Journal of Educational Psychology
2011, Vol. 103, No. 1, 105–118

0022-0663/11/$12.00 DOI: 10.1037/a0021949

Mathematics Attitudes and Mathematics Outcomes of U.S. and Belarusian Middle School Students

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Two multivariate studies examined the applicability of the theory of planned behavior in gauging students' attitudes toward mathematics, as well as the predictive power of mathematics attitudes in explaining students' grades in mathematics. Middle-school students from the United States (N = 382) and Belarus (N = 339) participated. Confirmatory factor analysis supported the viability of the theory for both samples. The analyses revealed that between 25% and 32% of the variance in mathematics grades could be explained by the theory of planned behavior components. In fact, 17% of the variation in test grades could be explained by the theory of planned behavior over and above the effects of mathematics ability test scores. Mean score differences between countries were small (ds = .15 to .27), with Belarusian students scoring more highly on attitudes and control but less highly on subjective norms and intentions. The article concludes with discussion of potential interventions and the need to expand results to different age groups and achievement domains, as well as the need for longitudinal and cross-cultural research.

Keywords: theory of planned behavior, mathematics achievement, mathematics attitudes, cross-cultural comparison

Mathematics proficiency has been increasingly recognized as vital to personal and economic success at both the individual and national levels. Numerous theoretical syntheses and empirical studies have illustrated that whereas mathematics-related skills are becoming ever more important, students from many nations are not performing at the level that they should. For example, recent results of the National Assessment of Educational Progress (NAEP) indicate that only 32% of U.S. eighth graders and 39% of U.S. fourth graders had reached expected proficiency (Lee, Grigg, & Dion, 2007). Such deficiencies in mathematics performance are consequential: Lack of mathematics skills relates to lower employability, wages, productivity, sense of well-being, and even the ability to make informed medical decisions directly affecting quality of life and longevity (e.g., Geary, 1996; Reyna & Brainerd, 2007; Rivera-Batiz, 1992). Additionally, the decline in mathematics proficiency among students has a nontrivial effect on a nation's economy (Geary, 1996).

Explanations for Mathematics Deficiencies

Although cognitive ability and students' exposure to mathematics resources are obvious prerequisites for mathematics achievement, these factors do not explain all of the differences among individuals in mathematics achievement (e.g., Floyd, Evans, & McGrew, 2003). Students' beliefs and expectations regarding the difficulty of mathematics, their levels of engagement, and their likelihood or perceived value of success can profoundly influence their achievement in mathematics (Singh, Granville, & Dika, 2002; Stevenson & Newman, 1986). In other words, attitudinal factors as well as cognitive factors may be important for mathematics achievement. The current article concentrates on the relationship of attitudinal factors to mathematics achievement, examining whether attitudes predict mathematics achievement independently of mathematics ability. We conceptualize attitudes according to Ajzen's (1991) theory of planned behavior (as described in more detail later in the article).

There appear to be significant correlations between students' mathematics attitudes and their score on mathematics achievement measures (Kloosterman, 1991; Minato & Yanase, 1984). Ma and

This article was published Online First January 24, 2011.

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This research was conducted while the first and second authors were completing postdoctoral fellowships at the Educational Testing Service. Numerous individuals at the Educational Testing Service were involved in test construction, data collection, and analyses. We thank them all. We extend special thanks to Andrey Tsobkalo, Larisa Tsobkalo, and Viktoria Tsobkalo for their help with the Belarusian study. The views expressed represent the views of the authors and not necessarily of the Educational Testing Service.

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Kishor's (1997) meta-analysis showed a positive (albeit weak) relationship between mathematics attitudes and mathematics performance, with longitudinal modeling suggesting that mathematics attitudes actually constitute a causal factor in mathematics achievement. The positive correlation between mathematics attitudes and mathematics achievement appears replicable across cultures, holding for international samples as well as for various ethnic groups within the United States (e.g., Chen & Stevenson, 1995; Randel, Stevenson, & Witruk, 2000).

Although observed effect sizes were found to be small, Ma and Kishor (1997) posited that true effect sizes may have been masked by certain psychometric limitations in assessments designed to measure mathematics attitudes. Other researchers have also documented the marginal reliability and questionable validity evidence of scores on the available mathematics attitudes instruments (Melancon, Thompson, & Becnel, 1994; Tapia, 2004). One possible reason for existing psychometric problems may be the lack of a robust theory driving the assessment development process. In the current studies, we propose that the theory of planned behavior (see e.g., Ajzen, 1991, 2006) provides a rigorous theoretical framework for developing mathematics attitude assessments. We used theory of planned behavior–based measures in the mathematics achievement domain to examine whether (a) the theoretical structure of the theory of planned behavior holds in the mathematics achievement domain, (b) there is a relationship between mathematics attitudes and mathematics achievement, and (c) the theoretical structure and attitude–achievement link hold across two different cultures (the United States and Belarus, specifically).

Mathematics Attitudes: The Cross-Cultural Context

Outside of the United States, relatively few studies have examined mathematics attitudes (see, however, Frenzel, Pekrun, & Goetz, 2007, who provide an exception). In order to redress the imbalance, we compared mathematics attitudes among representative samples of eighth graders from the United States and from Belarus (an Eastern European presidential republic). The official languages of Belarus are Russian and Belarusian, and ethnic minorities (mainly Russian, Polish, and Ukrainian) constitute approximately 20% of the population (compared with 26% in the United States). Schooling is compulsory until the age of 16 years, with close to 100% of individuals obtaining a high school diploma or its equivalent (Silich, 2007), compared with 84% in the United States (U.S. Census Bureau, 2004).

As is the case in several European countries, negative attitudes toward mathematics are not viewed as a cause for concern in Belarus (e.g., Lichkovsky, 2007). Studies have shown that high school students listed foreign languages and chemistry as subjects that are more disliked and anxiety provoking than mathematics (Shinkevich, 2006). Therefore, comparing mathematics attitude links to mathematics performance across the U.S. and Belarusian samples allowed us to test (a) the strength of the attitude–achievement relationship across different cultures and (b) the structure of mathematics attitudes in countries where students hold differing levels of negative attitudes toward mathematics.

The Theory of Planned Behavior

The theory of planned behavior may serve as a useful theoretical framework for both development of mathematics attitudes measures and subsequent interventions to remediate potential deficiencies. The theory of planned behavior is based on the psychological theory of reasoned action, which posits that the central determinant of volitional behavior is one's intention to engage in that behavior (Ajzen, 1991, 2002, 2006; Fishbein & Ajzen, 1975). Ajzen (1991) further discusses three determinants of behavior that exert their effects through intentions. These are (a) attitudes,[1] (b) subjective norms, and (c) perceived behavioral control. The theoretical model of the theory of planned behavior is shown in Figure 1.

Attitudes are defined as the overall positive or negative evaluation of the behavior. In general, the more favorable the attitude toward the behavior, the stronger the individual's intention is to perform it. Ajzen (1991, 2006) included both experiential and instrumental components of attitudes, where experiential attitudes carry an affective connotation (e.g., like–dislike) and instrumental attitudes have an evaluative connotation (e.g., important–not important). Subjective norms are defined as the social pressures to perform (or not to perform) a particular behavior. That is, if an individual perceives that significant others endorse (or disapprove of) the behavior, they are more (or less) likely to intend to perform it. An individual's perceived behavioral control acts as a codeterminant of behavior, the factor thought to affect both intentions and behavior (see Figure 1). Perceived behavioral control "provides information about the potential constraints on action as perceived by the actor, and is held to explain why intentions do not always predict behavior" (Armitage & Conner, 2001, p. 472).

