Achievement, motivation, and educational choices: A longitudinal study of expectancy and value using a multiplicative perspective

Jiesi Guo, Australian Catholic University (Australia)

Philip D. Parker, Australian Catholic University (Australia)

Herbert W. Marsh, Australian Catholic University (Australia), University of Oxford (UK), King Saud University (Saudi Arabia)

Alexandre J. S. Morin, Australian Catholic University (Australia)

Achievement, motivation, and educational choices: A longitudinal study of expectancy and value using a multiplicative perspective

Abstract

Drawing on the expectancy-value model, the present study explored individual and gender differences in university entry and selection of educational pathway (e.g., Science, Technology, Engineering, and Mathematics [STEM] course selection). In particular, we examined the multiplicative effects of expectancy and task values on educational outcomes during the transition into early adulthood. Participants were from a nationally representative longitudinal sample of 15-year-old Australian youths [N = 10,370]. The results suggest that (a) both math self-concept and intrinsic value interact in predicting advanced math course selection, matriculation results, entrance into university, and STEM fields of study; (b) prior reading achievement has negative effects on advanced math course selection and STEM fields through math motivational beliefs; (c) gender differences in educational outcomes are mediated by gender differences in motivational beliefs and prior academic achievement, while the processes underlying choice of educational pathway were similar for males and females.

Keywords: self-concept, expectancy-value, gender, STEM major, university entry

High-skilled professions often require university training, particularly in the STEM-related fields (science, technology, engineering and mathematics) which are critical for industrialized countries seeking to recover from the global financial crisis (International Monetary Fund, 2010; OECD, 2010). Unfortunately, in Western countries, many students who have the requisite ability do not pursue university education (Bowen, Chingos, & McPherson, 2009), and the proportion of students taking advanced math and science courses in senior high school and subsequently pursuing STEM pathways has declined in Australia (Lyons & Quinn, 2010) and elsewhere (see review by Bøe, Henriksen, Lyons & Schreiner, 2011). While females have made great strides in university enrollment parity with males and are even better represented than males in undergraduate degrees (Parker et al., 2012, 2013, 2014; OECD, 2010; Schoon & Polek, 2011), they are still substantially underrepresented in many STEM fields (Bøe et al., 2011).

Drawing upon Expectancy-Value Theory (EVT; Atkinson, 1957; Eccles, 2009, 2011; Eccles, et al., 1983), a lot of studies have been dedicated to the identification of factors that contribute to gender imbalance in the pursuit of educational pathways (e.g., Watt, et al., 2012; Watt, Eccles, & Durik, 2006; Guo, Marsh, Parker, Morin, & Yeung, 2015). Given that academic engagement and aspirations in high school are highly associated with educational career of the youth (Bowen et al., 2009; Hauser, 2010; Kimmel, Miller, & Eccles, 2012), much attention has been given to the interplay between academic achievement, math self-concept (expectancy) and task value in predicting high-school coursework choices and educational and occupational aspirations (e.g., Watt et al., 2006, 2012; Simpkins, Davis-Kean & Eccles, 2006; Wang, 2012). However, relatively little EVT research has been devoted to the post-high-school transition, which represents a critical point in decision making about pathways to university and the STEM fields of study (but see Parker et al., 2012, 2014; Guo, Marsh, Morin, Parker, & Kaur, 2015). In the present study, we adopt a holistic view and use the EVT framework to comprehensively test the longitudinal relationships among students' prior achievement (i.e., reading, math and science), and motivational beliefs (i.e., academic self-concept, intrinsic value, and utility value), in predicting two educational pathways (1: high school math course selection and STEM major choices; 2: matriculation results and entry into university), across the transition from high school (15-year-olds) into early adulthood (25-year-olds). More specifically, we mainly focus on the multiplicative effect of self-concept and task value, which was the critical feature of classical EVT (Atkinson, 1957) but has been less researched for several decades. Furthermore, we examine how the internal comparison process (Internal/External Frame of Reference Model [I/E model], Marsh, 1986, 2007) – where students contrast their own performance in one particular school subject against their performance in other school subjects – influence motivational beliefs and subsequent educational choices. Finally, we explore the gendered motivational process, thus providing insight into gender differences in the decision-making processes underlying educational pathway selections.

Expectancy Value Theory

Modern EVT (Eccles, 2009; Eccles, et al., 1983) is one of the major frameworks for achievement motivation and was developed to explain students' effort, choices and achievement in relation to academic and non-academic domains (e.g., sports, music and social activities) (Eccles & Wigfield, 2002). Modern EVT (Eccles, 2009, 2011) posits that achievement-related outcomes like university entry and STEM pathways are composed of a series of achievement-related performances and choices in adolescence, which are directly influenced by domain-specific expectancies for success (i.e., academic self-concept, competence beliefs, etc.) and subjective task value. Put simply, expectancies represent beliefs by young people that they have the capacity to succeed within a given post-school pathway, while task value represents evaluations by young people about the potential costs and benefits that are associated with that pathway (Eccles, 2011). These motivational beliefs are influenced by previous achievement-related experiences (e.g., domain-specific academic achievement) and individual characteristics (e.g., gender-role stereotyped socialization and family socioeconomic status). Thus, individual characteristics and previous academic achievement shape the development of task-related expectancies and value beliefs, which in turn, influence academic performance and coursework selection in high school and postsecondary educational and career choices (see Figure 1 for the conceptual model; also see Wang & Degol, 2013, for a review).

Expectancies for success is conceptualized as the task-specific beliefs about the possibility of experiencing future success in that task, which is directly linked to *ability self-concept* in a specific academic domain. Empirically, however, the two constructs (i.e., expectancies and self-concept) are indistinguishable (Eccles, 2009; Eccles & Wigfield, 2002). For this reason, typically academic self-concept has been used as a measure of the expectancies of success in empirical research (e.g., Wang & Eccles, 2013; Simpkins, Fredricks & Eccles, 2012). Also, subjective task value is known to be domain specific and is defined in terms of multiple components (Eccles & Wigfield, 2002). In the current study, we focus on two value components in the domain of math: *intrinsic value*, which refers to the enjoyment a person gains from performing an activity (in line with intrinsic motivation and interest), and *utility value*, which relates to how a specific task fits an individual’s future plans and objectives.

Relations Between Achievement, Motivational Beliefs and Choices

According to modern EVT (Eccles, 2009, 2011), achievement-related choices are influenced by a relative intra-individual hierarchy of self-concept and subjective task value across the set of perceived options. When individuals select the activities they want to pursue and make choices, domain comparisons within individuals are triggered (Eccles, 2009, 2011).

All such behavioral choices are assumed to be associated with costs as one choice often eliminates other options (following an ipsative process; Eccles, 2009; Eccles & Wigfield, 2002). Also, Eccles (2009) states that students' relative self-concept is formed as a function of comparing their performance with those of their peers (i.e., external comparison) and with their own performance across domains (i.e., internal comparison). These two types of comparisons have been explicated in the I/E model (Marsh, 1986, 2007). Specifically, internal comparison is an ipsative process, such that achievement in one subject domain has a negative effect on self-concept in another domain (Marsh, 2007) after controlling for achievement in the matching domain. The internal comparison process for self-concept and achievement between math and verbal domains has been widely supported by cross-cultural, longitudinal and experimental studies (e.g., Marsh, 2007; Möller, Pohlmann, Köller, & Marsh, 2009). Xu (2010) incorporated task value into the I/E model and found I/E-like patterns for self-concept and intrinsic value, but they were much weaker for attainment value and utility value. In addition, Nagy et al. (2006, also see Nagy et al., 2008) integrated notions of ipsative-like processes from EVT and the I/E model in a study of advanced coursework selection. Consistent with EVT, prior achievement predicted self-concept and interest, which in turn influenced coursework selection. Also, consistent with the I/E model, domain-specific self-concept and interest were positively related to achievement and course choices in the same domain, but negatively related to achievement and course choices in the other domain.

More recently, Möller and Marsh (2013) extended the I/E model into Dimensional Comparison Theory, and posited strong negative cross-subject effects of achievement on self-concept only for contrasting domains at opposite ends of the math-verbal continuum of academic self-concept (e.g., math & science versus reading) but much weaker negative or even positive assimilation effects for similar or complementary domains (near domains; e.g., math and science; also see Jansen, Schroeders, Lüdtke, & Marsh, 2015; Marsh et al., 2014).

Recently, Marsh et al. (2015) considered math/science-like subjects (i.e., biology, physics, and math) as near domain and found positive cross-subject effects of achievement on self-concept in these three domains controlling for matching achievement. However, there is insufficient research on the generalizability of the internal comparison process to different components of task value, particularly between the math and science domains, and how this comparison process influences subsequent educational choices (Möller & Marsh, 2013).

In relation to math course selection, there is strong evidence that math self-concept and task values are important predictors over and above prior math achievement (Parker et al., 2012, 2013, 2014; Simpkins et al., 2006, 2012; Wang, 2012; Watt, et al., 2006, 2012). Although modern EVT (Eccles, 2009) emphasizes that different value components should play differential roles in influencing educational choices, very few studies have considered multiple task value together with self-concept to examine their prediction of math participation (for exceptions, see Eccles, Barber, & Jozefowicz, 1999; Watt et al., 2012). For example, Eccles et al. (1999) found that utility value had stronger predictive power than intrinsic value and self-concept, suggesting that student might weight the usefulness of math for their future plan heavily in making their choices of taking advance math course. Also, a recent cross-cultural research found that math self-concept was more related to math achievement, whereas intrinsic and utility values were more related to math coursework selection (Marsh et al., 2013). In addition, most EVT studies have focused on the unique contributions of self-concept and task value (i.e., examining the effect of value controlling for self-concept; or including either self-concept or one value component at one time in the regression model) on achievement-related choices. However, recent research found that self-concept appeared to interact with task value in predicting educational outcomes (Nagengast et al., 2011; Trautwein et al., 2012; see further discussion below).

