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Got math attitude? (In)direct effects of student mathematics attitudes on intentions, behavioral engagement, and mathematics performance in the U. S. PISA

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ABSTRACT

Academic performance is predicted by a multitude of demographic, contextual, cognitive, and noncognitive factors. The noncognitive factors predicting achievement in mathematics that have previously been investigated in depth are study skills, confidence, self-efficacy, and personality traits (Kyllonen, 2012). Limited applied research has explored the predictive value of attitudes and beliefs in mathematics achievement using representative data of U.S. students. The current study uses the theory of planned behavior (TPB) to explain high school students' performance in mathematics in large-scale assessment data by using the PISA 2012. Along with key demographic factors, results indicated that students' attitudes, subjective norms, and perceived behavioral control beliefs explained 21.1% of the variability in intentions to pursue and major in mathematics in the future, 59.4% of the variability in behavioral engagement with mathematics learning, and 30.7% of the variability in mathematics performance.The study results have implications on: (1) the applicability of an attitude-behavior framework in educational research for understanding academic performance, (2) the importance of perceived control and self-efficacy beliefs for predicting behavioral engagement in mathematics (e.g., paying attention in class, completing homework, studying for exams) and subsequent mathematics performance, and (3) the practical significance of students' attitude towards mathematics on their intentions to pursue mathematics coursework in post-secondary education and possess math-relevant career aspirations.

1. Introduction

In one of the most recent global comparative educational assessments, 15-year-olds in the United States ranked in 31st place out of 35 Organisation for Economic Co-operation and Development (OECD) countries in the domain of mathematics (OECD, 2016). This relative underachievement is worrisome given the research findings that achievement in science, technology, engineering, and mathematics (STEM) fields promotes individual-level outcomes, such as high-status occupations, and nation-level outcomes, such as economic growth (Rindermann, 2012; Rindermann, Sailer, & Thompson, 2009). Achievement in mathematics, specifically, is a gateway to higher education, more lucrative career opportunities, and is an indicator of the ability to compete with the demands of a global economy (Jerald, 2008). Mathematical literacy – the ability to use mathematical reasoning and tools in personal and professional contexts – is essential for careers and general life functioning (OECD, 2013). Unfortunately, students from the United States lag in demonstrating mathematics competencies when compared to students from other developed nations (see Fig. 1). Large-scale international assessments such as the Program for International Student Assessment (PISA) and the Trends in International Mathematics and Science Study (TIMSS) demonstrate that students from many nations are not performing at expected levels in mathematics (Fleischman, Hopstock, Pelczar, & Shelley, 2010; Gonzales, Guzmán, Partelow, Pahlke, Jocelyn, Kastberg, & Williams, 2004; Miller, Sen, & Malley, 2007). Hence, examining factors that translate into greater performance in STEM is a global task.

Prior efforts to understand the variability in mathematics performance have primarily focused on demographic (e.g., SES, gender) (Sirin, 2005), cognitive (e.g., working memory, prior knowledge) (Deary, Strand, Smith, & Fernandes, 2007; Duncan et al., 2007; Luo, Thompson, & Detterman, 2003), noncognitive (e.g., motivation) (Pintrich & de

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Groot, 1990), personality (Poropat, 2009), and learning factors and skills (e.g., self-regulation) (Zimmerman, 1990). However, a comprehensive framework that relates noncognitive constructs of beliefs and attitudes to academic performance has largely remained unexplored in educational psychology research (Burrus & Moore, 2016). Prior studies that have specifically focused on noncognitive predictors of mathematics achievement primarily investigated student confidence in mathematics (Stankov, Lee, Luo, & Hogan, 2012; Stankov, Morony, & Lee, 2014), self-efficacy (e.g., Skaalvik, Federici, & Klassen, 2015), and motivational constructs (e.g., task interest, intrinsic motivation) (Cleary, Kitsantas, & Dowdy, 2017; Garon-Carrier et al., 2016). Thus, limited research has relied on the predictive value of other noncognitive factors such as attitudes and beliefs on mathematics achievement even though attitudes towards mathematics (in the remainder of this manuscript also referred to as math attitudes) (e.g., Lipnevich, MacCann, Krumm, Burrus, & Roberts, 2011) are a promising avenue for understanding the variability in mathematics achievement as indicated by, both, cross-sectional (Lipnevich et al., 2011) and longitudinal research (Niepel et al., 2018).

1.1. Theory of planned behavior

Academic achievement is attained through a series of behaviors that promote success (e.g., planning effectively, studying, applying effort, maintaining good attendance, submitting assignments, etc.). Those behaviors, however, are influenced by attitudes and belief dispositions. The theory of planned behavior (TPB) (Ajzen, 1991) was developed to understand links between attitudes and behavior in a variety of life domains (Conner & Armitage, 1998). The three attitude determinants (i.e., exogenous components) of the TPB (attitude towards the behavior, subjective norms, and perceived behavioral control), are hypothesized to predict behavioral intentions and subsequent attitude-related behavior. Intentions are conceptualized to act as a mediator between the three determinants and behavior and furthermore, the TPB posits that perceived behavioral control also has an indirect, that is, a mediated effect on behavior, through intentions (see Fig. 2). Overall, it is expected that the relations among the constructs within the TPB framework are positive such that the three determinants are positively related to intentions and behavior, and the construct of intentions is positively related to behavior. Empirical evidence confirms the viability of the model, with attitude and perceived behavioral control successfully predicting individuals' intention to carry out the behavior in question (Armitage & Conner, 2001; Trafimow, Sheeran, Conner, & Finlay, 2002). A meta-analysis of the efficacy of the TPB indicated that the model was useful in predicting behaviors even when accounting for objective or observed measures of behavior (Armitage & Conner, 2001). Despite this meta-analytic evidence, the applicability of this attitude framework to educational contexts (e.g., intentions to pursue a career, homework work ethic) has not been well explored. Prior studies that used the TPB framework have examined behaviors such as weight-loss, smoking habits, voting, spending habits, recycling, donating blood, and buying stocks and have found that the TPB effectively explains the variability across a wide range of behavioral domains (see Ajzen, 2005 for a review). However, the use of the TPB is scarce in educational research, although efforts to promote this theoretical model in understanding student behavior and achievement has been put forward (e.g., Cooper, Barkatsas, & Strathdee, 2016). In order to bridge the trasfer of the TPB framework to educational reserach, the following sections provide operational definitions of the constructs of the TPB with educationally-relevant examples.

Attitude. An attitude is an overall positive or negative evaluation towards an entity or behavior. This construct relies on an expectancy-value (EV) model of attitudes (Fishbein & Aizen, 1975), where the outcome's subjective value and the strength of the belief contribute to the attitude component of the model. Wigfield and Eccles (2000) have elaborated on this construct through decades of research and have defined several components of the E-V model in educational psychology. A number of expectancy-value models in both psychology and in economics have been proposed to integrate aspects of decision-making (i.e., behavior). One such model is Ajzen's (1991) theory of planned behaviour, which states that volitional behaviour is determined by specific attitudes (i.e. the value component) plus perceived behavioural control (i.e. the outcome expectancy component), which is further defined in the present study.

Subjective norms. Subjective norms is the extent to which people (i.e., referents) in the individual's immediate environments would endorse,

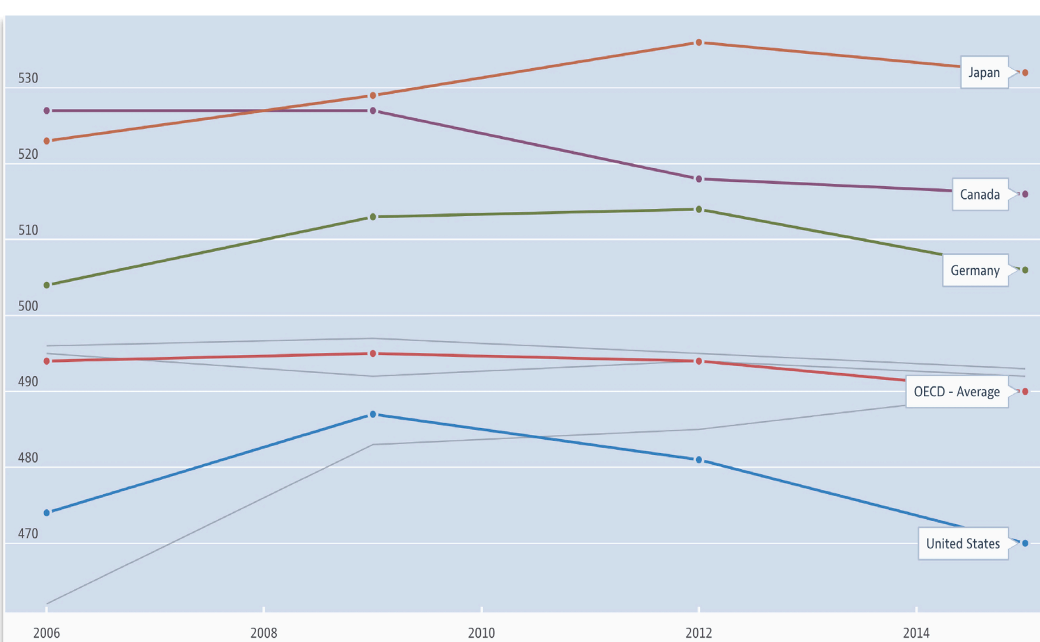

Fig. 1. Mathematics performance (PISA) Total, Mean score, 2006 – 2015. Graph depicting mathematics performance of the Group of Seven (G7) countries, the countries with the largest advanced economies in the world. The G7 counties not labeled on this figure are Italy, the UK, and France (these three countries had an average country score close to the OECD average in 2015).

