Young Women Face Disadvantage to Enrolment in University STEM Coursework Regardless of Prior Achievement and Attitudes

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Abstract

We evaluated STEM coursework selection by women and men (representative longitudinal sample, 10,370 Australians) in senior high school and university, controlling achievement and expectancy-value variables. A near-zero total effect of gender on high school STEM enrolment reflected pathways favoring boys through achievement and expectancy-value variables, but a counter-acting direct effect of gender favoring girls. In contrast, subsequent university STEM enrollment favored boys. In both high school and university, enrollments favored girls in life sciences and boys in physical sciences, but at university there was a leaky pipeline in which girls who qualified to pursue physical sciences opted for non-STEM subjects. Qualitative analysis supported quantitative results, but also highlighted alternative mechanisms of STEM engagement/disengagement, and mostly supported gender similarities rather than differences.

Keywords: educational attainment; expectancy value theory; gender; science education STEM enrolment;

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How can we encourage more young people, and in particular, more young women to enrol in STEM? Although women continue to be underrepresented in STEM disciplines, the gender gap has narrowed over the last two decades and the differences vary according to discipline (Ceci, 2018; Ceci, Williams, & Kahn, 2017; Wang & Degol, 2017a,b). Diverse explanations for the gender gap have been proposed including absolute and relative cognitive strengths, interests, domain specific self-beliefs, and life-style values (Ceci, 2018; Ceci et al., 2017; Parker, van Zanden, & Parker, 2018; Wang & Degol, 2017a, b). These may all contribute to a "leaky pipeline" whereby young women who start out in STEM early in their careers do not persist (e.g., Sells, 1980; also see Ceci, 2018). There has been a strong push from governments in post-industrial nations to increase the retention of students in science education and the representation of women in STEM education and careers (e.g., Diekman, Brown, Johnston, & Clark, 2010; Australian National Innovation and Science Agenda, 2017; U.S. National Science and Technology Council, 2013; U.S. Department of Education, 2010). Government policies have focused on the provision of economic stimulus packages for the STEM sector, financial incentives for employment and entrepreneurship in STEM fields, expansion of the current curriculum to include computer coding and to provide more time allocated to the teaching of STEM subjects, and the training of specialist primary school teachers in science (e.g., National Innovation and Science Agenda, 2017).

Despite strong public support for the aforementioned policies, there has been less attention on the psychological factors implicated in science engagement and disengagement, as well as a lack of focus on how to resolve low levels of student self-efficacy, self-concept, and aversive attitudes towards STEM. This is concerning given that expectancy-value theory (EVT) and related research provides a strong theoretical basis to suggest that motivational processes such as interest and enjoyment of STEM subjects, and positive self-beliefs in STEM, are likely to be integral in the decisions of young women to study STEM at a tertiary level (see Eccles, 1994 for an overview of EVT). Indeed, in their special issue on gender differences in STEM careers, Watt and Eccles (2008; also see Sells, 1980) speculate that participation in mathematics courses may be a critical filter in limiting women's representation in STEM careers—a critical focus of the present investigation. However, the degree to which EVT variables account for the magnitude of gender differences in university course enrolment remains relatively unclear. Finally, there has been a paucity of literature on the specific factors that would need to change in order for particularly young women to consider further study in STEM (Diekman et al., 2010).

Thus, the overarching aim of this study is to address these research gaps, by utilising a multi-method approach to understanding STEM educational attainment using the Longitudinal Survey of Australian Youth (LSAY), the longitudinal follow-up of the Program for International Student Assessment (PISA) 2003 data collection (OECD, 2005). By using complementary methods we identify the extent to which gender differences in STEM enrolment in high school and, subsequently, in university can be explained in terms of achievement and EVT variables (Study 1) and whether corresponding young peoples' qualitative responses support quantitative conclusions, and whether they offer alternative explanations for possible mechanisms behind gender gaps in STEM coursework selection (Study 2).

What Factors Predict Educational Attainment in STEM?

The issue of why students disengage from further STEM studies, and in particular why young women are so likely to disengage from STEM, is a controversial topic within education and educational psychology research (see Ceci, Williams, & Barnett, 2009; see also Ceci, 2018 for a review of women's underrepresentation in STEM). Here we discuss the key theories that explain gender differences in STEM coursework selection.

Achievement as a Predictor of Educational Attainment

To what extent do women disengage from STEM due to aptitude or ability in mathematics and science? Longitudinal research shows that prior achievement is predictive of enrolment in STEM and completing a STEM degree (Crisp, Nora, & Taggart, 2009). Moreover, on average, women tend to outperform men in verbal related tests of ability, whilst men tend to outperform women in tests of mathematical ability (Falch & Naper, 2013; Lietz, 2006; Machin & McNally, 2005; Machin & Pekkarinen, 2008; Voyer & Voyer, 2014; but also see Parker, et al. 2018). However, this finding is not clear, as the relationship between gender and mathematics performance appears to vary as a function of how achievement is operationally defined (Falch & Naper, 2013; see also Ceci et al., 2009 for a review of gender differences in achievement across varying methods of assessment). In fact, research on Hyde's gender similarities hypothesis (see Hyde, 2005) shows that there are more similarities than differences between genders for most abilities, aptitudes, and psychological variables, and when differences do arise they are usually small in size. Indeed, Hyde found that gender differences in mathematics ability are almost non-existent in terms of effect size. Thus, Hyde argues that historically, gender differences are consistently over-emphasized in the literature, while the overwhelming evidence of gender similarities across psychological variables has been ignored.

Recent research on achievement has indicated that achievement across different academic domains might provide a prediction of eventual enrolment. For instance, Wang, Eccles, and Kenny (2013) found that individuals who were highly capable in mathematics, but who also possessed high verbal skills, were less likely to pursue STEM careers than individuals with high mathematics skills, but moderate verbal skills (also see Ceci, 2018). They noted that the group with high mathematics and high verbal ability included more girls, and thus the issue of competing competencies provides evidence that achievement in verbal domains may steer students away from the pursuit of STEM careers. A possible mechanism behind this process might lie in Dimensional Comparison Theory (e.g., Moller & Marsh, 2013) and Marsh's (1986) Internal/External (I/E) Frames of Reference Model which has outlined how comparisons of performance in different domains of achievement can have negative consequences on self-concept in the opposing area of achievement (e.g., high verbal achievement resulting in lower mathematics self-concept).

In a particularly relevant test of the I/E model in combination with EVT, (Nagy, Trautwein, Baumert, Köller, & Garrett, 2006; also see Guo, Marsh, Parker, Morin, & Dicke, 2017) predicted coursework selection in mathematics and biology in Year 12 based on achievement, self-concept, and intrinsic value at Year 10. Consistent with EVT, prior achievement, self-concept and intrinsic value all had a substantial impact on subsequent coursework selection, and gender differences in coursework selection were entirely explained by achievement, self-concept, and intrinsic value. Consistent with the I/E model, domain specific self-concept and intrinsic values positively predicted coursework selection in the same domain, but negatively predicted choices in the other domain. Nagy et al. also reported that students' aspired university majors were substantially determined by coursework selection at the end of high school, leading them to conclude that in the German context, where high school students are forced to make early decisions about specialization, "High school course choice can be seen as a precursor of college course selection" (p. 342). In the present investigation we were unable to fully test this integration of the I/E and EVT models because the PISA/LSAY database used here only included mathematics self-belief and value constructs. However, based on this support of the I/E model, we have included verbal achievement as a predictor of STEM coursework selection to test how achievement in a contrasting domain impacts on STEM outcomes in the last two years of high school (senior high school) and university .

The Importance of Self-Beliefs and Attitudes: EVT Related Predictors

If mathematics and science achievement do not explain gender differences in STEM participation, what other mechanisms might be behind the gendering of STEM? One of the most influential theories to explain gendered educational and occupational outcomes is EVT, a theory that explains gendered educational choices as a result of gender differences in students' expectancies for success and their valuing of STEM (Eccles, 1994). Below we outline the key psychosocial factors put forth by EVT that are hypothesized to influence STEM educational attainment.

Expectancies for success. Expectancy for success can best be described as a person's belief that they can be successful in a task (e.g., I have the ability to do well in science). The importance of self-beliefs in predicting positive educational outcomes has long been recognized by researchers in the field. From Bandura's (1977) social-cognitive theories on self-efficacy, to Eccles' (1994) work on EVT and expectancy for success, and finally to Marsh's (1990; Marsh, Pekrun, et al., 2017) multidimensional self-concept model. Thus, modern day operational definitions of expectancy for success have broadened to incorporate constructs of self-efficacy and Marsh's self-concept theory (Marsh, Pekrun, Parker, et al., 2017). There is strong evidence to suggest that there are consistent gender differences in mathematics self-concept/expectancy for success favouring boys (e.g., Skaalvik & Skaalvik, 2004), suggesting that self-beliefs in mathematical ability could be critical in explaining the gender gap in STEM attainment.

Despite a strong emphasis on enhancement of self-beliefs as key goals of educators, Marsh, Pekrun, Ciarrochi, Parker, and Abduljabbar (2014) note that there has been limited research which has considered the role of academic self-beliefs in predicting university enrolment. Nonetheless, the limited research available suggests that these factors are important in student educational attainment. Self-efficacy, for example, has been linked with higher academic aspirations (Bandura, Barbaranelli, Capara, & Pastorelli, 1996). Research has also shown that self-concept is a significant predictor of university enrolment, even when controlling for prior achievement (Marsh, 1991; Parker, Schoon, et al., 2012; Parker, Nagy, Trautwein, & Lüdtke, 2014). More recent research has confirmed these findings in the STEM discipline. Mathematics self-efficacy at Year 12 has been linked to an intention to major in the STEM field at college (Wang et al., 2013). Finally, Parker et al.

(2014) showed that mathematics self-concept remains a significant predictor of STEM university enrolment, even when other demographic and achievement factors are controlled.

Values. Expectancy value theory built on previous literature by highlighting the importance of value judgements in shaping the education and career decisions of young people (Eccles, 1994). In making coursework decisions, students not only perform self-assessments of abilities but also rely heavily on their value judgments about the activity they are pursuing. For example, students are more likely to choose to enrol in a STEM course if they think that science and mathematics are interesting or enjoyable – described as intrinsic value in EVT. When students engage in a task that evokes intrinsic value, they are typically able to persist and sustain interest in that task for a long time (Wigfield & Cambria, 2010). Indeed, differences in interests have long been touted as a key mechanism behind gender differences in coursework selection by researchers from both gender essentialist and gender socialisation perspectives (Buss, 1991; Eccles, 1994), and gender differences in mathematics interest have been well documented (e.g., Preckel, Goetz, Pekrun, & Kleine, 2008). Furthermore, there is emerging evidence to suggest that interest and liking of mathematics are the strongest predictors of mathematics course selection in senior high school for Australian adolescents (Watt, Eccles, & Durik, 2006).

In addition to interest, other value beliefs have been found to be integral in predicting student choice behaviour (see Guo, Nagengast, et al., 2016). One of the most researched of these is utility value, commonly defined as the usefulness of a task in the immediate or long-term future (Wigfield & Cambria, 2010). Utility value has been discussed somewhat less in the literature on STEM university entrance predictions. However, recent work has indicated that these values, alongside interest, are important and are more powerful predictors than achievement or even prior enrolment in high school STEM (Maltese & Tai, 2011).

Costs: Drivers of STEM disengagement (mathematics anxiety). Other possible mechanisms behind gender differences in coursework selection include mathematics anxiety and costs of entering STEM (e.g., Perez, Cromley, & Kapaln, 2014). In EVT, cost refers to what an individual has to give up to engage in a task (e.g., studying for an upcoming chemistry test means I can't go out with my friends), and the anticipated effort that will be required for a task (Eccles, 1994). However, although an important component of EVT, limited research has been conducted in the area of cost in predicting educational outcomes. Nevertheless, research has begun to explore other drivers of disengagement in STEM, particularly in terms of emotional cost, stress, and anxiety. For example, the Perez et al. longitudinal study charting college chemistry students' intents to leave a STEM course found that perceptions of effort cost (e.g., drawbacks associated with time and effort, lost opportunities, stress, and anxiety) predicted intent to leave a chemistry degree. Importantly, research has demonstrated that girls are more likely to report greater levels of mathematics anxiety (e.g., Devine, Fawcett, Szűcs, & Dowker, 2012). Thus, although LSAY does not collect data on overall costs of entering STEM, we have incorporated mathematics anxiety into our analyses to account for the potential negative effects of emotional cost that may occur alongside the positive effects of expectancy and value.

Teacher support. Finally, a key aspect of EVT that is often overlooked is the importance of socialisers in influencing decisions. LSAY collects data about perceived teacher support in mathematics, and thus in this paper we utilize this teacher support variable as a proxy a for socialiser influence of educational outcomes. Teacher support may be an important motivator for students, but also a buffer against negative stereotypes. Indeed, qualitative research has found that women who enrolled in STEM university courses reflected that previous learning experiences were critical to their decision to enter into STEM, alongside with role models in the field and parental support (Bieri, Buschor, Berweger, Keck Frei, & Kappler, 2014; Fouad et al., 2010). Furthermore, in a review of the literature and in interviews with students, Fouad et al. showed that teachers had a strong influence on students' perceptions of supports and barriers for pursuing STEM.

The Present Investigation

The Australian Context

Our sample was taken from the 2003 cohort of the LSAY database: a large nationally representative sample of Australians tested each year from the age of 15 until their mid-twenties. The first wave of data consists of an Australian sample of the corresponding PISA data collection. Unlike PISA data collections in most countries, the Australian sample was retested in successive years, providing a unique opportunity to pursue longitudinal analyses typically not otherwise possible with PISA data.