Several meta-analyses support the general principles of the theory of planned behavior model, showing that the theory of planned behavior accounts for 27% and 39% of the variance in behavior and self-reported intentions, respectively, with perceived behavioral control independently accounting for an additional 6% of the variance in behavior (e.g., Sheeran, 2002). Armitage and Conner's (2001) meta-analysis suggested that participant-reported intentions (a) are most strongly predicted by attitudes ($\rho = .49$), (b) are strongly predicted by control ($\rho = .43$), and (c) show the weakest relationship with subjective norms ($\rho = .34$). Thus, we might expect paths to intentions to be strongest for attitudes and weakest for subjective norms. However, Armitage and Conner (2001) suggested that weak relationships between subjective norms and intentions may be due to problematic item development in many subjective norms scales.

Overall, the theory of planned behavior appears to be a viable theory for predicting volitional behavior. However, to our present knowledge, no studies have examined the effectiveness of the theory of planned behavior in predicting mathematics performance. The current investigation aimed to redress this imbalance while also extending the theory of planned behavior to the cross-cultural context.

Aims of the Present Research

On the basis of the preceding review of the literature, we tested four hypotheses over two studies. First, we proposed that the structure of the theory of planned behavior (Ajzen, 1991, 2006)

[1] Throughout the article, we use the term *attitudes toward mathematics* (or *mathematics attitude*) as an umbrella term covering all of the components of the theory of planned behavior.

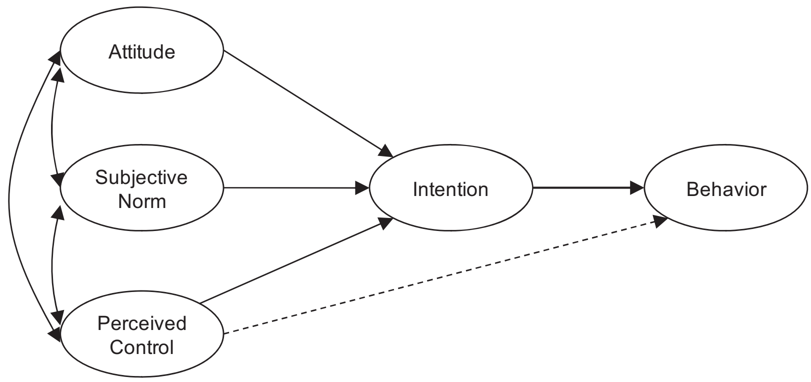

Figure 1. Theory of planned behavior—Attitudes: The overall evaluation of whether a behavior is positive or negative (based on prior behavioral contingencies). Subjective norms: the perceived social pressure to perform the behavior. Perceived control: the person's estimate of his or her capacity to perform the behavior. Intentions: the readiness or willingness to perform the behavior.

would be identified in U.S. eighth graders for the domain of mathematics (Study 1). Second, we predicted that a substantial amount of variance in mathematics grades would be explained by the theory of planned behavior (Studies 1 and 2). Third, we tested whether student-reported attitudes to mathematics would predict mathematics grades independently of mathematics test scores (Study 1). Finally, we hypothesized that the structure of the theory of planned behavior in the domain of mathematics would replicate outside of the United States, namely, in Belarus (Study 2).

Study 1: U.S. Sample

Method

Participants. A total of 382 students (51% male, 49% female) from five U.S. states participated. Most of the students were 13 years of age (73.8%; $M = 13.22$, $SD = 0.49$, range = 12 to 15). The majority of students lived in rural or suburban areas (62.8%). The median reported family income was between $66,000 and $80,000. The sample comprised the following self-reported ethnicities: White/other (71.5%), Hispanic (15.2%), and African American (13.4%), which is close to the general U.S. ethnic composition (67.4% White non-Hispanic, 14.5% Hispanic, and 12.1% African American; Grieco & Cassidy, 2001).

Procedure. This study used data collected during the third wave of a longitudinal study conducted in August 2006, March 2007, and December 2007. Students were recruited from five sites across the United States (Atlanta, GA; Chicago, IL; Denver, CO; Fort Lee, NJ; and Los Angeles, CA). Each student along with a parent or guardian who also was involved in the study (see passage below) was tested at a local site. Every parent or guardian completed and signed a consent form granting permission for his or her child to participate and received remuneration for the parent's and the child's participation. Students were taken to a testing room to complete several proctored assessments, starting with a paper-and-pencil mathematics test, followed by a computerized test battery that included assessments of several noncognitive constructs, including time management, life satisfaction, test anxiety, learning strategies, emotional reactions toward school, and attitudes toward mathematics. Within each test, item ordering was the same. However, the tests were given in random order. Testing took between 1.5 and 2 hr to complete, and students were prompted to take a break midway through the battery.

The parent or guardian, who came to the testing site with each student, completed a brief paper-and-pencil questionnaire. This document included a report of the child's grades from the previous semester. All tests and protocols were approved by the Educational Testing Service human ethics and fairness review committee.

Measures.

Mathematics Attitude Questionnaire (MAQ). The MAQ was developed to assess the four components of the theory of planned behavior (i.e., Attitudes, Subjective Norms, Perceived Behavioral Control, and Intentions). Students were asked to rate each item on a 5-point scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). The initial item pool contained 40 items (10 for each of the theory of planned behavior subscales: Attitudes, Subjective Norms, Perceived Behavioral Control, and Intentions). Exploratory factor analysis (with maximum-likelihood estimation and promax rotation) was used to reduce the item pool by removing items that loaded saliently ($>$.30) on a theoretical factor other than the one it was designed to measure (e.g., any Attitudes item that cross-loaded on subjective norms was removed). The U.S. sample was used as the basis for reducing the item pool. After reduction, 22 items remained. Six items represented attitudes (e.g., "I enjoy studying math"), five items represented subjective norms (e.g., "My friends think that math is an important subject"), five items represented perceived behavioral control (e.g., "If I invest enough effort, I can succeed in math"), and six items represented intentions (e.g., "I will try to work hard to make sure I learn math"). The total scores were calculated by summing students' responses for each of the four components.

Mathematics skills assessment. The mathematics skills test was administered in paper-and-pencil format at the beginning of the test session and included 19 retired items from the NAEP Math Achievement Test of 2007. Sixteen of these items were presented in a multiple-choice format, with five choices each (only one answer could be correct), and three were in an open-response format (e.g., "Determine if a given figure is a parallelogram and explain"). Altogether, five content areas were covered: (a) number properties and operations (e.g., "Identify number rounded to nearest hundred"), (b) algebra (e.g., "Identify point on a graph with specified coordinates"), (c) geometry (e.g., "Identify type of triangle from picture"), (d) measurement (e.g., "Determine value of marks on a scale"), and (e) data analysis and probability (e.g., "Find total cost based on unit price for a quantity"). The open-ended items were scored with established NAEP rubrics by a single trained scorer.

Student-reported grades. Students reported their mathematics grade from the previous semester. Grades were converted into a 13-point scale ranging from 0 (*E or Fail*) to 12 (*A+*). Some self-reports of grades were not interpretable (e.g., "pass," "honors") and had to be excluded from the conversion procedure. Mathematics grades were treated as a continuous variable in data analysis. After the conversion, the sample size was $N = 366$.