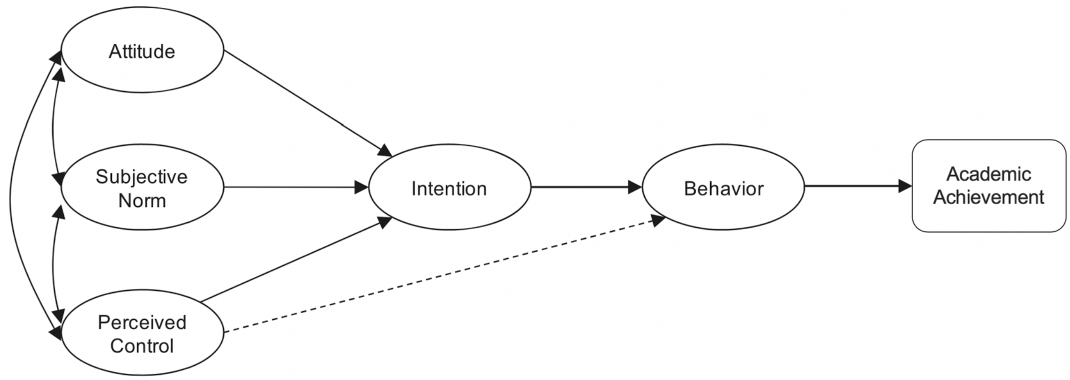

Fig. 2. The theory of planned behavior components (attitude, subjective norms, perceived control, intention, and behavior) predicting academic achievement. Adapted from Ajzen (1991) with the extension of academic achievement as an additional outcome variable.

engage in, approve, or disapprove of the given behavior (Ajzen, 1991). The referents may be important people in the individual's life originating from different types of relationships such as friends, parents, teachers, extended family members, and significant others. This construct is defined in regards to the standards, expectations, judgements, and pressures others set on an individual about the specific behavior. Subjective norms capture an individual's perception of the social pressures to engage (or not to engage) in an activity. Above and beyond the social situations that take place in classrooms and that make up the classroom "life" (e.g., routines, procedures, how students work together), an additional layer of social norms in mathematics classrooms incorporate the extent to which students engage with mathematical ideas, explanations, and disagreements. The difference between a general classroom norm and a sociomathematical norm in a classroom is such that "knowing that one is expected to explain one's thinking is a social norm; knowing what counts as an acceptable mathematical explanation is a sociomathematical norm" (Franke, Kazemi, & Battey, 2007, p. 239). Therefore, mathematics-specific norms and teachers' expectations around what it means to "mathematize" (e.g., provide sophisticated and efficient mathematical explanations) serve as indicators of subjective norms in the present study.

Perceived behavioral control. Perceived behavioral control (PBC) is defined as "the person's belief as to how easy or difficult the performance of the behavior is likely to be" (Ajzen & Madden, 1986, p. 457). PBC is composed of two aspects: (1) perceived controllability or one's belief of having control over the behavior and (2) perceived capability or one's perception of their ability to perform the behavior. Control beliefs are formed by the perception of the presence or absence of factors that may hinder or facilitate behavioral performance. Thus, individuals who believe that they possess the knowledge, skills, opportunities, and resources over performing the behavior, are thought to have high PBC. PBC is conceptually related to self-efficacy beliefs (Bandura, 1977) (i.e., perceived capability), but also incorporates the component of controllability. Self-efficacy is a self-constructed judgment of whether or not a desired outcome can be accomplished through one's actions Bandura (1977). It is one's sense of competency over accomplishing a particular action or goal. The construct of self-efficacy has shown to predict student performance outcomes in the domains of writing (Pajares, 2003), science (Britner & Pajares, 2006), mathematics (Kitsantas, Cheema, & Ware, 2011), as well as career choices and aspirations (Bandura, 2001).

Intentions. To have an intention means to have the willingness to exert a certain behavior (e.g., "I intend to work hard to make sure I learn math;" "I intend to pursue a mathematics-related career after I graduate"). The TPB posits that a core predictor of volitional behavior is a person's intention to engage in that behavior (Ajzen, 1991, 2005). A person's intention is mutually determined through attitudes towards the behavior, subjective norms, and perceived behavioral control. Meta-analyses across several psychology subfields have found the intention-behavior relation to be between 0.47 (Notani, 1998) and 0.53 (Sheppard, Hartwick, & Warshaw, 1988).

Behavioral engagement as mathematics work ethic. In this study, behavior refers to mathematics-related behaviors that demonstrate levels of work ethic in the context of engaging in mathematics. In our study, we use students' academic-related behaviors such as planning to study, submitting homework assignments on time, and minimizing distractions to measure behavioral engagement in accordance with Fung, Tan, and Chen (2018).

Behavioral Engagement as a Predictor of Mathematics Performance. Research indicates that a host of academic behaviors, such as good attendance (Conard, 2006), following instructions, inhibiting inappropriate actions in class (Sektnan, McClelland, Acock, & Morrison, 2010), executing effortful learning strategies (Pokay & Blumenfeld, 1990), and applying effort on homework assignments (Trautwein, 2007), are a few of the behavioral factors responsible for academic achievement. Academic behavioral engagement typically describes what students do during learning (e.g., working hard on mathematics homework) and while in school (e.g., paying attention in class) (Finn & Voelkl, 1993). Research indicates that students who are more behaviorally engaged attend class more regularly and put in more effort in their schoolwork (National Research Council, 2004). Behaviorally engaged students are more capable of overcoming learning difficulties and developing their learning of abstract mathematical concepts (Pierce & Stacey, 2004; vom Hofe, 2001), resulting in higher levels of mathematics achievement (Klem & Connell, 2004; Pierce & Stacey, 2004; vom Hofe, 2001). Research using data from 34 countries participating in the PISA 2012, showed that students who reported more learning-oriented behaviors and participated in a greater variety of mathematics learning activities within and beyond class, had higher levels of achievement (Fung et al., 2018).

Through the present research, we extended the TPB framework to differentiate between behavioral engagement and academic achievement by treating specific academic behaviors as predictors of achievement (see Fig. 2). Prior studies employing the TPB framework to predict educational outcomes have treated behavioral engagement as a proxy for academic achievement (e.g., Burrus & Moore, 2016; Lipnevich et al., 2011, 2016; Niepel et al., 2018). In the present study, we differentiated between these two educational outcomes and empirically examined the pre-existing TPB structural model (Ajzen, 1991) by treating academic behavioral engagement as a predictor of, rather than a proxy for, mathematics performance. Evaluating students' behaviors as independent from mathematics performance, positions us to create a clearer understanding of the behavior-achievement relations in educational research.

1.2. The importance and malleability of attitudes[1]

Attitudes are generally defined as a person's evaluation towards a(n) entity, object, target, or subject matter on a negative to positive (or favorable to unfavorable) continuum (Ajzen, 2005). In the context of the present studies the importance of examining whether, and to what degree, attitudes are related to mathematics performance partially draws upon the assumption that attitudes are malleable. Overall, the mean effect size reported by meta-analyses from laboratory settings and field interventions on the effect of attitude change, is around $d = 0.22$, indicating a small effect (Lemmer & Wagner, 2015; Steinmetz, Knappstein, Ajzen, Schmidt, & Kabst, 2016; Tyson, Covey, & Rosenthal, 2014). These meta-analyses range from topics of changing intergroup attitudes (Lemmer & Wagner, 2015), attitudes towards risky sexual behavior (Tyson et al., 2014), and changing attitudes in a variety of other domains including physical activity, nutrition, stress management, alcohol and drug use, and medical regimes (Steinmetz et al., 2016). This suggests that attitude change is generalizable to different domains and there is promise that attitudes are malleable, regardless of the context or entity that is being evaluated. In more educationally relevant attitude change interventions, studies show positive effects of changing women's implicit and explicit attitudes towards STEM fields (e.g., science, technology, engineering, and mathematics) and intentions to pursue STEM (Stout, Dasgupta, Hunsinger, & McManus, 2011). Overall, although the average effect size of attitude change is shown to be small in magnitude (i.e., about 1/3rd of a standard deviation), attitude change interventions can persist and accumulate over time (Albarracin & Shavitt, 2018).

In applied educational research on the effects of attitude interventions on changing attitudes, results indicate that students' attitudes towards domain-specific subjects become more positive as a result of experiential learning (Pugsley & Clayton, 2003), problem-based learning and student-centered pedagogy (Armbruster, Patel, Johnson, Weiss, & Tomanek, 2009), and constructivist learning environments (Oh & Yager, 2004). A study that aimed to change medical students' attitudes about collaboration by using interactive group-work (i.e., changing the subjective norms) showed positive influences on their perceived benefits of collaboration with interprofessional teams (Gould, Day, & Barton, 2017). A more recent study examined the effects of a mathematical literacy course (i.e., emphasis on formulating situations, reasoning mathematically, employing mathematical tools, applying and evaluating mathematical results as defined by the OECD, 2018a, 2018b) on community college students' attitudes toward mathematics. Results indicated that students in the mathematics literacy-focused course (i.e., focus on quantitative reasoning) section showed increased self-efficacy (i.e., a component of perceived behavioral control) and perceived usefulness for mathematics at the end of the course when compared to students who were enrolled in the traditional algebra-focused course (Ndiaye, 2019). The consensus is that students' attitudes towards mathematics can be changed by emphasizing the applicability of mathematics in everyday experiences (Willis, 2010) and shifting towards a collaborative process for engaging with mathematics to promote more positive norms (Gould et al., 2017).