In relation to educational choices during the post-high school transition, it has been well documented that general high-stakes achievement (i.e., final school year matriculation results) is an important precursor of educational attainment, such as university entry and long-term occupational and socio-economic attainment, but not of STEM major selection during post-school transition (Bowen et al., 2009; Hauser, 2010; Wang & Dogel, 2013). Although high school achievement, motivational beliefs and math course selection have been shown to significantly predict educational and career aspirations related to math (e.g., Watt et al., 2012; Wang, 2012), still little is known about how these high school predictors influence subsequent STEM major taking during the post-school transition.

Multiplicative Relation Between Self-Concept and Task Values

EVT had its origins in an early cognitive model (i.e., the risk-taking model of achievement motivation; Atkinson, 1957), superseding earlier behaviorist models of animal behavior. A core assumption of the original EVT (Atkinson, 1957) was the multiplicative combination of expectancies of success and subjective task value (i.e., expectancy by value interaction) (also see Feather, 1982 for a review). The multiplicative relation between expectancy and value implies a synergistic relation - high expectancy alone is not sufficient to motivate behaviors. Rather, to choose an advanced math course, students need not only to think that they are good at math but also to value it highly. Although Eccles (2009, p.84) believes that “the motivational power of ability self concepts to influence task choice is, at least partially, determined by the value individuals attach to engaging in the domain”, in modern EVT (Eccles et al., 1983; Eccles, 2009) the relation between expectancies and task value is often implicitly assumed to be additive rather than multiplicative in predicting educational outcomes (also see Nagengast et al., 2011). Additive relation suggests that expectancy and task value uniquely and independently predict achievement-related outcomes. However, multiplicative relations suggest that the relation between self-concept (expectancy) and outcomes depends on the extent to which an individual values a given domain and vice versa.

Thus, the proposition of a multiplicative relation between expectancy and task value has important theoretical and practical implications for researchers in applied motivation. For example, tackling either self-related belief in isolation is unlikely to be an effective way to promote students' engagement with the subject domain.

Researchers have argued that this is due to methodological limitations in detecting multiplicative effects between latent constructs in non-experimental studies, rather than to any defined theoretical position favoring additive relationship (Nagengast et al., 2011; Nagengast, Trautwein, Kelava & Lüdtke, 2013; Trautwein et al., 2012). Indeed, classic approaches to interaction effects, in the context of multiple regression, rely on product terms of manifest variables that not corrected for measurement error (thus multiplying error), considerably limiting the ability to detect interactions (Dimitruk, Schermelleh-Engel, Kelava & Moosbrugger, 2007; see Marsh, Hau, Wen, Nagengast, & Morin, 2013 for further discussion).

Recently, two empirical studies have used Structural Equation Models (SEMs) with latent interactions corrected for measurement error, providing important evidence for a multiplicative relation of self-concept and task value in predicting achievement-related behaviors (Nagengast et al., 2011; Trauwein et al., 2012). Nagengast et al. (2011) conducted a strong cross-national test using the Programme for International Student Assessment (PISA) 2006 data, demonstrating significant multiplicative effects of science self-concept and intrinsic value across 57 countries, both on engagement in science activities and intention to pursue scientific careers. Trautwein et al. (2012) also revealed, based on a large sample of German high school students, that the multiplicative terms self-concept, and four subcomponents of value beliefs (attainment, intrinsic value, utility value, and cost), had positive effects on English and mathematics achievement. However, an important limitation of these studies is their reliance on a single wave of data. Longitudinal studies would allow us to draw stronger conclusion about directional influences of self-concept and task value and the importance of their interactions. Thus, the present study is unique in that it draws on a longitudinal national sample to explore the interactive role of self-concept and task value in the process leading to entry into university and STEM fields of study.

Gender Effects

According to modern EVT (Eccles, 2009), gendered socialization experiences influence individuals' motivated achievement-related choices through the relation of the hierarchy associated with individuals' domain-specific self-concepts and subjective task values. Although growing evidence in cross-national meta-analyses showed gender similarities in math achievement (Else-Quest, Hyde, & Linn, 2012; Lindbery, Hyde, Petersen, & Linn, 2012), female adolescents had lower self-concept in math compared with male adolescents (Parker et al., 2012, 2013, 2014; Marsh et al., 2007, 2013). However, there was no gender difference in math task value when treated as a single, general value scale (Jacobs et al., 2002; Wang, 2012; Wang & Eccles, 2012; see Gaspard et al., 2014 more discuss). Nevertheless, researchers differentiating components of task value (intrinsic vs. utility value) have shown that male adolescents have higher interest in math and perceived math as more useful than female adolescents (e.g., Eccles, Barber, & Jozefowicz, 1999; Marsh et al., 2013; Gaspard et al., 2014; Updegraff, Eccles, Barber, & O'Brien, 1996). Importantly, their differences in motivational beliefs predict disproportionate gendered enrollment in math courses (Eccles et al., 1999; Watt et al., 2012; Nagy, et al., 2006, 2008; Wang, 2012) and subsequent math-intensive major selection in university (Parker et al., 2012, 2013, 2014).

Furthermore, to better understand gendered processes underlying choice of educational pathway, Eccles (2009) suggests that research should focus on gender differences, not only in mean-level of motivational beliefs and educational choices, but also in the relationships between these constructs. However, on the basis of EVT, the extant research investigating gender as a moderator has been limited and has yielded mixed evidence (e.g., Simpkins et al., 2012; Watt, et al., 2012; Wang, 2012). For example, based on a multi-cohort study using data from Australia, Canada and USA, math utility value was found to be a stronger unique predictor of female adolescents' math-related career choices compared to math self-concept and intrinsic value (Watt et al, 2012). In contrast, Wang (2012) found that the relations between math self-concept and task value, and math-related career aspirations and math course taken are invariant across gender based on U.S. high school students. Taken together, it is pivotal to integrate both types of gender effects, to gain a better understanding of gender differences in decision-making process leading to different educational pathways.

The Present Investigation

Drawing on EVT (Eccles, 2009), this study aims to examine a development model describing the gendered process through which 15-year-old students' prior achievement (reading, math and science) and motivational beliefs (self-concept, intrinsic value and utility value) influence math course selection at Grade 11 and 12, high-stakes achievement (i.e., Tertiary Entrance Rank [TER]; final school year matriculation results), subsequent STEM fields of study, and university entry during transition into early adulthood. The underlying conceptual model is presented in Figure 1. These relationships are tested using data from a 10-year longitudinal follow-up of a large nationally representative sample of Australian youth. Specifically, we attempted to fill a gap in the literature on the motivation pathways to educational choices during the critical transition point with respect to three deficiencies. First, little longitudinal research has explored the interactive role of self-concept and task value on long-term educational outcomes. Second, few studies have investigated internal comparison processes between multidimensional achievement and motivational constructs, and how these internal comparison processes influence educational choices. Third, attempts to systematically examine whether the gendered relationships among academic achievement, motivational beliefs, and long-term educational outcomes are lacking.

It should be noted that although the hypothesized model depicts paths leading for prior achievement to motivational construct and subsequent educational outcomes, we do not make assumptions about the directions of causal relations among these constructs in the context of the current research. Our main research hypotheses were as follows:

Hypothesis 1: Of central importance to the investigation, we hypothesized that self-concept, task value and their interaction would positively predict TER scores and math course selection (e.g., Nagengast et al., 2011; Trautwein, et al., 2012), which would be respectively associated with a greater likelihood of entering university (e.g., Hauser, 2010) and undertaking a STEM major (e.g., Parker et al., 2012, 2013, 2014).

Hypothesis 2: Prior domain-specific achievement would influence educational achievement and choices, directly or indirectly, through math self-concept and task value (e.g., Nagy et al., 2006, 2008; Parker et al., 2012). More specifically, according to the internal comparison process posited in I/E model (Marsh, 2007) and Dimensional Comparison Theory (Möller and Marsh, 2013), it is expected that prior reading achievement would negatively predict motivational beliefs and choices related to math, while prior science and math achievement would positively predict math-related motivational beliefs and choices. Nonetheless, domain-specific achievement scores would positively predict general (non-domain-specific) high-stakes TER scores.

Hypothesis 3: In relation to the effect of gender, we expect the predictive effect of gender in educational outcomes would in part be mediated through motivational beliefs (e.g., Parker et al., 2012; Schoon & Polek, 2011; Eccles, et al., 1999). Further, given the absence of strong theoretical or empirical evidence regarding the extent to which the proposed relations vary by gender, we explore whether the effects of EVT predictors on educational outcomes differ as a function of gender.

In the present investigation, we reintroduce a longstanding substantively important issue—the omission of multiplicative relationships between expectancy and task value—and extend the integration of substantive theories (i.e., EVT and DCT models). To tackle these complex issues, we apply strong and evolving methodological approaches to create more appropriate tests of latent-variable models of the direct and indirect effects of continuous and dichotomous outcomes. Thus, our study is a substantive-methodological synergy (Marsh & Hau, 2007), using advanced statistical methodology to address substantive issues with important theoretical and practical implications for researchers in applied motivation.

Method

Participants

The data used in the present study came from the 2003 cohort of the Longitudinal Study of Australian Youth (LSAY03) extension of PISA 2003 (PISA2003). The LSAY03 was a multi-wave longitudinal follow-up study, with a nationally representative sample of 15-year-old students in Australia secondary schools (N = 10370). At the initial survey wave, integrated with PISA2003, a two-stage sampling procedure was employed. The first stage comprised a sample of 314 schools selected from a complete list of schools, with probabilities proportional to their size, and then an average of roughly 33 students were elected randomly from each of the selected schools. As a result of this selection process, the majority of the sample was in the first year of upper high school in Australia (Year 10, N = 7,378, 71.1%), followed by Year 11 students (N = 2,105, 30.3%) and Year 9 students (N = 868, 8.4%). The sample comprised nearly equal numbers of females (N = 5,149) and males (N = 5,221). These participants were then surveyed each subsequent year, for the ten years following 2003.