Particularly in relation to coursework selection, it is important to have some understanding of the Australian school system. Although the specific requirements vary from state-to-state, Australian students generally take a broad diversity of coursework during their first 10 years of formal schooling, but the final two years (senior high school) are largely spent in preparation for discipline-specific exams taken at the end of Year 12. During these last two years, students specialize in a limited number of courses for which they are assessed. These courses are chosen by students from more than 100 alternatives—though not all alternatives are available at all schools. Based on the LSAY follow-up of the PISA data used here, respondents indicated that only about half took a STEM course during their last two years of high school.

Scores on these final examinations are scaled to put marks for all courses on a common metric. Enrollment into university is based largely on performance on a scaled aggregate of the best marks obtained by students in different subject-specific exams and coursework. Students use these scores to apply for a particular degree program rather than the university in general. Thus, cut-off values vary substantially as a function of both the discipline area of the degree as well as the university. In addition, different courses sometimes require that students have studied and been assessed in relevant courses during their last two years of high school. In this sense, students must decide their university major at the end of high school and have already taken relevant coursework for this major during the last two years of high school. Indeed, the majority of a student's university coursework will be in their major discipline and switching majors after starting university is not common.

This system is particularly relevant to the present investigation in that in order to be admitted to a university in a STEM discipline, students are often required to have studied and been assessed in a STEM discipline during their last two years of high school (although some universities provide bridging courses for students who want to pursue a STEM course but did not pursue senior STEM coursework during the last two years of high school). From this perspective, a critical determinant of majoring in a STEM subject at university is having been assessed in a STEM subject at the end of high school. Hence, all the predictors of coursework selection considered here (achievement, self-beliefs, values, etc.) are likely to be relevant for predicting high school coursework selection, which acts as a filter to university coursework selection. Of course, these predictors are likely to be highly predictive of studying a STEM subject during the last two years of high school. However, their effect on university coursework selection will be substantially mediated by (and explained in terms of) the selection of coursework at the end of high school which is a primary determinant of selection of coursework at university. In this way, our study is similar to the Nagy et al. (2006) study in the German system that led them to conclude that advanced coursework at the end of high school was the primary determinant of university coursework selection and that coursework selection in the last two years of high school acts as a filter in terms of majoring in STEM subject at university (Watt & Eccles, 2008).

Research Questions: Study 1

Despite considerable theory and research in the field as summarized above, there is still little consensus on how well achievement and EVT variables explain the gender gap in STEM enrolments (e.g., see Ceci et al., 2009; see also Ceci, 2018, for an overview). Thus, the major focus of this longitudinal study is on the relation of gender to STEM coursework selection in high school and, subsequently, in university. In different analyses we evaluate whether the effects of gender can be explained by a block of three achievement scores and/or by a block of six EVT variables (Table 1). Although the effects of individual variables within each of these blocks is of interest, the main focus is on how control for each block of variables – separately or in combination – changes the effect of gender on STEM coursework selection. Because of the nature of our longitudinal data, our main focus is the extent to which the total effects of gender can be explained by the blocks achievement and of EVT variables. More specifically our main research questions are:

1. (a) To what extent is gender related to STEM coursework selection in senior high school?
   (b) To what extent is this effect explained in terms of control for blocks of achievement scores and of EVT variables?
   (c) To what extent do gender differences in STEM coursework selection in senior high school vary as a function of coursework selection in life versus physical sciences?
2. (a) To what extent is gender related to STEM coursework selection in university among students who completed STEM coursework in high school?
   (b) To what extent are these effects explained in terms of control for blocks of achievement test scores and of EVT variables.
   (c) To what extent do gender differences in STEM university coursework selection vary as a function of coursework selection in life versus physical sciences?
3. Consistent with dimensional comparison theory, does verbal achievement negatively predict EVT predictors of STEM coursework selection, in contrast to the positive predictions based on mathematics achievement?

Method: Study 1

Participants

The sample was taken from the 2003 cohort of LSAY (N = 10,370; 50.82% male) that is an extension of the Australian PISA data. LSAY follows large nationally representative samples of Australian youth from the age of 15 every year until their mid-twenties (for more detail on participants, see earlier discussion and Supplemental Materials; also see Figure 1). Data for achievement, self-beliefs, and attitudes came from Wave 1 (PISA data) when students were 15 year-olds. Coursework selection was based on responses in the last year of high school at age 18 (n = 6,658), and on university STEM course enrolment at age 19 (n = 2,235).

Importantly, participants in our final data wave at age 19 were a subsample of the larger database, whereby only students who enrolled in senior high school STEM courses were asked follow-up questions regarding whether or not they continued their STEM studies at university (see Figure 1 for a visual representation). Out of the 6,658 students who provided data for course selection, 49.4% (n = 3,286) had enrolled in a senior STEM course during the last two years of high school (noting that in Australia, all students are required to take mathematics and science courses during the first four years of high school, but not in the last two years of high school). In general, it is these students who completed STEM coursework in the last two years of high school who are eligible to major in a STEM subject at university (see earlier discussion). At the fifth wave of data collection 2,235 of these students who had studied a STEM course at the end of high school provided responses as to whether or not they had continued their STEM education into university. From this subsample of participants (n = 1,221, 54.6% of the young people surveyed) reported that they were currently studying a STEM course at university.

Measurements

STEM course selection. High school students were asked if they had completed a STEM course (1 = yes; 0 = no) during their last two years of high school (which we refer to as senior high school). We argue that this self-perception of STEM participation is a critical outcome variable that finesses potentially intractable problems in classifying many 100s of course titles where the actual content varies from school-to-school and across different school systems. Nevertheless, in supplemental analyses we classified the actual courses that students reported taking into life science, physical Science, and non-STEM categories (See Supplemental Materials for the list of courses used in this tripartite classification). Extending our main analysis of STEM coursework we related gender, achievement test scores, and EVT variables to coursework selection in each of these three categories.

Following high school graduation, participants who had previously provided data that they had enrolled in a high school STEM course (1 = yes; 0 = no) were asked if they were currently studying in a STEM field at a tertiary level. Those who reported studying in a STEM field at a tertiary level were coded as one; those who were not were coded as zero. In supplemental analyses we classified the university courses that students reported taking into life, physical Science, and non-STEM categories (See Supplemental Materials). Extending our main analysis of STEM coursework we related gender, achievement test scores, and EVT variables to university coursework selection in each of these three categories.

Mathematics self-beliefs. Mathematics self-beliefs incorporated in this study were the PISA items for mathematics self-efficacy and mathematics self-concept. Each scale was rated on a 4-point Likert scale ranging from strongly agree to strongly disagree. The PISA mathematics self-efficacy index was based on Bandura's (1997) conceptualisation of self-efficacy, with items measuring an individual's self-confidence in doing a number of applied mathematical tasks (e.g., "How confident do you feel about having to do the following mathematics tasks? – Calculating how much cheaper a TV would be after a 30% discount."). Mathematics self-concept focused on the ability component of subject specific self-concept beliefs as described by Eccles and Wigfield (1995) and as measured in Marsh's (1990) measure for self-concept (e.g., "In my mathematics class, I understand even the most difficult work."; see Supplemental Materials for a list of all items). Cronbach's alphas for the Australian subset of PISA 2003 (the sample used in this study) were as follows: Mathematics self-efficacy (α = 0.86); mathematics self-concept (α = 0.89; OECD, 2005).

Mathematics attitudes and affect. Attitudes and affect towards mathematics were measured by the PISA items for mathematics interest, instrumental motivation (hereafter referred to as utility value), and anxiety. Items from each scale were rated on a 4-point Likert scale (strongly agree to strongly disagree). Mathematics interest was based on what Wigfield et al. (1997) called the enjoyment aspect of task value (e.g., "I do mathematics because I enjoy it"). Mathematics anxiety was based on Wigfield and Meece's (1988) feelings of worry, stress, and helplessness when doing mathematics (e.g., "I get very nervous doing mathematics problems"). Mathematics utility value measured the extent to which students were motivated to learn mathematics because of benefits for future studies and career (e.g. "I will learn many things in mathematics that will help me get a job"; see Supplemental Materials for list of all index items). Cronbach's alphas for the

Australian subset of PISA 2003 (the sample used in this study) were as follows: Mathematics interest ($\alpha = 0.90$); mathematics utility value ($\alpha = 0.89$); and mathematics anxiety ($\alpha = 0.82$; OECD, 2005).

Teacher support. Teacher support was measured by PISA as an indicator of perceived teacher support in mathematics lessons, and was rated on a 4-point Likert scale ranging from “every lesson”, “most lessons”, “some lessons”, to “never or hardly ever” (e.g., “The teacher shows an interest in every student’s learning). Cronbach’s alpha for the Australian subset of PISA 2003 (the sample used in this study) was $\alpha = 0.87$ (OECD, 2005).

Academic achievement. Mathematics, science, and reading achievement were measured by PISA achievement tests (see OECD, 2005 for detailed information on development and validation). Achievement tests featured multiple choice questions as well as closed and open ended responses. Mathematics achievement measured ability in the areas of space and shape, quantity, change in relationships, and uncertainty. Reading achievement measured ability in retrieving information, interpreting, and reflecting. Science achievement measured ability in describing, explaining and predicting; interpreting scientific evidence; and understanding scientific investigation. PISA assessments of ability utilize matrix sampling, and consequently use item response theory to create a set of 5 plausible values for each individual’s underlying achievement in each domain (e.g., 5 scores for mathematics, 5 scores for science, and 5 scores for reading). PISA survey organizers scale these scores (across all OECD countries) to have a mean of 500 points and a standard deviation of 100. OECD (2005) reports for reliabilities of achievement scales were as follows: mathematics achievement ($\alpha = 0.89$); science achievement ($\alpha = 0.84$); and reading achievement ($\alpha = 0.85$). We ran all analyses for each plausible value separately and combined the results using the formulas defined by Rubin (1987; see Supplementary Materials for further details).

Data Analysis

In each analysis, three blocks of variables were used to predict STEM coursework: gender, the set of achievement scores, and the set of EVT-related variables. This was done in four models: 1) the effect of gender independently of the effects of other predictor variables; 2a) gender and the block of achievement test scores; 2b) gender and the block of EVT-related variables; 3) gender and both the block of test scores and the EVT-related variables. The aim of this was to identify the unique contribution of gender in predicting STEM educational attainment once other critical known achievement and EVT-related predictors had been controlled. In other words, we asked the question: "How much of the effect of gender can be explained by currently known mechanisms of achievement, attitudes, and teacher support?" Standard multiple regression textbooks (e.g., Pedhauzur, 1997; Cohen & Cohen, 1983; Cohen, Cohen, West, & Aiken, 2003) describe this block-wise approach to hierarchical regression (also referred to as variance partitioning and communality analysis) in which the unique variance associated with different blocks or sets of variables are juxtaposed. Initially popularized by Cohen and Cohen (1983; also see Mood, 1971), Pedhauzur (1997; also Cohen et al., 2003) described the approach in detail as a way to circumvent problems associated with multicollinearity associated with multiple blocks of predictors in large scale survey studies. The approach continues to be widely used, particularly in educational research (e.g., Kraha, et al., 2012; Marsh, 2016; Nathans, Oswald, & Nimon, 2012).

Because coursework selection variables are nominal, we conducted logistic regression that uses a logit link function to estimate the probability of the outcomes from a linear combination of predictors (Jaccard, 2001). To facilitate interpretation, the logistic regression coefficients were transformed into odds ratios, a standard measure of effect size for describing the strength of association between variables in a logistic regression, and the corresponding probabilities (Jaccard, 2001). For descriptive purposes, predicted probabilities were calculated from the log-odds with continuous covariates constrained to the mean and categorical variables constrained to the modal category.

LSAY is a large longitudinal database that utilizes complex sampling procedures in order to capture the experiences of a diverse range of young Australians. To do this, LSAY employs oversampling of some demographic groups. Consequently, we used sampling weights provided by LSAY to correct for any sampling bias in the analyses. Another complexity of the LSAY database is the issue of attrition due to the passing of time between data collection points. We utilized attrition weights provided by LSAY to take into account any bias from participant attrition. LSAY also has a complex structure with schools as the primary sampling unit. To account for this complex design we used the 80 balanced repeated replication weights provided by the survey organisers to ensure correct standard errors (see Lumley, 2010). Finally, continuous variables were standardized to a common metric ($M = 0$; $SD = 1$) to facilitate the comparison of parameter estimates (see Supplementary Materials for further details).

Results: Study 1

Gender Differences in Key Variables

We begin with a preliminary summary of gender differences (see correlations in Table 1) in each of the different set of variables considered here: block 1 (achievement test scores), block 2 (EVT variables), and coursework selection outcome variables. Gender is significantly related to all three achievement test scores in block 1. Girls had lower mathematics and science test scores but higher reading test scores. Gender is also significantly related to all the EVT variables in block 2 except for teacher support in mathematics class. Relative to boys, girls had higher mathematics anxiety and lower self-efficacy, self-concept, interest, and utility value in relation to mathematics. Importantly, girls did not differ from boys in terms of STEM course enrolment in high school but had significantly lower STEM enrolment in university courses.

Past achievements in all domains (mathematics, science, and reading) had the strongest correlations with senior high school STEM course selection. EVT variables such as self-efficacy, self-concept, interest, and utility value were also significantly positively correlated with senior high school STEM course selection, whereas mathematics anxiety was negatively correlated with STEM coursework selection in high school.