1.3. Research on attitudinal constructs and educational outcomes

Student attitudes and behaviors have been related to important educational outcomes such as academic achievement, level of classroom engagement, and perceived academic competence (Akey, 2006). A meta-analysis found that students' dispositions towards academic tasks (e.g., academic interest, a positive attitude toward studying) are positively related to overall academic achievement in college (Credé & Kuncel, 2008). Another meta-analysis of studies on the relation between reading achievement and attitudes towards reading indicated that there was an overall moderate relation between the two factors ($r = 0.32$) for elementary and middle school students (Petscher, 2010).

Attitudes towards mathematics have been a particularly important component of understanding achievement in comparative analyses of large-scale assessments across countries (Papanastasiou, 2000). Using data from the PISA 2003 assessment, positive correlations were found among mathematics dispositions, self-beliefs, mathematics self-efficacy, and mathematics performance across several countries including Singapore, Switzerland, Shanghai-China, Hong Kong-China, and Slovenia (OECD, 2003). By utilizing survey responses from the TIMSS 2003 data, math attitudes (i.e., self-confidence in learning mathematics and favoring mathematics) were shown to be significant predictors of mathematics achievement in almost all countries that were studied, which included the United States, Sweden, Japan, and England (Kadijevic, 2008). In an exploratory study of the PISA, mathematics-related attitudes (e.g., mathematics self-concept, self-efficacy, subjective norms) showed significant relations to mathematics test scores in the following samples: Slovenia, Canada, Germany and the United States (Straus, 2014).

Other empirical research has showed some discrepancies in the positive attitude-achievement relation. Across several analyses using the TIMSS 1995 data, relations between attitudes and mathematics achievement were statistically significant in few (i.e., Hong Kong, Sweden, and Belgium (Flemish)) of the 34 countries examined (Martin, Mullis, Gregory, Hoyle, & Shen, 2000). A significant relation was not found in countries such as the United States, Singapore, Germany, Canada or England. In a study of the PISA 2003, 2009, and 2012 datasets on the relation between general attitudes towards school and reading and mathematics achievement, a moderately strong relation between attitudes and achievement was observed only in sub-groups of students in very few (i.e., Qatar, Iceland, and Australia) of the 64 countries examined (Lee, 2016). Generally, it is the case that mathematics attitudes and mathematics achievement are related across diverse samples (OECD, 2003; Straus, 2014) but that the relation is stronger when attitudes are measured through a viable, theoretical lens (as in Lipnevich et al., 2011; Niepel et al., 2018).

Research on TPB and Mathematics Performance. To our knowledge, only few studies have examined mathematics attitudes through the TPB framework (Lipnevich et al., 2011, 2016). Lipnevich et al. (2011) successfully applied a TPB based questionnaire on mathematics attitudes (MAQ) to predict mathematics achievement and were able to explain up to 32% of variance in mathematics grades in Belarusian and US samples. Further, Lipnevich et al. (2016) examined the incremental validity of mathematics attitudes above and beyond cognitive ability and Big 5 personality traits and revealed that math attitudes explained up to 25% of incremental variance in math achievement. Burrus and Moore (2016) conducted a similar study with a sample of high school juniors and seniors who took the ACT (American College Testing), a standardized test used for college admissions in the United States. Results indicated that TBP components were all significantly correlated with mathematics grades in school and mathematics test scores. The attitude constructs also incrementally predicted $\Delta R^2 = 2.9\%$ of the variability in ACT mathematics scores above and beyond important factors such as student demographics, conscientiousness, and the number of mathematics courses previously taken.

The applicability of noncognitive constructs using large, nation-wide data, for understanding mathematics performance has largely been applied to non-U.S. contexts. In a sample of over 14,000 Australian students who participated in PISA, researchers found that the TPB components (attitude, social norms, perceived behavioral control) were generally poor predictors of mathematical intentions and indirect, weak predictors of mathematical behavior (Skrzypiec & Lai, 2017). One reason for finding only a weak, but statistically significant relation could

[1] Throughout this paper, the term "attitudes" (plural) is used as an umbrella term referring to all of the exogenous components (i.e., attitude determinants) of the theoretical framework. The term "attitude" (singular) refers to the specific attitudinal construct, representing attitude towards a behavior.

be that the behavior factor was too broad (e.g., “I talk about mathematics problems with my friends” and “I help my friends with mathematics”), not theoretically justified, and did not capture mathematics behaviors related to learning.

The Greek sample of the PISA 2012 (Pitsia, Biggart, & Karakolidis, 2017) revealed that instrumental motivation and attitudes towards school predicted mathematics performance after controlling for important demographic factors such as gender and socio-economic status (SES). In a similar study using the same sample, results revealed that self-beliefs about mathematics, in particular self-efficacy (i.e., a component of perceived behavioral control), explained significant variability in mathematics outcomes (Karakolidis, Pitsia, & Emvalotis, 2016). Similarly, using the United Arab Emirates sample of the PISA 2012, results indicated that high subjective norms (e.g., parent thinks math is important for future career, parent likes mathematics) was related to students' mathematics work ethic (Areepattamannil et al., 2015). Similar results were found in the Qatari sample of the PISA 2012 where researchers found that students' attitudinal beliefs (dispositional, normative, and control beliefs) about mathematics were associated with mathematics behaviors and mathematics performance (Areepattamannil et al., 2016). To our knowledge, the only study employing the TPB with large-scale data of the U.S. sample, is the research conducted by Walker (2017). This dissertation work indicated that attitudes ($\beta = 0.36$) and perceived control ($\beta = 0.30$), but not subjective norms ($\beta = 0.08$), were related to intentions and that perceived control also had a direct effect on mathematics performance ($\beta = 0.18$). One of the most important limitations of the research findings presented by Walker (2017) is that it utilized analytic shortcuts, such as omission of sampling weights, which inhibit generalization of findings to the U.S. high school student population at large. Overall, cross-contextual research indicates that the TPB is a viable framework for predicting mathematics performance in large-scale, international education data.

1.4. Present study and research questions

Overall, the relation between attitudes and school performance outcomes is positive and significant (Guzmán, Santiago-Rivera, & Hasse, 2005; Juter, 2005; Reynolds & Weigand, 2010). To date, educational research on the specific relation between student attitudes and mathematics performance using viable theoretical frameworks has either relied on non-United States student samples (e.g., Areepattamannil et al., 2016; Ayob & Yasin, 2018; Lipnevich et al., 2011; Lipnevich, Preckel, & Krumm, 2016; Pitsia et al., 2017) or has not utilized U.S. nationally representative datasets (e.g., Burrus & Moore, 2016; Lipnevich et al., 2011, 2016; Niepel et al., 2018), limiting generalizability to the complex and diverse U.S. context. Apart from Walker (2017), there have been no other known efforts to understand the influence of students' attitudes and behaviors on mathematics achievement, as measured through international assessments (Burrus & Moore, 2016). Given the relative underperformance of U.S. students in mathematics in comparison to students in other industrial countries (see Fig. 1), it is especially important to understand the factors that explain mathematics achievement by utilizing nationally representative datasets.

Using data from the US sample of the PISA 2012, this study aimed to answer a series of questions on the (in)direct effects of students' mathematics attitudes on students' intentions to pursue mathematics, behavioral engagement, and mathematics performance. The TPB is a seminal theoretical framework in psychology, and its widespread consideration in educational research has long been overdue. The PISA 2012 data is well-suited to test the viability of the framework as the TPB was intentionally used as the theoretical model underpinning the development of the student background questionnaire portion of the PISA 2012 to measure students' self-related beliefs (OECD, 2013). Large-scale national and international assessment of attitudes provide us with valuable information about student achievement across many grade levels, contexts, and outcomes of interest. Assessments such as the PISA are internationally recognized efforts of evaluating achievement and performance standards in specific subject areas. In addition to domain-specific assessments, the data collected includes student background characteristics (e.g., approach towards subject area, attitudes, utility for subject area, positive or negative affect towards subject, academic self-beliefs) to measure factors that may influence achievement. To assess both the measurement and structural viability of the TPB framework by using the PISA 2012 data the following research questions (RQs) were examined for the United States sample:

1. Which indicators best measure the latent constructs of the attitude determinants (attitude towards behavior, subjective norms, perceived behavioral control), intentions to pursue mathematics, and behavioral engagement?
2. Is the structure of the theory of planned behavior (Ajzen, 1991, 2005) identified in the U.S. PISA 2012 sample?
3. How much variability in mathematics performance is explained by the theory of planned behavior?
4. What are the magnitudes of the direct and indirect effects of (a) the attitude determinants on intentions, behavioral engagement, and mathematics performance, (b) intentions on mathematics behavioral engagement and mathematics performance, and (c) mathematics behavioral engagement on mathematics performance?
5. Does perceived behavioral control have a significant, indirect effect on mathematics performance through behavioral engagement alone?

