8, p. = .773		
Step 2	Chi Squared	2.798, df = 3, p. = .424			36.592, df = 3, p. <.001			2.289, df = 3, p. = .515			25.539, df = 3, p. <.001		
	Nagelkerke pseudo R^2	16%			19%			11%			14%		
	Hosmer & Lemeshow test	4.569, df = 8, p. = .765			5.448, df = 8, p. = .702			6.211, df = 8, p. = .621			4.748, df = 8, p. = .776		
Step 3	Chi Squared	27.334, df = 4, p. <.001			33.648, df = 4, p. <.001			28.510, df = 4, p. <.001			34.436, df = 4, p. <.001		
	Nagelkerke pseudo R^2	21%			23%			16%			18%		
	Hosmer & Lemeshow test	11.428, df = 8, p. = .287			9.427, df = 8, p. = .336			3.435, df = 8, p. = .888			8.304, df = 8, p. = .426		

p $< .05$.

Note: No male students had taken less than an algebra course while in high school. Therefore, this variable was removed from the model.

Note. Parents' income was measured on a9-point scale ranging from $24,000 or less to $150,000 or more; gender (male =0, female =1); parents' educational level was measured on a 8-point scale where 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, White. African American was used at the reference category ; College Prep High School Curriculum measured whether the student was exposed to college preparatory high school curriculum (yes=1, no=0),:< Algebra II, Trig+ and Calculus measures whether the students took various mathematics courses (took less than Algebra II, took Algebra II, Took Trigonometry or other advanced mathematics course, beginning calculus). Algebra II was the reference group. Honors Mathematics indicates whether the student took honors mathematics (yes=1, no=0).