A critical finding was that gender was not significantly related to senior high school STEM course selection. Prior to controlling for any other variables, girls were no less likely than boys to complete STEM coursework during the last two years of high school that provides a foundation for pursuing STEM coursework at university. This finding was in direct contrast to our expectation that girls would be less likely to enrol in STEM courses. Because achievements and EVT variables are related to both gender and STEM coursework selection, they are critical in understanding the effect of gender on coursework selection. It is important, however, to emphasize that even if the gender effect can be explained by subsequent achievement (block 1) and EVT variables (block 2), the total effect of gender is still close to zero. In the next sections we explore further issues related to the surprising lack of gender difference in STEM high school course selection.

Gender Differences in High School STEM Enrolment Controlling for Achievement and EVT Variables (Research Questions 1a and 1b)

Our major focus is on the total effect of female gender on coursework selection (Research Question 1a) and how this effect of gender changes when various intervening variables are controlled (Research Question 1b). Because of the nature of our longitudinal data, the total effect of female gender is merely the effect of gender in Step 1 (Table 2a) that is non-significant. After controlling for the effects of achievement on STEM coursework selection, the direct effects of gender are still non-significant ($\beta = .12$, $SE = .10$, in Step 2a). However, the direct effect of female gender on STEM coursework selection is positive after controlling for EVT variables; β = .47, *SE* = .08, *OR* = 1.60 (with no controls for achievement in Step 2b) and β = .29, *SE* = .10, *OR* = 1.34 (in Step 3 with controls for both achievement and EVT variables). Translating the gender differences into predicted probabilities (Table 2b), controlling for both achievement and EVT variables in Step 3, girls were 7 percentage points more likely to enrol in high school STEM courses than were boys. We emphasize that these findings are in direct contrast to our expectation that girls would be less likely to enrol in STEM courses. Indeed, the near-zero total effect of gender observed in Step 1 reflects two counter-balancing effects: the direct positive effect of gender on high school STEM selection in Step 3 and the negative indirect effects of gender that is explained by other variables, particularly EVT constructs, in the models 2b and 3.

Our main focus and research questions are on gender differences in STEM enrolment, but we were also interested in the effects of the different achievement and EVT variables on STEM enrollment. Zero-order correlations (Table 1) provide some insight into these effects. Nevertheless, analysing their unique contributions (Models 2a, 2b and 3 in Table 2) is complicated by the high-to-moderate correlations, particularly among the three achievement variables (.76 to .86), but also the set of seven EVT variables (absolute value of correlations vary from .17 to .69, median *r* = .40). Achievement and EVT variables (except teacher support) are all significantly related to STEM coursework selection in senior high school (Table 1). In the models 2a and 3 (Table 2), previous mathematics achievement exerted the largest influence on STEM course selection. In models 2b and 3, mathematics self-efficacy, mathematics utility value, mathematics self-concept, and mathematics interest, uniquely contributed to the prediction of STEM high school course enrolment, whereas the effects of teacher support and mathematics anxiety were non-significant predictors. We note, however, that the lack of predictive power for variables such as mathematics anxiety, arose in part because the variance predicted by these variables in the univariate model were explained in terms of other variables that were also in the final regression equation. Thus anxiety was significantly correlated with STEM coursework selection (*r* = -.23, Table 1), but was also substantially correlated with mathematics self-concept (*r* = -.69) so that anxiety made no unique contribution beyond its contribution shared with other EVT variables.

Gender Differences in High School STEM Enrolment for Life and Physical sciences (Research Question 1c)

A unique feature of our study is that the main dependent variable was a simple yes-no (1 = yes; 0 = no) question as to whether students perceived that they had enrolled in a STEM course during the last two years of high school. Arguably, the student's own self-perception of whether or not they had taken a STEM subject is more important than a classification by an external observer as to whether students had actually taken a STEM course. Also, particularly in a large sample covering many different educational systems, it is not always clear from the course title as to whether courses with apparently similar titles reflect the same content, which courses are STEM courses, and how to classify STEM course into more specific discipline areas. To some extent, these intractable difficulties were finessed by using student self-perceptions. Nevertheless, when responding to this question in the present investigation, students were NOT asked what STEM courses they had actually taken. Because of the potential importance of this issue, we undertook supplemental analyses to address this issue.

For the high school coursework, students had previously indicated from an extensive list of 100s of school subjects, the high school courses that they had taken. Based on the students who provided a self-perception of whether or not they had taken a STEM course during the last two years of high school we decomposed the STEM group into two categories. More specifically, we classified the courses that they had actually taken in to three categories; (1) students who had taken a course in the engineering/physical/IT sciences (hereafter referred to as "Physical" sciences); (2) students who had not taken a Physical science course but had taken a course in the biological/medical sciences (hereafter referred to as "Life" sciences); and (3) students who had not taken any STEM course (i.e., were not in either of the first two classifications). Detailed presentation of coursework titles that went into each of these classifications is presented in Supplemental Materials

We began by validating our tripartite classification of courses in relation to the two-category student self-perceptions of whether or not they had taken a STEM course. The extent of agreement between the two was very high. In particular, forf the 3 (tripartite) x 2 (binary) cross-tabulation, there was 94% agreement between the two classifications. This high level of agreement provides support for the validity of the student self-perception data that were the basis of our original analyses as well as our tripartite classification scheme of courses. Based on the tripartite classification, for the students who were classified as having taken a STEM course, 43.5% were placed in the physical sciences category and 56.5% were placed in life sciences category.

We re-analyzed the data in relation to this tripartite classification scheme (i.e., the main dependent variable was a three-classification multinomial variable rather than a two-classification binomial STEM coursework outcome considered earlier. In these multinomial analyses we treated each of the three multinomial categories as the left out category. Thus, for example, using the "non-science" category as the left out category we related gender, test scores, and EVT variables to the life science and physical science categories (Table 3a). In order to clarify these results, the multinomial gender differences were also transformed into predicted probability differences (Table 3b). Although the analyses are more complicated, the results are quite clear and consistent with results based on the self-perception variable. Particularly in relation to gender, the near-zero effect of gender on STEM coursework with no controls (Step 1 in Table 2) reflects a positive effect for life science (β = .43, *SE* = .05; a gender difference favoring girls relative to the reference category—not taking a STEM course; Table 3a) and a negative effect physical sciences (β = -.36, *SE* = .05; favoring boys). Furthermore, the results are similar in Step2a that for achievement. Translating these results into predicted probabilities (Table 3b, Step 1), girls were more likely to select life science courses (25 percentage points) than were boys (15 percentage points), whereas boys were more likely to select physical science courses (39 percentage points) than were girls (28 percentage points). Boys and girls were equally likely to select non-science courses. The gender differences are statistically significant for both life (in favor of girls) and physical (in favor of boys) sciences. However, it is interesting to note that even girls were at least as likely to select physical science courses (28 percentage points) as life science courses (25 percentage points) and that there were no significant gender differences in the likelihood of choosing a non-science course. Again, we note that whereas the total effects of gender might differ from the direct effects of gender after controlling for achievement and EVT variables (in Steps 2a, 2b and 3), the gender differences in Step 1 still reflect the total effects of gender .

When controlling for EVT variables (Steps 2a and 3 in Table 3a and b) the gender effect in favor of girls selecting STEM courses is primarily a function of girls' increased probability of enrolling in life sciences (Tables 3a and 3b). Relative to non-science courses when controlling for EVT variables, girls are not significantly more or less likely to enroll in physical science courses (β =.12, *SE* = .05) and even the non-significant difference is in the direction of higher course enrollment for girls (Step 2b). When controlling for both achievement and EVT variables (Step 3) the gender difference in favor of girls in life sciences becomes less positive (β = .46, *SE* = .06) but remains significant, whereas the gender difference in physical sciences remains non-significant (β = -.13, *SE* = .07). However, in all four models the gender difference in the contrast between life and physical sciences is highly significant such that girls are more likely to enroll in life science courses and boys are more likely to enroll in physical science courses. In summary, the new results suggest that gender differences in STEM coursework selection differ substantially for physical and life science disciplines.

Gender Differences in University STEM Enrolment Controlling for Achievement and EVT Variables (Research Questions 2a and 2b)

In our second set of longitudinal analyses (Table 4) of subsequent university STEM enrolment, we again focused on the total effect of female gender on coursework selection (Research Question 2a) and how this effect of gender changes when various intervening variables are controlled (Research Question 2b). Importantly these analyses are based high school students who had already completed STEM coursework in the final two years of senior high school (noting that only about half of the students had enrolled in a STEM course; see Figure 1). In results based on high school course selection, we showed that these students had previously taken STEM coursework in high school also had higher achievement and more positive EVT variables. In this sense, we are evaluating effects on university enrolment beyond the substantial influence of gender, achievement, and EVT variables, collected at age 15. It is important to note that that the high school coursework selection can be seen as a critical precursor of university coursework selection. The results show a starkly different pattern of results for gender. In contrast to our high school model where the total effects of gender were non-significant, the model predicting university STEM enrolment consistently showed that gender was the strongest predictor. Female gender was significantly negatively related with university STEM enrolment for students already engaged in STEM study at the senior high school level.

The total effect of female gender is highly significant and negative (β = -.59, *SE* = .11; Step 1, Table 4). Translating the gender differences into predicted probabilities, boys were 15 percentage points more likely to enrol in university STEM courses than were girls, whereas girls were correspondingly less likely to have taken a STEM course. After controlling for the effects of achievement on STEM coursework selection, the direct effects of gender are still highly significant (β = -.50, *SE* = .12; Step 2a) and little changed from Step 1. Controlling EVT variables led to a slight reduction in the direct negative effect of female-gender, but the effect was still highly significant (β = -.43, *SE* = .11; Step 2b), as was the case when both achievement and EVT variables were controlled (β = -.42, *SE* = .12; Step 3). In model 3, controlling for achievement and EVT variables, boys were still 10 percentage points more likely to enrol in university STEM courses than were girls.

The achievement and EVT variables considered here are based on the data collected when students were 15 years of age. Hence, the caveats about complications in evaluating the effects of individual variables in earlier discussion apply here as well. Based on the zero-order (univariate) results, mathematics and science (but not reading) achievement and all the EVT variables (except teacher support) all significantly related to STEM university coursework selection (Table 4). However, although the three achievement scores were positively related to STEM coursework selection, mathematics self-concept, self-efficacy, interest, utility value, and anxiety were even stronger predictors (Table 4). This indicates that the decision to disengage from further university STEM study after senior high school STEM study is influenced more by EVT variables than achievement. Indeed, after controlling for the effect of gender (Step 2a), the effects were non-significant for each of the measures of achievement. However, when all seven EVT variables were considered simultaneously (Step 3b), the positive effect of utility value was the only EVT variable that was statistically significant. Again in the final model that included gender, achievement and EVT variables, the negative effect of female gender (β = -.42, *SE* = .12) and the positive effect of utility value (β = -.25, *SE* = .06) were the only effects to reach statistical significance.

Gender Differences in University STEM Enrolment for Life and Physical Sciences (Research Question 2c)

As in the analysis of high school course selection, we supplemented analyses to address the issue of how our results varied as a function of life and physical sciences based on university students' responses to what courses they had taken at university (see Supplemental Materials). Validating our tripartite classification of courses, the extent of agreement with the two-category student self-perceptions of whether or not they had taken a STEM course was 94% agreement. For the students who indicated that they had taken a STEM course, 52% took a physical science and 48% took a life science. In our multinomial analysis of the three-category course selection (Tables 5a and 5b), girls are substantially more likely to take a life science than a physical science course whereas boys are substantially more likely to take a physical science than a life science course (Table 5a, Step 1). Translating these differences into predicted probabilities, girls were 10 percentage points (Table 5b) more likely than boys to take a life science course, whereas boys were 24 percentage points more likely than girls to take a physical science course. However, even among this sample of students who had all taken STEM subjects in high school, girls were still 14 percentage points more likely than boys to take no STEM subjects in university.

These gender differences at Step 1 (Tables 5a and b) reflect the total effects of gender. Controlling for achievement (Step 2a) had little effect on these gender differences. Indeed, the positive effect of mathematics achievement on the contrast between physical science and non-STEM was the only significant effect of achievement. Whereas the direct effect of gender after controlling for EVT variables (Steps 2b and 3) was slightly smaller than the total effect of gender (Step 1), the pattern was very similar: boys were significantly more likely than girls to have taken a physical science (20 percentage points), whereas girls were significantly more likely than boys to have taken a life science (10 percentage points) or to not have taken a STEM subject at all (10 percentage points). In summary, these supplemental analyses suggest that gender differences in university STEM coursework selection differ substantially for physical and life science disciplines. However, consistent with the leaky pipeline hypothesis, many girls who might have been expected to, and were eligible to take university STEM courses, did not do so.

Dimensional Comparison Theory of Relative Ability Effects (Research Question 3).

Ceci (2018; Ceci et al., 2017), Wang and Degol (2017a, b), and others have noted that both the absolute and relative achievement levels of boys and girls in different subject areas needs to be considered to better understand gender differences in coursework selection. Students with strong mathematics skills are less likely to pursue STEM coursework if their verbal skills are even stronger than their mathematics skills, because they have more options (Wang et al., 2013). This suggestion is consistent with Marsh's (1986) I/E model positing that students engage in dimensional comparisons in relation to mathematics and verbal achievement. Being stronger in verbal skills than mathematics skills will have a negative effect on mathematics self-beliefs and attitudes (but a positive effect on verbal constructs even though they are not measured here). In other words, students will have relatively more positive self-beliefs and attitudes in their best subject, and relatively more negative self-beliefs and attitudes in their worst subject, independent of whether their overall achievement relative to others is good or not. Thus, controlling for mathematics achievement, the effect of verbal achievement is predicted to be negative for the mathematics-related EVT constructs considered here. We note, however, that even though the empirical results are consistent with these theoretical predictions, the nature of these correlational data preclude rigorous tests of causality to fully predict the theoretical predictions. Nevertheless, there also exists longitudinal studies (e.g., (Nagy, Trautwein, Baumert, Köller, & Garrett, 2006; also see Guo, Marsh, Parker, Morin, & Dicke, 2017) and even experimental studies in which feedback on the different domains was experimentally manipulated (e.g., (Möller & Köller, 2001;Pohlmann & Möller, 2009).