2. Method

2.1. Data and sample

The United States PISA 2012 public-use data file was used for the present study. The 2012 assessment period was used because mathematics performance was the academic competency domain of focus during the 2012 assessment year. Data were downloaded from the National Center for Education Statistics (1995) (NCES) access to the public-use data file. The complex survey design and sampling of the PISA studies are intended to make generalizations to the population possible. The descriptive statistics of demographic variables indicated in the dataset reflected that of the US 15-year-old high school student population in the 2012 assessment year. The dataset included N = 4,978 participants (51% male). The mean age of students participating in the assessment was 15.82 years of age, where 10.2% repeated at least one school grade between grades 1–6, 3.6% repeated between grades 7–9, and 1.9% repeated between grades 10–12. Over 50% of the students identified as White, 12.5% as Black or African American, 24.5% as Hispanic, 5.1% as Asian, 4.6% as multiracial, and 2% as other. Over 90% of the students were born within the US and 7.7% were born in another country. Over half of those students (54.8%) arrived to the US before the age of 6 and 14.1% of students spoke a language other than English at home.

2.2. Variables and measurement

Control Variables. Given the research basis that there are gender (Else-Quest, Hyde, & Linn, 2010; Lindberg, Hyde, Petersen, & Linn, 2010; Stoet & Geary, 2013), racial/ethnic (Lubienski, 2002; Vanneman, Hamilton, Anderson, & Rahman, 2009), and socioeconomic status (SES) (McGraw, Lubienski, & Strutchens, 2006) variations in mathematics performance, those variables were controlled for in the analyses. Gender (male, female) and race/ethnicity (i.e, RACETHC as either White, Black, Hispanic, Asian, or Other) were derived from the student questionnaire. The PISA index of economic, social and cultural status (ESCS) was used as a socioeconomic status variable. The ESCS in PISA 2012 consisted of three sub-components: the highest parental occupation (HISEI), the highest parental education expressed as years of schooling (PARED) and the index of home possessions (HOMEPOS). The home possessions index was based on scales of wealth, cultural possessions, home educational resources, and books in the home (ST28Q01) recoded into a four-level categorical variable (e.g., fewer than or equal to 25 books, 26–100 books, 101–500 books, and>500 books). The wealth scale (WEALTH) was derived based on household possessions (e.g., a room of your own, cellular phone, computer), the cultural possessions scale (CULTPOS) was based on home possessions such as classic literature, books of poetry and works of art, and the home educational resources scale (HEDRES) was derived from items such as having a quiet place to study at home, having a desk to study at, and having books to help with school work.

Latent Variables: Attitudinal Constructs, Intentions, and Behavioral Engagement. In the self-report background questionnaire of the PISA, students provided responses to survey questions relevant to attitude towards school, instrumental motivation of mathematics, perceived levels of teacher support in mathematics class, classroom disciplinary climate, and problem-solving strategies, among other noncognitive constructs. Following the TPB framework (Ajzen, 1991), the items that were conceptually relevant to either students' attitudes (attitudes towards mathematics , subjective norms, perceived behavioral control), intentions, and behavioral engagement (mathematics-related behaviors, mathematics work ethic) were considered for analysis. All items were rated on a scale of 1 through 4 (e.g., frequently to rarely, strongly agree to strongly disagree), except for the items measuring the intentions factor, which were forced-choice (e.g., "I intend to take additional mathematics versus language courses after high school"). First, the items were grouped by construct at face validity, based on the operational definitions given (e.g., the "Whether or not I do well in mathematics is completely up to me" was considered to be a potential indicator of the perceived behavioral control factor). Then, items that were conceptually similar to one another and indicated statistically significant correlations, were averaged to create composite variables (i.e., item parcels). Multiple item parcels were considered in the development and analyses of measuring each of the latent factors. A list of all of the variables from the dataset that were considered for analysis, the variable names (as indicated on the PISA 2012 reports, raw datasets, and questionnaires), and the reliability statistics of the item parcels are presented in Appendix A of the supplementary materials document and are thematically organized by the constructs of interest in this study.

Plausible values of mathematics performance. To appropriately assess mathematics proficiency, PISA uses an imputation methodology referred to as plausible values (PVs). For mathematics performance, all students only receive a subset of the pool of test items and an missing data technique is used to generate student proficiencies (Mislevy, 1993; OECD, 2013). In the PISA 2012, five plausible values per student are included in the national database. One approach for making inferences to mathematics performance includes using each plausible value as an outcome and averaging across the estimates (e.g., correlation coefficients, beta coefficients) by taking into account the standard errors of each estimate generated by each one of the five analyses, one for each plausible value of mathematics performance, which is the analytic strategy implemented in the present study.

In the PISA, mathematics performance was measured through test questions gauging mathematics literacy, which is the ability to formulate (i.e., identifying the use of mathematics), employ (i.e., apply mathematical tools and solutions), and interpret (i.e., reflect on solutions in the context of problems) mathematics across multiple contexts. The real-world contexts of the mathematics literacy items range from personal, occupational (e.g., accounting, architecture), societal (e.g., demographics), and scientific (i.e., applications to issues concerning environment and technology). The broad mathematical concepts that are assessed within the mathematics literacy domain include change and relationships, space and shape, quantity, and uncertainty and data. Additional information about the conceptual background of the mathematical literacy domain and the specific competencies and content that is covered on the assessment can be accessed through the PISA 2012 assessment framework (OECD, 2013).

2.3. Analytic plan

First, the data were downloaded, cleaned, recoded and reverse coded, where necessary, using IBM SPSS Version 24. Descriptive statistics, composite variables to be used as indicators of latent constructs, and demographic characteristic, and descriptive statistics analyses were run by using the final student weight function (WFSTUWT) on SPSS to generate appropriate descriptive statistics estimates. Due to the rotated questionnaire design of the student background questionnaire the data that were used from all three questionnaire sets resulted in a large proportion of missing data (>2/3). However, because missing data resulting from the rotated questionnaire design is considered to be missing completely at random (MCAR), a multiple imputation procedure for the background variables was not used. Instead, full information maximum likelihood (FIML) was implemented in Mplus (Muthén & Muthén, 2017) using of all available data to estimate models. FIML estimation has been shown to produce unbiased parameter estimates and standard errors under the assumptions of missing at random (MAR) and missing completely at random (MCAR) (Enders & Bandalos, 2001). All factor analyses, measurement model invariance comparisons, and structural equation model (SEM) analysis were executed using Mplus Version 8.1 (Muthén & Muthén, 2017). Due to the complex sampling of the PISA 2012 assessment in order to make generalizations to the student population, the replicate weights were used in the SEM analysis. The REPWEIGHT command was implemented (REPWEIGHT = WFSTR1 - WFSTR80), which composes a set of 80 replicate estimates by multiplying the survey weights (e.g., non-response, sample selection probabilities) in order to adjust for the sampling variance. In the SEM model, when predicting to mathematics performance, the 5 plausible values were tested simultaneously where the model estimates and their standard errors were accounted for to produce final model, average estimates of the SEM analyses by indicating TYPE = Imputation. Due to the categorical nature of some of the indicators, the WLSMV (mean- and variance-adjusted weighted least squares) estimator was used. The WLSMV is a robust estimator typically have larger variance but are also less sensitive to model assumptions and when indicators are not normally distributed.

In order to examine the first research question regarding the measurement of attitudes, intentions, and behaviors, a series of confirmatory factor analyses (CFA) were conducted. CFA models were compared on the basis of global model fit indices. Model fit were assessed following existing conventions: the comparative fit index (CFI) and the Tucker Lewis index (TLI), each at > 0.900 (preferably > 0.950), the root mean square error of approximation (RMSEA) < 0.10 (preferably < 0.05), and the standardized root mean square (SRMR) < 0.08 (e.g., Browne & Cudeck, 1993; Hu & Bentler, 1999; Kline, 2005; MacCallum, Browne, & Sugawara, 1996; West, Taylor, & Wu, 2012). After the first CFA iteration, the model fit indices were examined and indicators that had a standardized factor loading $\lambda \geq 0.5$ were included as an item in the factor. In subsequent CFA models, items were removed based on their factor loadings and model fit indices were examined to determine if an alternative factor model resulted in better fit. In order to examine research questions 2 through 5, the CFA model that indicated the best model fit was used as the basis of the structural model. In the SEM model the following direct effects were specified: (1) the exogenous attitude constructs (attitude towards mathematics behaviors, subjective norms, perceived behavioral control) on intention to pursue mathematics, (2) intention to pursue mathematics on mathematics behavioral engagement, and mathematics behavioral engagement on mathematics performance. The indirect relation of perceived behavioral control (X) on behavioral engagement (Y), through intention (M) was also examined. All paths controlled for student gender, race/ethnicity, and socioeconomic status. Standardized coefficients and 95% confidence intervals for all direct and indirect estimates were also generated.

3. Results

3.1. Descriptive statistics

Means, standard deviations, and range for all variables of the current study are presented in Table 1. The reliability statistics for each of these item parcels, the indicators from the raw dataset, and the original variable names and labels as downloaded from the National Center for Education Statistics (1995) (NCES) public-use data file are presented as part of the Online Supplementary Files, to facilitate replication of the study's findings. Items were initially reverse coded, where necessary, to imply more positive attitudes for greater numerical values. The socio-economic and cultural status index that was used as an additional control variable was centered close to zero (M = 0.174, SD = 0.974), ranging from −3.8 to 3.12. The means of the five plausible values for mathematics performance of the U.S. PISA 2012 sample, ranged from M = 480.715 to M = 482.537. As indicated by numerous technical reports, the average performance of students in the US lags behind the international OECD average of M = 494 (OECD, 2013). The descriptive statistics of the item parcels that were created to serve as indicators of each of the attitudinal latent constructs are reported in Table 1. The correlation and partial correlation matrices among all study variables are presented in in Appendix B of the supplementary file. The majority of the correlation coefficient estimates were positive, suggesting positive relations among the attitude indicators and between attitudes and mathematics performance. All correlation coefficients were statistically significant at $p < 0.01$.

