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The Incremental Validity of Beliefs and Attitudes for Predicting Mathematics Achievement

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ABSTRACT

STEM-related industries are a major driver of U.S. economic growth and possessing mathematics skills is a central component of success in STEM fields. Thus, it is important to identify predictors of mathematics achievement in high school students. Some previous research has shown that students' beliefs and attitudes are important predictors of their mathematics grades and achievement. In the present paper, we examined the ability of mathematics beliefs and attitudes to predict ACT mathematics test scores by analyzing data from a questionnaire designed using the Theory of Planned Behavior framework given to high school juniors and seniors who had recently taken the ACT. Results revealed that mathematics attitudes, subjective norms, perceived control, and intentions were all significantly correlated with mathematics course grades and ACT mathematics scores. Attitudes also incrementally predicted ACT mathematics scores over several key variables. The article concludes with a discussion of limitations and future directions.

Abstract Word Count: 147

Keywords: mathematics attitudes; theory of planned behavior; mathematics achievement; mathematics grades; mathematics beliefs

The Incremental Validity of Beliefs and Attitudes for Predicting Mathematics Achievement

1.0 Introduction

It is widely believed that scientific innovation is a major driver of the national economy (e.g., Adkins, 2012; Rothwell, 2013). In fact, it has been estimated by the U.S. Department of labor that 50% of the U.S.'s economic expansion is due to workers employed in science and engineering fields (Adkins, 2012). Clearly, it is in the national interest for students to graduate with the skills taught in science, technology, engineering, and mathematics (STEM) fields. However, it has been estimated that only 13% of entering postsecondary students start school with a STEM major and only 6% start and graduate with a STEM major (Carnevale, Smith, & Melton, 2011). One possible explanation for these low numbers is that many entering postsecondary students have not yet developed the requisite skills necessary to succeed in STEM majors. Key among those skills are mathematics skills (Carnevale et al., 2011).

A recently published report underscores the fact that many students are lacking the mathematics skills to succeed in STEM. Specifically, the authors found that the most frequent mathematics course taken by a first year STEM major is calculus 1 and the ACT (formerly known as American College Testing) mathematics score associated with 50% chance of earning a B or higher in that course is 27 (Mattern, Radunzel, & Westrick, 2015). However, most STEM students are not ready to succeed in calculus 1; only 32% of STEM majors from the 2005 through 2009 cohorts reached a 27 on the ACT mathematics test (Mattern et al., 2015). Far fewer non-STEM majors reach that score. It thus seems possible that improving math achievement in high school may ultimately lead to greater readiness to succeed in STEM, and improved outcomes for individual students and the U.S. economy as a whole. An important question remains: What are the most important predictors of mathematics achievement? In this paper, we propose that student beliefs and attitudes are important factors in mathematics achievement and we expand on previous work to further examine this issue. We begin with a brief discussion of beliefs and attitudes below.

1.1 Beliefs and Attitudes.

Students acquire new knowledge (e.g., 12 X 5 = 60) and experience new situations (e.g., "I was nervous yesterday when I had to solve a math problem in front of the class") every day. The extent to which they believe this knowledge or experience is true ("I'm very confident that 12 X 5 = 60"; "I'm not sure how nervous I really was yesterday") is called a *belief* (Wyer & Albarracin, 2005). During the course of his or her education, each student develops a set of beliefs about mathematics. Some example beliefs about mathematics may be, "math is easy," "math is difficult," "math can help me get a job one day," "my friends do not like math," or "boys are good at math". Beliefs are typically formed from one's own experience or from learning about another's experience (Bandura, 1977) and, as such, math beliefs are formed from one's own, or another's, experiences with math. Over time, students can develop beliefs about their future interactions with math. These beliefs about the future are called *expectations.*