Parent-reported grades. For each child, one parent also reported his or her child's mathematics grade for the previous semester. Grades were converted to the same 13-point scale as for child-report grades, also removing noninterpretable grades in the same way. After conversion, the sample size for parent-reported grades was $N = 367$. Grade information from both parent reports and self-reports was available for 353 students. Parent-reported grades were collected to test the accuracy of self-reported grades as a result of concerns that students might overestimate their grades or otherwise report grades inaccurately. A dependent sample t test showed no significant difference between self-reported grades ($M = 8.55$, $SD = 2.76$) and parent-reported grades ($M = 8.46$, $SD = 2.75$), $t(352) = 0.87$, $p = .37$, indicating that self-reports were not inflated estimates of grades. The correlation between self- and parent-reported mathematics grades was .74, indicating that self-reported grades are reasonably reliable.

Data analysis steps.

Testing measurement models. Before testing structural models of the theory of planned behavior, confirmatory factor analyses (CFAs) were fit separately for the independent variables (i.e., a three-factor CFA of Attitudes, Subjective Norms, and Perceived Behavioral Control) and the dependent variable (i.e., a one-factor CFA of Intentions).

Testing structural models. Two models were tested with structural equation modeling: (a) Model 1, where Intentions are predicted by the other theory of planned behavior components (Attitudes, Control, and Subjective Norms), and (b) Model 2, where mathematics grades are predicted by the theory of planned behavior structure specified in Model 1 (i.e., the model specifies that Intentions fully mediate the role of Attitudes and Subjective Norms in mathematics grades and partly mediate the role of Perceived Control in predicting grades).

Hierarchical linear regression. A hierarchical linear regression predicting students' mathematics grades was conducted, in which students' mathematics proficiency (NAEP score) was entered in Step 1, and the four theory of planned behavior components were entered in Step 2. This model allows a test of whether the theory of planned behavior predicts mathematics achievement independently of mathematics proficiency.

We conducted all structural equation modeling with the LISREL Version 8.8 program, using a polychoric correlation matrix and asymptotic covariance matrix as input and using a diagonally weighted least squares estimator (i.e., item responses were treated as ordinal, as ratings were on a 5-point scale). When evaluating model fit, we used the following set of rough guidelines based on the range of different cutoff values for fit indices suggested by different researchers in the structural equation modeling literature: (a) acceptable fit: root-mean-square error of approximation (RMSEA) $\leq .08$, standardized root-mean-square residual (SRMR) $\leq .09$, and comparative fit index (CFI) $\approx .90$; (b) good fit: RMSEA $\leq .05$ (or 90% confidence interval [CI] of the RMSEA including .05), SRMR $\leq .09$, and CFI $\geq .95$ (e.g., Beauducel & Wittmann, 2005; Browne & Cudeck, 1992; Hu & Bentler, 1999; Marsh, Hau, & Wen, 2004).

Results

Descriptive statistics. Means, standard deviations, and reliability estimates for the measures used in the current study are presented in Table 1. Table 1 also shows the sample mean for the mathematics skills assessment, which was very similar to the 2007 national average ($M = 10.44$, $SD = 5.65$; $d = 0.10$) on this set of 19 items (i.e., the current sample appears similar to the previous students tested on NAEP in terms of their mathematics skills at this age).

Table 1
Reliability, Descriptive Statistics, Gender Differences, and Criterion Correlations for the Four MAQ Scales and MAQ Total for the U.S. Sample

					Criterion correlation	
Measure	α	*M*	*SD*	Gender *d*	Math test	Math grade
Intentions (6 items)	.84[a]	22.15	4.40	−0.29**	.08	.31**
Perceived Behavioral Control (5 items)	.70[a]	19.93	3.41	0.01	.29**	.31**
Attitudes (6 items)	.85[a]	18.43	5.18	−0.11	.16**	.44**
Subjective Norms (5 items)	.76[a]	17.10	3.63	−0.10	.08	.19**
Total scale (22 items)	.89[a]	77.61	12.57	−0.17	.19**	.42**
Math test (19 items)	.72[a]	10.90	3.56	0.43**		
Math grade (self-report)		8.52	2.80	−0.24*		

Note. Gender differences were calculated using Cohen's *d*, with boys having negative values indicating higher scores for girls. MAQ = Mathematics Attitude Questionnaire.
[a] Reliability is Cronbach's alpha.
* $p < .05$. ** $p < .01$

Boys scored significantly higher than girls on the mathematics skills assessment, consistent with national data. However, girls had significantly higher mathematics grades than boys. Gender differences on the MAQ scales were slight and favored girls: Only the Intentions subscale showed a significant gender difference, with girls scoring 0.29 of a standard deviation higher than boys. All MAQ scales predicted mathematics grades, with correlations of small to moderate magnitude. However, both Intentions and Subjective Norms subscales did not significantly predict mathematics test scores, though control and attitudes showed small (but significant) relationships with mathematics test scores. Mathematics grades and test scores were correlated at $r = .23$ ($p < .01$).

Measurement models.

Independent variables. A three-factor CFA representing Attitudes, Subjective Norms, and Perceived Behavioral Control latent factors showed good fit to the data: Satorra–Bentler $\chi^2(98) = 239.36$, RMSEA = .063 (90% CI: .053 to .073), normed fit index (NFI) = .949, comparative fit index (CFI) = .969, and SRMR = .068. Standardized estimates of the factor loadings ranged from .51 to .86 and were all significant at $p < .05$. Correlations between latent variables were .46 (Attitudes and Subjective Norms), .58 (Attitudes and Perceived Behavioral Control), and .41 (Norms and Perceived Behavioral Control).

Dependent variables. A one-factor CFA of the six Intentions subscale items showed good fit to the data: Satorra–Bentler $\chi^2(8) = 21.21$, RMSEA = .067 (90% CI: .033 to .103), NFI = .987, CFI = .992, and SRMR = .043. Standardized estimates of the factor loadings ranged from .57 to .83 and were all significant at $p < .05$.

Structural model predicting intentions. The structural diagram and path coefficients for Model 1 (where Attitudes, Subjective Norms, and Perceived Behavioral Control predict intentions according to the theory of planned behavior) are shown in Figure 2. All paths were significant at $p < .05$. Model 1 fit the data well: Satorra–Bentler $\chi^2(199) = 398.09$, RMSEA = .052 (90% CI: .045 to .060), NFI = .962, CFI = .980, and SRMR = .063. In this model, 62.6% of the variation in Intentions was explained by the other three components. Correlations among subscales were high. Intentions correlated at .65, .72, and .52 with Perceived Behavioral Control, Attitudes, and Subjective Norms, respectively. Perceived Behavioral Control and Attitudes correlated at .57, and Norms related at .41 and .46 to Perceived Behavioral Control and Attitudes, respectively. All paths to Intentions were significant and were strongest for Attitudes and weakest for Subjective Norms, as expected.

Structural model predicting mathematics grades. The theory of planned behavior model, in which Subjective Norms, Attitudes, and Perceived Behavioral Control predict Intentions, is often used to predict criteria (in this case, mathematics grades at school). Model 1 was thus expanded to include the prediction of self-reported mathematics grades (Model 2, as shown in Figure 3). Correlations between latent variables for Model 2 are shown in Table 2.