3.2. Confirmatory factor analysis

Iterations of five-factor CFAs representing attitude (Cronbach's α = 0.892), subjective norms (α = 0.881), perceived behavioral control (α = 0.782), intentions (α = 0.759), and behavioral engagement (α = 0.839) as latent factors were performed to generate a measurement model with appropriate model fit (see Appendix C of the supplementary file). Model 1 contained all of the indicators (e.g., item parcels) that were initially considered as conceptually relevant based on the operational definitions of each construct. Model 1 showed unacceptable model fit: RMSEA = 0.052, 90% CI [0.050, 0.053]; CFI = 0.799; TLI = 0.781; SRMR = 0.103. Model 2 used a more stringent standardized factor loading cut-off of $\lambda \geq 0.5$ (Tabachnick & Fidell, 2001; Worthington & Whittaker, 2006) where items with low factor loadings were dropped during this iteration, which resulted in acceptable model fit; RMSEA = 0.057, 90% CI [0.056, 0.058]; CFI = 0.802; TLI = 0.779; SRMR = 0.100. Model 3 used a more conservative standardized factor loading cut-off of $\lambda \geq 0.6$ and additionally modeled six residual covariance residual specifications between items and three cross-loadings as suggested by the modification indices to improve model fit (Worthington & Whittaker, 2006). Measurement Model 3 showed good model fit as indicated by conventional indices; RMSEA = 0.029, 90% CI [0.028, 0.030]; CFI = 0.959; TLI = 0.952; SRMR = 0.037. In Model 3, residual covariance specifications were applied between items that were highly correlated within the same factor and cross-loadings were specified for items that indicated high factor loadings in more than one attitudinal factor. Where appropriate, items remained in measurement models despite their factor loadings due to conceptual significance and consistency in construct operationalization among studies examining attitudinal constructs through the TPB lens (see notes section of Appendix C). All factor loadings across

Table 1
Descriptive Statistics of Study Variables.

Construct	Variable	Mean	Median	SD	Range	Min	Max
ESCS	Economic, social, cultural status index	0.174	0.26	0.974	6.92	−3.8	3.120
Mathematics Performance	Plausible value 1 in math	480.715	476.873	90.038	647.998	174.022	822.021
	Plausible value 2 in math	480.93	476.873	89.723	601.963	206.037	808.000
	Plausible value 3 in math	481.09	476.873	89.826	563.717	220.525	784.242
	Plausible value 4 in math	482.537	478.743	89.814	585.451	190.458	775.908
	Plausible value 5 in math	481.561	477.652	89.912	613.959	183.214	797.173
Attitude	Attitude – School, Waste of time	3.05	3	0.659	3	1	4
	Attitude – School, Useful for Future Job and College	3.59	3.67	0.477	3	1	4
	Attitude Instrumental Motivation - Worthwhile for Work	3.05	3	0.817	3	1	4
	Attitude Instrumental Motivation - Worthwhile for Career Chances	3.07	3	0.794	3	1	4
	Attitude Instrumental Motivation - Important for Future Study	3.03	3	0.82	3	1	4
	Attitude Instrumental Motivation - Helps to Get a Job	2.9	3	0.893	3	1	4
Subjective Norms	Norms - Friends	2.5	2.67	0.509	3	1	4
	Norms - Parents	3.06	3	0.574	3	1	4
	Norms - Classroom, Teacher Directed Instruction	2.986	3	0.654	3	1	4
	Norms - Classroom, Formative Assessment	2.548	2.5	0.786	3	1	4
	Norms - Classroom, Student Orientation	1.958	1.75	0.683	3	1	4
	Norms - Classroom, Cognitive Activation Thinking	3.064	3	0.614	3	1	4
	Norms - Classroom, Cognitive Activation Problem-solving	2.558	2.5	0.816	3	1	4
	Norms - Classroom, Cognitive Activation Learning from Mistakes	2.98	3	0.802	3	1	4
	Norms - Classroom, Cognitive Activation Explaining Thinking	3.07	3	0.698	3	1	4
	Norms - Classroom, Teacher Support	3.122	3	0.664	3	1	4
Perceived Behavioral Control	Control - Success is Controllable and Internal	3.309	3.333	0.565	3	1	4
	Control - Success is Uncontrollable and External	2.827	3	0.642	3	1	4
	Self-efficacy - Math Understanding	3.142	3	0.666	3	1	4
	Self-efficacy - Math Calculations	2.997	3	0.725	3	1	4
	Self-efficacy - Math Geometry	2.843	3	0.771	3	1	4
	Self-efficacy - Math Solving Equations	3.459	3.5	0.662	3	1	4
Intentions	Intentions - Mathematics vs. Language Courses After School	0.539	1	0.498	1	0	1
	Intentions - Mathematics vs. Science Related Major in College	0.417	0	0.493	1	0	1
	Intentions - Study Harder in Mathematics vs. Language Classes	0.594	1	0.491	1	0	1
	Intentions - Take Maximum Mathematics vs. Science Classes	0.449	0	0.497	1	0	1
	Intentions - Pursuing a Career in Mathematics vs. Science	0.407	0	0.491	1	0	1
Behavioral Engagement	Behavior - Work Ethic on Homework	3.068	3	0.671	3	1	4
	Behavior - Work Ethic on Studying	2.735	2.667	0.668	3	1	4
	Behavior - Work Ethic on Attentiveness	3.239	3	0.614	3	1	4
	Behavior - Work Ethic on Metacognition	2.871	3	0.688	3	1	4

measurement model iterations were statistically significant at $p < 0.001$.

The measurement model that was accepted for subsequent analyses was Model 3, which was the best fitting model among the iterations (see Appendix C). The finalized standardized estimates of the factor loadings of measurement Model 3 from the structural model analysis, with the exception of one reverse coded item on the perceived behavioral control factor, ranged from $0.501 \leqq \lambda \leqq 0.957$, and were all significant at $p < 0.001$ (see Table 2). The indicators that best measured each attitudinal construct (RQ1) were related to: (1) the usefulness and importance of studying mathematics for future study and career chances (attitude); (2) socio-mathematical classroom norms and expectations (e.g., teacher encourages to reflect on problems and gives problems that require thinking) (subjective norms); (3) internal and controllable attributions (e.g., "I can succeed in mathematics with enough effort" and "Doing well in mathematics is completely up to me") as well as self-efficacy beliefs for solving mathematical equations (perceived behavioral control); (4) pursuing a career that involves mathematics versus science (intentions); and (5) work ethic on preparing and studying for mathematics exams (behavioral engagement).

Table 2
Final Standardized Factor Loadings from Structural Equation Model Results.

Variable	λ (SE)	95% CI	R^2 (S.E.)
Attitude			
Attitude – School, Waste of time	0.558 (0.018)	[0.522, 0.593]	0.311 (0.020)
Attitude – School, Useful for Future Job and College	0.794 (0.010)	[0.775, 0.813]	0.630 (0.015)
Attitude Instrumental Motivation – Worthwhile for Career Chances	0.814 (0.008)	[0.799, 0.830]	0.663 (0.013)
Attitude Instrumental Motivation - Important for Future Study	0.840 (0.009)	[0.823, 0.857]	0.706 (0.014)
Attitude Instrumental Motivation - Helps to Get a Job	0.779 (0.010)	[0.759, 0.799]	0.607 (0.016)
Subjective Norms			
Norms – Parents' expectations	0.634 (0.018)	[0.599, 0.669]	0.402 (0.022)
Norms - Classroom, Teacher Directed Instruction	0.721 (0.011)	[0.700, 0.742]	0.520 (0.016)
Norms - Classroom, Formative Assessment	0.625 (0.010)	[0.606, 0.645]	0.391 (0.012)
Norms - Classroom, Cognitive Activation Thinking	0.749 (0.011)	[0.727, 0.771]	0.561 (0.017)
Norms - Classroom, Cognitive Activation Learning from Mistakes	0.678 (0.013)	[0.652, 0.703]	0.459 (0.018)
Norms - Classroom, Cognitive Activation Explaining Thinking	0.658 (0.015)	[0.628, 0.688]	0.433 (0.020)
Norms - Classroom, Teacher Support	0.646 (0.013)	[0.621, 0.671]	0.417 (0.017)
Perceived Behavioral Control			
Control - Success is Controllable and Internal	0.644 (0.012)	[0.620, 0.668]	0.415 (0.016)
Control - Success is Uncontrollable and External	0.367 (0.018)	[0.332, 0.401]	0.134 (0.013)
Self-efficacy - Math Understanding	0.481 (0.016)	[0.451, 0.512]	0.232 (0.015)
Self-efficacy - Math Calculations	0.501 (0.017)	[0.468, 0.534]	0.251 (0.017)
Self-efficacy - Math Geometry	0.521 (0.018)	[0.485, 0.556]	0.271 (0.019)
Self-efficacy - Math Solving Equations	0.580 (0.015)	[0.550, 0.610]	0.336 (0.018)
Intentions			
Mathematics vs. Language Courses After School	0.786 (0.014)	[0.758, 0.813]	0.617 (0.022)
Mathematics vs. Science Related Major in College	0.949 (0.006)	[0.937, 0.961]	0.901 (0.011)
Study Harder in Mathematics vs. Language Classes	0.676 (0.015)	[0.647, 0.704]	0.457 (0.020)
Take Maximum Number of Mathematics vs. Science Classes	0.827 (0.008)	[0.811, 0.842]	0.683 (0.013)
Pursuing a Career That Involves Mathematics vs. Science	0.957 (0.005)	[0.947, 0.968]	0.917 (0.010)
Behavioral Engagement			
Work Ethic on Homework	0.727 (0.011)	[0.705, 0.750]	0.529 (0.016)
Work Ethic on Studying	0.775 (0.013)	[0.750, 0.800]	0.600 (0.020)
Work Ethic on Attentiveness	0.698 (0.013)	[0.673, 0.724]	0.488 (0.018)
Work Ethic on Metacognition	0.678 (0.015)	[0.649, 0.708]	0.460 (0.021)

Note. Results draw from replicate weights, finalized loadings. All factor loadings were statistically significant at the $p < 0.001$ level. Intentions factor was measured through dichotomous indicators, which were specified as categorical variables.