Measures

Although academic achievement in reading, mathematics and science were assessed in PISA2003, only math-related motivation items were included in the questionnaire (see OECD, 2005). All motivation items were coded on a Likert scale, with 1 indicating that the participants "strongly agree" and 4 indicating "strongly disagree". However, for the present purposes, responses were reverse-scored, so that higher values represent more favorable responses and thus, higher levels of motivation (see Appendix 1 in the Supplemental Materials for more detail regarding the items used and the scale-score reliability estimates).

Math self-concept. Mathematics self-concept in the PISA2003 database was measured with five items (e.g., "I learn Mathematics quickly."). These items were partly based on the Academic Self-Description Questionnaire-II (Marsh, 1990, 1993).

Math intrinsic value. Four items were used to assess the affect students experienced when participating in mathematics-related activities (e.g., "I am interested in the things I learn in mathematics").

Math utility value. In line with the notion of utility value in the modern EVT (Eccles, et al., 1983), four items were used to assess how well mathematics learning relates to current and future goals (e.g., "Learning mathematics is worthwhile for me because it will improve my career").

Academic achievement. Participants' academic abilities were measured by academic achievement test items, a combination of multiple choice and written tasks in pencil and paper format. To prevent biased population estimates, the PISA measured reading, mathematics and science abilities, using five plausible values for each subject (with a mean of 500, standard deviation of 100). Hence, in the current study, to be able to correct the measurement error appropriately, these sets of plausible values were used to measure students' achievement (see OECD, 2005).

High school mathematics course selection. Participants were asked to report the level of mathematics class they had taken or were taking in Grade 11 and Grade 12, when Math coursework is no longer a compulsory subject and Math courses are designed according to course demand and difficulty. We treated the response of math course selection as a continuous variable, ranging from (1) “no math course”, (2) “basic math course” (i.e., Essential Mathematics), (3) “general math course” (i.e., General Mathematics), (4) “medium math course” (i.e., Mathematical Method), to (5) “advanced math course” (i.e., Specialist Mathematics). A higher value on these items indicates that students took a more complex math course in senior high school. If more than one category was chosen by participants, the more complex math class was coded.

Postsecondary STEM major selection. Participants were asked whether they were studying in a STEM major at the tertiary level. This dichotomous item was only available at Wave 5 (2 year post-secondary education), when participants were 19 years old. Those studying in a STEM major were coded as 1, while those who were not were coded as 0.

Tertiary entrance rank. The tertiary entrance rank (TER) was a tertiary entrance score, consisting of standardized tests and school based assessment. These ranks were awarded to students at Year 12 (average age 17), the final year of high school, and were the primary metric on which university and university course placement were determined in Australian universities. This item was collected from Wave 3 to Wave 6, in which each participant only has one TER score. TER was measured by a combination of school-based achievement and state-wide standardized testing, with a 100-point scale in all states except Queensland (100 being the highest possible TER rank). However, a 25-point scale instead was used in Queensland, with 1 being the highest possible TER rank (see Marks et al., 2001 for more details). For the present purposes, the TER scores in Queensland were reversed, and all the TER scores were standardized (z-scored) within each state.

University entry. Participants were asked if they were studying or had studied in university since Wave 1. This item had been updated at the following wave. Those who entered university study at any stage from 2003 to 2012 were coded 1, whereas those who had never entered university prior to 2012 were coded 0.

Covariates. Gender (0 = male, 1 = female), and SES (Economic, Social and Cultural Index [ESCS]; see OECD, 2005) were treated as covariates, in which the effect on all variables was freely estimated. Specifically, the ESCS was created on the basis of the variables relating to family background, including the highest occupational status of parents, the highest educational level and an estimate related to household possessions. Furthermore, given that the PISA samples are age-based, grade level (hereafter Year) differed across participants and was found to be significantly associated with motivational beliefs and educational outcomes in the PISA data (Parker et al., 2013). Therefore, Year was also included as a covariate in our hypothesized model.

Data Analysis

Missing data. The amount of missing data for motivational items and academic achievement at Time 1 was small (ranging from .6% to 1.4% per item). Since the LSAY data covers a ten-year period and includes post-high-school transition, the sample attrition rate was relatively large, particularly for post-school outcomes, which typically were estimated several years after the initial time wave (14.8% for Mathematics course selection; 26.5% for university entry; 28.2% for TER scores; 34.8% for STEM major selection). In the present study, missing data were handled using multiple imputation, which has been shown to be robust to departures from normality assumptions and to provide adequate results even for high rates of missing data (Graham, Cumsille, & Elek-Fisk, 2003; Schafer & Graham, 2002). Given that participants who come from more disadvantaged SES backgrounds or have lower self-beliefs are much more likely to drop out of the study (see Parker et al., 2013), the items pertaining to demographic background and motivational beliefs were all included as auxiliary variables in multiple imputations[1]. To fully account for the plausible values of academic achievement, two sets of missing data imputations were created for each plausible value, meaning that in total, ten imputations were created for the analysis, using the R package Amelia II (Honaker, King, & Blackwell, 2011). All categorical variables (e.g., STEM and University entry) were treated as nominal variables in multiple imputation process. All data analyses were run separately and the results were aggregated appropriately, in order to obtain unbiased estimates (Rubin, 1987).

Estimator. Structural equation modeling (SEM) with Mplus 7.11 (Muthén & Muthén, 2008—2013) was used to examine the hypothesized relations among latent constructs and outcome variables. In the present study, three latent constructs were measured: math self-concept, intrinsic value and utility value. In relation to estimator, robust maximum likelihood (MLR) with the LINK = PROBIT option was used. The relationships between covariates, prior academic achievement, motivational constructs, math high school course selection and TER were estimated by MLR, while probit regression was used to estimate the relations to binary outcomes—university entry and STEM major selection.

To allow for probit regression coefficients to be interpreted in a more intuitive manner, these coefficients were converted to probability value according to the instruction presented in the Mplus User's Guide (Muthén & Muthén, 1998-2013, p.492). The probability differences presented in the Figure 2 indicated that the likelihood of entering university or choosing a STEM major, with changes of one SD increase in the continuous predictor variable, when all other continuous independent variables were held at their mean and discrete independent variable (i.e., gender) was set to its mode value. For gender, a positive

[1] Supplemental analysis: we created an attrition group variable coded one for participants who left the study during the post-secondary school transition and zero otherwise. We used t-tests to examine mean differences by two groups (attrition group vs the group with full data) in SES and motivational beliefs. The results revealed that compared to the group with full data, attrition group was lower on SES (.40 *SD*), math self-concept (.51 *SD*), intrinsic value (.39 *SD*) and utility value (.38 *SD*).

probability value indicated a higher probability to enter university and STEM fields of study in favor of females (also see Wang, 2013, p.24 for more discuss).

Analysis plan. To address the research questions, we began with a SEM based on the conceptual model (Figure 1) but excluded latent interactions. The indirect and total effects were assessed using the MODEL CONSTRAINT command, where the delta method was utilized to estimate the standard errors of indirect effects (MacKinnon, 2008). After examining direct and indirect relations, latent interactions between math self-concept and task values were incorporated into the path model using the latent moderated structural (LMS) equations approach (Klein & Moosbrugger, 2000). The advantage of the LMS approach is that it corrects for measurement error of latent constructs and provides unbiased estimates of latent interaction effects. Further, LMS represents the nonnormal distribution as a mixture of conditionally normal distributions, thus separate indicators of the product terms are not required (Kelava et al., 2011).

The LSAY database has a nested data structure in which students are nested within schools. To account for this nested structure, we used the TYPE = COMPLEX option in Mplus to adjust the standard errors. In relation to fit indices, the comparative fit index (CFI), the root-mean-square error of approximation (RMSEA) and the Tucker-Lewis Index (TLI) were used to determine model fit. Values greater than .95 and .90 for CFI and TLI typically indicate excellent and acceptable fits respectively, to the data. RMSEA values of less than .06 and .08 are considered to reflect good and acceptable statistical fits, respectively, to the data (Marsh, Hau, & Grayson, 2005).

To explore whether the hypothesized relations in the final model vary as a function of gender, we conducted a multi-group comparison analysis in SEM (Bollen, 1989) and tested a series of increasingly stringent invariance constraints on the parameters of measurement and structural model, in which little or no change in goodness of fit supported invariance of the factor structure (Millsap, 2011, see Appendix 3 in the Supplemental Materials for more detail).

In order to enhance the interpretation of the results, we standardized (z-scored) all the variables to be Mean (*M*) = 0, Standard Deviation (*SD*) = 1, except for the dichotomous variables (see Raudenbush & Bryk, 2002).

Results

A Confirmatory Factor Analysis (CFA) was employed to examine the factor structure of math self-concept and task values. The measurement model provided an adequate fit (CFA model: $\chi^2(42)$= 1523.437, df = 62, CFI = .977, TLI = .971, RMSEA = .048). Latent correlations indicated that math self-concept was moderately correlated with utility value (r = .49) and somewhat more highly correlated with intrinsic value (r = .70), while the correlation between intrinsic value and utility value was .59. Further, supporting the construct validity of motivational beliefs, math self-concept and task values were all more highly correlated with achievement in math than in reading and science. Compared to task values, math self-concept was more strongly correlated with academic achievement, math course selection and TER. Gender differences in math motivational beliefs and math course selection favoring males were moderate in size, whilst males were favored to a small extent in math achievement. However, females scored substantially higher in reading achievement and TER than males. Females were more likely to attend university but opted out of advanced math courses and further STEM majors (see Appendices 2–3 of the Supplemental Materials for the full correlation matrix and more details about gender difference).

To explore direct and indirect relationships between domain-specific academic achievement, motivational factors, TER and educational choices, the SEM model was analyzed, based on the whole sample. The model accounted for 53.1%, 22.4%, 40.7% and

27.5% of the variance in university entry, STEM major selection, TER and high school math course selection respectively. The model also explained 25.4%, 10.2% and 10.4% of the variance in math self-concept, intrinsic value and utility value respectively. The standardized path coefficients of direct, indirect and total effects are presented in Tables 1 and 2. Probability differences for statistically significant direct effect on university entry and STEM major selection are also included.