Model 2 explained 24.5% of the variation in mathematics grades and showed good fit to the data: Satorra–Bentler $\chi^2(217) = 483.29$, RMSEA = .058 (90% CI: .051 to .065), CFI = .975, SRMR = .064. In this model, the path from Perceived Behavioral Control to mathematics grades was not significant and was virtually zero, whereas the path from Intentions to grades was of large

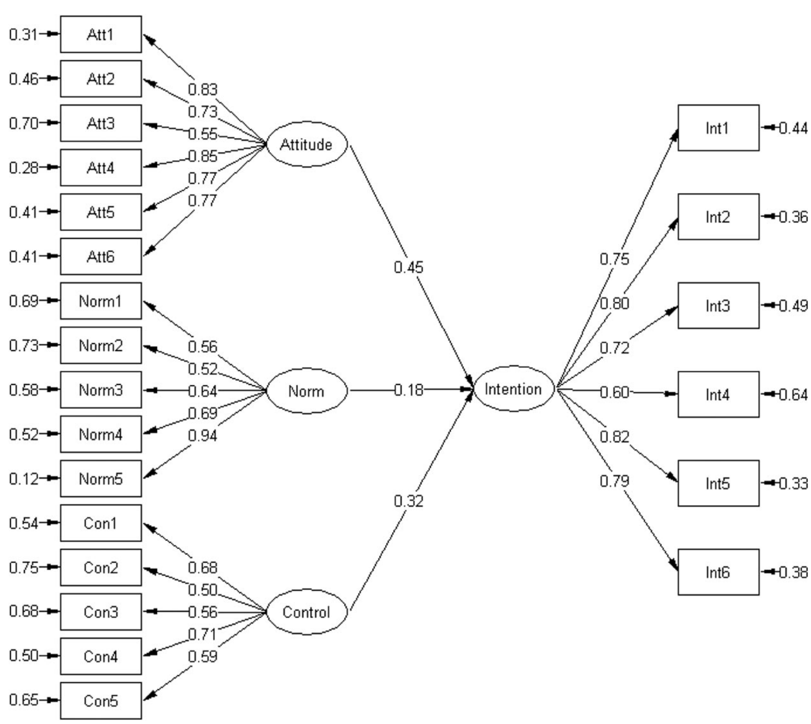

Figure 2. Standardized solution obtained for the theory of planned behavior Model 1 in a U.S. sample (all latent variables are allowed to correlate freely, and no correlated error terms are included in the model).

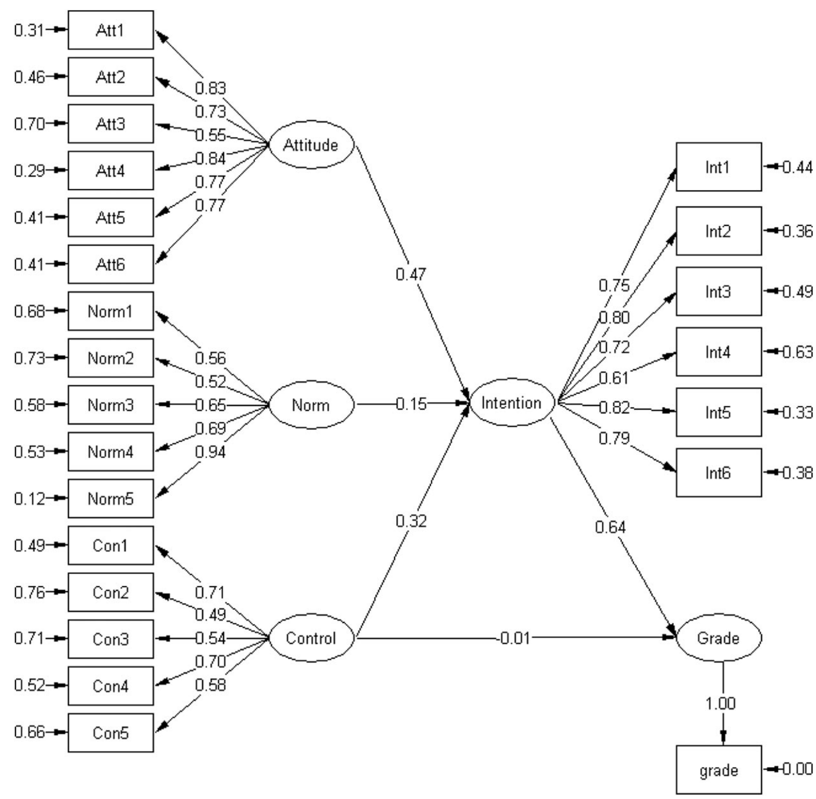

Figure 3. Standardized solution obtained for the theory of planned behavior Model 2 predicting self-reported mathematics grades scores in a U.S. sample (all latent variables are allowed to correlate freely, and no correlated error terms are included in the model).

magnitude. Correlations between latent variables of this model (see also Table 2) indicated that all four components of the theory of planned behavior relate to mathematics grades at .30 or greater.

Hierarchical regression predicting grades from test scores and theory of planned behavior components. Table 3 shows the results of a hierarchical regression predicting mathematics grades from mathematics test scores at Step 1 and mathematics attitudes at Step 2. Mathematics test scores accounted for about 5% of the variation in mathematics grades, and the theory of planned behavior components explained an additional 17% of the variation in grades not accounted for by mathematics ability. Of the four theory of planned behavior components, Attitudes showed the strongest link with achievement, Perceived Behavioral Control was also significantly linked with achievement, but neither Intentions nor Subjective Norms was significantly related to students' mathematics grades.

Discussion

Study 1 showed that the current sample's performance on the (retired) NAEP mathematics items was equivalent to the NAEP sample, allowing inferences drawn from this study to be stronger than might otherwise have been the case. Structural models illustrated the utility of applying the theory of planned behavior to the mathematics domain, with MAQ scores predicting 25% of the variation in mathematics grades. In addition, results from a hierarchical regression demonstrated that the relationship between

Table 2
Correlations Between Latent Variables for Model 2 for the U.S. Sample (Below the Diagonal) and the Belarus Sample (Above the Diagonal)

Variable	Grade	Intentions	Attitudes	Norms	Control
Grade	—	.44	.54	.17	.23
Intentions	.32	—	.80	.30	.58
Attitudes	.46	.73	—	.29	.65
Subjective Norms	.31	.50	.46	—	.34
Perceived Behavioral Control	.41	.66	.58	.41	—

Table 3
Hierarchical Multiple Linear Regression Predicting Mathematics Grade From Mathematics Ability and Mathematics Attitudes

Predictor	Life satisfaction	
	ΔR^2	β
Step 1	.051**	
NAEP Mathematics score		.117*
Step 2	.173**	
Theory of planned behavior: Intentions		.039
Theory of planned behavior: Perceived Behavioral Control		.124*
Theory of planned behavior: Attitudes		.335**
Theory of planned behavior: Subjective Norms		.007
Total R^2	.224**	

Note. NAEP = National Assessment of Educational Progress.
* $p < .05$. ** $p < .01$.

MAQ components and mathematics grades was, in fact, independent of students' mathematics proficiency.

The structure of mathematics attitudes in eighth-grade U.S. students. Hypothesis 1—that the structure of mathematics attitudes would follow the theory of planned behavior model—was supported by the data. Fit statistics from Model 1 demonstrated that the theory of planned behavior model fit the data well. The strongest links to Intentions were found for Attitudes and the weakest for norms, in line with Armitage and Conner's (2001) meta-analysis. All three components significantly related to Intentions, combining to predict a substantial amount of the variance in Intentions. Indeed, the amount of variance explained in our study was higher than previously reported (63% vs. 39% reported in Armitage & Conner, 2001). A possible reason for this difference might be the populations studied: Studies included in the meta-analysis mainly involved specialized samples of adults (e.g., smokers, HIV-positive individuals) such that restriction of range on relevant components might be expected. In contrast, our study focused on a heterogeneous group of middle-school students rather than only on those students who struggled with mathematics.