All TPB-based components were found to be positively intercorrelated, as expected. Attitude was most highly correlated with perceived behavioral control (r = 0.578), followed by subjective norms (r = 0.579), behavior (r = 0.556), and intentions (r = 0.413). Subjective norms was correlated with perceived behavioral control (r = 0.524), intentions (r = 0.194), and behavior (r = 0.518). Perceived behavioral control was correlated with intentions (r = 0.276), and behavior (r = 0.551). Finally, intentions was correlated with behavior (r = 0.237). In sum, the highest correlation was observed between attitude and perceived behavioral control (r = 0.593) and the weakest correlation was observed between subjective norms and intentions (r = 0.194). All correlations among latent constructs were statistically significant at $p < 0.001$.

3.3. Predicting students' mathematics intentions, behavioral engagement, and achievement

The structure of the TPB predicting to mathematics work ethic behaviors and extending to predicting mathematics performance (RQ2) was identified in the U.S. PISA 2012 data. Model fit information from the SRMR (i.e., Standardized Root Mean Square Residual) index was M = 0.069, SD = 0.00 across the five successful computations for each of the SEM iterations, predicting to each one of the plausible values at a time, indicating acceptable model fit. Alternative conventional model fit indices (e.g., RMSEA, CFI) were not available with the use of replicate weights and the incorporation of categorical indicators (as was the case for the indicators of the intentions factor). A saturated SEM model (i.e., where all possible direct effects were specified among constructs) resulted in a SRMR = 0.064, also indicating acceptable model fit. Only two structural equation model versions were empirically tested for fit to the data for comparison purposes— the theoretical model with the predefined paths (Fig. 2) and a saturated model. In order to obtain the most parsimonious model that best fit the data, the proposed conceptual model was concluded to be a better approach for identifying the TPB on the dataset, when compared to the saturated model.

Variability explained in academic-relevant outcomes. A statistically significant proportion of the variation (RQ3) (21.1%) in intentions was explained by the exogenous attitude determinants (attitude, subjective norms, perceived behavioral control); $R^2 = 0.211$ (0.013), $p < 0.001$. Almost 60% of the variability in behavior was explained by the attitude determinants and the intentions factor; $R^2 = 0.594$ (0.022), $p < 0.001$. Lastly, over 30% of the variability in mathematics performance was explained by the attitude determinants, intentions, and behavioral engagement; $R^2 = 0.307$ (0.013), $p < 0.001$.

Direct effects of demographiccontrol variables on outcomes. The direct standardized effects and effect sizes of gender, race/ethnicity, and socioeconomic and cultural status index on academic outcomes are reported on Table 3 and controlled for in subsequent analyses. Briefly, results of these student demographic characteristics indicated that females indicate lower intentions to pursue mathematics (β = -0.324, 95% CI [-0.379, −0.268]), report higher behavioral engagement (β = 0.223, 95% CI [0.166, 0.280]), and show lower mathematics performance (β = -0.129, 95% CI [-0.175, −0.084]) when compared to male students. There were racial/ethnic differences in intentions where most students identifying as racial/ethnic minorities reported greater intentions to pursue mathematics and higher behavioral engagement in mathematics when compared to White students.Black/African American, Hispanic,

Table 3
Direct Standardized Effects of Gender, Race/Ethnicity, and Socioeconomic and Cultural Status Index on Academic Outcomes.

Variable	Intentions					Behavior					Mathematics Performance				
	β	*SE*	*p*	95% CI	*d*	*β*	*SE*	*p*	95% CI	*d*	*β*	*SE*	*p*	95% CI	*d*
Gender (1 = Female)	−0.324	0.028	0.000	[-0.379, −0.268]	0.685	0.223	0.029	0.000	[0.166, 0.280]	0.458	−0.129	0.023	0.000	[-0.175, −0.084]	0.260
Race/Ethnicity (Ref = White)															
Black/African-American	0.103	0.052	0.051	[0.000, 0.205]	0.207	0.190	0.043	0.000	[0.106, 0.274]	0.387	−0.859	0.051	0.000	[-0.959, −0.758]	3.356
Hispanic and/or Latino/a	0.158	0.055	0.004	[0.050, 0.266]	0.320	0.124	0.050	0.013	[0.026, 0.222]	0.249	−0.284	0.042	0.000	[-0.366, −0.201]	0.592
Asian	0.171	0.088	0.052	[-0.002, 0.344]	0.347	0.383	0.089	0.000	[0.207, 0.558]	0.829	0.431	0.067	0.000	[0.299, 0.563]	0.955
Multiracial	−0.047	0.062	0.448	[-0.170, 0.075]	0.094	0.056	0.076	0.456	[-0.092, 0.205]	0.112	−0.115	0.052	0.025	[-0.217, −0.014]	0.232
Other race	−0.085	0.172	0.620	[-0.422, 0.251]	0.171	−0.270	0.130	0.038	[-0.525, −0.015]	0.561	−0.598	0.071	0.000	[-0.738, −0.459]	1.492
Socioeconomic Index (ESCS)	−0.035	0.020	0.086	[-0.075, 0.005]	0.070	0.178	0.021	0.000	[0.138, 0.219]	0.362	0.298	0.015	0.000	[0.269, 0.327]	0.624

multiracial, and students who identified as "other race" showed lower mathematics performance than White students, when the alternative demographic variables were controlled for. The effect of higher socioeconomic and cultural status index (ESCS) was positive on behavioral engagement and positive on mathematics performance with effect sizes estimated at $d = 0.362$ and $d = 0.624$, respectively.

Direct and indirect effects of attitude determinants on academic outcomes. The SEM results (RQ4) of the direct and indirect standardized regression coefficients with 95% CIs, controlling for student gender, race/ethnicity, and socioeconomic and cultural status index are reported on Table 4. Results of direct effects indicated that attitude toward mathematics was positively and statistically significantly related to intentions; $\beta = 0.420$, $SE = 0.026$, $p < 0.001$. Subjective norms had a surprisingly negative, albeit weak, direct effect on intentions to pursue mathematics-related majors in college and choose career pathways that require mathematics knowledge; $\beta =$ -0.083, $SE = 0.030$, $p < 0.05$. Alternatively, perceived behavioral control was not significantly related to intentions; $\beta = 0.058$, $SE = 0.031$, $p = 0.132$. The direct effects of perceived behavioral control ($\beta = 0.719$, $SE = 0.018$, $p < 0.001$) and intentions ($\beta = 0.064$, $SE = 0.019$, $p < 0.05$) on mathematics work ethic behaviors were positive and statistically significant. Finally, mathematics work ethic behaviors were directly related to mathematics performance; $\beta = 0.255$, $SE = 0.016$, $p < 0.001$. All indirect effects of the attitude determinants on behavior and mathematics performance as well as intention on mathematics performance are also reported on Table 4. Although these indirect effects were not specified in the conceptual model or in the SEM model, they are reported in order to contextualize the broader results of the present study. Briefly stated, the indirect effects of the attitude determinants on mathematics performance indicated positive and weak relations with attitude, $\beta = 0.006$, $p = 0.018$; negative and weak relations with subjective norms, $\beta =$ -0.001, $p =$ 0.001; and positive and strong relations with perceived behavioral control, through behavior alone, $\beta = 0.184$, $p < 0.001$.

Mediation analyses (RQ5) indicated that the specific indirect effect of perceived behavioral control on behavior through intentions was not statistically significant; $\beta = 0.004$, $SE = 0.002$, $p = 0.134$. That is, the intentions factor did not mediate the relation between perceived behavioral control and behavioral engagement; total effect was $\beta =$ 0.723, $SE = 0.018$, $p < 0.001$. Moreover, the specific indirect effect of perceived behavioral control on mathematics performance through intentions and behavior (i.e., multiple mediators) was not statistically significant; $\beta = 0.001$, $SE = 0.001$, $p = 0.129$. Contrastingly, the specific indirect effect of perceived behavioral control on mathematics performance through behavior alone, was statistically significant; $\beta = 0.184$, $SE = 0.015$, $p < 0.001$. The mediation results suggest that mathematics behavioral engagement, not intentions to pursue a mathematics-

Table 4
SEM Results of Direct and Indirect Standardized Regression Coefficients with Confidence Intervals, Controlling for Gender, Race/Ethnicity, and Socioeconomic and Cultural Status Index.