When an evaluation becomes attached to a belief (e.g., "I was nervous yesterday when I had to solve a math problem in front of the class and I HATED it!"), then an *attitude* is formed (e.g., Ajzen, 1991; Eagly & Chaiken, 1993). Attitudes are simply evaluations of people, objects, or events (Eagly & Chaiken, 1993). Beliefs and attitudes can have powerful effects on behavior and educational outcomes (e.g., Bandura, 1977; Lee, 2014; Lipnevich, MacCann, Krumm, et al., 2011; Nye, Su, Rounds, & Drasgow, 2012; Rounds & Su, 2014; Wigfield & Eccles, 2000). For example, Eccles and colleagues (e.g., Wigfield & Eccles, 2000) have put forth an expectancy-value theory that states that, among other constructs, *intrinsic value* (how interested one is in a topic; how much they like doing the activity) and *utility value* (how much they believe an activity will help them achieve a goal) influences the extent to which a student engages in a topic. Recent cross-cultural research employing data from the PISA 2009 international dataset has demonstrated the importance of intrinsic value in predicting educational attainment (Lee, 2014). Specifically, enjoyment of reading predicted PISA 2009 reading scores in each of the 13 countries examined, and across Western, Eastern, and Pancultural countries. Furthermore, there is evidence that another type of attitude, *interests*, or preferences to perform certain activities (Rounds & Su, 2014), serve to motivate behavior. Accordingly, a recent meta-analysis found that interests predicted important performance outcomes both at school and at work (Nye et al., 2012). Furthermore, beliefs in one's ability to perform certain behaviors are known as *self-efficacy* beliefs. Research has found that those high in self-efficacy tend to expend more sustained effort and are more resilient to failure than those low in self-efficacy (Bandura, 1993).

Other work has successfully predicted achievement by utilizing similar belief and attitude-based constructs as those discussed above. For example, using the framework of the *Self-Systems Model* (Skinner, Kindermann, Connell, &Wellborn, 2009), Green, Liem, Martin, et al. (2012) recently conducted a longitudinal study of 1866 Australian students over a period of one year, finding that positive attitudes toward school predicted achievement test scores. This relationship was mediated by class participation, homework completed, and absenteeism. Furthermore, attitude toward school was predicted by adaptive motivation, impending motivation, maladaptive motivation (negatively), and academic self-concept. Interestingly, most of these constructs also consist of attitude and belief components. Adaptive motivation, impending motivation, and academic self-concept are measured, in part, by items such as "learning at school is important to me" (attitude), I'm often unsure how I can avoid doing poorly at school" (belief), and "I am good at most school subjects" (belief), respectively.

Specific to mathematics, attitudes and beliefs have been shown to predict mathematics performance and achievement, although effect sizes are often small (e.g., Hembree, 1990; Lipnevich et al., 2011; Ma & Kishor, 1997; Simzar, Martinez, Ruthorford et al., 2015). For instance, *math anxiety*, which is related to negative math attitudes, is predictive of lower performance on math achievement tests (Hembree, 1990). Consistent with this, Bong, Cho, Ahn, and Kim (2012) found that text anxiety was negatively related to math achievement in a sample of Korean elementary and middle-school students. Furthermore, they found that self-concept predicted math achievement in most of their analyses. More recently, Simzar and colleagues (2015) found that student mathematics self-efficacy predicts achievement test scores in 10th grade students. Look at the red papers above for specific math beliefs one to talk about here. Also add the Mimi Bong paper the Green et al, and the Lee and Stankov PISA one. Maybe move this sentence down or delete it. Furthermore, Lipnevich and colleagues (2011) predicted mathematics grades in 8th grade students incrementally over math achievement scores using a questionnaire they developed that asked students about their math attitudes and beliefs.

The questionnaire developed by Lipnevich and colleagues was based on a well-established model for behavioral prediction from the field of social psychology known as the *Theory of Planned Behavior* (TPB; Ajzen, 1991). In the TPB, behavior is directly predicted by *intentions*. Intentions, in turn, are predicted by one's attitude and two types of beliefs. The first belief type is *subjective norms*, which refers to perceived social pressure from important others (e.g., friends, family) to perform, or not perform, the behavior. The second belief type is *perceived control*, which refers to the belief that one is capable of performing the behavior. The

TPB has been used to predict numerous types of behaviors, with one meta-analysis finding that intention predicted behavior ($r = .47$); while attitudes ($r = .49$), subjective norms ($r = .34$), and perceived control ($r = .43$) all predicted intentions (Armitage & Conner, 2001). Very little of the research on the TPB, however, has been conducted in the field of education (see Fishbein & Ajzen, 2010 for a review). One notable exception is the work conducted by Lipnevich et al. (2011).