Prediction of mathematics grades. Hypothesis 2 posited that theory of planned behavior components would predict mathematics grades and was supported by the data. The theory of planned behavior model explained 25% of the variance in mathematics grades. This proportion of variation in grades explained by the model is quite high for a noncognitive characteristic, with mathematics performance generally predicted better by intelligence, working memory, and other cognitive attributes (e.g., Swanson & Kim, 2007). However, the individual components of the theory of planned behavior showed some surprising relationships with achievement criteria. Perceived Behavioral Control showed no direct effects on students' grades, despite the strong role theorized for this component in the theory of planned behavior.

Hypothesis 3 posited that theory of planned behavior components would incrementally predict mathematics grades over and above the effects of mathematics ability. The regression model demonstrated that the theory of planned behavior components accounted for 17% of the variance in grades that could not be explained by students' results on a standardized mathematics test. This result demonstrates that students' MAQ scores are not simply proxy measures for their mathematics ability but are indexing something quite separable and unique that helps to explain the variability in mathematics achievement.

Study 2: Belarusian Sample

Study 2 was conducted to cross-validate the structure of the theory of planned behavior on a different sample. We also aimed to find out whether the predictive power of the theory of planned behavior components on mathematics grades could be established in a country where negative attitudes toward mathematics have not (at least at the time of this writing) been deemed an issue of concern in education (Lichkovsky, 2007).

Method

Participants. A total of 339 students (48% male, 52% female) from six regions of Belarus participated. A school in each of the six regions of Belarus was selected according to the following criteria: (a) the school had to be large enough to have at least 40 eighth graders and (b) the school had to be public, with instruction adhering to the national standardized curriculum. Written informed consent was obtained from students' parents or legal guardians granting permission for their child's participation in the study. Each student received remuneration. The average age was 13.40 years ($SD = 0.55$), and ages ranged from 12 to 15 years of age. Although Belarusian students were significantly older than U.S. students at the time of testing, $t(719) = 4.62$, $p < .01$, the average difference in age was only 2 months.

Measures.

Mathematics Attitudes Questionnaire. The theory of planned behavior–based MAQ, described in Study 1, was translated into Russian by the first author. The translated questionnaire was then back-translated by an independent, professional translator. Any differences between the original instrument and the back-translation were discussed with the professional translator, and appropriate corrections were made (Brislin, 1986). In this way, we were confident that the translation of the questionnaire into Russian was conducted according to best practices.

Student-reported grades.[2] Students were instructed to report the mathematics grades they had received in the previous semester. The range of grades was between 1 and 10, with 10 being the highest. All students reported their grades ($N = 339$). Mathematics grades were treated as a continuous variable in data analysis.

Procedure. All participants completed the questionnaire in paper-and-pencil format in large classrooms in a proctored testing session of up to 90 min duration. Students' participation was voluntary, with the parents' permission obtained prior to the beginning of the study. All tests and protocols were approved by the Educational Testing Service's human ethics and fairness review committee.

Data analysis steps.

Step 1. Examining the difference in the theory of planned behavior component means. Summed-score means for attitudes, perceived behavioral control, subjective norms, and inten-

[2] Parent-reported grades were not collected for the Belarusian sample.

tions were compared across the U.S. and Belarus samples. Mean differences were compared with Cohen's *d*, where values .20, .50, and .80 denote small, medium, and large differences between groups (Cohen, 1988).

Step 2. Testing measurement models. As for the U.S. sample, a three-factor confirmatory factor analysis of Attitudes, Subjective Norms, and Perceived Behavioral Control was fit (representing the measurement model for the independent variables), and a one-factor CFA of Intentions was fit (representing the measurement model for the dependent variable).

Step 3. Testing structural models. As for the U.S. sample, three regression models predicting Intentions, mathematics test scores, and mathematics grades were fit following the same methods as in Study 1 (including interpretation of fit indices). These models were tested on the Belarusian sample only.

Step 4. Testing invariance across samples. The invariance of Model 1 (the theory of planned behavior model predicting Intentions) was assessed across the U.S. and Belarusian samples in a stepwise approach as recommended by Byrne (2004). Invariance was assessed in four steps: (a) configural or structural invariance (i.e., parameters are free to vary but the structure is the same), (b) invariance of factor loadings, (c) invariance of factor loadings and covariances, and (d) invariance of loadings, covariances, and regression paths. The chi-square difference in model fit was calculated for each additional set of equality constraints (using the scaling correction for the Satorra–Bentler chi-square detailed in Satorra & Bentler, 2001). The Akaike information criterion (AIC) was additionally considered to compare models.

Results

Descriptive statistics and comparisons between samples. Descriptive statistics and internal consistency estimates for the MAQ scales and grades are shown in Table 4, along with group differences between the Belarusian and U.S. samples. As in the U.S. sample, gender differences were of small to trivial effect size for MAQ components. However, as in the United States, girls scored significantly higher than did boys on Attitudes. In addition, Belarusian girls also scored significantly higher on Perceived Behavioral Control than did Belarusian boys. Compared with the U.S. sample, reliability was significantly lower for Intentions, Perceived Behavioral Control, and Attitudes scales (though note that marginally lower estimates would be expected in a second sample not used to select items). Nevertheless, alphas were at or above .69 for all but the Perceived Behavioral Control scale (.53). Item-level analysis identified three problematic items with very low item-total correlations that lowered the reliability of their respective subscales: (a) Perceived Behavioral Control Item 1 (i.e., "It is impossible for me to succeed at math"), (b) Attitudes Item 6 (i.e., "I enjoy working on math homework"), and (c) Subjective Norms Item 1 (i.e., "Most of my friends fail math courses").

Item variability was much higher for the Belarusian sample than for the U.S. sample for every single MAQ item. The Belarusian students used the two most extreme scale points much more frequently than did the U.S. students, selecting *strongly agree* or *strongly disagree* 41.4% of the time (compared with 28.0% of the time for U.S. students), $\chi^2(1) = 2{,}352$, $p < .001$. The three problematic items were rated *strongly agree* 3% to 5% of the time by the U.S. sample and 10% to 18% of the time by the Belarusian sample. Belarusian students obtained higher scores than did U.S. students on Perceived Behavioral Control and Attitudes, and U.S. students obtained higher scores on Intentions and Subjective Norms. Effects for all mean differences were small in size (see Cohen, 1988, for guidelines).

Measurement models.

Independent variables. A three-factor CFA representing Attitudes, Subjective Norms, and Perceived Behavioral Control latent factors showed reasonable fit to the data: Satorra–Bentler χ^2 (98) = 243.30, RMSEA = .066 (90% CI: .056 to .077), NFI = .913, CFI = .946, and SRMR = .079. The Attitudes Item 6 did not load significantly on the Attitudes factor ($\lambda = .12$). All other item loadings were significant at $p < .05$, with standardized estimates ranging from .32 to .90. Correlations between latent variables were .27 (Attitudes and Subjective Norms), .65 (Attitudes and Perceived Behavioral Control), and .30 (Subjective Norms and Perceived Behavioral Control).