The results of our study provide clear support for these predictions (Table 6) in that the effect of reading achievement after controlling for mathematics and science achievement is negative for mathematics self-concept, self-efficacy, interest, and utility value, and positive for mathematics anxiety. These results, in favor of the I/E model, are particularly relevant to the evaluation of gender differences in that girls, compared to boys, have substantially higher reading achievement scores (d = .32, Table 1), but somewhat lower mathematics (d= -.16) and science (d = -.10) achievement scores. Hence, girls' higher verbal achievement detracts from positive mathematics self-beliefs and attitudes, independently of their mathematics achievement scores. Nevertheless, the effect of reading achievement on STEM coursework selection continues to be positive even after controlling for mathematics-related EVT constructs (Step 3 in Table 2).

Study 2

Results in Table 4b (step 1) show that boys were 15 percentage points more likely than girls to enroll in university STEM courses prior to control for achievement and EVT variables. Although achievement and EVT variables accounted for one third of the gender effect (reducing the advantage for boys to 10 percentage points), two-thirds remain unexplained by these variables. What additional variables explain the remaining difference? A potentially powerful strategy is to simply ask students. In pursuit of this strategy, in Study 2 we extended our research to evaluate a more detailed qualitative perspective of gender differences, but also to provide an alternative perspective on how gender differences for EVT constructs relate to university coursework selection.

Research Questions: Study 2

Study 2 used a mixed method approach to extend and refine existing theory. We sought to identify new and novel themes in the self-reported attitudes of young people regarding their choices to engage or disengage from STEM study that are not adequately represented in the current literature. More specifically, we evaluated whether there were substantial differences between the responses of young women and young men in terms of frequency and also content of their qualitative responses about continuing STEM study at university. Research aims and questions guiding this research included: exploring reasons for engagement/disengagement in STEM study; juxtaposing identified themes with current theoretical models (e.g., EVT and I/E models) and results from Study 1; identifying changes needed to make STEM majors more attractive; and investigating gender-role issues.

Method: Study 2

Participants

Participants for Study 2 were a subset of those from Study 1 (see Figure 1) based on Wave 5 (2007) of the LSAY data collection when respondents were approximately 19 years of age. This subset comprised young people who had previously studied a STEM course in senior high school (again noting that only about half the respondents enrolled in mathematics or science courses in senior high school, the last two years of high school; see Figure 1). Young people who had indicated yes to this question were then directed to one of two series of questions depending on whether they had or had not enrolled in a STEM course at tertiary level. Thus, the data for Study 2 (n = 1396) can be divided into two subsets consisting of those who had (n = 447) or had not (n = 949) continued their high school STEM coursework in university.

Procedure

Data were collected from participants through a structured telephone interview as part of the LSAY survey, and responses were transcribed verbatim by survey administrators. Depending on whether or not participants indicated that they were enrolled in a tertiary STEM course, they were asked one of two series of closed and open-ended questions (see interview schedule in Supplemental Materials). Close-ended questions (see Supplementary Materials) required participants to assign a numerical value from 1-5 (1 = very important, 2 = important, 3 = neither important or unimportant, 4 = not important, 5 = not at all important), indicating the degree to which they endorsed particular statements in relation to choosing to study STEM or choosing to not study STEM *(*e.g., You were influenced by your parents). Responses to open-ended questions (e.g., What would need to change for you to consider choosing to study science, engineering, maths or IT*?*) were transcribed by interviewers and responses were kept in written-form alongside a participant ID number that corresponded to the rest of the quantitative LSAY data, so that the quantitative and qualitative data could be merged.

Data Analysis

Content analysis is a flexible and complex data analysis strategy that can be used on a diverse range of data, alone or in conjunction with other methods, and can be modified to suit both theory and data driven approaches to analysis (Ello & Kings, 2008). A content analysis methodology was used to code open-ended responses into categories that summarize the content of the data and evaluating the frequency of these categories (Downe-Wamboldt, 1992; Wilkinson, 2000) to enhance the interpretation of results. The qualitative analysis process involved two separate strategies. The first focused on a deductive approach in which coding was guided by the expectancy value model (see coding framework in Supplementary Materials). The second was a more exploratory, an inductive data-driven coding process. Both inductive and deductive analyses have similar preparation phases (Elo & Kyngas, 2008). Thus, the first stage of the analysis was to decide on the unit of analysis (as recommended by Guthrie, Petty, Yongvanich, & Ricceri, 2004). In this case, the units of analyses were the sentences or short responses that each participant gave in response to their respective questions. Coding focused on recognising themes and patterns within these responses. Themes were coded each time they were raised in response (e.g., if a young person said they chose science because they found it interesting and they wanted a job with good income, the response was coded once for intrinsic value and once for utility value). Thus, the percentages within each cluster (Table 8) can sum to greater than 100% because responses by a given person can be coded into more than one theme.

The next stage of analysis involved a repeated reading of the data in order to achieve immersion and a sense of familiarity with the data as a whole (Tesch, 1990). The key aim of this process is to gain an overall sense of 'what is going on' in the data before beginning the coding process (Elo & Kyngas, 2008). Once immersion had been achieved, we proceeded to analyse the two datasets separately (those who had enrolled in STEM courses, and those who had not).

Results: Study 2

Summary of Close-ended Questions

We begin with a summary of the closed-ended questions presented at the start of the interview (Table 7). For those continuing their STEM study at the university level, the most important reasons were: providing a basis for employment that respondents wanted to pursue; wanting to pursue a STEM career; and being good at the STEM subject. Although having good mathematics and science teachers in high school was also important, the influence of significant others was relatively less important. Of particular relevance, there were no significant gender differences in the relative importance of any of the eight close-ended reasons provided to respondents. Indeed, the rank ordering of the relative importance for each reason was nearly the same for young women and men. In this sense, the results support the notion of gender similarities rather than differences (Table 7).

For those not continuing their STEM study at the university level, the most important reasons were having no desire to work in a STEM field and the influence of significant others (Table7). Less important were the choices of friends and a possible negative image of STEM in the community. There were small, statistically significant gender differences for three of seven reasons. Young men, compared to young women, rated poor salary potential, the influence of parents, and the negative perception of science in the community, as more important in their decision to discontinue science education. None of the seven reasons for discontinuing STEM study at the university were rated as more important for young women than young mem. Furthermore, in support of gender similarities, the rank ordering of the seven reasons is the same for young men and young women (Table 7).

The results from both sets of close-ended responses support a gender similarities perspective, particularly in terms of reasons for continuing STEM study at university (also see Zafar, 2013). Thus, even though women were more likely than men to discontinue STEM study, the few gender differences that were statistically significant indicated reasons why men were more disinclined to continue STEM study than women. Hence, whereas these close-ended responses provide important information about why students in general do or do not continue STEM study at university, they do not provide much insight into why young women are disproportionately likely to discontinue their STEM study. However, as part of the interview, students were asked for other factors that were important in their decision, and these additional reasons provided by students were fully probed and recorded verbatim. We now turn to a content analysis of these transcripts to provide more insight into why students chose to continue or discontinue their STEM study and gender differences in making this decision.

Factors Motiving Enrolment in STEM (Table 8a)

Common themes. Consistent with the results of Study 1, students overwhelmingly reported that they were motivated to enter STEM primarily because of EVT variables, in particular the intrinsic and utility value of STEM. Intrinsic value included responses that focused on enjoyment, interest, curiosity, and liking of STEM study or careers. Responses coded for utility value reflected three major themes: future study opportunities, career opportunities, and financial gain. A smaller number of students reported they saw STEM study as a pathway to a desirable lifestyle. Other themes in student responses were: attainment value (i.e., describing STEM as a long-held life goal or passion); influence of family and friends; previous exposure to STEM in either education, work experience or outside of school; concern for society and the environment; and entering STEM due to a lack of other options.

Interestingly, positive self-beliefs in relation to STEM were not frequently mentioned as another factor in addition to those provided by the close-ended responses. However, it is relevant to note that students had previously indicated that being good at the STEM subject was one of the most important reasons for choosing to continue STEM study. Hence, it may be that students felt that their response to the close-ended item did not require further qualification in their open-ended comments. It is also interesting that the influence of family and friends, and previous exposure to STEM, were frequently mentioned as influencing young people's decisions to continue STEM study at university. These findings provide alternative explanations that were not well-covered in Study 1, the quantitative component of our research, but are integral to the formation of self-beliefs and values according to expectancy value theory.

Gender differences and similarities across responses. Overall, both men and women show similar patterns of responses, with the exception of a few themes (see Figure 2a; also see Supplemental Materials). There were similar numbers of men and women endorsing intrinsic value, utility value (study/career opportunities and pathway to a good lifestyle), expectancy for success, previous exposure to STEM, family/friend/mentor influence, and attainment value as the reason choosing a STEM major at university. A chi-square significance test showed that young men were more likely to report financial gain as being a motivator of their decision to study STEM at university (χ^2 (1, 447) = 11.83, p = .00). In contrast, young women were significantly more likely to say that they entered STEM studies because of a concern for society and/or the environment (χ^2 (1, 447) = 8.40, p = .00), or that they felt they had no other options (χ^2 (1, 447) = 5.69, p = .02). Gender differences were non-significant in other themes (e.g., family, friends, and mentors; attainment value). Thus, overall results showed that there were more gender similarities than differences across the responses of students in relation to why they had chosen to study STEM at university.

Perceived Barriers to Further STEM Study (Table 8b)

Common themes and alternative explanations for STEM disengagement. In keeping with the above findings, a lack of interest or positive affect towards STEM was the most frequently cited reason for choosing not to study STEM at a university level. However, a key finding was the substantial number of young people who responded that they were drawn away from STEM due to competing interests in other non-STEM areas (see

Figure 2c). For example, one young woman reflected, *"I was interested in those areas, but as a career, I wanted to teach special needs children instead."* Importantly, like many other current quantitative studies in the area we did not have a directly relevant measure of this alternative in Study 1, suggesting there is a need to develop measures around these explicit trade-offs. However, we do note that this is apparently related to dimensional comparison theory that posits that understanding self-beliefs and attitudes in relation to one particular domain requires consideration of the juxtaposition of multiple domains. Interestingly, there was little mention of a lack of utility value as being a perceived barrier to entering STEM. This was in contrast to our quantitative, longitudinal findings on utility value as being central to predicting STEM educational attainment. Again, however, this lack of mention might be due to the fact that utility in the open-ended responses might be due to the fact that students felt that this theme had already been covered in the close-ended responses.

In line with previous literature (see earlier discussion), a lack of perceived competence in STEM was the third most commonly cited theme. Again, a pattern of dimensional comparison influence seemed to arise, whereby students reported that they perceived themselves to have better academic strengths in non-STEM areas. The following two responses by young women reflected these overall themes: *"I just chose to continue with my strongest subjects and what I enjoy most. I love literature and reading",* "*Because I performed better in other subjects e.g., English and History, than I did in science and maths subjects."*

Other key themes that emerged from the data were that STEM was perceived as a difficult and demanding discipline to study at university, and many students expressed concerns that the effort required or the study load would be too much. Participants also commented that STEM did not align with their personality or values.

Gender differences and similarities. Again, overall there were more similarities than differences in the responses of young men and women. The only statistically significant difference was for the theme "grades not high enough", whereby young men were more likely to say they did not enrol in STEM due to low scores on assessments (e.g., tertiary entrance ranks, class grades, noting that in Australia entry into university courses is subject specific, whereby different degrees have different entry score requirements). There were other differences across gender for some themes, but none of these were statistically significant. Again, the overwhelming picture was one of gender similarities as opposed to gender differences.

What Would Need to Change? (Table 8c)

Common themes and alternative explanations for STEM engagement. Most young people in the subsample were unsure or unable to provide suggestions about what would need to change in order for the students surveyed to consider studying STEM at university. Of those who did provide a suggestion the most common themes centred on changes in interest. Over 30% of responses by young women and 24% of those by young men indicated that they would need their personal affect or interest levels to change in order for them to consider studying STEM. These findings are consistent with our findings in Study 1 that showed interest as a crucial factor in predicting university entrance to STEM. Again, dimensional comparison type responses emerged, with a number of young people recounting that a change of interest or career goals in STEM areas relative to non-STEM areas would be required for them to consider studying STEM. Alongside the responses for perceived barriers to STEM, these findings suggest that dimensional comparison processes may be an underemphasized factor, critical to the formation of young people's career and study plans.

Other themes that were coded in responses included: a change in perceived competence in STEM; increased information or exposure to STEM; provision of better career opportunities; financial incentives or support to study STEM; improved teaching; changes to STEM curriculum; supportive and inclusive STEM environments; greater flexibility in studying and working in STEM; increased relevancy for daily life; and a change to self or one's personality.

Gender differences and similarities. Overall, there were more similarities than differences in young people's suggestions for change. However, gender differences in a few themes did reach statistical significance (see Figure 2c). Young women, compared to young men, were more likely to report a change of interest or affect towards STEM and better self-perceptions of competence would be required to consider enrolment in a STEM course. On the other hand, young men compared to young women were more likely to report that financial incentives and better career opportunities would be useful in encouraging more students to study STEM at university.