As briefly stated above, Lipnevich and colleagues predicted mathematics grades in 8th grade students in the United States incrementally over math achievement scores with a 22 item questionnaire developed based on the principles of the TPB. Example items included: Intention, “I will try to work hard to make sure I learn math”; attitude, “I enjoy studying math”; subjective norms, “My friends think that math is an important subject”; and perceived control, “If I invest enough effort, I can succeed at math”. A structural equation model showed that intention predicted math grades ($\beta = .64$), and attitude ($\beta = .45$), subjective norms ($\beta = .18$), and perceived control ($\beta = .32$) all predicted intention. The TPB structure was later replicated in a sample of Belarusian students. Given the success of this study, it is somewhat surprising that little-to-no work has been done to replicate and extend this work. It is worth noting that the TPB was used as a theoretical framework in the development of the background variables for the PISA 2012 mathematics assessment (OECD, 2014). To our knowledge, however, no peer-reviewed papers have yet to be published on the results of this data collection.

1.2
The Current Study

The purpose of the current study is to replicate and extend the Lipnevich et al. study in several ways. First, whereas Lipnevich et al. tested 8th graders; we administered a TPB-based mathematics questionnaire to a large sample of 11th and 12th grade students in the United States who had recently completed the ACT. Additionally, Lipnevich et al. used the TPB questionnaire to predict grades incrementally over achievement scores, whereas we use the TPB questionnaire to predict ACT mathematics scores incrementally over high school mathematics grades, number of mathematics courses taken, gender, race/ethnicity, and socioeconomic status. Finally, we also administered a measure of conscientiousness (e.g., tendency to work hard and be organized; Benet-Martinez & John, 1998) to examine whether the TPB predicts ACT mathematics scores incrementally over that construct. Meta-analysis has found that conscientiousness predicts academic performance at all levels of education (Poropat, 2009).

In the current study, we tested two research questions. First, does the structure of the TPB model for mathematics beliefs and attitudes hold for high school students? Second, do the individual components of the TPB (intentions, attitudes, subjective norms, perceived control) predict ACT mathematics test scores incrementally over the host of variables listed above?

2.0
Method

2.1

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).

2.2

Procedure. An online survey was administered to a random sample of test takers (N = 37,000) who had completed the ACT in December of 2014. 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 survey stayed open for two weeks. 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., parents income) provided at the time of test administration.

2.3

Measures.

2.4

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 subject 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"). Lipnevich et al. reported internal consistencies for these scales ranging from $\alpha = .70$ (perceived control) to $\alpha = .85$ (attitudes). Some of the Lipnevich et al. items were modified for a high school population (e.g., changing the wording to be more applicable and increasing the scale from 5-points to 6-points). Subscale scores were calculated by summing up the scores for each of the four TPB components. Some respondents did not answer all survey questions and as such the sample size was reduced in the analytic sample (attitude N = 1803; subjective norm N = 1715; perceived control N = 1663; intentions N = 1604). Those who answered at least 50% of the items associated with a subscale received a subscale score. Those who did not answer at least 50% of the items on a scale were treated as missing.

2.5

Conscientiousness. Conscientiousness was measured with the 9 item conscientiousness scale of the Big Five Inventory (BFI; Benet-Martinez & John, 1998). Participants responded on 6-point scales ranging from 1 (*strongly disagree*) to 6 (*strongly agree*). Example items include "I stick to a task until it is finished" and "I tend to be disorganized". One subscale score was calculated by summing up the scores across the 9 conscientiousness items. In the paper outlining the development of the BFI, the conscientiousness scale demonstrated high internal consistency in a U.S. sample ($\alpha = .82$; Benet-Martinez & John, 1998). A total of 1,569 students received a conscientiousness subscale score.

2.6

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 (N = 1958).