Table 4
Reliability, Descriptive Statistics, Gender Differences, and Criterion Correlations for the Four Subscales and Total Scale of Mathematics Attitudes for the Belarus Sample

						Criterion correlations	
Measure	α	*M*	*SD*	Gender *d*	U.S. *d*	Math test	Math grade
Intentions (6 items)	.72[a]	21.43	5.31	−0.10	0.15*	.37**	.36**
Perceived Behavioral Control (5 items)	.53[a]	20.48	3.49	0.24*	−0.16*	.25**	.27**
Attitudes (6 items)	.69[a]	19.23	5.07	0.24*	−0.16*	.45**	.45**
Subjective Norms (5 items)	.72	16.03	4.27	0.09	0.27**	.04	.10
Total scale (22 items)	.85[a]	77.17	13.35	0.14	0.03	.40**	.42**
Math assessment		6.06	1.86	−0.20			
Math grade		6.25	1.63	−0.20			

Note. Group differences were calculated using Cohen's *d*, with boys and U.S. students as the reference groups (negative values indicate higher scores for females or for Belarus students).
[a] These alpha reliability coefficients are significantly lower for the Belarus sample than for the U.S. sample, according to the test developed by Hakstian and Whalen (1976).
* $p < .05$. ** $p < .01$.

Table 5
Testing Model Invariance of Configuration, Loadings, Correlations, and Regression Weights Across U.S. and Belarus Samples

Model	$SB\chi^2$	$NT\chi^2$	*df*	$\Delta\chi^2_{corrected}$	Δdf	*p*	AIC	RMSEA	CFI
Model 1[a]	924.13	1,757.00	398				1,140.12	.059	.975
Model 2[b]	949.34	1,773.55	417	14.08	19	.7790	1,127.34	.058	.975
Model 2b[c]	1,033.43	1,940.08	420	126.76	22	<.0001	1,205.43	.062	.971
Model 3[d]	1,067.05	2,018.31	427	28.53	7	.0001	1,225.05	.063	.969
Model 4[e]	1,064.79	2,021.28	430	1.04	3	.7915	1,216.79	.063	.970

Note. $SB\chi^2$ = Satorra–Bentler chi-square; $NT\chi^2$ = normal theory chi-square; $\Delta\chi^2_{corrected}$ = the difference in chi-square for each successive model change (Model 1 to Model 2 and Model 2b, Model 2 to Model 3, and Model 3 to Model 4), with the correction factor calculated according to Satorra and Bentler's (2001) method for comparing values of the Satorra–Bentler chi-square for nested models; AIC =Akaike's information criterion; RMSEA = root-mean-square error of approximation; CFI = comparative fit index.
[a] Model 1 = configural invariance (same pattern). [b] Model 2 = invariant loadings except for three items: Control 1, Attitude 6, and Norms 1. [c] Model 2b = invariant loadings for all items. [d] Model 3 = invariant loadings and correlations. [e] Model 4 = invariant loadings, correlations, and regression paths.

Dependent variables. Fit indices for a one-factor CFA of the six Intentions items indicated overfitting, where chi-square values are less than the degrees of freedom: Satorra–Bentler $\chi^2(8) = 7.71$, RMSEA = .000 (90% CI: .000 to .031), NFI = .994, CFI = 1.000, and SRMR = .033. Standardized estimates of the factor loadings ranged from .50 to .86 and were all significant at $p < .05$.

Structural model predicting intentions.

Model replication. The structural model of the theory of planned behavior is depicted in Figure 4, showing factor loadings and path coefficients for the Belarusian sample. The model explained 65.0% of the variation in Intentions and fit the data well: Satorra–Bentler $\chi^2(199) = 462.31$, RMSEA = .063 (90% CI: .055 to .070), CFI = .959, SRMR = .075. All factor loadings were significant at $p < .05$, with only one loading less than .30 (Attitudes Item 6, which showed a low item-total correlation in reliability analysis). As in the U.S. sample, the strongest path to Intentions was for Attitudes. The paths from Perceived Behavioral Control and Subjective Norms were not significantly different from zero.

Multigroup comparison. Measurement invariance for Model 1 (the theory of planned behavior structural model predicting intentions) was compared for U.S. and Belarusian samples, with the fit indices for these analyses reported in Table 4. As three loadings were known to be particularly low in the Belarus sample, invariance of factor loadings was conducted in two steps: (a) equivalent factor loadings for all but the three problematic items (Perceived Behavioral Control Item 1, Attitudes Item 6, and Subjective Norms Item 1) and (b) equivalent loadings for all items.

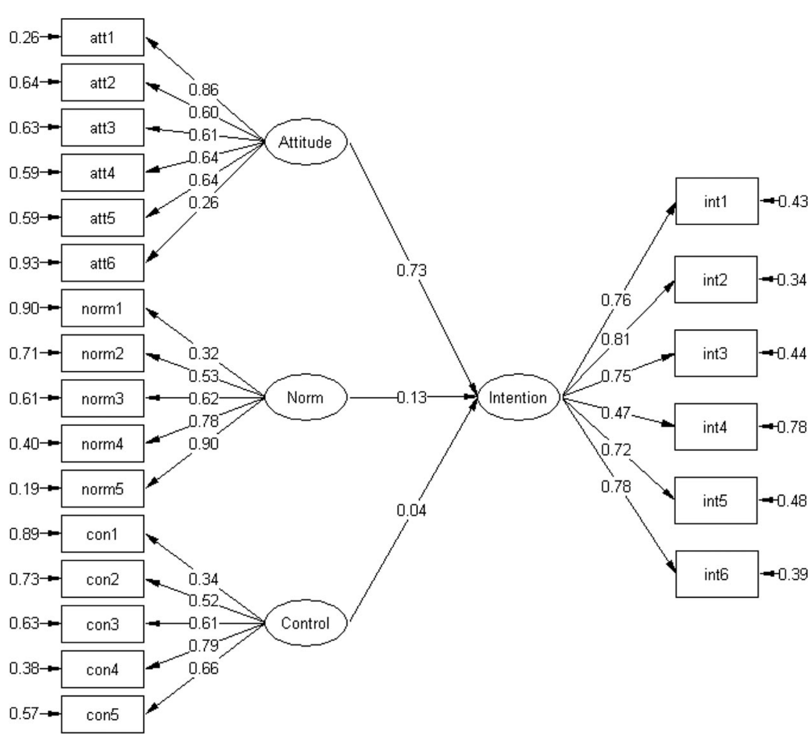

Figure 4. Standardized solution obtained for the theory of planned behavior Model 1 in a Belarus sample (all latent variables are allowed to correlate freely, and no correlated error terms are included in the model).

Examination of differences in chi-square and AIC showed that (a) model fit did not change significantly when invariant loadings were specified for all but the three problematic items, (b) model fit significantly decreased when specifying invariance over all loadings, (c) specifying invariant variances and covariances significantly lowered model fit, and (d) model fit did not change significantly when imposing invariant regression paths. RMSEA and CFI fit indices were acceptable for all models. Further analysis revealed that it was the difference in factor covariances rather than variances that led to a decrease in fit. When the variance of the latent variables was specified to be equivalent, model fit was not significantly worse than when only the loadings were specified to be equivalent: Satorra–Bentler χ^2 = 1,036.66, normal theory $\chi^2(424)$ = 1,962.51, AIC = 1,200.66, $\Delta\chi^2_{\text{corrected}}(\Delta df = 4) = 6.32$, p = .176, with the Satorra and Bentler (2001) $\Delta\chi^2$ scaling correction. Covariances were lower for the Belarusian sample (.07 to .25) than for the U.S. sample (.13 to .38). Generally, group comparison results demonstrated equivalence across U.S. and Belarusian samples, with the provision that three of the 22 items of the MAQ are not functioning equivalently in U.S. and Belarusian samples and that the various components may not be as strongly related in the Belarusian sample as in the U.S. sample.