Overall Summary of Themes and Alternative Mechanisms

Overall, responses indicated that the strongest motivators for engagement and disengagement from STEM study were in keeping with EVT constructs. The strongest themes in the open-ended responses (Table 8a) were intrinsic value and, to a lesser extent, utility value (study/career opportunities). In addition, self-perceptions of competence was one of the strongest reasons in the closed-ended responses concerning why students chose to continue STEM study, and in the open-ended questions it was frequently mentioned as a barrier for those who chose not to continue STEM and something that would have to change for students to consider STEM enrolment. However, perhaps a more pertinent question is whether the interview data revealed any alternative mechanisms that could explain both the effect of gender, and also STEM university course selection, more generally.

Arguably, the most convincing alternative explanation for explaining STEM course selection was the presence of dimensional comparison processes and competing interests. In particular, a number of young people stated that they engaged in an internal comparison process whereby they compared their interests or competence in the STEM field compared to their interests or competence in non-STEM disciplines. Hence, it was not so much negative perceptions in relation to STEM, but that they had more positive perceptions in relation to non-STEM disciplines.

There were not many students who raised concerns over gender issues when recounting their decisions to either enter STEM or their perceived barriers to entry. However, although our analyses focused on recording frequencies of responses, most research on interview data aims to go beyond merely counting numbers - themes with lower frequency counts can still be practically significant. Thus, although gender did not emerge as an independent theme, we believed it was pertinent to note the experiences of young women who, without prompting, spontaneously recalled explicit accounts of gender being a barrier to their entry in STEM at university. For example, one interviewee's reply to her being asked about the reasons she did not enter STEM was, "*Male dominated, and lots of facts and figures".* There was evidence that some young women are aware of gender imbalances, but used this as motivation to enter STEM, "*There are not many women in that area so we need to boost the numbers in that area".* However, other young women indicated that gender issues needed to change for them to consider STEM study. When asked what would need to change in order for them to consider a STEM degree one young woman said, "*Making it easier for women to work in those fields,"* and another, *"I think you'd need it to be a bit more girly – it's a very man oriented job"*. Finally, one young woman reflected, *"Maybe more support from the industry, there is not much support for people in those fields, for females such as engineering for men, like work experience in this field – I've tried and been knocked back".* Again, we are cautious to not over-emphasize these responses in relation to the overwhelming responses referring to interest and utility value factors as crucial to influencing their study decisions. However, the role of gender roles and how they influence the degree to which young women feel comfortable in STEM remains a possible factor in accounting for the effects of gender that are unexplained by individual level factors such as achievement and attitudes.

Overall Discussion of Studies 1 and 2

The results of Studies 1 and 2 illustrate the practical significance of EVT variables like values, interests and self-beliefs in determining young people's engagement and disengagement with STEM at senior high school and university levels. Achievement across all domains and positive attitudes toward mathematics were associated with a greater likelihood of choosing STEM coursework at senior high school. However, results highlighted the complexities underlying the relationships between gender and STEM educational attainment. While our research shows that traditional individual-level variables (e.g., achievement, self-beliefs, interests and values) can explain at least some of the gender gap in university STEM enrolment, there still remains a substantial amount of unexplained variance. Moreover, results for high-school STEM enrolment reveal that gender does not just have a singular consistent effect but that competing mechanisms may be in operation for at least some STEM related choices. In particular, there was clear evidence in both high school and university studies that gender differences in STEM coursework selection differ substantially for physical and life science disciplines. Further, considering qualitative data about individual self-reported reasons for choosing or not choosing STEM university courses provided critical insights but only incrementally added to our understanding of gender differences in this area. In our discussion, we summarise the key findings from Studies 1 and 2, and discuss their significance to theory and practice in STEM education.

Girls and Boys Equally Were Likely to Select High School STEM Courses

Perhaps our most unexpected finding was that gender was the only non-significant univariate predictor of senior high school STEM enrolment (Tables 1 and 2). Thus the total effects of gender were non-significant. This finding is in contrast to a wealth of literature that has speculated that the representation of girls in STEM decreases during high school as part of the "leaky pipeline" (e.g., Sells, 1980; also see Ceci, 2018). Even more surprising was that once prior achievement and EVT variables were controlled, gender differences in favor of girls were positively related to senior high school STEM course selection. These results indicate that for boys and girls of equal abilities and attitudes, girls are more likely to enrol in high school STEM, despite assertions that the gender gap in STEM careers begins with a lack of engagement in the senior levels of high school mathematics and science. However, this finding requires careful interpretation. Although girls are more likely to take senior STEM coursework than are boys of equal abilities, self-beliefs, and values, there are gender differences in these variables. Given that the total effects of gender on high school STEM coursework are close to zero and the direct effects are positive, the indirect (mediated) effects explained by these intervening variables are negative. In addition, when these results were decomposed into results for life and physical sciences, the results consistently showed that girls were more likely to enrol in life science courses and boys are more likely to enrol in physical science courses. Hence, gender differences in STEM coursework selection differ substantially for physical and life science disciplines.

Mechanism favouring boys. Further analyses of gender effects show that traditional predictors of educational attainment (e.g., achievement and attitudes) can explain at least some of the effect in gender. A strong pattern of gender stereotypical effects was evident (boys were stronger in mathematics self-concept, self-efficacy, interest, utility value, and to a lesser degree mathematics achievement; girls were higher in mathematics anxiety and reading achievement). This pattern was reflected in our multiple regressions whereby attitudes and achievement accounted for a notable change in predicted probabilities for entering high school STEM.

Mechanism favouring girls. However, it is also important to note that results suggest that there was also a counter-mechanism at play that leads to girls being more likely to enrol in high-school STEM once attitudes and achievement had been taken into account. What can explain the residual positive effect of being a girl and enrolling in STEM that is unaccounted for by prior achievement and attitudes? We speculate that it may be due to the utility value: that particularly in the Australian system, senior courses in STEM may have a pay-off in terms of boosting students' university entrance marks (i.e., that preferential weighting of good performance in STEM subjects compared to other options make choosing these subjects attractive). Girls have greater aspirations and motivation for university attainment compared to boys (e.g., Schoon, 2010). As such, girls may be more motivated to take advantage of strategies that boost their chance of entering university given their more ambitious aspirations. In this sense, the utility value associated with taking STEM courses in high school is not about STEM utility value per se but rather a perceived means of getting a higher university entrance mark—even if this advantage is used to get into a highly competitive non-STEM university course (e.g.. Law). Clearly this remains speculative and possibly idiosyncratic to the Australian system, and requires further research into the strategic aspects of course selection.

Predicting University Enrolment: Explaining the Emergence of Gender Gaps in Attainment

Our longitudinal analyses showed that there were critical differences in the factors that prompted continued engagement from senior high school science/mathematics to STEM at a university level. For students already enrolled in senior high school STEM, university STEM enrolment was not significantly related to prior achievement in middle adolescence in models controlling for gender– a finding that was, perhaps, unsurprising given that achievement was a key predictor of senior high STEM enrolment. EVT variables remained significant predictors of STEM enrolment, despite the five year gap between data collection of predictor and outcome variables. In particular, mathematics utility value at age 15 was a key predictor of choosing to study STEM at high school—even after controlling for achievement and other EVT variables, and provides further predictive power for choosing to continue STEM coursework at university.

However, the relation of gender to university STEM enrolment was perhaps the most noteworthy finding. In contrast to high school STEM selection, young women who had enrolled in high school STEM classes were far less likely to enrol into STEM at university than young men. Hence, unlike the high school results, this juxtaposition between the high school and university results provides clear support for the leaky pipeline hypothesis in that women qualified to undertake university STEM coursework were less likely to do so than were equally qualified men. We emphasize again that this analysis was a sub-sample of those who chose to do STEM related courses in Years 11 and 12 (however we also emphasize that undertaking STEM in senior high-school is often a requirement for undertaking STEM at university). As we controlled for prior achievement and EVT variables, this negative relationship remained strong. Calculating predicted probabilities of undertaking STEM at university the gender gap favouring males declined by only 5 percentage points (from a 15 percentage points to 10 percentage points) after controlling for achievement and attitudes. Thus, young women had substantially lower odds of entering a STEM university course, even when we compared young men and women of equal abilities, similar self-beliefs, interests, and attitudes towards mathematics at age 15. This suggests that current theoretical models of gender and educational choice are lacking and that innovation in theory is required.

We suspected that qualitative interviews with participants might shed some light on where theory will need to develop. We discuss these results below.

Why Did Our Results Differ for High School Enrolment and University Enrolment in STEM?

Our research tracked students from high school to university STEM enrolment amongst a sample of students who had already enrolled in senior high school STEM courses. Thus, for our first dependent variable (choosing STEM at high school) we looked at students choosing to study STEM outright, while our second sample (choosing STEM at university) followed only the students who had previously indicated they had taken senior STEM coursework during the last two years of high school (roughly half the sample). Thus, it is no surprise that variables such as achievement and attitudes become less important in further continuation of STEM study, as most students enrolling in senior high school STEM were already relatively high in achievement and attitudes towards STEM. Thus, it seems that after drawing from a pool of relatively strong achievers with positive attitudes towards mathematics, there would be different factors that become more important in terms of who continues to engage in STEM at a university level. Put simply, there may be little incremental role of EVT variables when considering STEM transitions for already high achieving and engaged students.

Relatedly, it is important to emphasize that the achievement and attitude variables that we used to predict university course enrolment were collected at age 15, several years prior to actual enrolment in university. Hence it is likely that subsequent measures of achievement and mathematics-related attitudes collected at the time students actually made university coursework selection would be even better predictors of coursework selection than the same variables collected when participants were 15.

Furthermore, the choice of choosing what to study at high school, and what to study at university are fundamentally very different decisions. In Australia students often choose subjects to study in senior high-school in order to maximize their chances for a high university entrance rank (this score is used to assign university places in Australia and consists of a combination of school assessment and standardized testing). In contrast to the United States, Australian university course selection requires a student to make a forced choice, whereby they must choose to focus on a specific discipline. We contend that this may explain why we see such a stark change in the relationship between gender and STEM enrolment across high school and university course selection. In particular, we speculated that young women are more likely to enter into STEM in high school when they are able to study STEM alongside other subjects, however, when forced to choose one discipline of study, young women on average are more likely to gravitate towards non-STEM disciplines. We also note that whilst the EVT variables collected at age 15 were not very powerful in predicting university STEM enrolment, they were important in the prediction of senior high school STEM enrolment that acts as a filter to university coursework selection.

Gender Differences in University STEM Enrolment for Life and Physical Sciences

Our results for gender differences of STEM coursework selection when students were in high school and again in university both demonstrated that gender differences varied substantially for physical and life sciences. At least superficially and consistent with gender stereotypes, both sets of results were similar in showing that girls and young women were more likely to select life sciences, whereas men were more likely to select physical sciences. However, a more nuanced juxtaposition of the two sets of results reveals some important differences. For high school students (Table 3b) the gender difference in life sciences favouring girls (10 percentage points) was nearly the same as the gender difference favouring boys in the physical sciences (9 percentage points), such that the gender difference in non-STEM courses was not statistically significantly. However, when these students progressed to university (Table 5b), the gender difference in life sciences in favor of girls (10 percentage points) was still about the same, whereas the gender difference in physical sciences in favor of males (24 percentage points) was substantially larger. Importantly, among students qualified to study science, girls were now much more likely than boys to select non-STEM courses (14 percentage points). Hence, although there was no evidence in support of a leaky pipeline at the high school level, there was clearly a leaky pipeline at the university level. However, for life sciences there did not appear to be a leaky pipeline even at the university level. Rather, this leaky pipeline was primarily at the expense of young women who were qualified to study physical sciences opting out of STEM altogether, and choosing instead to study non-STEM courses.

Young People's Qualitative Perspectives on STEM Engagement and Disengagement

Our longitudinal findings showed that the most critical factors in determining whether young people continue to remain engaged in STEM study were utility value, interest, and gender. However, changes in predicted probabilities indicated that there still remains a great deal of unexplained variance in our attempts to model STEM university enrolment with prior attitudes and achievement. Our analysis of interview data aimed to identify potentially overlooked factors important to young people's engagement with STEM study.

Overall, interview data supported the initial conclusions drawn from our longitudinal quantitative analyses. Namely, young people responded that interest and utility value (e.g., financial gain and career opportunities) were critical to their decisions to continue studying STEM at a tertiary level. This trend continued to young people's discussions of perceived barriers to STEM study, whereby lack of interest was a key theme.

However, perhaps a more critical question was whether the interview data provided alternative explanations for STEM engagement and disengagement. After analysing the responses of young people, several new lines of enquiry for further research have been identified. Namely, responses of young people illustrated the significance of dimensional comparisons in not only self-assessments of ability, but also interests and career goals in determining choice behaviour. In line with previous literature emphasizing relative abilities and attitudes in STEM and non-STEM disciplines (e.g., Ceci, 2018; Ceci et al., 2017; Wang, et al. 2017a,b), it seems that young people are deterred from STEM, not simply because they do not like or enjoy STEM, but because they have competing interests elsewhere. Indeed, there was good support for key predictions based on the I/E model in relation to the effect of reading achievement on mathematics attitudes (negative for mathematics self-concept, self-efficacy, interest, and utility value; positive for mathematics anxiety. Table 6).

Did Interview Data Explain the Unexplained Gender Effect of Study 1?