2.7

Mathematics Courses. At the time of registering for the ACT, students were asked to indicate the types of mathematics courses they have completed. These courses included: algebra I, algebra II, geometry, trigonometry, beginners calculus, and other advanced mathematics. A summed score was calculated to indicate the number of mathematics courses taken. Values ranged from 0 (i.e., none of the courses have been taken) to 6 (i.e., all six courses on the list have been taken). These data were treated as continuous in the data analysis (N = 1958)

2.8

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 (N =1791). 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).

2.9

Parental Income. At the time of registering for the ACT, students were asked to answer the question "To plan for financial aid for entering students, colleges need to know financial background of their students. Please estimate the approximate total combined income of your parents before taxes last year". A nine-point scale was provided with 1 representing less than $24,000 and 9 indicating more than $150,000. This measure was treated as continuous in the data analysis (N =1465).

2.10

Father's Educational Level. Students were also asked, at the time of test-taking, to answer the question "What is the educational level of your father/guardian? An eight-point scale was provided 1= less than high school; 8 = Doctorate or professional degree (Ph.D., MD, JD, etc.). This measure was treated as continuous in the data analysis (N =1669). Father's and mother's education levels were highly correlated ($r = .61$, $p < .01$), so we included only father's education level to simplify the analyses.

2.11

Race. Students were also asked to indicate their race and ethnicity at the time of completing the ACT. Race/ethnicity was labeled: Black/African American = 1; American Indian/Alaska Native = 2; White = 3; Hispanic/Latino = 4; Asian = 5; Native Hawaiian/Other Pacific Islander = 6; Two or more races = 7; prefer not to respond = 8. For the purposes of this analysis, these options were recoded so that American Indian, Native Hawaiian, and Two or more races were collapsed into an "other" category. This resulted in five racial/ethnic categories. These categories were dummy coded with white as the referent (N = 1958).

2.12

Gender. Gender was self-reported by students. Gender was coded as 0 = female; 1 = male (N = 1958).

2.13

Data Analysis Steps.

2.14

Testing measurement models. Before running a hierarchical linear regression model that examined the ability of the TPB to predict students' ACT mathematics scores, two confirmatory factor analyses (CFAs) were fit. 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 linear regression together at the third step.

Conventional guidelines found in the structural equation literature were used to evaluate model fit. They include: (a) acceptable fit: root-mean-square error of approximation (RMSEA) of .08, and comparative fit index (CFI) ~ .90; (b) good fit: RMSEA .05 (or 90% confidence interval [CI] of the RMSEA including .05), and CFI ~ .95 (e.g., Beauducel & Wittmann, 2005; Browne & Cudeck, 1992; Hu & Bentler, 1999; Marsh, Hau, & Wen, 2004).

2.15

Hierarchical linear regression. A hierarchical linear regression predicting students' ACT mathematics score was conducted, in which mathematics course GPA was entered in step 1, conscientiousness was entered at step 2, and the four TPB components were entered in step 3. Students' background information – number of mathematics courses taken, parental income, father's educational level, race/ethnicity (white 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 mathematics test scores independently of mathematics course taking, previous performance in mathematics classes (as measured by GPA), conscientiousness, and student demographics.

3.0
Results

3.1

Descriptive statistics. A total of 1,059 students were part of the analytic sample used to answer the central research questions. Table 1 presents Cronbach's alpha, means, and standard deviations for the measures used in the current study; Table 2 displays the complete zero-order correlations. Table 1 also shows the zero-order correlation coefficients of the TPB and conscientiousness measures with both mathematics course GPA and ACT mathematics score. The ACT mathematics scores are slightly higher than national average for all test-takers (M = 21). All variables but conscientiousness and "other" race/ethnicity were significantly correlated with ACT mathematics scores, and most variables were significantly correlated with mathematics course GPA.

Table 1

Reliability, Descriptive Statistics, and Criterion Correlations for the Four MAQ Scale and Conscientiousness (N = 1059).