Effects of Prior Achievement on Motivational Beliefs and Educational Outcomes

Consistent with our hypotheses, three achievements (math, reading and science) were all statistically significantly associated with motivational beliefs. Specifically, math and science achievement were each positively associated with math self-concept and intrinsic and utility values, although the effect sizes relating to science achievement were relatively small. Nevertheless, reading achievement was negatively associated with math motivational beliefs. Only math achievement significantly positively predicted math course selection, and there were no significant direct effects of prior achievement on STEM major selection. All three achievements were positively associated with TER, whereas math and reading achievement were significant predictors of university entry. In terms of probability difference, the results revealed that one SD increase from the mean in math and reading scores led to .04 and .06 increases respectively in the probability of entering university.

In addition, motivational beliefs fully mediated the relationships between reading and science achievements and selections of math course and STEM major. Specifically, reading achievement had negative indirect effects on math course and STEM major selections, whereas science slightly positively predicted these outcomes. Similarly, reading achievement exerted negative indirect effects on TER via math motivational beliefs, but was offset by the positive corresponding direct effect. Math achievement indirectly and positively predicted all educational outcomes.

Effects of Motivational Beliefs on Educational Outcomes

Math self-concept, intrinsic value and utility value positively predicted math course selection in high school, whereas only math intrinsic value and utility value had positive direct effects on STEM major selection. As stated previously, in probability terms, one SD increase from the mean in math intrinsic value and utility value led to similar probability increases (.04 and .06 respectively) of selecting a STEM major. The relationship between math self-concept and STEM major selection was fully mediated by math course selection. Although math self-concept and intrinsic value were significant predictors of TER, they did not directly predict subsequent university entry. In contrast, utility value positively predicted university entry but not TER. The relationships between math self-concept and intrinsic value and university entry were fully mediated by TER. In total, each motivational belief had similar predictive power on university and STEM entrance.

Finally, postsecondary STEM major choice was predicted by math high school course selection, while university entry was substantially predicted by TER. In probability terms, here one SD increase from the mean in math course selection and TER led to a relatively higher probability increase (.08 and .15 respectively) of entering a STEM major and university respectively.

Multiplicative Effect of Math Self-Concept and Task Value

To test the multiplicative relation between math self-concept and task values, we added the latent interaction between self-concept and intrinsic value and between self-concept and utility value to predict TER and educational choices, based on the conceptual model (Figure 1[2]). The results show that the interaction between math self-concept and intrinsic value

[2] Supplemental analyses: we examined the interaction effect between self-concept and value based on two hypothesized models where only one value component (intrinsic or utility value) was included. We found self-concept, intrinsic value and their interaction significantly positively predicted TER and math course selection (ranging from .07 to .20). However, only intrinsic value had a direct predictive effect on entrance into university and STEM major selection (.17 and .14 respectively). Similar patterns were found for the model involving

positively predicted math course selection (main effect: self-concept [β = .18], intrinsic value [β = .07]; interaction effect: [β = .07]) and TER (main effect: self-concept [β = .18], intrinsic value [β = .08] and interaction effect: [β = .08], $p < .001$). The simple-slopes in Figure 3 show that math self-concept had a positive effect on the two outcomes at different levels of intrinsic value (i.e., mean and one SD below and above the mean). When self-concept was at nearly 1 SD below the mean, different levels of intrinsic value tended to predict similar outcome levels. This finding supports the synergistic relation of math self-concept and intrinsic value in predicting the two outcomes: Choice of advanced mathematics course, and high TER scores, occurred only when self-concept and intrinsic value were both relatively high. Interestingly, math self-concept and intrinsic value positively interact in predicting university entry and STEM major selection through their influence on the TER and math course selection (i.e., *moderated mediation;* Preacher, Rucker, & Hayes, 2007; also see Muller, Judd, & Yzerbyt, 2005). The indirect effect of math self-concept on university entry and STEM major selection, via TER, varied with level of intrinsic value (i.e., the indirect effect became larger as intrinsic value increased; also see Appendix 4 in the Supplemental Materials). However, the multiplicative effects between self-concept and utility value on course selection and TER were not statistically significant. All path coefficients in the model with interactions are similar with those without interactions (i.e., Figure 2; see Appendix 5 in the Supplemental Materials for more details).

---

utility value, with an exception that the predictive effect of self-concept on STEM major selection became significant (.10). In sum, for the model involving one value component, the interactions between self-concept and intrinsic value as well as between self-concept and utility value positively predicted TER and math course selection, whereas only the interaction between self-concept and intrinsic value was statistically significant when the model included both value components and their interactions with self-concept. The significant interaction effects for different models were similar in size. The interaction effects on entrance into university and STEM major selection were fully mediated by TER and math course selection respectively (also see Appendix 7-8 in Supplemental Materials for more details).

Predictive Effects of Gender on motivational beliefs and educational outcomes

As hypothesized, gender was negatively associated with math achievement, math self-concept and intrinsic and utility values, indicating that males had higher math achievement and motivation beliefs, controlling for SES and school year. Similarly, gender was negatively associated with math course and STEM major selection. Nonetheless, gender was positively associated with reading achievement, TER and university entry. The results indicate that, in terms of gender difference in probability, males had a higher probability of opting for a STEM major (-.04), whereas females had a higher probability of entering university (.06). In relation to indirect effects, academic achievement partially mediated the relationships among gender and self-concept and intrinsic value. Similarly, academic achievement and motivational beliefs partially mediated the relationship between gender and math course and STEM major selections.

In addition, we conducted supplemental analyses to test the moderating role of SES on gendered relations among achievement, motivation beliefs and educational outcomes. Specifically, we added the product term between gender and SES into the hypothesized model to examine the effects of this interaction on prior achievement, educational beliefs and educational outcomes. However, this interaction effect was statistically non-significant, indicating that SES did not moderate the relations between gender and achievement, motivational beliefs and educational outcomes. Detailed results and discussion of the effect of SES are provided in Appendix 6 in Supplemental Materials.

Moderation Effect of Gender

Before examining whether the hypothesized relations vary by gender, based on the final structural model, we tested the invariance of the confirmatory factor analysis (CFA) measurement model for males and females. The measurement invariance test showed that the changes in model fits were negligible (see Appendix 3 in the Supplemental Materials for more details).

After examining measurement invariance, all paths were constrained to be equal in multi-group SEM models. As fit statistics are not available for models that have categorical outcomes, -2 times the log-likelihood difference (i.e., -2ΔLL), which was distributed as Chi-square and equivalent to the chi-square difference test ($\Delta\chi^2$), was used to compare nested models. The change in -2LL between the unconstrained (i.e., path-non-invariant) and path-invariant SEM model was statistically significant (-2ΔLL (53) = 71.79, p < .001). Given the sample size, however, this difference was marginal. Further post hoc analyses showed that there were significant differences across gender in the relation between math achievement and utility value ($\Delta\chi^2(1) = 4.61$, $p < .05$) as well as between reading achievement and utility value ($\Delta\chi^2(1) = 8.50$, $p < .01$). Math achievement was more strongly associated with utility value for males (.24, $p < .001$) than for females (.15, $p < .001$). Reading achievement was a negative predictor of utility value for males (-.14, $p < .001$), whereas the corresponding effect was not statistically significant for females (-.02, $p = .593$). In addition, the result showed gender differences in the relation between math achievement and math course selection ($\Delta\chi^2(1) = 5.21$, $p < .05$). Similarly, math achievement was more strongly associated with math course selection for males (.24, $p < .001$) than for females (.17, $p < .001$). All other relations in the conceptual model did not vary as a function of gender. Taken together, we found only three significant gender-differentiated patterns out of 63 cases.

Discussion

The current study represents one of the most comprehensive tests of Eccles's (2009, 2011) model of achievement-related choices, simultaneously testing the effect of achievement, expectancy, value and expectancy-value interactions, in predicting a sequence of educational choice, both before and after the transition from high-school. As expected, students' achievement predicts math self-concept, math intrinsic value and utility value. In turn, students who master math skills and find math interesting or useful are more likely to take advanced math courses and to achieve high TER scores, which predict post-secondary educational choices. More importantly, these results provide longitudinal support for the multiplicative effect of math self-concept and intrinsic value in predicting educational outcomes.

Predictive Effect of Self-Concept, Task Value and Their Interaction

This study extends prior research on motivational pathways to STEM choices by linking high school math motivational beliefs and math course selection to further STEM major taking. Each math motivation belief has a significant contribution in math course selection after controlling for prior achievement, suggesting that expectancy-value motivations are independent predictors and facilitates students' willingness to take the more difficult math courses in senior high school, over and above achievement. However, the task value that students attach to math, particularly for utility value, is more directly related to STEM major selection and university entrance compared to math self-concept, even though these three motivation beliefs have similar predictive power on postsecondary educational choices in terms of the total effects. In contrast, math self-concept is a stronger predictor of high-stakes TER scores compared to task value, but relates to STEM major selection and university entrance via the different level of math courses students adopt and TER scores in senior high school respectively. These findings are partially consistent with previous studies demonstrating that academic self-concept is more related to academic achievement, whereas task value is more related to educational choices. (e.g., Marsh, Trautwein, Lüdtke, Köller, & Baumert, 2005; Marsh et al., 2013; Eccles et al., 1999). Given that most EVT research only included a general task value or one of value components in the regression model to assess educational choices (e.g., Wang, 2012; Simpkins et al., 2006; Watt et al., 2006), our finding adds further nuances to our understanding of how self concept and different value components contribute to the decision making process, thus providing empirical evidence for the importance of differentiating and incorporating multiple value components.

One of the central contributions of this study is the examination of longitudinal predictions of the self-concept by value interaction in relation to modern EVT (Eccles, 2009). Consistent with our expectations, we found that the synergistic, multiplicative, relation between math self-concept and intrinsic value predicted both math course selection and TER. More importantly, this is the first study to test this hypothesized latent interaction between self-concept and task value on long-term attainment and critical educational choices. Our finding indicates that the multiplicative effects of self-concept and intrinsic value on postsecondary educational choices are fully mediated through math course selection and TER. The observed synergistic relations suggest that students with high math self-concept and intrinsic value are more likely to select advanced math courses, achieve more academically, enter university, and pursue STEM fields of study. However, students with high self-concept are unlikely to attain these educational outcomes if they ascribe a low level of intrinsic value to math. Similarly, students who value math are also unlikely to attain these outcomes if their math self-concept remains low. Aligning with recent cross-sectional studies of the interactive role of self-concept and value (Trautwein et al., 2012; Nagengast et al., 2011; 2013), our results provide longitudinal evidence and strong support for theoretical assumption that self-concept and value interact in predicting achievement-related outcomes and underscore the importance of taking the expectancy by value interaction into account in future EVT studies.