Generally, there were more gender similarities than differences amongst the qualitative responses of young people. The only exceptions were that young men were more likely to report that they were motivated by financial gain associated with STEM study, while young women were more likely to be motivated by concern for society and the environment, or that they entered into STEM because they felt they lacked other options. In terms of barriers and factors that would need to change to encourage STEM enrolment, young men were more likely to report low grades as the reason they did not enter STEM. Finally, young men were more likely to report that financial incentives could have changed their decision to disengage from STEM study, while more young women were likely to report that a change in interest towards STEM would be required for them to consider studying STEM at a tertiary level. Even these differences, however, were small and the overwhelming story from our interview data was one of gender similarities, as opposed to differences.

Thus, an important question remains unanswered: If gender differences cannot be explained by our EVT variables in our longitudinal analyses (Study 1) or our interview data (Study 2), then what factors can account for the effect of gender that is unexplained by prior achievement, self-beliefs, and attitudes towards STEM?

Indeed, most of the arguments for biological differences as drivers of gendered choice focus on ability and interests. Likewise, psychological research coming from a gender socialisation standpoint has focused on self-beliefs, interests, and values as key mechanisms behind gendered choice behaviours. However, the present investigation shows that the substantial gender effect in university coursework selection cannot be fully explained by individual-level characteristics such as ability and attitudes, and a large proportion of the gender effect for STEM university entry is unexplained. The two-third residual unexplained gender effect for university level STEM found in this research then might have its roots in structural inequality. For example, more abstract concepts such as gender roles, STEM stereotypes, overt and covert discrimination may play a more powerful role in influencing decisions independently of indirect effects through changes in interest and self-beliefs. Even if a young woman is both interested and good at STEM, she still might choose to avoid that career path if she perceives STEM careers as having hostile or unfriendly environments, or if she sees STEM as incongruent with femininity.

Interviewees in this study were not asked directly about structural inequality or gender roles (given the often insidious effect of gender roles and structural inequalities, it is unclear that this would have been helpful to do so in any case). Nevertheless, there were some interview responses that alluded to these issues. Overall, responses showed that although the vast majority of young women did not mention gender issues in their decisions, there were some participants who explicitly stated concerns with gender – even though they were not prompted to do so. This finding illustrates that the influence of gender seems to have an impact on at least some young women, in terms of major decisions such as whether or not to enrol in a STEM course. However, due to the abstract nature of gender roles and societal norms, it is most likely difficult for participants (especially younger participants) to identify how societal influences and structural inequality impacts their decisions without being specifically prompted to reflect on these processes.

Conclusions and Directions for Future Research

This study provided a unique contribution to the literature by testing what current known factors predict high school and university STEM enrolment independently of one another. Perhaps the most important contribution is the finding that gender still exerts a significant and large influence on selection of university majors even when past achievements, self-beliefs, values, interest, anxiety, teacher support, and previous STEM coursework selection are controlled. This indicates that there is a need for new research to explore other potential mechanisms that may further explain the gender gap in STEM educational attainment, particularly the role and influence of structural gender inequalities on STEM enrolment in university.

Another finding of interest was that gender did not have a significant impact on senior high school selection, but negatively predicts entry into university STEM study. While we are cautious to avoid over-interpretation of these findings, it seems that interventions to attract young women into STEM may be better placed to focus on highlighting STEM university study, as opposed to the benefits of senior high school study. Findings suggest that utility value and interest in mathematics are key factors that need to be addressed in interventions to encourage retention of students in STEM areas at a university level. Nevertheless, we note the need to test the generalizability of this finding to other countries where students are not admitted to universities to study a specific subject as is the case in Australia and some other countries (e.g., UK)

Finally, longitudinal results demonstrated that attitudes, especially utility value, self-concept, self-efficacy and interest assessments made at ages as young as 15 remain powerful predictors of, not only course selection in senior high school, but also decisions made during the early adulthood post-school transition period. Thus, educators and policymakers aiming to attract young people to the sciences should aim to focus interventions not only in the immediate time frame before university, but also during earlier adolescence.

Our research also has implications for interventions and policy relevant to further reducing the gender gap in STEM coursework selection. An important focus of our research is the effects of EVT variables on gender differences. Girls have less favourable results in relation to most mathematics-specific EVT variables (see Table 1) and favourable EVT variables are related to STEM coursework selection in both high school and university. There is also clear evidence that systematic intervention can improve subject-specific EVT variables such as mathematics self-concept. For example, the O'Mara, Marsh, Craven, and Debus (2006) meta-analysis of self-concept interventions found that domain-specific self-concept interventions (e.g., mathematics self-concept) had a substantial effect on self-concepts in that domain ($d = 1.16$) that were maintained at follow-up. The most effective interventions incorporated appropriate praise and feedback strategies that are contingent upon performance that is attributional (focus on effort and strategy attributions rather than ability attributions) and goal-relevant. Hence, if mathematics self-concept interventions were specifically targeted towards girls, it would logically reduce or even eliminate the gender gap in mathematics self-concept. Relatedly, growth mindset training, in one study, led to increases in mathematics motivation and achievement and that girls benefited more than boys which eliminated gender differences in performance in the control group (Dweck, 2007). More broadly, in their review of strategies to reduce STEM gender gaps, Wang and Degol (2017a) emphasized the need to capitalize on girls' cognitive strengths, emphasize effort and hard work rather than talent, and cultivate girls' interest in mathematics and science. Nevertheless, they also emphasized that although recommendations are based on research evidence, there remains the need to translate research-supported results into effective intervention practice (Liben &Coyle 2014). Following Liben and Coyle, Wang and Degol called for stronger research design as well as the evaluation of unintended outcomes.

Readers should be aware of several limitations within this study. Firstly, our analyses are based within an Australian context, and thus, patterns of STEM enrolment may differ across different educational systems. Secondly, our research on university entrance applies to students already enrolled in STEM at senior high school, rather than those who are not. Thus, readers should not discount the role of mathematics and science achievement in predicting STEM entry from the general population of students. Nonetheless, we maintain that following students who are already enrolled in STEM at high school is important, because these relatively high achieving students are arguably the group of students with the greatest potential to remain engaged in STEM at a tertiary level. Also, because of the nature of the EVT variables available in the PISA data (that is the first wave of LSAY data) all of the EVT variables are specific to mathematics. In this sense, the only tests of the dimensional comparisons are the juxtaposition of verbal and STEM (mathematics and science) achievement on the mathematics EVT and coursework selection. Hence, a direction for further research is to consider verbal EVT variables that would extend tests of dimensional comparison theory considered here as well as the implications of relative ability and EVT variables for STEM coursework selection. Finally, our attitudinal and achievement data stems from age 15, to predict outcomes at age 19. Despite a 4-year difference between attitudinal and achievement data and the outcome variable of university entrance, there still were significant effects from attitudes at age 15, showing the powerful role of attitudes about mathematics from an early age. Nonetheless, readers are reminded that some of the effect sizes may be diminished because of the four year gap between time waves at age 15 and university study.

Further research is needed to establish whether attitudes formed at even younger ages can predict similar outcomes in adulthood. Finally, interventions aimed at attracting more young women into STEM should focus on increasing interest, levels of usefulness, and self-beliefs such as self-efficacy and self-concept. Furthermore, further research on the role of dimensional comparisons in self-beliefs, interest, and career goals looks to be a promising line of enquiry that may help to explain why young women disengage from STEM. Indeed, these results, combined with recent research, indicate that women disengage, not simply due to deficits in self-beliefs or interests, but rather competing interests and values that are incongruent with enrolment in STEM (see related discussion by Wang & Degol, 2017a, b).

References

Bandura, A. (1977). Self-efficacy: toward a unifying theory of behavioral change. *Psychological Review*, *84*(2), 191-215. doi:10.1037/0033-295X.84.2.191

Bandura, A., Barbaranelli, C., Caprara, G. V., & Pastorelli, C. (1996). Multifaceted impact of self-efficacy beliefs on academic functioning. *Child Development*, *67*(3), 1206–1222. doi: 10.2307/1131888

Bieri, Buschor, C., Berweger, S., Keck Frei, A., & Kappler, C. (2014). Majoring in STEM what accounts for women's career decision making? A mixed methods study. *The Journal of Educational Research*, *107*(3), 167-176. doi: 10.1080/00220671.2013.788989

Buss, D. M. (1991). Evolutionary personality psychology. *Annual Review of Psychology,* 42, 459-491. doi: 10.1146/annurev.ps.42.020191.002331

Ceci, S. J. (2018). Women in academic science: Experimental findings from hiring studies. Educational Psychologist, 53, 22-44.

Ceci, S. J., Williams, W. M., & Barnett, S. M. (2009). Women's underrepresentation in science: sociocultural and biological considerations. *Psychological Bulletin*, *135*(2), 218. doi: 10.1037/a0014412

Ceci, S. J., Williams, W. M., & Kahn, S. (2017). (Eds.). Underrepresentation of women in science: International and cross-disciplinary evidence and debate [Research topic]. Frontiers in Psychology

Cohen, J., & Cohen, P. (1983). Applied multiple regression/correlation analysis for the behavioral sciences (2nd. ed.). Hillsdale, NJ: Lawrence Erlbaum Associates.

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). Applied multiple regression/correlation analysis for the behavioral sciences. New York, NY: Routledge.

Crisp, G., Nora, A., & Taggart, A. (2009). Student characteristics, pre-college, college, and environmental factors as predictors of majoring in and earning a STEM degree: An analysis of students attending a Hispanic serving institution. *American Educational Research Journal*, *46*(4), 924-942. doi: 10.3102/0002831209349460

Devine, A., Fawcett, K., Szűcs, D., & Dowker, A. (2012). Gender differences in mathematics anxiety and the relation to mathematics performance while controlling for test anxiety. *Behavioral and brain functions*, *8*(1), 33.doi: 10.1186/1744-9081-8-33

Diekman, A. B., Brown, E. R., Johnston, A. M., & Clark, E. K. (2010). Seeking congruity between goals and roles a new look at why women opt out of science, technology, engineering, and mathematics careers. *Psychological Science*, *21*(8), 1051-1057.

Downe-Wamboldt, B. (1992). Content analysis: method, applications, and issues. *Health Care for Women International, 13*(3), 313-321. doi:10.1080/07399339209516006

Dweck, C. (2007). Is math a gift? Beliefs that put females at risk. In S. J. Ceci & W. M. Williams (Eds.), Why aren't more women in 1460 science? Top researchers debate the evidence (pp. 47–55). Washington: APA Press. doi:10.1037/11546-004

Eccles, J. S. (1994). Understanding women's educational and occupational choices. *Psychology of Women Quarterly,* 18(4), 585-609. doi: 10.1111/j.1471- 6402.1994.tb01049.x

Eccles, J. S., & Wigfield, A. (1995). In the mind of the actor: The structure of adolescents' achievement task values and expectancy-related beliefs. *Personality and Social Psychology Bulletin, 21*(3), 215-225. doi: 10.1177/0146167295213003

Elo, S., & Kyngäs, H. (2008). The qualitative content analysis process. *Journal of Advanced Nursing, 62*(1), 107-115. doi: 10.1111/j.1365-2648.2007.04569.x

Falch, T., & Naper, L. R. (2013). Educational evaluation schemes and gender gaps in student achievement. *Economics of Education Review*, 36, 12-25. doi: 10.1016/j.econedurev.2013.05.002

Fouad, N. A., Hackett, G., Smith, P. L., Kantamneni, N., Fitzpatrick, M., Haag, S., & Spencer, D. (2010). Barriers and supports for continuing in mathematics and science: Gender and educational level differences. *Journal of Vocational Behavior, 77*(3), 361-373. doi: 10.1016/j.jvb.2010.06.004

Guo, Marsh, H. W., Parker, P. D., Morin, A.J.S. , & Dicke, T. (2017). Extending expectancy-value theory predictions of achievement and aspirations in science: Dimensional comparison processes and expectancy-by-value interactions. Learning and Instruction, 49, 81-91.

Guo, J., Nagengast, B., Marsh, H. W., Kelava, A., Gaspard, H. Brandt, H., Cambria, J., Flunger, B., Dicke, A-L. Häfner, I., Brisson, B., Trautwein, U. (2016). Probing the Unique Contributions of Self-Concept, Task Values, and Their Interactions Using Multiple Value Facets and Multiple Academic Outcomes. AERA Open.

Guthrie, J., Petty, R., Yongvanich, K., & Ricceri, F. (2004). Using content analysis as a research method to inquire into intellectual capital reporting. *Journal of Intellectual Capital, 5*(2), 282-293. doi: 10.1108/14691930410533704

Hyde, J. S. (2005). The gender similarities hypothesis. *American Psychologist, 60*(6), 581. doi:10.1037/0003-066X.60.6.581

Jaccard, J. (2001) Interaction Effects in Logistic Regression, Issue 135. SAGE.

Kraha, A., Turner, H., Nimon, K., Zientek, L. R. & Henson, R, K. (2012). Tools to support interpreting multiple regression in the face of multicollinearity. *Frontiers in psychology. 3*. 44. 10.3389/fpsyg.2012.00044.

Liben, L. S., & Coyle, E. F. (2014). Chapter three-developmental interventions to address the STEM gender gap: exploring intended and unintended consequences. Advances in Child Development and Behavior, 47, 77–115.

Lietz, P. (2006). A meta-analysis of gender differences in reading achievement at the secondary school level. *Studies in Educational Evaluation*, *32*(4), doi: 317344.10.1016/j.stueduc.2006.10.002

Lumley, T. (2010). Complex surveys: A guide to analysis using R. Hoboken, NJ: Wiley.