				Criterion Correlation	
Measure	α	M	SD	Mathematics Course GPA	ACT Mathematics
Attitudes (6 items)	.91	4.23	1.28	.39**	.42**
Subjective Norms (5 items)	.87	4.10	1.11	.16**	.21**
Perceived Control (5 items)	.86	5.05	1.01	.28**	.29**
Intentions (6 items)	.94	4.78	1.09	.22**	.18**
Conscientiousness (9 items)	.77	4.58	0.72	.14**	.01
Parental Income		4.79	2.55	.26*	.39**
Father's Educational Level		4.41	2.16	.24**	.38**
African American		0.11		-.22**	-.28**
Hispanic		0.10		-.03	-.07*
Other race/ethnicity		0.08		-.04	<.01
Asian		0.06		.09*	.10**
Female		0.66		-.04	-.20**
Math Courses		4.06	1.04	.28**	.55**
Mathematics Course GPA		3.48	.62		
ACT Mathematics		23.15	5.33		

**$p < .05$

Table 2
Correlations coefficients for all study variables.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1.ACT Mathematics	1.00														
2.Mathematics Course GPA	0.55	1.00													
3.Mathematics Courses	0.53	0.28	1.00												
4.Parental Income	0.39	0.26	0.17	1.00											
5.Female	-0.20	-0.04	-0.11	-0.09	1.00										
6.Father’s Educational Level	0.38	0.24	0.23	0.56	-0.08	1.00									
7.African American	-0.28	-0.22	-0.08	-0.24	0.04	-0.15	1.00								
8.Other race/ethnicity	0.00	-0.04	0.00	-0.04	0.01	0.05	-0.10	1.00							
9.Hispanic	-0.07	-0.03	-0.01	-0.17	-0.04	-0.20	-0.12	-0.10	1.00						
10.Asian	0.10	0.09	0.10	-0.05	-0.06	-0.02	-0.09	-0.07	-0.09	1.00					
11.Conscientiousness	0.01	0.14	0.03	-0.03	0.07	0.03	-0.02	-0.02	-0.02	-0.09	1.00				
12.Attitudes	0.42	0.39	0.25	0.10	-0.20	0.10	-0.03	-0.06	0.04	0.12	0.07	1.00			
13.Subjective Norms	0.21	0.16	0.12	0.17	-0.09	0.15	-0.06	-0.03	0.01	0.10	0.03	0.37	1.00		
14.Perceived Control	0.29	0.28	0.16	0.08	-0.17	0.07	0.03	-0.03	0.04	0.06	0.06	0.61	0.29	1.00	
15.Intentions	0.18	0.22	0.11	0.03	-0.07	0.04	0.08	-0.03	0.01	0.07	0.22	0.62	0.34	0.45	1.00

3.2

Measurement models. 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) = 174.65, RMSEA = .072 (90% CI: .062 to .082), normed fit index (NFI) = .94, and comparative fit index (CFI) – .95. Standard estimates of the factor loadings ranged from .31 to .68 and were all significant at $p < .05$. The second was a five-factor CFA representing the four components of the TPB as well as conscientiousness. For this model, the fit indices were: Satorra-Bentler χ^2 (419) = 3839.23, RMSEA = .078 (90% CI: .076 to .081), 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), .29 (subjective norms and intentions), .51 (perceived control and intentions), .32 (conscientiousness and intentions), .08 (conscientiousness and subject norms), .16 (conscientiousness and attitude), .18 and .175 (conscientiousness and perceived control).