These findings suggest that interventions targeting the promotion of academic performance and math participation, as well as university and STEM pathways, should seek to enhance both math self-concept and intrinsic value. To do this, utility-value interventions, such as identifying personal utility-value connections between students' lives and what they are learning in class, have been found to be effective to trigger students' interest and promote academic performance in STEM topics (Hulleman & Harackiewicz, 2009; Hulleman, Godes, Hendricks & Harackiewicz, 2010; also see Harackiewicz, Tibbetts, Canning, & Hyde, 2014 for a review). For interventions aiming to increase academic self-concept, meta-analyses (Huang, 2011; O'Mara, Marsh, Craven, & Debus, 2006) suggest that self-enhancement and skill development should be integrated in interventions targeting a specific domain rather than global or skill-based self-concepts. More importantly, the observed synergistic relation also suggests that multi-component interventions (e.g., Martin, 2008; Guthrie, Wigfield, & VonSecker, 2000) may be more effective in promoting students' motivation than those based on self-concept and value interventions individually. For example, the Concept-Oriented Reading Instruction (CORI) intervention (Guthrie et al., 2000) was designed to target five motivational processes, including self-efficacy and mastery (self-concept) and intrinsically motivating activities (task value). The CORI has been shown to boost students' reading motivation (Guthrie, McRae, & Lutz Klauda, 2007). However, such multiple-component intervention has not yet been fully investigated in relation to math and science school learning.

Internal Comparison Process

Consistent with our hypotheses, math self-concept, intrinsic value and utility value are positively associated with prior math and science achievements, but negatively associated with prior reading achievement. These findings suggest that academic self-concept and task value are involved in the internal comparison process between math and verbal domains, while the ipsative process is not triggered between the math and science domains, due to their proximity on the academic continuum. In addition, all achievements are found to be more strongly predictive of math self-concept than task values. This result is consistent with previous studies (e.g., Eccles et al., 1999; Eccles, 2009) suggesting that the formation of relative self-concept is more dependent on prior performance, while the formation of relative task value is more dependent on an individual's personal and collective identities, as well as on social and psychological experiences (also see Marsh et al., 2005). For instance, the value of participating in a particular task depends on the individual's needs, motives and personal values (i.e., their personal identity) and on whether the task fulfills his/her collective/social role (e.g., gender role) (Eccles, 2009).

Importantly, our results explicitly explain how the internal comparison process influences math-related educational choices. Students with high reading ability are more likely to have relatively low math self-concept and task values. This in turn, adversely influences math course taking and subsequent STEM major selection. Hence, this finding adds to the notable evidence that individuals who have both high mathematical and verbal ability are less likely to pursue careers in the STEM fields, compared to those with high mathematical but only moderate verbal ability (Chow & Salmela-Aro, 2011; Wang, Eccles, Kenny, 2013).

Gender Differences

As expected, gender differences in achievement-related behaviors are partially mediated by gender differences in prior academic achievement and math motivational beliefs. Specifically, gender differences in math motivational beliefs favoring boys partially mediate gender disparity in math course and STEM major selections when prior achievement is controlled. This finding supports the premise that girls would, on average, be less likely than boys to enroll in advanced math courses, as a result of their having lower math self-concepts and lower intrinsic math motivation, and due to placing less extrinsic value than boys on math (Nagy et al., 2006; 2008; Eccles et al., 1999; Simpkins et al., 2006). Consequently, gender difference in STEM is partially mediated by gender difference in math course selection. This finding aligns with other research (Watt, 2010; Watt et al., 2012) showing that girls often opt out of the math “pipeline” during senior high school, leading to the constraining of educational choice related to STEM fields. Effective preventative interventions that aim to enhance girls’ retention in math through high school would be beneficial in supporting girls to pursue STEM careers. In contrast, girls’ overrepresentation in tertiary education is partially mediated by gender difference in TER marks, and thus particular interventions that focus on boys’ underperformance in high school are required.

In spite of gender differences in the mean-level of math motivational beliefs and educational outcomes, gender did not largely moderate the relations between these factors. Post hoc analysis showed that only three paths did vary by gender (see Appendix 3 in Supplemental Materials for more discuss). These results suggest that similar interventions would promote adolescent males’ and females’ pursuit of math course and STEM majors. However, given that the effect sizes of gender-differentiated patterns are marginal in terms of the sample size of the present study, replication studies are warranted.

Limitations of This Study

Some limitations should be considered when interpreting the results. First, this study only examines the roles of students’ math motivational beliefs in the process leading to entrance into university and STEM fields of study. Given that reading and science self-concept and task values also have substantial impacts on this process, the further inclusion of multiple domain-specific self-concept and task values would provide a more comprehensive picture to illuminate the roles of motivational beliefs. Second, while our model addresses the reciprocal process between academic achievement and the motivational beliefs described in Eccles’s expectancy-value model (Eccles, 2009, 2011), the data related to domain-specific achievement and motivational beliefs was collected within a single wave. Also, Eccles notes that the relations between motivational beliefs and educational choices appear to be reciprocal. For example, attending a different level of math course would provide a different social context to students, in which their math motivation beliefs, subsequently, would be shaped by their subjective interpretation of those experiences within the new class context (Eccles, 2009). Therefore, further research using fine-grained longitudinal studies is needed, to explore the reciprocal processes of motivational beliefs and achievement-related behaviors. Additionally, motivational beliefs are likely to play different roles in the decision-making processes in educational pathways across different countries (Parker et al., 2012; Watt et al., 2012). Future comparison of longitudinal studies across different national/international samples would be of use in clarifying whether the findings identified in the present study are unique to this Australian sample, or whether they represent a generalizable decision-making process. Finally, an important direction for further research would be to take ethnicity and its interaction with gender into account, thus providing a more nuanced understanding of individual ethnic and gender differences in choices of education pathways.

Conclusion

This present research shows a vital secondary-postsecondary nexus in the pursuit of university and STEM educational pathways, by revealing the impact of individual characteristics, prior domain-specific achievement, math motivational beliefs and achievement-related behaviors. One important conclusion of this study is that to achieve high academic performance and take more advanced math courses in senior high school, both math self-concept and intrinsic value need to be high. Also, the synergistic relation between self-concept and intrinsic value contributes to the prediction of entrance into university and STEM fields of study. Furthermore, prior math and science achievement positively predicted math motivational beliefs and all educational outcomes, whereas prior reading achievement had adverse influences on math courses and STEM major selection, through its negative association with math motivational beliefs. Finally, gender differences in educational outcomes are mediated by gender differences in motivational beliefs and prior academic achievement, while the process underlying choice of educational pathways was similar for males and females. Taken together, and supporting the importance of substantive-methodological synergies (Marsh & Hau, 2007), the application of strong and evolving methodological approaches in the present study leads to substantively important findings with practical implications for educational policy-makers and practitioners seeking to promote equity engagement in university and STEM fields of study.

References

Atkinson, J. W. (1957). Motivational determinants of risk-taking behavior. *Psychological review, 64, Part 1*(6), 359–372.

Bollen, K. A. 1989. Structural equations with latent variables. New York: Wiley.

Bowen, W. G., Chingos, M. M., & McPherson, M. S. (2009). *Crossing the finish line: Completing college at America's public universities*. Princeton, NJ: Princeton University Press.

Bøe, M. V., Henriksen, E. K., Lyons, T., & Schreiner, C. (2011). Participation in science and technology: young people's achievement-related choices in late-modern societies. *Studies in Science Education, 47*(1), 37–72. doi:10.1080/03057267.2011.549621

Chow, A., & Salmela-Aro, K. (2011). Task-values across subject domains: A gender comparison using a person-centered approach. *International Journal of Behavioral Development*, *35*(3), 202–209. doi:10.1177/0165025411398184

Dimitruk, P., Schermelleh-Engel, K., Kelava, A., & Moosbrugger, H. (2007). Challenges in Nonlinear Structural Equation Modeling. *Methodology: European Journal of Research Methods for the Behavioral and Social Sciences*, *3*(3), 100–114. doi:10.1027/1614-2241.3.3.100

Eccles, J. S. (2009). Who am I and what am I going to do with my life? Personal and collective identities as motivators of action. *Educational Psychologist, 44*(2), 78–89. doi:10.1080/00461520902832368

Eccles, J. S. (2011). Gendered educational and occupational choices: Applying the Eccles et al. model of achievement-related choices. *International Journal of Behavioral Development*, *35*(3), 195–201. doi:10.1177/0165025411398185

Eccles, J. S., Barber, B., & Jozefowicz, D. (1999). Linking gender to education, occupation, and recreational choices: Applying the Eccles et al. model of achievement-related choices. In W. B. Swann, J. H. Langlois, & L. A. Gilbert (Eds.), *Sexism and stereotypes in modern society: The gender science of Janet Taylor Spence* (pp. 153–192). Washington, DC: APA Press.

Eccles (Parsons), J. S., Adler, T. F., Futterman, R., Goff, S. B., Kaczala, C. M., Meece, L. J., & Midgley, C. (1983). Expectancies, values, and academic behaviors. In J. T. Spence (Ed.), *Achievement and achievement motivation: Psychological and sociological approaches* (pp. 75–146). San Francisco, CA: Freeman

Eccles, J. S., & Wigfield, A. (2002). Motivational beliefs , values , and goals. *Annual Review of Psychology, 53*(1), 109–132.