Structural model predicting mathematics grades (Belarusian sample). As for the U.S. sample, a structural model was conducted to test the prediction of mathematics grades according to the theory of planned behavior. The theory of planned behavior predicted 31.5% of the variation in mathematics test grades in the Belarusian sample, and the model showed acceptable fit: Satorra–Bentler χ^2 = 510.52 (217), RMSEA = .063 (90% CI: .056 to .070), NFI = .930, CFI = .958, incremental fit index (IFI) = .958, SRMR = .076, goodness-of-fit index (GFI) = .962. As in the measurement model, only Attitudes significantly predicted Intentions (λ = .74). Subjective Norms (λ = .06) and Perceived Behavioral Control (λ = .07) did not significantly predict Intentions. There was a large and positive path coefficient from Intentions to grades (γ = .90) but a significant and negative path from Perceived Behavioral Control to grades (γ = –.28). However, the correlations between grades and the latent variable of Perceived Behavioral Control was positive and of reasonable magnitude (correlations between latent variables are shown in Table 2).

Discussion

Results from Study 2 demonstrated that the theory of planned behavior approach to assessing mathematics attitudes generalized from a U.S. to a Belarusian sample and that the theory of planned behavior is potentially a useful tool in the prediction of mathematics achievement. Specifically, results showed that (a) Theory of planned behavior components predicted intentions, (b) theory of planned behavior components predicted mathematics achievement, (c) the theory of planned behavior model was invariant across groups, and (d) only small differences in mathematics attitudes between U.S. and Belarusian eighth graders were observed, with Belarusians showing more positive attitudes and perceived behavioral control but U.S. students showing more positive subjective norms and greater intentions to achieve at mathematics.

The structure of attitudes in eighth-grade Belarusian students. Hypothesis 4 (that the structure of the theory of planned behavior in the mathematics domain would be replicated in a Belarusian sample) also received some support. As in Study 1, the theory of planned behavior components predicted both the intentions and mathematic achievement of the Belarusian students. However, only the Attitudes component had a significant positive direct effect on Intentions, with Perceived Behavioral Control and subjective norms not contributing significantly to individuals' intention. The amount of variance in intentions explained in Study 2 was higher than previously reported in the literature (65% vs. 39% reported in Armitage & Conner, 2001) and similar to 63% obtained in Study 1.

Prediction of mathematics test scores and grades. Hypothesis 2 was supported: A substantial amount of the variance in grades (28%) was explained by the theory of planned behavior components in the Belarusian sample. Over both U.S. and Belarusian samples, Intentions showed the strongest role in predicting mathematics grades, with Perceived Behavioral Control showing a nonsignificant or negative contribution. That is, students' Intentions (to achieve) were the strongest predictor of actual achievement, with Perceived Behavioral Control mediated by intentions. The suppression effect for Perceived Behavioral Control is an unexpected finding that may merit further investigation. Although Perceived Behavioral Control was positively correlated with grades, it negatively predicted grades in the structural model for the Belarusian sample. It seems that unless a student's feelings of Perceived Behavioral Control are invested in Intentions to achieve, Perceived Behavioral Control is not a strong predictor of students' achievement at school. In fact, any feelings of Perceived Behavioral Control not invested in an achievement goal (i.e., when the residual variance was not accounted for by Intentions) showed a negative relationship to achievement. Perceived Behavioral Control without Intentions or planning to achieve might conceivably look more like overconfidence than an accurate representation of one's capabilities.

Mean differences on the MAQ between Belarus and the U.S. Although there were significant differences between Belarus and U.S. samples on all four subscales, effect sizes were quite small (.16 to .27). Belarusian students scored marginally higher on Attitudes and Perceived Behavioral Control, whereas U.S. students scored higher on Subjective Norms and Intentions. The only difference above Cohen's (1988) cutoff for a small effect was that the U.S. students had higher Subjective Norms regarding mathematics performance than did the Belarusian students. The difference in response scale use was striking, with Belarusian students showing a much stronger pattern of extreme responding (i.e., selecting points 1 and 5) than the U.S. students. This difference, rather than any difference in Attitudes, may conceivably be the source of mean differences in MAQ scores.

General Discussion

In the current study, the theory of planned behavior was successfully applied to the domain of mathematics attitudes, with structural models supporting the theory and components predicting mathematics grades for both the United States and Belarus. Results highlight the importance of noncognitive variables in predicting academic achievement, with mathematics attitudes explaining from 25% to 32% of the variance in mathematics achievement, with much of the explained variation independent of mathematics ability. In comparison, meta-analyses show that broadly defined noncognitive constructs (typically the Big Five Conscientiousness dimension) usually predicted no more than 10% of the variation in academic and workplace performance (e.g., Noftle & Robins, 2007; O'Connor & Paunonen, 2007; Schmidt & Hunter, 1998).

There are two potential reasons that current results show such improved levels of prediction: (a) more specific conceptualizations of the criterion space and (b) more specific and theoretically driven conceptualizations of the predictor space. The criterion of interest in the current study was mathematics achievement—a much more specific criterion than overall academic achievement. Conceivably, mathematics achievement may have a different etiology than achievement in the arts, the social sciences, or other domains frequently aggregated to create an academic achievement outcome space. Specific outcomes, such as mathematics achievement, may be more strongly predicted by specific traits, particularly when these traits are carefully constructed in line with a well-defined theory such as the theory of planned behavior.

Recent research on noncognitive constructs has demonstrated that the more specific facets of personality (rather than the broad dimensions) show higher criterion correlations (e.g., MacCann, Duckworth, & Roberts, 2009; B.W. Roberts, Chernyshenko, Stark, & Goldberg, 2005). By assessing mathematics attitudes with the theory of planned behavior model, we developed not only a specific and relevant assessment for mathematics achievement but also an assessment that was theoretically driven and directly linked to the development of interventions. Thus, the current study illustrates not only the utility of the theory of planned behavior as a model for developing noncognitive assessments for education but also the importance of using conceptually specific facets carefully theoretically matched to the outcome of interest—in this case, mathematics attitudes to mathematics achievement rather than, for example, achievement motivation or conscientiousness to general academic achievement.

Cross-Cultural Comparisons of Mathematics Attitudes

Generally, mean differences in the MAQ scales were small, with the U.S. students scoring more highly on Intentions and Subjective Norms and the Belarusian students scoring more highly on Perceived Behavioral Control and Attitudes. Collectively, these data suggest trivial differences in mathematics attitudes across cultures. However, there are some differences in the structure of the theory of planned behavior and the prediction of mathematics achievement across cultures. First, there appeared to be some differences in how the Belarusian students approach the 5-point rating scale itself, showing a more extreme responding style than students in the U.S. sample, consistent with research suggesting that more collectivist cultures (Belarus) show more extreme responding styles than individualistic cultures (United States) (van Herk, Poortinga, & Verhallen, 2004). It seems likely that such an extreme responding style might account for differences in the factor loadings of three extreme items, especially in those instances where loading invariance was not found. Second, Norms and Perceived Behavioral Control did not predict Intentions in the Belarusian sample, suggesting that the theory of planned behavior model may be less appropriate outside of an American or Western context where the theory was developed. Bagozzi, Wong, Abe, and Bergami (2000) found similar results for the theory of reasoned action (the precursor to the theory of planned behavior): Stronger path coefficients to Intentions and to Perceived Behavioral Control were found in a U.S. sample than in Italian, Chinese, or Japanese samples.

Analysis of structural invariance demonstrated that loadings were similar (with the exception of the three extreme items), meaning that the measurement of the constructs was generally equivalent across countries. However, the relationship between the constructs was demonstrably different (demonstrated by the lack of invariance for factor covariances), with smaller relationships among Attitudes, Subjective Norms, and Perceived Behavioral Control for Belarus than for the United States. However, despite such differences in model structure, there was invariance in the path to Intentions, suggesting that Attitudes constitute the most important predictor variable for both Belarusian and U.S. students.