3.3

Hierarchical regression predicting ACT mathematics. Table 3 shows the results of the hierarchical regression predicting ACT mathematics scores from mathematics course GPA, mathematics courses taken, and student demographic variables entered at Step 1, conscientiousness entered at Step 2, and attitudes, subject norms, perceived control, and intentions entered at Step 3. Mathematics course GPA, mathematics courses taken, and demographic variables accounted for 53.7% of the variation in ACT mathematics scores while conscientiousness accounted for less than 1% (i.e., .2%) although it did show a statistically significant relationship with ACT mathematics scores. The TPB components accounted for an additional 2.9% of variance in ACT mathematics scores not accounted for by conscientiousness, course GPA, mathematics courses taken, or student demographic information. Of the TPB components, attitudes most strongly predicted ACT mathematics scores. To illustrate the practical significance of attitudes, a one unit increase in attitudes predicted nearly a one point (.86) increase in ACT mathematics scores. Clearly, a one point increase in test scores has practical importance when high-stakes decisions, such as college admissions decisions, are being made. Neither perceived control nor subject norms were significant predictors in the regression model, unlike in the zero-order correlations, while intentions negatively predicted ACT mathematics scores. These results mostly mirror the findings of Lipnevich et al. (2011), who found that attitudes significantly predicted student grades, although their study showed a positive effect for intentions. The difference in sign for the effect for intention between the Lipnevich et al. study and the current study may be due to differences in the criteria being predicted (Lipnevich et al. predicted grades whereas we predicted ACT Mathematics scores).

Table 3

Hierarchical Multiple Linear Regression Predicting ACT Mathematics Scores

Predictor		ACT Math Score	
		ΔR^2	β
Step 1		.537	
	Mathematics Course GPA		.357**
	Parental Income		.143**
	Father's Educational Level		.095**
	African American		-.119**
	Hispanic		-.031
	Other		0.005
	Asian		.026
	Female		-.121**
	Mathematics Courses		.352**
Step 2		.002	
	Conscientiousness		-.046*
Step 3		.029	
	Attitudes		.207**
	Subject Norms		.004
	Perceived Control		.026
	Intentions		-.059*

*p <.05, **p<.01

4.0 Discussion

The current study adds to the research literature on mathematics beliefs and attitudes (e.g., Hembree, 1990; Lipnevich et al., 2011; Ma & Kishor, 1997; Simzar et al., 2015), further demonstrating that beliefs and attitudes are important predictors of important outcomes. Specifically, measures of mathematics-related beliefs and attitudes, as measured through the framework of the TPB, were all significantly correlated with both high school mathematics course GPA and ACT mathematics test scores. Importantly, mathematics attitudes demonstrated incremental validity in predicting ACT mathematics test scores over important student background variables such as mathematics courses taken, GPA in mathematics courses, gender, race/ethnicity, socioeconomic status, and conscientiousness.

We believe the negative effect of intentions on ACT mathematics could be due to intentions' relationship with attitudes (r = .62). The unique contribution of intentions on ACT mathematics was illustrated in the regression model, intentions' shared variance with attitude was removed, and a negative effect resulted. The moderate correlation between attitudes and intentions, normal VIF indices, and the importance of including measures that represent TPB theory lead us to believe that including both measures in the predictive model was important.

This study represents a significant extension of the Lipnevich et al. (2011) work in predicting a new outcome (ACT mathematics scores) with a larger sample of an older population of students (high school juniors and seniors), while controlling for a number of important variables that Lipnevich and colleagues were unable to control for in their original study. This provides support for previous research and theorizing that suggests that beliefs and attitudes serve to motivate engagement and sustained effort in academic pursuits (e.g., Bandura, 1993; Nye et al., 2012; Wigfield & Eccles, 2000).

One important future direction will to be to look at behavioral mediators of our effects. Recall from the introduction section that Green et al. (2012) found that belief and attitudinal constructs had an effect on test performance, and that these effect was mediated by class participation, homework completed, and absenteeism. It would be interesting to examine whether the effect of the current attitudinal and belief measures also predicted ACT mathematics performance via participation in math class, math homework completed, and absenteeism from math classes.

4.1

Limitations and Future Directions

This study is not without limitations. One limitation is that we relied on a sample with a relatively low response rate. This makes it entirely possible that students who responded to the survey invitation may have different characteristics than typical ACT test takers. For instance, they may have been more conscientious, may have been more interested in mathematics, and may have been higher achievers than those who did not respond. In fact, we do have some evidence that survey respondents were higher achievers, as their average ACT mathematics score was 2 points above the national average. In addition, the fact that the majority of respondents were females could mean that they were experiencing more stereotype threat toward their mathematics performance (Spencer, Steele, & Quinn, 1999) than would a group with more males and, in extension, this also might have indirectly influenced their perceived subjective norms. It is also possible that students who took the ACT during the time period that our sample took the test were not representative of all 11th and 12th grade students. Future work should replicate this study with a representative national sample.