Machin, S., & McNally, S. (2005). Gender and student achievement in English schools. *Oxford Review of Economic Policy, 21*(3), 357-372. doi:10.1093/oxrep/gri021

Machin, S., & Pekkarinen, T. (2008). Global sex differences in test score variability. *Science*. *322*(5906), 1331-1332. doi: 10.1126/science.1162573

Maltese, A. V., & Tai, R. H. (2011). Pipeline persistence: Examining the association of educational experiences with earned degrees in STEM among US students. *Science Education*, *95*(5), 877-907. doi: 10.1002/sce.20441

Marsh, H. W. (1986). Verbal and math self-concepts: An internal/external frame of reference model. *American Educational Research Journal, 23*(1), 129-149. Retrieved from http://journals.sagepub.com/doi/pdf/10.3102/00028312023001129

Marsh, H. W. (1990). A multidimensional, hierarchical model of self-concept: Theoretical and empirical justification. *Educational Psychology Review*, *2*(2), 77-172. doi:10.1007/BF01322177

Marsh, H. W. (1991). Failure of high ability schools to deliver academic benefits commensurate with their students' ability levels. *American Educational Research Journal,* 28(2), 445-480. doi: 10.3102/00028312028002445

Marsh, H. W. (2016). Cross-cultural generalizability of year in school effects: Negative effects of acceleration and positive effects of retention on academic self-concept. Journal of Educational Psychology, 108(2), 256-273.

Marsh, H. W., Pekrun, R., Murayama, K., Arens, A. K., Parker, P. D., Guo, J., & Dicke, T. (2018). An Integrated Model of Academic Self-Concept Development: Academic Self-Concept, Grades, Test Scores, and Tracking Over 6 Years. Developmental Psychology, 54, 263-280. http://dx.doi.org/10.1037/dev0000393

Marsh, H. W., Pekrun, R., Ciarrochi, J., Parker, P. D. & Abduljabbar, A. S. (2014). Juxtaposing math self-efficacy and self-concept as predictors of long-term achievement outcomes. *Educational Psychology*, *34*(1), 29-48. doi: 10.1080/01443410.2013.797339

Marsh, H. W., Pekrun, R., Parker, P. D., Murayama, K., Guo, J. & Dicke, T. (2018). The murky distinction between self-concept and self-efficacy: Beware of lurking jingle-jangle fallacies. Journal of Educational Psychology. Online first publication.

Mood, A. M. (1971). Partitioning variance in multiple regression analyses as a tool for developing learning models. American Educational Research Journal, 8, 191-202.

Möller, J., & Köller, O. (2001). Dimensional comparisons: An experimental approach to the internal/external frame of reference model. Journal of Educational Psychology, 93, 826–835. doi:10.1037/0022- 0663.93.4.826

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

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*, 12, 23-345, doi:10.1080/13803610600765687.

Nathans, L L., Oswald, F. L. & Nimon, K. (2012). Interpreting multiple linear regression: A guidebook of variable importance. Practical Assessment, Research & Evaluation, 17, no. 9. http://hdl.handle.net/1911/71096.

National Innovation and Science Agenda, Australian Government (2017). *National innovation and science agenda*. Retrieved from http://www.innovation.gov.au/page/agenda

National Centre for Vocational Education Research (2017). Longitudinal Surveys of Australian Youth. Retrieved from https://www.lsay.edu.au/

National Science and Technology Council, Office of Science Technology Policy, US. Government Washington D.C. (2013). https://www.whitehouse.gov/sites/default/files/microsites/ostp/stem_stratplan_2013.p df

OECD. (2005). *PISA 2003 Technical Report.* Retrieved from https://www.oecd.org/edu/school/programmeforinternationalstudentassessmentpisa/35 188570.pdf

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

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

Parker, P.D., Nagy, G., Trautwein, U., & Lüdtke, O. (2014). Predicting career aspirations and university majors from academic ability and self-concept: a longitudinal application of the internal–external frame of reference model. In I. Schoon & J.S. Eccles *Gender differences in aspirations and attainment: A life course perspective*, 224-246. Cambridge University Press.

Parker, P. D., Schoon, I., Tsai, Y., Nagy, G., Trautwein, U., & Eccles, J. (2012). Achievement, agency, gender, and socioeconomic background as predictors of postschool choices: A multi-context study. *Developmental Psychology, 48*(6), 1629– 1642. doi: 10.1037/a0029167

Parker, P.D., van Zanden, B., & Parker, R.B. (2018). Girls get smart, boys get smug: Historical changes in gender differences math, English, and academic social comparison and achievement. *Learning and Instruction, 54,* 125-137.

Pedhazur, E. J. (1997). Multiple Regression In Behavioral Research Explanation And Prediction (3rd ed.). Wadsworth. Singapore.

Perez, T., Cromley, J. G., Kaplan, A. (2014). The role of identity development, values, and costs in college STEM retention. *Journal of Educational Psychology*, *106*(1), 3015- 329. doi: 10.1037/a0034027

Pohlmann, B., & Möller, J. (2009). On the benefit of dimensional comparisons.Journal ofEducational Psychology, 101(1), 248–258.https://doi.org/10.1037/a0013151.

Preckel, F., Goetz, T., Pekrun, R., & Kleine, M. (2008). Gender differences in gifted and average-ability students: Comparing girls' and boys' achievement, self-concept, interest, and motivation in mathematics. *Gifted Child Quarterly*, *52*(2), 146-159. doi: 10.1177/0016986208315834

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

Schoon, I. (2010) Planning for the future: Changing education expectations for three British cohorts, *Historical Social Research*, 35, 99–119. Retrieved from http://www.jstor.org/stable/20762452

Sells, L. W. (1980). Mathematics: The invisible filter. *Engineering Education, 70*(4), 340- 341.

Skaalvik, S., & Skaalvik, E. M. (2004). Gender differences in math and verbal self-concept, performance expectations, and motivation. *Sex Roles*, *50*(3-4), 241-252.doi: 10.1023/B:SERS.0000015555.40976.e6

Tesch, R. (1990). *Qualitative research: Analysis types and software tools*. New York: Falmer Press.

U.S. Department of Education. 2010. *Science, technology, engineering, and math: Education for global leadership*. Washington, DC: U.S. Department of Education.

Voyer, D., & Voyer, S. D. (2014). Gender differences in scholastic achievement: A meta- analysis. *Psychological Bulletin,* 140(4), 1174. doi: 10.1037/a0036620

Wang, M.-T., & Degol, J. L. (2017a). Gender Gap in Science, Technology, Engineering, and Mathematics (STEM): Current Knowledge, Implications for Practice, Policy, and Future Directions. Educational Psychology Review, 29(1), 119–140. http://doi.org/10.1007/s10648-015-9355-x

Wang, M.-T., & Degol, J. L. (2017b). Who chooses stem careers? Using a relative cognitive strength and interest model to predict careers in science, technology, engineering, and mathematics. Journal of Youth Adolescence, 46, 1805–1820. DOI 10.1007/s10964-016-0618-8

Wang, M. T., Eccles, J., & Kenny, S. (2013). Not lack of ability but more choice: Individual and gender differences in choice of careers in science, technology, engineering, and mathematics. *Psychological Science, 24*(5), 770-775. doi: 10.1177/0956797612458937

Watt, H. M., & Eccles, J. S. (2008). *Gender and occupational outcomes: Longitudinal assessments of individual, social, and cultural influences*. American Psychological Association, Washington D.C.

Watt, H. M., 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

Wigfield, A., & Cambria, J. (2010). Students' achievement values, goal orientations, and interest: Definitions, development, and relations to achievement outcomes. *Developmental Review, 30*(1), 1-35. doi: 10.1016/j.dr.2009.12.001

Wigfield, A., Eccles, J. S., Yoon, K. S., Harold, R. D., Arbreton, A., Freedman-Doan, C., et al (1997). Changes in children's competence beliefs and subjective task values across the elementary school years: A three-year study. *Journal of Educational Psychology*, 89, 451–469, doi: 10.1037/0022-0663.89.3.451

Wigfield, A., & Meece, J. L. (1988). Math anxiety in elementary and secondary school students. *Journal of Educational Psychology, 80*(2), 210. doi: 10.1037/00220663.80.2.210

Wilkinson, S. (2000). Women with breast cancer talking causes: Comparing content, biographical and discursive analyses. *Feminism & Psychology*, *10*(4), 431-460. doi: 10.1177/0959353500010004003

Zafar, B. (2013). College major choice and the gender gap. Journal of Human Resources, 48, 545-595.

Table 1
Descriptive Statistics: Correlations Among Variables And Gender Difference (In Effect Sizes)

	1	2	3	4	5	6	7	8	9	10	11
Mathematics achievement (1)	-										
Science achievement (2)	.83	-									
Reading achievement (3)	.76	.84	-								
Mathematics self-concept (4)	.42	.33	.21	-							
Mathematics self-efficacy (5)	.54	.52	.38	.56	-						
Mathematics interest (6)	.21	.13	.05	.64	.40	-					
Mathematics utility value (7)	.18	.15	.08	.43	.35	.55	-				
Mathematics anxiety (8)	-.36	-.30	-.19	-.69	-.46	-.43	-.25	-			
Teacher support in mathematics (9)	.10	.12	.11	.22	.18	.28	.22	-.17	-		
High school STEM major selection (10)	.46	.43	.4	.32	.36	.26	.27	-.23	.12	-	
Gender (Female) (11)	-.08	-.05	.16	-.17	-.21	-.12	-.11	.17	.03	.01	-.13
Gender Differences (Cohen's D)	-.16	-.10	.32	-.35	-.43	-.24	-.22	.35	.06	.02	-.26

Note. Sample sizes are range from 6,562 to 6,658. Cohen's D is difference between boys and girls in a standard effect size metric. All correlation coefficients and gender difference effect sizes (Cohen's D) are statistically significant at $p < .01$, except for those shaded in grey.

Table 2a

High School Coursework Selection: Gender Difference in STEM Enrollment

	Step 1	OR	Step 2a	OR	Step 2b	OR	Step 3	OR
	(*N* = 6,658)		(*N* = 6,658)		(*N* = 6,562)		(*N* = 6,562)	
Gender (Female)	.04(.08)	1.04	.12(.10)	1.13	.47(.08)*	1.60	.29(.10)*	1.34
Mathematics achievement			.83*(.11)	2.29			.59(.12)*	1.80
Science achievement			.31*(.13)	1.36			.21(.13)	1.23
Reading achievement			.15(.11)	1.16			.30(.11)*	1.35
Mathematics self-concept					.25(.05)*	1.28	.12(.06)	1.13
Mathematics self-efficacy					.69(.04)*	1.99	.26(.05)*	1.30
Mathematics interest					.01(.06)	1.01	.18(.06)*	1.20
Mathematics utility value					.30(.04)*	1.35	.35(.05)*	1.42
Mathematics anxiety					-.08(.06)	.92	.02(.06)	1.02
Teacher support in mathematics					.02(.03)	1.02	.02(.04)	1.02
Pseudo R-squared	0.00		0.19		0.14		0.23	
Area under the curve	0.50		0.71		0.68		0.73	

Notes. OR = odds ratio. Coefficients are log odds. Table 2 shows variables from age 15 predicting senior high school course selection in Grade 12. All scales are z-scored. Univariate effects are presented first, followed by the multiple regressions. Multiple regression results are presented in steps: 1) gender; 2a) gender controlling for cognitive factors, 2b) gender controlling for non-cognitive variables; 3) gender controlling for cognitive factors and non-cognitive factors. Each log-odd represents the unique contribution of a variable.

Table 2b

High School Coursework Selection: Predicted Probability for Gender Differences in in STEM Enrollment

	Non-STEM	STEM
	Step1	
Girls	.45(.02)	.55(.02)
Boys	.46(.02)	.54(.02)
Diff	-.01ns	.01ns
	Step2a	
Girls	.48(.02)	.52(.02)
Boys	.51(.02)	.49(.02)
Diff	-.03ns	.03ns
	Step2b	
Girls	.42(.01)	.58(.02)
Boys	.53(.02)	.47(.01)
Diff	-.12*	.12*
	Step3	
Girls	.44(.01)	.56(.02)
Boys	.52(.02)	.48(.01)
Diff	-.07*	.07*

Notes. Diff = difference. Predicted probabilities shown here are a simple transformation of the multinominal logistic regression results in Table 2a.