Implications for Intervention and Training Programs

The Attitudes component of the theory of planned behavior was the strongest predictor of students' mathematics grades in both the United States and Belarus. In fact, for the Belarusian sample, the Attitudes component was the only significant predictor of intentions. One implication of this finding is that interventions designed to improve student attitudes have the potential to positively influence student grades.

A great deal of research in education has focused on identifying the antecedents and consequences of student intrinsic motivation (see Middleton & Spanias, 1999, for a review specific to research on motivation in mathematics). Intrinsic motivation can be thought of as similar to Attitudes, as possession of intrinsic motivation necessitates a positive attitude: "Academic intrinsic motivation is the drive or desire of the student to engage in learning 'for its own sake.' Students who are intrinsically motivated engage in academic tasks because they enjoy them" (Middleton & Spanias, 1999, p. 66). When one enjoys a task, it can be said that the individual holds a positive experiential attitude toward the task.

One intervention that may increase student intrinsic motivation would be to train teachers to demonstrate more support for their students. Teacher support, defined as student perceptions of teachers' caring, friendliness, and fairness, has been demonstrated to be related to student ratings of the intrinsic value, perceived importance, and usefulness of mathematics (Midgley, Feldlaufer, & Eccles, 1989). In a 2-year longitudinal study, Midgley et al. (1989) followed students during the transition from elementary to middle school and found that students with the most supportive mathematics teachers had the most positive attitudes toward mathematics and those with the least supportive mathematics teachers had the most negative attitudes toward mathematics. Furthermore, student attitudes toward mathematics became more negative when they went from a supportive to an unsupportive teacher and vice versa.

Another classroom intervention that may be useful in improving student attitudes toward mathematics is cooperative learning in groups rather than individually and rewarding students as groups rather than individuals (e.g., Slavin, 1983, 1984). The logic behind this intervention is that placing students in groups motivates them to help each other because they are rewarded as a group. Additionally, it helps them to create positive attributions, as they can attribute success to themselves but failure to the group, potentially further increasing intrinsic motivation (Middleton & Spanias, 1999). There is some empirical support demonstrating the efficacy of cooperative group learning in improving mathematics achievement and attitudes (e.g. Slavin, 1983, 1984).

Relatively simple classroom interventions involving the use of classroom tools and technology have also been shown to improve student attitudes toward mathematics. For example, a meta-analysis revealed that use of concrete materials as instructional tools, such as bean sticks, Cuisenaire rods, geoboards, and paper folding, can improve student attitudes toward mathematics (Sowell, 1989). Furthermore, another meta-analysis showed that the use of handheld calculators was associated with better attitudes toward mathematics (Hembree & Dessart, 1986). Although both of these meta-analyses are somewhat dated, it can be inferred that tools that allow students to learn mathematics in a hands-on manner have the potential to improve student attitudes.

Those wishing to design mathematics attitude interventions would also be advised to consult the long tradition of research on attitude change in the field of social psychology (see Albarracin, Johnson, & Zanna, 2005, for several reviews). A general finding in this field is that attempts to change attitudes that focus on basic human behaviors and needs tend to be successful.

Therefore, interventions can be designed that take advantage of modeling by emphasizing teacher, parent, and peer modeling of positive attitudes toward mathematics. Interventions that focus on the principles of persuasion in changing attitudes can also be created (see Cialdini & Goldstein, 2004, for a review). Such principles work to influence attitudes by appealing to basic human needs such as the need to affiliate with others and the need to hold an accurate view of the world. These and several other strategies have been shown to effectively influence attitudes and subsequent behaviors (Albarracin, Johnson, & Zanna, 2005; Cialdini & Goldstein, 2004).

Results from the hierarchical regression in the U.S. sample also suggest that perceived behavioral control plays a role in predicting mathematics performance. Specialized instruction aimed at increasing students' perceptions of control could be another avenue that researchers may wish to take. According to Ajzen (2006), perceived behavioral control consists of two aspects: *capability,* which refers to how difficult one believes that the behavior is, and *controllability,* which refers to whether one feels that performing the behavior is or is not up to him or her. Items of the MAQ Perceived Behavioral Control scale capture both capability and controllability, and interventions aimed at increasing perceived behavioral control might focus on one or both. Capability can be thought of as identical to self-efficacy (Ajzen, 2002), and thus interventions designed to increase self-efficacy can also have the effect of increasing perceived behavioral control. The literature on interventions in self-efficacy is too large to review here; however, several principles might be followed when building interventions (Margolis & McCabe, 2004; Schunk, 2003). These principles include helping students create a positive self-evaluation, teaching effective learning strategies, stressing effort over success and failure, encouraging facilitative attributions, and helping students create goals.

Limitations and Future Directions

The causal direction between attitudes and achievement needs to be examined carefully, as it is possible that success (or failure) at mathematics may cause mathematics attitudes, rather than the reverse, that is, mathematics attitudes causing the mathematics achievement. As the U.S. study is part of a multiwave project, students' future grades will become available as the study progresses, allowing longitudinal modeling of the link between attitudes and achievement. In Study 2, attitudes and achievement were assessed at two different time points, and intentions were positively related to achievement.

The theory of planned behavior links volitions or intentions to behaviors, whereas our analyses link intentions to results of desired behaviors. That is, mathematics achievement is the result of behaviors, such as the amount of effort and time devoted to mathematics study; the amount of help requested from teachers, parents, or peers; and even attendance and the degree of attention sustained in mathematics classes. Our statistical models did not include these behaviors, although they are implicit in the reasoning of how intentions to achieve in mathematics actually affect mathematics achievement itself. Explicitly measuring and modeling the behaviors themselves would constitute an important step forward for understanding the process by which attitudes toward mathematics may be translated into mathematics achievement. Ajzen's (2006) specific guidelines for defining the behavior of interest in terms of its target, action, context, and time could be used to expand the current version of the MAQ to explicitly target a wide range of behaviors relevant to achievement in mathematics.

The current research addressed mathematics attitudes and achievement at the eighth-grade level, a time before calculus or trigonometry are commonplace (certainly in the U.S. curriculum). As the nature of mathematics changes with advanced schooling, the attitudinal predictors of mathematics achievement may also change. Therefore, future research should examine mathematics attitudes in high school and college populations to determine whether results can be generalized. Likewise, different subject areas (e.g., computer technology) may also usefully be predicted by theory of planned behavior–based assessments, although the degree of prediction might prove slightly different in these different domains. If the present results are confirmed in longitudinal designs, in high school and college populations, or for different subject matter, cross-national comparisons of attitudes might follow. These constructs have some potential for explaining cross-national differences in mathematics achievement as demonstrated by Trends in International Mathematics and Science Study, the International Association for the Evaluation of Educational Achievement, and the Programme for International Student Assessment (Gonzales et al., 2004; Miller, Sen, & Malley, 2006). Additionally, future inquiries may examine reasons behind existing differences in attitudinal profiles of students from different countries.

Finally, Ajzen (1991) suggested that the components of the theory of planned behavior can be influenced through interventions. Future studies could build and subsequently investigate the quality and effectiveness of the theory of planned behavior–based remediation programs as described previously. If these subsequently result in mathematics gains, validated assessments of mathematics attitudes might become standard practice in the classroom.

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Received June 4, 2008
Revision received September 23, 2010
Accepted September 27, 2010 ■