Another limitation is related to the self-report nature of the TPB and conscientiousness measures. Although the survey instructions stated that students' responses would not affect their ACT score and would not be seen by colleges, it is possible that students either did not fully believe this statement or did not read it. As such, they may have been motivated to distort their responses to these items in order to present themselves in the best possible light (e.g., Burrus, Naemi, & Kyllonen, 2011). Future research can combat this potential problem by attempting to measure attitudes and conscientiousness with items that are less susceptible to distortion than the self-report Likert item-type used in the current study. Example alternate item types that show promise include forced-choice items (e.g., Stark, Chernyshenko, & Drasgow, 2005) and situational judgment tests (e.g., McDaniel, & Nguyen, 2001).

The result showing that conscientiousness was unrelated to ACT mathematics scores is also interesting in itself. One the one hand, this finding might not be surprising. Some research suggests that ACT scores tend to be highly correlated with tests of general cognitive ability (e.g., Koenig, Frey, & Detterman, 2007), and previous research has found that conscientiousness tends to be either unrelated (e.g., Ackerman & Heggestad, 1997) or slightly negatively related (e.g., Djapo, Kolenovic-Djapo, Djokic & Fako, 2011) to general intelligence. On the other hand, conscientiousness is predictive of grades at all levels of schooling (Poropat, 2009) and, to the extent that the ACT is reflective of what one has learned in school, we would expect conscientiousness to also predict scores on the ACT. Future work should focus on when, and why, conscientiousness does and does not predict ACT (and other standardized test) scores. One factor to examine will be to test whether the facets (lower levels) of conscientiousness differentially predict ACT scores. Previous research has shown that conscientiousness is composed of 2 to 8 facets, and that these facets demonstrate differential patterns of prediction with academic outcomes (e.g., MacCann, Duckworth, & Roberts, 2009).

Another limitation of the current study is its cross-sectional design. In the current study, a survey we administered was used to retrospectively predict ACT mathematics test scores. Additionally, data on the control variables we used (e.g., course taking, SES variables) were gathered prior to test administration. Ideally, this study would have been conducted using a true longitudinal design, with math attitude and conscientiousness scales administered prior to the ACT mathematics test being administered and prior to the students taking their high school mathematics courses. Such a design would allow for increased confidence in making inferences about the extent to which attitudes cause achievement, and also the extent to which attitudes influence course taking, and vice-versa. However, most of the current sample knew their ACT scores at the time of taking the survey, so reverse causality is also a possibility. Finally, future work should also focus on using the components of the TPB to predict major and career choice. Although the TPB was intended to predict behavior, in the current study we predicted mathematics grades and achievement. Although grades and achievement are certainly related to behavior, they are not pure measures of behavior. As such, we would predict that the TPB-based questionnaire used in the current study would be a powerful tool for predicting whether one chooses to major in a mathematics-related major, and ultimately, choose a mathematics-related career. If this is the case, then such a tool can be important in helping us determine why some students choose STEM majors and careers while others do not.

4.2
Conclusion

Beliefs and attitudes are important predictors of motivation and behavior related to mathematics achievement and paying attention to them can help us to predict which students will do well in mathematics. Furthermore, attitudes and beliefs can be altered with simple interventions that attempt to change a student’s false misconceptions (e.g., Ajzen, Albarracín, & Hornik, 2007; Yeager & Walton, 2011), and these interventions can sometimes have powerful effects on behavior and educational outcomes. To provide one example, Blackwell, Trzesniewski, and Dweck (2007) administered an 8-week intervention to low income Black and Latino 7th-graders designed to influence their belief that intelligence is malleable rather than fixed. The study found that students who took part in the intervention had higher grades at the end of the year than a control group. Changing students’ attitudes and beliefs about mathematics could thus have an important impact on their mathematics achievement. As such, it is our own belief that studying beliefs matters greatly and we urge others to continue this pursuit.

5.0

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