Else-Quest, N. M., Hyde, J. S., & Linn, M. C. (2010). Cross-national patterns of gender differences in mathematics: a meta-analysis. *Psychological Bulletin, 136*(1), 103–27. doi:10.1037/a0018053

Feather, N. T. (1982). Expectancy-value approaches: Present status and future directions. *Expectations and actions: Expectancy-value models in psychology*, 395–420.

Gaspard, H., Dicke, A.-L., Flunger, B., Schreier, B., Häfner, I., Trautwein, U., & Nagengast, B. (2014, October 27). More Value Through Greater Differentiation: Gender Differences in Value Beliefs About Math. *Journal of Educational Psychology*. Advance online publication. http://dx.doi.org/10.1037/edu0000003

Graham, J. W., Cumsille, P. E., & Elek-Fisk, E. (2003). Methods for Handling Missing Data. In A. S. & W. F. Velicer (Ed.), *Research Methods in Psychology* (pp. 87–114). John Wiley & Sons, Inc. doi:10.1002/0471264385.wei0204

Guo, J., Marsh, H. W., Morin, A. J. S., Parker, P., & Kaur, G. (2015). Directionality of the Associations of High School Expectancy-Value, Aspirations and Attainment over Eight Years: A Multiwave, Longitudinal study. *American Educational Research*

Journal, *52*(2), 371–402. doi:10.3102/0002831214565786

Guo, J., Marsh, H. W., Parker, P. D., Morin, A. J. S., & Yeung, A. S. (2015). Expectancy-Value, Gender and Socioeconomic Background as Predictors of Achievement and Aspiration: A Multi-cohort Study. *Learning and Individual Differences, 37*, 1–8. doi:10.1016/j.lindif.2015.01.008

Guthrie, J. T., McRae, A., & Klauda, S. L. (2007). Contributions of concept-oriented reading in- struction to knowledge about interventions for motivations in reading. *Educational Psychologist*, 42(4), 237-250.

Guthrie, J. T., Wigfield, A., & VonSecker, C. (2000). Effects of integrated instruction on motivation Hauser, R. M. (2010). Causes and Consequences of Cognitive Functioning Across the Life Course. *Educational Researcher, 39*(2), 95–109. doi:10.3102/0013189X10363171

Hauser, R. M. (2010). Causes and consequences of cognitive functioning across the life course. *Educational Researcher*, *39*(2), 95–109. doi:10.3102/0013189X10363171

Honaker, J., King, G., & Blackwell, M. (2011). Amelia II: A program for missing data. *Journal of Statistical Software, 45*, 1–47. Retrieved from http://www. jstatsoft.org/v45/i07.

Huang, C. (2011). Self-concept and academic achievement: A meta-analysis of longitudinal relations. *Journal of School Psychology*, *49*(5), 505–528. doi:10.1016/j.jsp.2011.07.001

Hulleman, C. S., Godes, O., Hendricks, B. L., & Harackiewicz, J. M. (2010). Enhancing interest and performance with a utility value intervention. *Journal of Educational Psychology*, *102*(4), 880–895. doi:10.1037/a0019506

Hulleman, C. S., & Harackiewicz, J. M. (2009). Promoting interest and performance in high school science classes. *Science, 326*(5958), 1410–1412. doi:10.1126/science.1177067

Harackiewicz, J. M., Tibbetts, Y. Canning, E., & Hyde, J. S. (2014). Harnessing Values to Promote Motivation in Education. *Motivational Interventions, 18,* 71-105. doi:S0749-742320140000018002

International Monetary Fund. (2010). *World economic outlook: Recovery, risk and rebalancing*. Washington, DC: International Monetary Fund.

Jacobs, J. E., Lanza, S., Osgood, D. W., Eccles, J. S., & Wigfield, A. (2002). Changes in children's self-competence and values: Gender and domain differences across grades one through twelve. *Child Development*, *73*(2), 509–527. doi:10.1111/1467-8624.00421

Jansen, M., Schroeders, U., Lüdtke, O., & Marsh, H. W. (2015, February 9). Contrast and assimilation effects of dimensional comparisons in five subjects: An extension of the I/E model. *Journal of Educational Psychology*. Advance online publication. http://dx.doi.org/10.1037/edu0000021

Kelava, A., Werner, C. S., Schermelleh-Engel, K., Moosbrugger, H., Zapf, D., Ma, Y., … West, S. G. (2011). Advanced nonlinear latent variable modeling: distribution analytic lms and qml estimators of interaction and quadratic effects. *Structural Equation Modeling*, *18*(3), 465–491. doi:10.1080/10705511.2011.582408

Kimmel, L. G., Miller, J. D., & Eccles, J. S. (2012). Do the Paths to STEMM Professions Differ by Gender? *Peabody Journal of Education*, *87*(February 2015), 92–113. doi:10.1080/0161956X.2012.642276

Klein, A., & Moosbrugger, H. (2000). Maximum likelihood estimation of latent interaction effects with the LMS method. *Psychometrika*, *65*(4), 457–474. Retrieved from http://link.springer.com/article/10.1007/BF02296338

Lindberg, S. M., Hyde, J. S., Petersen, J. L., & Linn, M. C. (2010). New trends in gender and mathematics performance: a meta-analysis. *Psychological Bulletin*, *136*(6), 1123–35.

doi:10.1037/a0021276

Lyons, T., & Quinn, F. (2010). Choosing science. Understanding the declines in senior high school science enrolments. Armidale, NSW: University of New England.

MacKinnon, D. P. (2008). *Introduction to statistical mediation analysis.* New York: NY: Erlbaum.

Marks, G., McMillan, J., & Hillman, K. (2001). Tertiary entrance performance: The role of student background and school factors. Camberwell: ACER.

Marsh, H. W. (1986). Verbal and math self-concepts: An internal/external frame of reference model. *American Educational Research Journal, 23*(1), 129–149.

Marsh, H. W. (1990). The structure of academic self-concept: The Marsh/Shavelson model. *Journal of Educational Psychology*, 82(4), 623–636.

Marsh, H. W. (1993). Academic self-concept: Theory, measurement and research. In J. Suls (Ed.), *Psychological perspectives on the self* (Vol. 4, pp. 59–98). Hillsdale, NJ: Erlbaum.

Marsh, H. W. (2007). *Self-concept theory, measurement and research into practice: The role of self-concept in educational psychology*. Leicester, England: British Psychological Society.

Marsh, H. W., Abduljabbar, A. S., Abu-Hilal, M. M., Morin, A. J. S., Abdelfattah, F., Leung, K. C., … Parker, P. D. (2013). Factorial, convergent, and discriminant validity of timss math and science motivation measures: A comparison of Arab and Anglo-Saxon countries. *Journal of Educational Psychology*, *105*(1), 108–128. doi:10.1037/a0029907

Marsh, H. W., & Hau, K.-T. (2007). Applications of latent-variable models in educational psychology: The need for methodological-substantive synergies. *Contemporary Educational Psychology*, *32*(1), 151–170. doi:10.1016/j.cedpsych.2006.10.008

Marsh, H. W., Hau, K-T., & Grayson, D. (2005). Goodness of fit evaluation in structural equation modellling. In A. Maydeu-Olivares & J. McArdle (Eds). *Contemporary psycholometrics. A festschrift for Roderick P. McDonald* (pp. 275-340). Mahwah, NJ: Erlbaum.

Marsh, H. W., Hau, K-T.,Wen, Z., Nagengast, B. & Morin, A. J. S. (2013) Statistical Models of Moderation. In Little, T. (Ed.), *Oxford Handbook of Quantitative Methods*. New York: Oxford University Press.

Marsh, H. W., Kuyper, H., Seaton, M., Parker, P. D., Morin, A. J. S., Möller, J., & Abduljabbar, A. S. (2014). Dimensional comparison theory: an extension of the internal/external frame of reference effect on academic self-concept formation *Contemporary Educational Psychology*, *39*, 326-341.

Marsh, H. W., Lüdtke, O., Nagengast, B., Trautwein , U., Abduljabbar, A. S. (2015). Dimensional Comparison Theory: Paradoxical relations between self-beliefs and achievements in multiple domains. *Learning and Instruction*, *35*, 16-32

Marsh, H. W., Trautwein, U., Lüdtke, O., Köller, O., & Baumert, J. (2005). Academic self-concept, interest, grades, and standardized test scores: reciprocal effects models of causal ordering. *Child Development*, *76*(2), 397–416. doi:10.1111/j.1467-8624.2005.00853.x

Martin, A. J. (2008). Enhancing student motivation and engagement: The effects of a multidimensional intervention. *Contemporary Educational Psychology*, *33*, 239–269. doi:10.1016/j.cedpsych.2006.11.003

Millsap, R. E. (2011). *Statistical approaches to measurement invariance.* New York: Routledge/Taylor & Francis Group.

Muller, D., Judd, C. M., & Yzerbyt, V. Y. (2005). When moderation is mediated and mediation is moderated. *Journal of Personality and Social Psychology*, *89*(6), 852–63. doi:10.1037/0022-3514.89.6.852

Muthén, L. K., & Muthén, B. (1998–2013). *Mplus user's guide.* Seventh Edition. Los Angeles: Muthén & Muthén.

Möller, J., & Marsh, H. W. (2013). Dimensional comparison theory. *Psychological Review*, *120*(3), 544–60. doi:10.1037/a0032459

Möller, J., Pohlmann, B., Koller, O., & Marsh, H. W. (2009). A meta-analytic path analysis of the internal/external frame of reference model of academic achievement and academic self-concept. *Review of Educational Research*, *79*(3), 1129–1167. doi:10.3102/0034654309337522

Nagengast, B., Marsh, H. W., Scalas, L. F., Xu, M. K., Hau, K.-T., & Trautwein, U. (2011). Who took the "x" out of expectancy-value theory? A psychological mystery, a substantive-methodological synergy, and a cross-national generalization. *Psychological Science, 22*(8), 1058–1066. doi: 10.1177/0956797611415540

Nagengast, B., Trautwein, U., Kelava, A., & Lüdtke, O. (2013). Synergistic effects of expectancy and value on homework engagement: The case for a within-person perspective. *Multivariate Behavioral Research, 48*(3), 428–460. doi:10.1080/00273171.2013.775060

Nagy, G., Garrett, J., Trautwein, U., Cortina, K., Baumert, J., & Eccles, J. S. (2008). Gendered high school course selection as a precursor of gendered careers: The mediating role of self-concept and intrinsic value. In H. M. G. Watt & J. S. Eccles (Eds.), *Gender and occupational outcomes: Longitudinal assessments of individual, social, and cultural influences* (pp. 115–143). Washington, DC, US: American Psychological Association. doi:10.1037/11706-004

Nagy, G., Trautwein, U., Baumert, J., Köller, O., & Garrett, J. (2006). Gender and course selection in upper secondary education: Effects of academic self-concept and intrinsic value. *Educational Research and Evaluation*, (February 2013), 37–41. Retrieved from http://www.tandfonline.com/doi/abs/10.1080/13803610600765687

OECD. (2005). PISA 2003 data analysis manual: SPSS users. Paris: OECD.