Independent (X)	Dependent (Y)	Type of Effect	Mediator(s) (M)	*β*	*SE*	*p*	95% CI	*d*
Direct effects								
Attitude	Intention	Direct	N/A	0.420	0.026	0.000	[0.369, 0.482]	0.942
Subjective Norm	Intention	Direct	N/A	−0.083	0.030	0.005	[-0.146, −0.026]	0.173
Perceived Behavioral Control	Intention	Direct	N/A	0.058	0.039	0.132	[-0.025, 0.142]	0.116
Intention	Behavioral Engagement	Direct	N/A	0.064	0.019	0.001	[0.020, 0.100]	0.120
Perceived Behavioral Control	Behavioral Engagement	Direct	N/A	0.719	0.018	0.000	[0.688, 0.758]	2.162
Behavioral Engagement	Math Performance	Direct	N/A	0.255	0.016	0.000	[0.211, 0.279]	0.505
Indirect effects								
Attitude	Behavioral Engagement	Total	Intention	0.027	0.009	0.009	[0.006, 0.045]	0.052
Subjective Norm	Behavioral Engagement	Total	Intention	−0.005	0.002	0.007	[-0.009, −0.001]	0.010
Perceived Behavioral Control	Behavioral Engagement	Total	Intention	0.723	0.018	0.000	[0.691, 0.762]	2.111
		Total indirect	Intention	0.004	0.002	0.134	[-0.001, 0.008]	0.008
		Specific indirect	Intention	0.004	0.002	0.134	[-0.001, 0.008]	0.008
Attitude	Math Performance	Total	Intention, Behavior	0.006	0.018	0.009	[0.002, 0.011]	0.012
Subjective Norm	Math Performance	Total	Intention, Behavior	−0.001	0.000	0.010	[-0.002, 0.000]	−0.002
Perceived Behavioral Control	Math Performance	Total	Intention, Behavior	0.184	0.014	0.000	[0.149, 0.207]	0.362
		Total indirect	Intention, Behavior	0.184	0.014	0.000	[0.149, 0.207]	0.362
		Specific indirect	Behavior	0.184	0.014	0.000	[0.148, 0.206]	0.360
		Specific indirect	Intention, Behavior	0.001	0.001	0.129	[0.000, 0.002]	0.002
Intention	Math Performance	Total	Behavior	0.015	0.005	0.003	[0.005, 0.025]	0.030

relevant career, facilitate the relation between attitudinal beliefs (mainly, perceived behavioral control) and mathematics performance.

4. Discussion

The goal of the present study was to use Theory of Planned Behavior and apply it to the domain of mathematics attitudes in order to predict mathematics performance, as measured by large-scale international assessments. Results indicate that the TPB is a viable theoretical framework for predicting U.S. high school students' mathematics performance, as measured by the PISA 2012 – suggesting that the theory is applicable to educational research. We found that students attitudes explained over 20% of the variability in intentions to pursue and major in mathematics versus a science related major in college, almost 60% of the variability in mathematics behaviors, and over 30% of the variability in mathematics performance. Overall, the results of the structural model suggest that there were inconsistencies in the directionality and significance of the relations between the attitude determinants and the intentions factor (positive and significant with attitude, negative and significant with subjective norms, and not significant with perceived behavioral control). As expected, the direct effects of intentions and perceived behavioral control on behavior as well as the direct effect of behavior on mathematics performance were positive and statistically significant. Mediation analyses indicated that the intentions factor did not mediate the relations between perceived behavioral control and neither behavioral engagement nor mathematics performance. Further, perceived behavioral control had an indirect effect on mathematics performance through behavioral engagement alone (i.e., one specific mediator). This finding is consistent with the research that has demonstrated the unique role of control beliefs on adolescents' achievement across major ethnic groups in the United States (You, Hong, & Ho, 2011).

Attitude towards mathematics was positively and directly related to intentions and indirectly related to behaviors and mathematics performance. The relation between attitude and intentions was the strongest and showed a large effect in terms of effect size whilst the other effects were near zero, albeit statistically significant. This indicates that attitude, overall, has a positive relation to academic outcomes of interest, but that the size of their positive effect differs, depending on how proximal (e.g., intentions) or distal (e.g., mathematics performance) the outcome is. Promoting students' attitude towards mathematics is expected to have a positive effect on academic intentions, behaviors, and achievement. Conversely, subjective norms had negative direct and indirect effects on outcomes. The direct effect was strongest with intentions, followed by the indirect effect on behavior, followed by the indirect effect on mathematics performance. Perceived social pressures seem to have an overall negative effect on important educational outcomes – this finding has important implication for interventions, as discussed further on. The last attitudinal determinant, perceived behavioral control, was not directly related to intentions but was largely related to behavior and indirectly related to mathematics performance, through behavior alone. The influence of control beliefs on these outcomes indicates that although students' intentions are not altered as a result of self-efficacy and control beliefs, their behavior and subsequent achievement is. Furthermore, intentions to pursue mathematics had positive, albeit weak, effects on behavior (direct) and mathematics performance (indirect, through behavior), whereas behavior had a moderate effect on mathematics performance. Intentions to pursue mathematics in the future may not serve as a strong mechanism for promoting students' work ethic and behavioral engagement in mathematics (weak intention-behavior consistency among adolescents), however, more frequent behavioral engagement with learning is important for performance in mathematics.

Several moderate effect sizes were found among high school students' attitudes, intentions, behaviors, and mathematics performance: (1) perceived behavioral control on behavior, (2) attitude on intentions, (3) behavior on mathematics performance, and (4) perceived behavioral control on mathematics performance, through behavior. The findings of the present study overall emphasize: (1) the importance of control beliefs and self-efficacy beliefs for predicting mathematics-related behaviors (e.g., paying attention in class, completing homework, studying for math exams) and subsequent mathematics performance, (2) the importance of students' mathematics-related behaviors for mathematics performance, and (3) the significance of students' attitude towards mathematics for their intentions to pursue mathematics coursework and mathematics-relevant careers.

Attitude determinants and academic outcomes. We found that attitude had the strongest relation to intentions, among the outcomes of interest in this study, where $r = 0.426$. Other studies examining TPB have also found that attitudes and intentions were significantly related, indicating that the magnitude of the relation ranged from $r = 0.36$ (Walker, 2017) to $r = 0.64$ (Lipnevich et al., 2011) in United States samples and as high as $r = 0.62$ and $r = 0.73$ in German and Belarusian samples, respectively (Lipnevich et al., 2011, 2016). As expected, the subjective norms factor was a weak (in terms of effect size) predictor of the study's outcomes; this finding is supported by prior work (Areepattamannil et al., 2016; Burrus & Moore, 2016; Lipnevich et al., 2011, 2016; Walker, 2017). In this study, the attitude determinant that showed the strongest relation with the primary outcomes of interest (behavior, mathematics performance) was perceived behavioral control; effect sizes ranging from $0.116 \leq d \leq 2.162$ and standardized effect was as high as $\beta = 0.734$ for predicting to behavior. This finding shows support for the extension (i.e., the addition of achievement as a result of behavior) of the theoretical framework as applied to the educational context. This is consistent with empirical work that has highlighted the importance of control beliefs and self-efficacy beliefs for a range of achievement outcomes above and beyond other noncognitive factors (e.g., instrumental motivation) (Lee & Stankov, 2013; Lee, 2009).

The finding that social norms were negatively related to the academic outcomes of interest in this study (intentions, behavior, and subsequent mathematics performance) is consistent with few prior findings (e.g., Areepattamannil et al., 2016; Skrzypiec & Lai, 2017), but not the majority of prior research using the TPB framework predicting similar outcomes (Areepattamannil et al., 2016; Burrus & Moore, 2016; Lipnevich et al., 2011, 2016; Walker, 2017). In this study, we operationalized and adapted social norms from the broader psychological literature on attitudes to capture sociomathematical norms, a concept that is more relevant to education. However, the PISA index of subjective norms was made up of a multitude of items related to the disposition of persons in an adolescent's social environment – mainly comprising friends, parents, peers, and teachers. Although prior research has shown the positive influence on school engagement and achievement of academically-oriented peers who model positive learning behaviors (e.g., Rice, Barth, Guadagno, Smith, & McCallum, 2013), social pressures originating from parenting and other social environments may actually be increasing anxiety and hindering performance. Thus, what could be explaining the weak, and often negative effect, of social norms on intentions could be the individual's perceptions of social norms as either a social pressure (a negative connotation) versus a realistic expectation for achievement. Areepattamannil et al. (2015) provided some insights regarding this distinction. In their study, they demonstrated that adolescents who perceived that their parents considered mathematics was important to study (social norm, low social pressure) performed better on the mathematics assessment. Conversely, adolescents who perceived that their parents considered mathematics to be important for their children's career (social norm, high social pressure) reported higher levels of mathematics anxiety. The distinction between these two forms of parental expectations lies in the pressure to perform well for intrinsic purposes (e.g., important to study mathematics, important to know mathematics well) versus extrinsic purposes (e.g., important for career). This may suggest that social norms that emphasize future goals and intentions for extrinsic, high-stakes purposes – such as career choice and job prospects – may induce mathematics anxiety, resulting in a decrease in students' intentions to pursue mathematics. Triangulating this with the research that indicates that high mathematics test taking anxiety is negatively correlated with mathematics performance (Ashcraft & Kirk, 2001), gives some insight as to why social norms that manifest themselves as social pressures, have a negative relation with intentions to pursue mathematics. Other relevant research suggests that high social pressures, as exerted by parental overaspiration (i.e., the extent to which parental aspiration exceeds parental expectation) contributes to a children's emotion control and academic disengagement (Gurland & Grolnick, 2003; Roth, Assor, Niemiec, Deci, & Ryan, 2009). More recent work has found that parental aspiration that exceeded their expectation (i.e., overaspiration) had negative reciprocal relations with children's mathematical achievement across middle school and high school, which suggests that unrealistic high parental aspirations can be detrimental for children's academic achievement (Murayama, Pekrun, Suzuki, Marsh, & Lichtenfeld, 2016). These findings replicated across two longitudinal samples of German children in grades 5th-10th and nationally representative U.S. adolescents in 10-12th grade, after controlling for a host of demographic (e.g., child gender, family SES) and contextual variables (e.g., school type). In sum, normative beliefs can have positive and negative manifestations from multiple sources (teachers, parents, peers) where high-stakes social pressures for future career choices and overaspirations may have overall negative effects on students' mathematics-related intentions, work ethic, and performance. Furthermore, the magnitude and direction of the effect of social norms on mathematics performance may be moderated by developmental differences as research using the Early Childhood Longitudinal Study – Kindergarten Sample, another large-scale dataset, shows that greater parental expectations (e.g., expecting their child to attain a high educational degree) is a *positive* predictor of early mathematics competencies (Kindergarten – 3rd grade) (Byrnes & Wasik, 2009).