OECD. (2010). Education at a glance: OECD indicators. Paris: OECD

O'Mara, A. J., Marsh, H. W., Craven, R. G., & Debus, R. L. (2006). Do self-concept interventions make a difference? A synergistic blend of construct validation and meta-analysis. *Educational Psychologist*, *41*(3), 181–206. doi:10.1207/s15326985ep4103_4

Parker, P. D., Marsh, H. W., Ciarrochi, J., Marshall, S., & Abduljabbar, A. S. (2013). Juxtaposing math self-efficacy and self-concept as predictors of long-term achievement outcomes. *Educational Psychology*, (July), 1–20. doi:10.1080/01443410.2013.797339

Parker, P.D., Nagy, P.D., Trautwein, U., & Lüdtke, O. (2014) The Internal/External frame of Reference as Predictors of Career Aspirations and University Majors. In J. Eccles & I. Schoon (Eds.) *Gender Differences in Aspirations and Attainment: A Life Course Perspective.* Cambridge University Press.

Parker, P. D., Schoon, I., Tsai, Y.-M., Nagy, G., Trautwein, U., & Eccles, J. S. (2012). Achievement, agency, gender, and socioeconomic background as predictors of postschool choices: a multicontext study. *Developmental Psychology*, *48*(6), 1629–42. doi:10.1037/a0029167

Preacher, K. J., Rucker, D. D., & Hayes, A. F. (2007). Addressing moderated mediation hypotheses: Theory, methods, and prescriptions. *Multivariate Behavioral Research*, *42*(1), 185–227.

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models*. Thousand Oaks, CA: Sage.

Rubin, D. B. (1987). *Multiple imputation for nonresponse in surveys*. New York: John Wiley & Sons.

Schafer, J. L., & Graham, J. W. (2002). Missing data: Our view of the state of the art. *Psychological Methods*, *7*, 147–177. doi:10.1037/1082-989X .7.2.147

Schoon, I., & Polek, E. (2011). Teenage career aspirations and adult career attainment: The role of gender, social background and general cognitive ability. *International Journal of Behavioral Development*, *35*(3), 210–217. doi:10.1177/0165025411398183

Simpkins, S. D., Davis-Kean, P. E., & Eccles, J. S. (2006). Math and science motivation: A longitudinal examination of the links between choices and beliefs. *Developmental Psychology*, *42*(1), 70–83. doi:10.1037/0012-1649.42.1.70

Simpkins, S. D., Fredricks, J. A, & Eccles, J. S. (2012). Charting the Eccles' expectancy-value model from mothers' beliefs in childhood to youths' activities in adolescence. *Developmental Psychology*, *48*(4), 1019–32. doi:10.1037/a0027468

Trautwein, U., Marsh, H. W., Nagengast, B., Lüdtke, O., Nagy, G., & Jonkmann, K. (2012). Probing for the multiplicative term in modern expectancy–value theory: A latent interaction modeling study. *Journal of Educational Psychology, 104*(3), 763–777. doi: 10.1037/a0027470

Updegraff, K., Eccles, J., Barber, B., & O'Brien, K. (1996). Course enrollment as self-regulatory behavior: Who takes optional high school math courses? *Learning and Individual Differences*, *8*(3), 239–259. doi:dx.doi.org/10.1016/S1041-6080(96)90016-3

Wang, M. T. (2012). Educational and career interests in math: a longitudinal examination of the links between classroom environment, motivational beliefs, and interests. *Developmental Psychology*, *48*(6), 1643–57. doi:10.1037/a0027247

Wang, M. T., & Degol, J. (2013). Motivational pathways to STEM career choices: Using expectancy–value perspective to understand individual and gender differences in STEM fields. *Developmental Review*, *33*(4), 304–340. doi:10.1016/j.dr.2013.08.001

Wang, M. T., & Eccles, J. S. (2013). School context, achievement motivation, and academic engagement: A longitudinal study of school engagement using a multidimensional perspective. *Learning and Instruction*, *28*, 12–23. doi:10.1016/j.learninstruc.2013.04.002

Wang, M. T., Eccles, J. S., & Kenny, S. (2013). Not lack of ability but more choice: indi vidual and gender differences in choice of careers in science, technology, engineering, and mathematics. *Psychological Science*, *24*(5), 770–5. doi:10.1177/0956797612458937

Wang, X. (2013). Why students choose stem majors: motivation, high school learning, and postsecondary context of support. *American Educational Research Journal*, *50*, 1081–1121. doi:10.3102/0002831213488622

Watt, H. M. G. (2010). Gender and Occupational Choice. In J. C. Chrisler & D. R. McCreary (Eds.), *Handbook of Gender Research in Psychology* (pp. 379–400). New York, NY: Springer. doi:10.1007/978-1-4419-1467-5

Watt, H. M. G., Eccles, J. S., & Durik, A. M. (2006). The leaky mathematics pipeline for girls: A motivational analysis of high school enrolments in Australia and the USA. *Equal Opportunities International*, *25*(8), 642–659. doi:10.1108/02610150610719119

Watt, H. M. G., Shapka, J. D., Morris, Z. A, Durik, A. M., Keating, D. P., & Eccles, J. S. (2012). Gendered motivational processes affecting high school mathematics participation, educational aspirations, and career plans: a comparison of samples from Australia, Canada, and the United States. *Developmental Psychology*, *48*(6), 1594–611. doi:10.1037/a0027838

Xu, M. K. (2010). *Frame of Reference Effects in Academic Self-concept: An Examination of the Big-Fish-Little-Pond Effect and the Internal/External Frame of Reference Model for Hong Kong Adolescents* (Unpublished doctoral dissertation). Department of

Education, University of Oxford, UK.