The role of intentions to pursue mathematics. We found that intentions to pursue mathematics was not a pragmatically important factor for predicting mathematics achievement when students' mathematics behavioral engagement was accounted for (d of indirect effect $= 0.03$). This is contrary to findings of other studies (Lipnevich et al., 2011; Niepel et al., 2018) that showed meaningful relations between students' intentions to study hard in mathematics and their grades in mathematics. This relation may have been overestimated in prior research due to the complete omission of measuring students' behavioral engagement, potentially resulting in an inflated importance of students' intentions. Students' intentions to pursue mathematics-relevant coursework or careers post-high school, are important for predicting their day-to-day work ethic on mathematics homework, exam preparations, and being attentive in class. Regarding the indirect effect of perceived behavioral control on behavior, intentions is not a particularly useful factor in mediating that relation. This indicates that students' sense of self-efficacy and control beliefs of engaging with mathematics, is irrelevant to their intention to pursue mathematics in the future. This finding has important implications for academic motivation research and practice, and suggests that students' beliefs about their capabilities, not their long-term goals, mainly influence their academic math-related behavioral engagement. Conversely, students' attitudes and perceived social pressures relate to their mathematics related behaviors, partially through their intentions to pursue mathematics.

Students' behavioral engagment matters for achievement. A major limitation of prior studies (Burrus & Moore, 2016; Lipnevich et al., 2011, 2016; Niepel et al., 2018; Walker, 2017) employing the TPB to understand the variability in mathematics achievement was in conflating academic behaviors and academic achievement. In this study, by conceptualizing and measuring behavioral engagement as separate from achievement, we were able to determine the pathways by which attitudinal beliefs explained academic performance in the domain of mathematics. Thus, the effect of students' work ethic and study habits has been undermined and entirely omitted in prior research (Niepel et al., 2018). Results showed that the direct effect of behavior on math performance was estimated to be $\beta = 0.25$ and was moderate in terms of effect size, $d = 0.505$. One prior meta-analysis (Credé & Kuncel, 2008) has highlighted the relation between study skills and habits on college academic achievement (e.g., first semester, freshman, and overall GPA) and found the relation to be approximately $r = 0.28$. Behavioral engagement indicators such as completing mathematics homework on time, working hard on mathematics homework, preparing for exams, studying for quizzes, paying attention in class, and avoiding distractions when studying, should be explicitly prioritized, developed, and encouraged in academic settings and further examined in future research.

4.1. Implications for applied contexts

To date, the majority of educational and psychological research attempting to explain the factors contributing to adolescents' academic performance has utilized diverse theoretical frameworks to explain academic engagement and performance. In this study, we demonstrated that the theory of planned behavior (TPB; Ajzen, 1991; 2005) served as a viable theoretical framework for understanding mathematics performance of adolescent students in the United States, as measured by national large-scale assessment data. Overall, the results suggest that: (1) attitude towards math has a positive relation to academic outcomes, (2) social norms have an overall negative effect on academic outcomes, (3) self-efficacy and control beliefs have a strongest effect on mathematics behaviors, and (4) behavioral engagement is a predictor of achievement. To optimize student outcomes, instruction and social supports should focus on promoting the value for mathematics, reducing social pressures, increasing self-efficacy, and explicitly teaching effective mathematics-related behaviors such keeping work organized and planning to submit mathematics homework on time - - just as a plethora of prior research has already alluded to (e.g., Areepattamannil et al., 2015; Areepattamannil et al., 2016; Burrus & Moore, 2016; Cleary et al., 2017; Kitsantas et al., 2011; Lipnevich et al., 2011; Lipnevich et al., 2016; Niepel et al., 2018; Papanastasiou, 2000; Pitsia et al., 2017; Walker, 2017).

Based on these findings, we argue that important implications for applied educational contexts are to focus on developing students' positive attitudes and self-efficacy beliefs in mathematics through changes in instructional practices (e.g., explicitly teaching, and supporting the implementation of positive academic behaviors such as minimizing distractions while in class and maintaining school work organized) and educational interventions (e.g., Ndiaye, 2019). There is research evidence that more explicit instruction regarding the usefulness and applicability of mathematics in everyday life, in postsecondary education, and in career choice promotes more positive attitudes towards mathematics (e.g., Perin, 2011) and grades in mathematics (Woolley, Rose, Orthner, Akos, & Jones-Sanpei, 2013). More specifically, in a randomized control trial of a professional development series, the effectiveness of instructional strategies that focus on the occupational relevance of what students are learning (i.e., career relevant instruction) in core subjects have shown an effect on increasing mathematics performance. The premise of this theory of change model is that when students understand and are aware of the relevance of what they are learning to solve real-world problems, students are more motivated to learn (Means, Jonassen, & Dwyer, 1997). Adapting towards mastery learning instructional approaches can also have benefits for promoting students' self-efficacy beliefs – this is done through checking on students' learning progress by providing formative feedback on students' individual learning difficulties in order to master the material at hand (Bloom, 1984; Guskey, 2007, 2010). Supporting self-efficacy calls for specific instructional strategies that require minimal teacher training an effort. Strategies such as asking students to record something new they learned that day or something at which they excelled, prompting students who perform poorly to attribute their failures to lack of effort and encouraging them to try harder, drawing students' attention to their growth and praising them on their specific skills, and helping students to practice lack-of-effort explanations when they perform poorly – have all been shown to promote student self-efficacy among students (Siegle & McCoach, 2007). Finally, professional development training that promotes study skills instruction can have positive impacts on students' attitudes toward mathematics and perceived behavioral control beliefs, in particular (Banks, 2015).

4.2. Limitations and future directions

First, researchers have recognized the design limitations of studies such as the Programme for International Student Assessment (PISA), Trends in International Mathematics and Science Study (TIMSS), and Progress in International Reading Literacy Study (PIRLS) despite their important role in educational research and policy (e.g., Baird et al., 2011; Grek, 2009) for providing evidence of causation (Caro, Sandoval-Hernandez, & Ludtke, 2014; Gustafsson, 2013; Leung & van de Vijver, 2008). Additionally, omitted variable bias (e.g., unobserved variable bias) is a concern. In this study we were unable to control for student general cognitive ability prior to the mathematics performance assessment. The lack of longitudinal designs in most large-scale assessments are another limitation of using secondary data sources. However, this is not a great concern given the research findings that international assessments are equally as effective for evaluating causal order of events through retrospective responses and structural modeling strategies (Wunsch, Russo, & Mouchart, 2010). Future studies can examine reciprocal effects between attitudes and achievement related outcomes by using nationally representative datasets with longitudinal designs, such as the Educational Longitudinal Study (ELS) conducted by the National Center for Educational Statistics. Alternative analytic methods such as bivariate dual-change score models (McArdle & Hamagami, 2001), combining the benefits of cross-lagged regression models and latent growth-curve models, can be utilized with such designs.

5. Conclusion

A conceptual model of mathematics attitudes, as specified by the TPB, was applied to the PISA 2012 United States sample. Results indicated that between 20% to almost 60% of the variability in academic outcomes (i.e., intentions to pursue mathematics, work ethic in mathematics, and mathematics performance) were explained by the attitude determinants (i.e., attitudes, subjective norms, and perceived behavioral control) and important student demographic characteristics (i.e., SES, gender, race/ethnicity). This finding is consistent with the research that has demonstrated the unique role of self-efficacy and control beliefs on adolescents' achievement across major ethnic groups in the United States (You, Hong, & Ho, 2011). The findings of the present study emphasize (1) the importance of control beliefs and self-efficacy beliefs on predicting mathematics behavioral engagement (e.g., paying attention in class, completing homework, studying for math exams) and subsequent mathematics performance and (2) the practical significance of students' attitude towards mathematics (i.e., instrumental motivation, an overall positive evaluation of mathematics) on their intentions to pursue mathematics coursework and math-relevant careers in the future.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cedpsych.2021.102019.

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