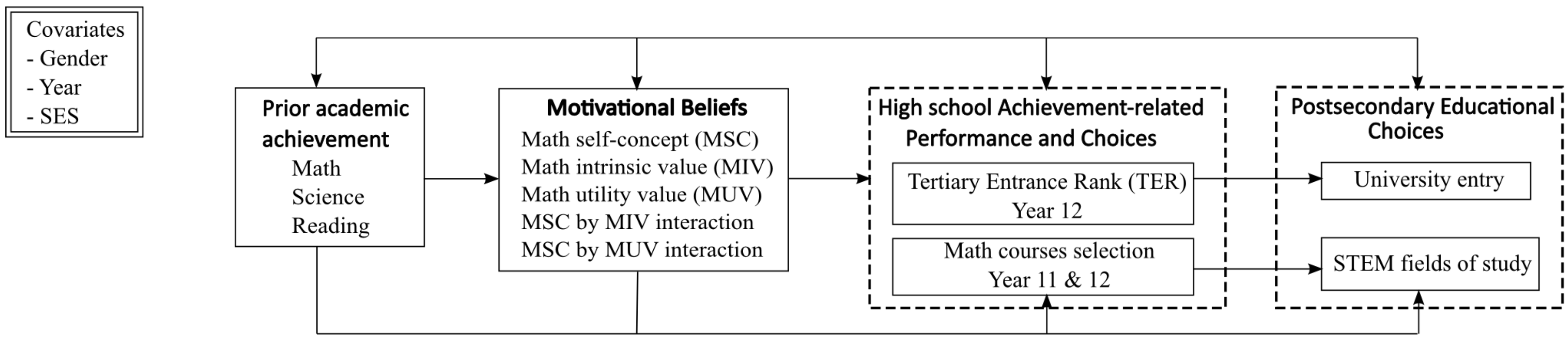

Figure 1. Conceptual model

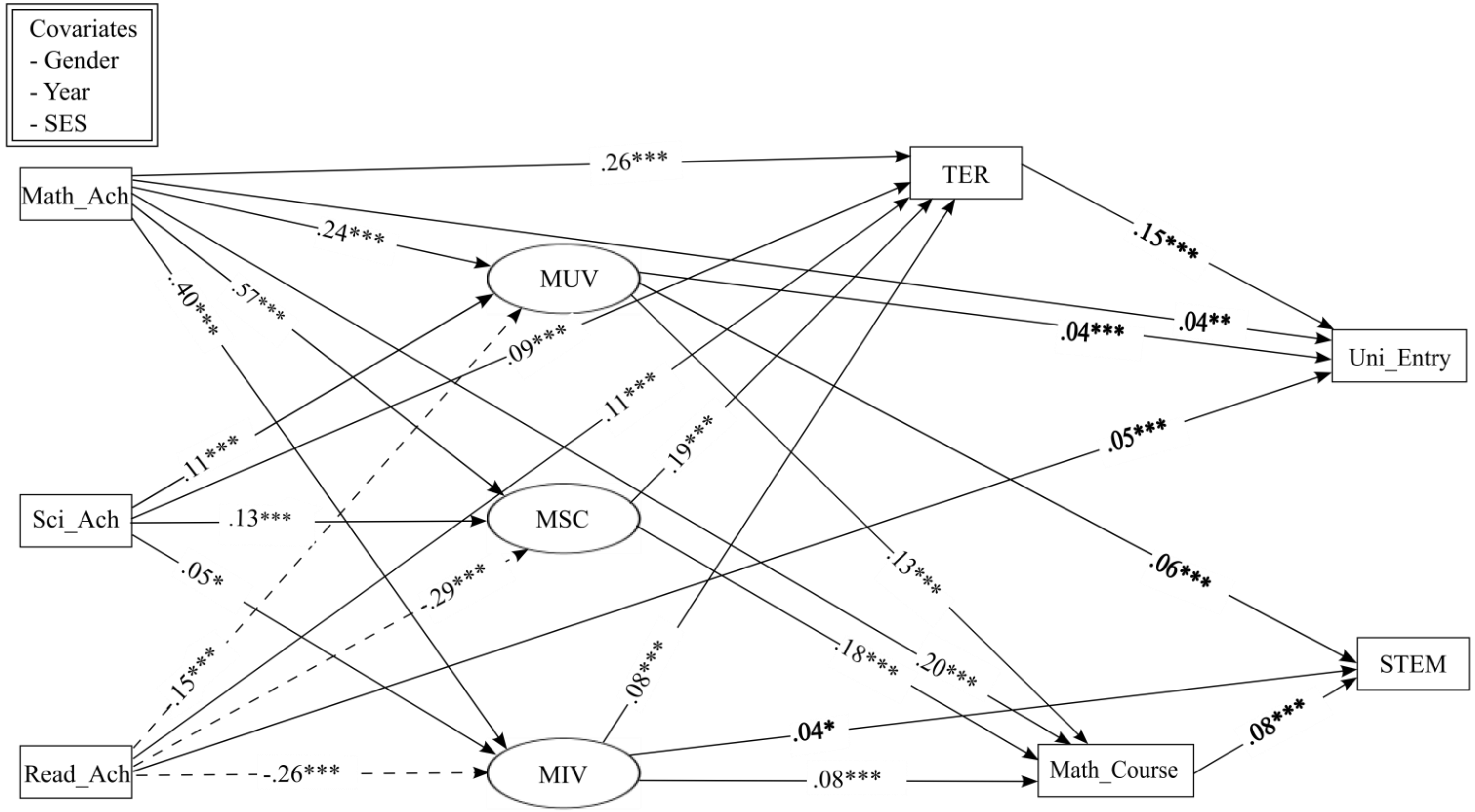

Figure 2. Path model depicting the hypothesized relations, excluding latent interaction, controlling for gender, Grade and SES. Only statistically significant paths are presented in the model, for clarity; all coefficients shown are standardized. Coefficients displayed in boldface type are the probability differences calculated from probit regression.

Note. Dashed arrows represent negative association between reading achievement and motivational beliefs. ASC = math academic self-concept; MIV = math intrinsic value; UV = math utility value; Math_Ach = math educational achievement; Read_Ach = reading educational achievement; Sci Ach = science educational achievement; TER = Tertiary Entrance Rank; Math_Course = high school math course selection; Uni_Entry = university entrance; STEM = university STEM major selection; * $p < .05$, ** $p < .01$, *** $p < .001$.

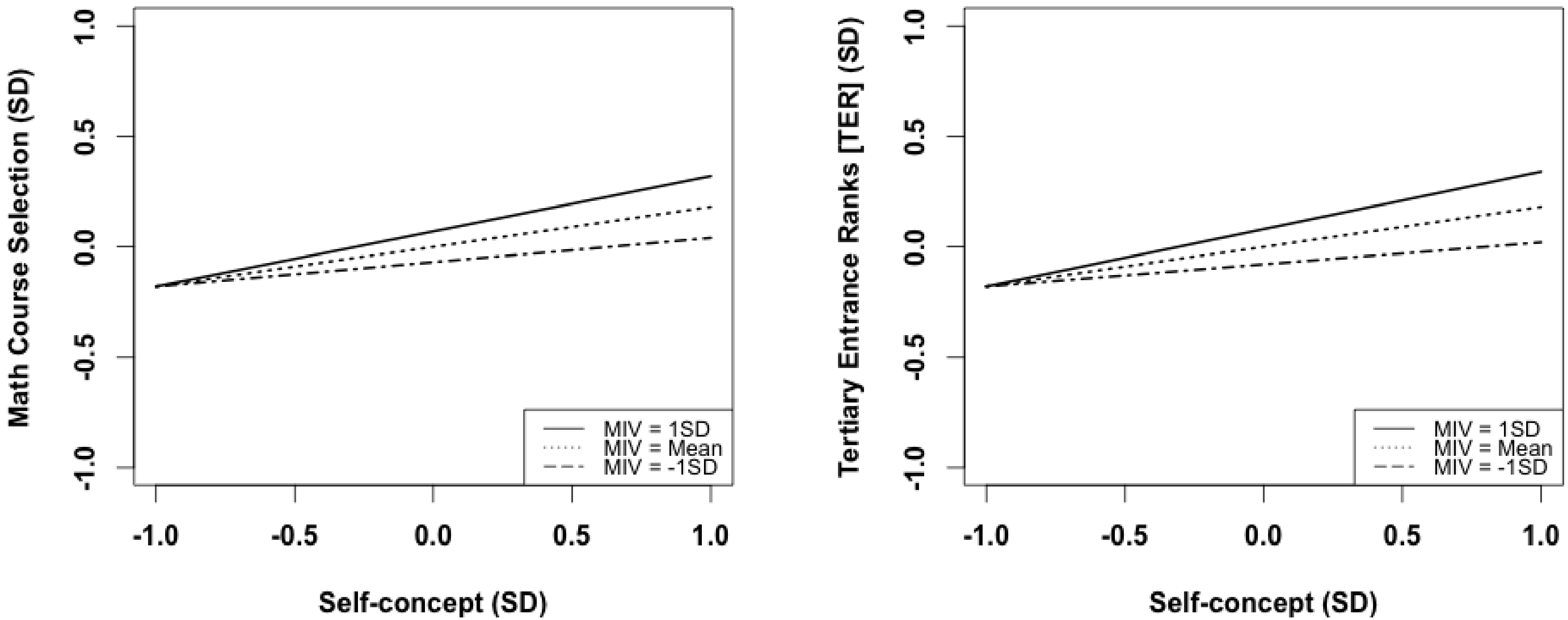

Figure 3. Simple-slopes for the multiplicative effects of math self-concept and intrinsic values on math course selection and Tertiary Entrance Rank [TER]

Note. MIV = math intrinsic value.

Table 1

Standardized Direct, Indirect, and Total Effect for the Path Model Without Latent Interaction

Predictor and covariate	Course			TER			STEM			Uni_entry		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
Math_ach	.20***	.16***	.36***	.26***	.14***	.40***	.02	.18***	.21***	.10** [.04]	.25***	.35***
Read_ach	.01	-.09***	-.09***	.11***	-.08***	.03	.00	-.08**	-.08*	.14*** [.05]	-.02	.12**
Sci_ach	.04	.04***	.08***	.10***	.03**	.12***	.05	.04**	.09*	.04	.05**	.10*
MSC	.18***	–	–	.19***	–	–	.06	.04**	.10*	.03	.09***	.12**
INV	.08**	–	–	.08***	–	–	.09* [.04]	.02	.11*	.06	.04**	.10*
MUV	.13***	–	–	.01	–	–	.16*** [.06]	.03*	.19***	.10*** [.04]	.01	.11**
Course	–	–	–	–	–	–	.20*** [.08]	–	–		–	–
TER	–	–	–	–	–	–		–	–	.48*** [.15]	–	–
Covariate												
Gender	-.04**	-.07***	-.11***	.11***	-.04**	.07**	-.10*** [-.04]	-.06**	-.17***	.17*** [.06]	.06**	.23***
SES	.01	.13***	.14***	.12***	.20***	.32***	-.01	.08**	.07*	.16*** [.06]	.27***	.43***
Year	.15***	.04**	.19***	-.07***	.09***	.02	-.01	.03	.02	.04* [.02]	.06**	.10*

Note. Coefficients in brackets are the probability differences calculated from probit regression. ASC = math academic self-concept; MIV = math intrinsic value; UV = math utility value; Math_Ach = math educational achievement; Read_Ach = reading educational achievement; Sci_Ach = science educational achievement; TER = Tertiary Entrance Rank; Math_Course = high school math course selection; Uni_Entry = university entrance; STEM = university STEM major selection; * $p < .05$, ** $p < .01$, *** $p < .001$. Dashes indicate that it was not possible to compute coefficients.

Table 2

Standardized Direct, Indirect, and Total Effect for the Path Model Without Latent Interaction

Predictor and covariate	MSC			INV			MUV			Math_ach	Read_ach	Sci_ach
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Direct	Direct
Math_ach	.57***	–	–	.40***	–	–	.24***	–	–	–	–	–
Read_ach	-.29***	–	–	-.26***	–	–	-.15***	–	–	–	–	–
Sci_ach	.13***	–	–	.05**	–	–	.11***	–	–	–	–	–
Covariate												
Gender	-.09***	-.09***	-.18***	-.04**	-.07***	-.11***	-.07***	-.04	-.11***	-.06***	.18***	-.02
SES	-.02	.15***	.13***	.00	.07***	.07***	.01	.08***	.08***	.37***	.38***	.39***
Year	-.08***	.10***	.02	-.05***	.05***	.00	-.12***	.05***	-.07***	.22***	.18***	.18***

Note. ASC = math academic self-concept; MIV = math intrinsic value; UV = math utility value; Math_Ach = math educational achievement; Read_Ach = reading educational achievement; Sci_Ach = science educational achievement; TER = Tertiary Entrance Rank; Math_Course = high school math course selection; Uni_Entry = university entrance; STEM = university STEM major selection; *p* < .05, ** *p* < .01, *** *p* < .001. Dashes indicate that it was not possible to compute coefficients.

Table 3

The Conditional Indirect Effect of Self-Concept on University Entry and STEM Major Selection

Moderator	STEM (via Math_course)	Uni_Entry (via TER)
MIV = +1SD	.05**	.13***
MIV = mean	.04**	.09***
MIV = -1SD	.02*	.05***

Note. MIV = math intrinsic value; UV = math utility value; Math_Course = high school math course selection; Uni_Entry = university entrance; STEM = university STEM major selection; *p* < .05, ** *p* < .01, *** *p* < .001.