Table 3a

High School Coursework Selection: Gender Difference in Selection of Life Science, Physical Science, and Non-Science

	Step 1			Step 2a			Step 2b			Step 3		
	LS vs Non	PS vs. Non	LS vs. PS	LS vs Non	PS vs. Non	LS vs. PS	LS vs Non	PS vs. Non	LS vs. PS	LS vs Non	PS vs. Non	LS vs. PS
	Coef (SE)	Coef (SE)	Coef (SE)	Coef (SE)	Coef (SE)	Coef (SE)	Coef (SE)	Coef (SE)	Coef (SE)	Coef (SE)	Coef (SE)	Coef (SE)
	(*N* = 6,658)			(*N* = 6,658)			(*N* = 6,562)			(*N* = 6,562)		
Gender (Female)	.43(.05)*	-.36(.05)*	.79(.05)*	.37(.06)*	-.30(.07)*	.67(.06)*	.66(.05)*	.12(.05)	.54(.05)*	.46(.06)*	-.13(.07)	.60(.06)*
Mathematics achievement				.54(.07)*	1.05(.10)*	-.51(.10)*				.40(.08)*	.75(.11)*	-.35(.11)*
Science achievement				.19(.09)	.44(.11)*	-.25(.08)*				.12(.09)	.33(.12)*	-.21(.11)
Reading achievement				.21(.07)*	.07(.09)	.14(.07)				.27(.07)*	.28(.10)*	-.02(.08)
Mathematics self-concept							.14(.03)*	.36(.03)*	-.21(.03)*	.05(.04)	.21(.04)*	-.15(.04)*
Mathematics self-efficacy							.58(.03)*	.83(.03)*	-.24(.03)*	.27(.03)*	.30(.03)*	-.03(.03)
Mathematics interest							-.08(.03)*	.09(.03)*	-.17(.03)*	.06(.03)	.31(.04)*	-.26(.03)*
Mathematics utility value							.12(.02)*	.47(.02)*	-.35(.02)*	.15(.03)*	.56(.02)*	-.41(.02)*
Mathematics anxiety							-.08(.04)	-.08(.03)*	.00(.03)*	.00(.04)	.05(.04)	-.05(.04)
Teacher support in Mathematics							.04(.02)	-.02(.02)	.06(.02)*	.03(.02)	-.02(.02)	.05(.02)

Notes. LS = Life Science; PS = Physical Science; Non = Non-Science. . *Coef = coefficient parameter estimates are log odds.* . *SE = standard error.*

* p = <.01;

Table 3b

High School Coursework Selection: Predicted Probability for Gender Differences in Enrolment in Non-STEM, Life Science, and Physical Science Fields.

	Non-STEM	Life science	Physical science
		Step1 (*N* = 6,658)	
Girls	.48(.02)	.25(.01)	.28(.01)
Boys	.46(.01)	.15(.01)	.39(.01)
Diff	.02ns	.10*	-.09*
		Step2a (*N* = 6,658)	
Girls	.48(.02)	.27(.01)	.25(.01)
Boys	.47(.02)	.19(.01)	.34(.01)
Diff	.01ns	.09*	-.09*
		Step2b (*N* = 6,562)	
Girls	.42(.01)	.28(.01)	.29(.01)
Boys	.51(.02)	.18(.01)	.32(.01)
Diff	-.09*	.11*	-.03
		Step3 (*N* = 6,562)	
Girls	.46(.02)	.30(.01)	.24(.01)
Boys	.49(.02)	.20(.01)	.31(.01)
Diff	-.03ns	.10*	-.07*

Notes. Diff = difference. Predicted probabilities shown here are a simple transformation of the multinominal logistic regression results in Table 3a.

Table 4a

University Coursework Selection: Gender Difference in STEM Enrollment

	Univariate	OR	Step 1	OR	Step 2a	OR	Step 2b	OR	Step 3	OR
	N (2,227 to 2,235)		(*N* = 2,235)		(*N* = 2,235)		(*N* = 2,227)		(*N* = 2,227)	
Gender (Female)	-.59(.11)*	.55	-.59(.11)*	.55	-.50(.12)*	.61	-.43(.11)*	.65	-.42(.12)*	0.66
Mathematics achievement	.25(.06)*	1.28			.23(.12)	1.26			.10(.12)	1.13
Science achievement	.19(.06)*	1.21			.06(.11)	1.06			.04(.12)	1.13
Reading achievement	.07(.09)*	1.07			-.11(.16)	.90			-.01(.15)	1.16
Mathematics self-concept	.37(.05)*	1.45					.11(.10)	1.12	.09(.10)	1.11
Mathematics self-efficacy	.28(.05)*	1.32					.04(.07)	1.04	.00(.08)	1.08
Mathematics interest	.40(.05)*	1.49					.18(.10)	1.20	.19(.09)	1.09
Mathematics utility value	.39(.05)*	1.48					.24(.06)*	1.27	.25(.06)*	1.06
Mathematics anxiety	-.27(.05)*	.76					-.02(.08)	.98	-.02(.08)	1.08
Teacher support in mathematics	.08(.05)	1.08					-.05(.06)	.95	-.04(.06)	1.06
Pseudo R-squared			0.02		0.02		0.05		0.05	
Area under the curve			0.56		0.56		0.60		0.60	

Notes. OR = odds ratio. Coefficients are log odds. Table 4 shows variables from age 15 predicting university STEM enrolments at age 19. All scales are z-scored. Univariate results are presented first, followed by multiple regressions. Multivariate results are presented in steps: 1) gender; 2a) gender controlling for cognitive factors, 2b) gender controlling for non-cognitive variables; 3) gender controlling for cognitive factors and non-cognitive factors. Each log-odd represents the unique contribution of a variable controlling for other variables in each step. * p = <.01.

Tabl4 4b

University Coursework Selection: Predicted Probability for Gender Differences in STEM Enrollment

	Non-STEM	STEM
	Step1 (N = 2,235)	
Girls	.50(.02)	.50(.02)
Boys	.35(.02)	.65(.02)
Diff	-.15*	.15*
	Step2a (N = 2,235)	
Girls	.48(.02)	.52(.02)
Boys	.36(.02)	.64(.02)
Diff	-.12*	.12*
	Step2b (N = 2,227)	
Girls	.49(.02)	.51(.02)
Boys	.38(.02)	.62(.02)
Diff	-.11*	.11*
	Step3 (N = 2,227)	
Girls	.47(.01)	.53(.02)
Boys	.37(.01)	.63(.02)
Diff	-.07*	.10*

Notes. Diff = difference. Predicted probabilities shown here are a simple transformation of the multinominal logistic regression results in Table 4a.

Table 5A

University Coursework Selection: Gender Difference in Selection of Life Science, Physical Science, and Non-Science

	Step 1			Step 2a			Step2b			Step3		
Predictor Variables	LS vs Non Coef(SE)	PS vs. Non Coef(SE)	LS vs. PS Coef(SE)	LS vs Non Coef(SE)	PS vs. Non Coef(SE)	LS vs. PS Coef(SE)	LS vs Non Coef(SE)	PS vs. Non Coef(SE)	LS vs. PS Coef(SE)	LS vs Non Coef(SE)	PS vs. Non Coef(SE)	LS vs. PS Coef(SE)
		(*N* = 2,235)			(*N* = 2,235)			(*N* = 2,227)			(*N* = 2,227)	
Gender (Female)	-.01(.06)	-1.33(.06)*	1.33(.06)*	.05(.07)	-1.21(.08)*	1.26(.08)*	.10(.07)	-1.16(.06)*	1.26(.06)*	.10(.08)	-1.14(.07)*	1.24(.08)
Math achievement				.10(.06)	.27(.09)*	-.18(.09)				.01(.06)	.15(.09)	-.14(.09)
Science achievement				.09(.08)	.04(.07)	.05(.09)				.08(.08)	.01(.09)	.07(.11)
Reading achievement				-.04(.08)	-.14(.10)	.09(.11)				.01(.08)	-.02(.11)	.04(.11)
Math self-concept							.09(.05)	.08(.05)	.01(.05)	.08(.05)	.05(.05)	.03(.05)
Math self-efficacy							.07(.04)	.00(.05)	.06(.05)	.02(.04)	-.06(.05)	.07(.05)
Math interest							.18(.05)*	.17(.06)*	.00(.07)	.19(.05)*	.19(.06)*	.00(.07)
Math utility value							.15(.03)*	.46(.04)*	-.31(.05)*	.16(.03)*	.47(.04)*	-.32(.05)*
Math anxiety							.05(.04)	-.12(.05)*	.17(.05)*	.05(.04)	-.12(.05)*	.17(.05)*
Teacher support in Math							-.06(.03)	-.03(.03)	-.02(.03)	-.06(.03)	-.03(.03)	-.03(.03)

Notes. LS = Life Science; PS = Physical Science; Non = Non-Science. Coef = coefficient parameter estimates are log odds.. *SE = standard error.*

* p = < .01.

Table 5b

University Coursework Selection: Predicted Probability for Gender Differences in Enrolment in Non-STEM, Life Science, and Physical Science Fields

	Non-STEM	Life science	Physical science
		Step1	
Girls	.49(.01)	.34(.01)	.17(.01)
Boys	.35(.01)	.24(.01)	.41(.02)
Diff	.14*	.10*	-.24*
		Step2a	
Girls	.48(.02)	.34(.01)	.18(.01)
Boys	.36(.02)	.24(.01)	.40(.02)
Diff	.12*	.10*	-.22*
		Step2b	
Girls	.47(.02)	.35(.01)	.18(.01)
Boys	.37(.02)	.25(.01)	.38(.02)
Diff	.10*	.10*	-.20*
		Step3	
Girls	.47(.02)	.35(.01)	.18(.01)
Boys	.37(.02)	.25(.01)	.38(.02)
Diff	.10*	.10*	-.20*

Notes. Diff = difference. Predicted probabilities shown here are a simple transformation of the multinominal logistic regression results in Table 5A.

Table 6
Effect of Reading Achievement (Controlling for Mathematics and Science Achievement) on Non-Cognitive Variables

	β	SE
Mathematics self-concept	-0.33*	0.04
Mathematics self-efficacy	-0.28*	0.04
Mathematics interest	-0.26*	0.03
Mathematics utility value	-0.19*	0.04
Mathematics anxiety	0.27*	0.03
Teacher support in mathematics	-0.01	0.03

Notes. Results are based on a series of regression models in which the critical parameter is the effect of reading achievement, controlling for the effect of math and science achievement. Sample sizes are range from 6,562 to 6,658; All scales are z-scored so that βs are in a standardized metric.
* *p = <.01*

Table 7

Ratings of importance for choosing STEM course	**Female Mean**	**Male Mean**	**Total Mean**
You were good at science, engineering, maths or IT	1.95 (0.99)	1.84 (0.91)	1.90 (0.95)
You wanted to pursue a career in science, engineering, maths or IT	2.07 (1.21)	2.02 (1.01)	2.04 (1.11)
You were influenced by career advice provided by your teachers or career advisers	3.24 (1.26)	3.21 (1.21)	3.23 (1.24)
You were influenced by having good science or maths teachers in high school	2.22 (1.09)	2.24 (1.09)	2.23 (1.09)
You were influenced by your parents	2.68 (1.26)	2.53 (1.18)	2.60 (1.22)
You were influenced by one or more science related ‘experiences’ at high school	2.74 (1.19)	2.67 (1.18)	2.70 (1.19)
You have an employer who supports your study in this field	3.26 (1.38)	3.47 (1.31)	3.37 (1.34)
The course you are doing provides a good basis for employment in areas you like	1.61 (0.87)	1.52 (0.68)	1.56 (0.77)

Ratings on 1-6 scale, 1= most important, 5 = not at all important 6 = don't know

Ratings of importance in not choosing STEM	**Female Mean**	**Male Mean**	**Total Mean**
You had no desire to work in science, engineering, maths or IT	2.74 (1.38)	2.78 (1.34)	2.76 (1.36)
You thought those fields would not get you a well paid job	3.80 (0.93)	3.54 (1.07)	3.70 (1.00)
You were influenced by advice from teachers and career advisers to consider orher careers	3.24 (1.21)	3.25 (1.21)	3.24 (1.21)
Your parents influenced you to do other things.	3.44 (1.18)	3.26 (1.18)	3.37 (1.18)
Science and maths teachers didn’t inspire you enough to consider careers in science, engineering, maths or IT	3.53 (1.10)	3.52 (1.10)	3.53 (1.10)
Your friends did not study science, engineering, maths or IT	3.99 (0.75)	3.91 (0.80)	3.96 (0.77)
You were influenced against science, engineering, maths or IT by the negative image of them in the community	4.10 (.67)	3.99 (0.75)	4.06 (0.70)

Ratings on 1-6 scale, lower scores are indicate higher importance, measures with statistically significant mean differences (p = <.05) highlighted

Table 8

Coding Framework, Frequency Counts and Significance For Open-Ended Interview Items (Study 2)

	Women	Men	
A. Coding Framework for motivation to study STEM			
Previous exposure to STEM	9%	9%	
Family, friends, mentors	12%	8%	
Concern for society and environment	3%	0%	*
Attainment value (long-term goal)	9%	10%	
Utility value (lifestyle)	5%	3%	
Utility value (study/career opportunities)	20%	20%	
Utility value (finamncial gain)	4%	13%	*
Intrinsic value	50%	52%	
Expectancy for success	3%	5%	
Lack of other options	3%	0%	*
Number	205	242	
B. Coding framework for barriers to study STEM			
Did not align with personality or values	5%	6%	
Social and cultural influences	1%	2%	
Lack of intrinsic value (interest or positive affect)	44%	39%	
Attracted to other non-STEM areas	24%	32%	
Lack of perceived competence	14%	16%	
Perception of being better in non-STEM areas	6%	3%	
Low grades	2%	6%	*
Teacher influence	2%	1%	
Lack of career opportunities or pathways	3%	4%	
Family and friends	2%	2%	
STEM perceived as too difficult/too much effort	6%	6%	
Number	261	154	
C. Coding framework for what would need to change to study STEM			
No suggestion	30%	31%	
Change in affect or interest towards STEM	30%	24%	*
Change in interests/goals in non-STEM area	10%	11%	
Change in perceived competence	9%	6%	
Increased exposure/information about STEM careers	3%	4%	
Better career opportunities	3%	6%	*
Better teaching	4%	2%	
Change to content or curriculum	2%	3%	
Financial incentives or support	2%	6%	*
Easier entry	1%	2%	
Supportive and inclusive environment	2%	1%	
Flexibility in study and work	3%	2%	
Change in self or personality	2%	2%	
Relevancy to life	2%	2%	
Number	574	375	

Note. Responses by a given person could be coded into more than one theme so that the percentages within cluster of responses sum to greater than 100%.

.* p = <.05

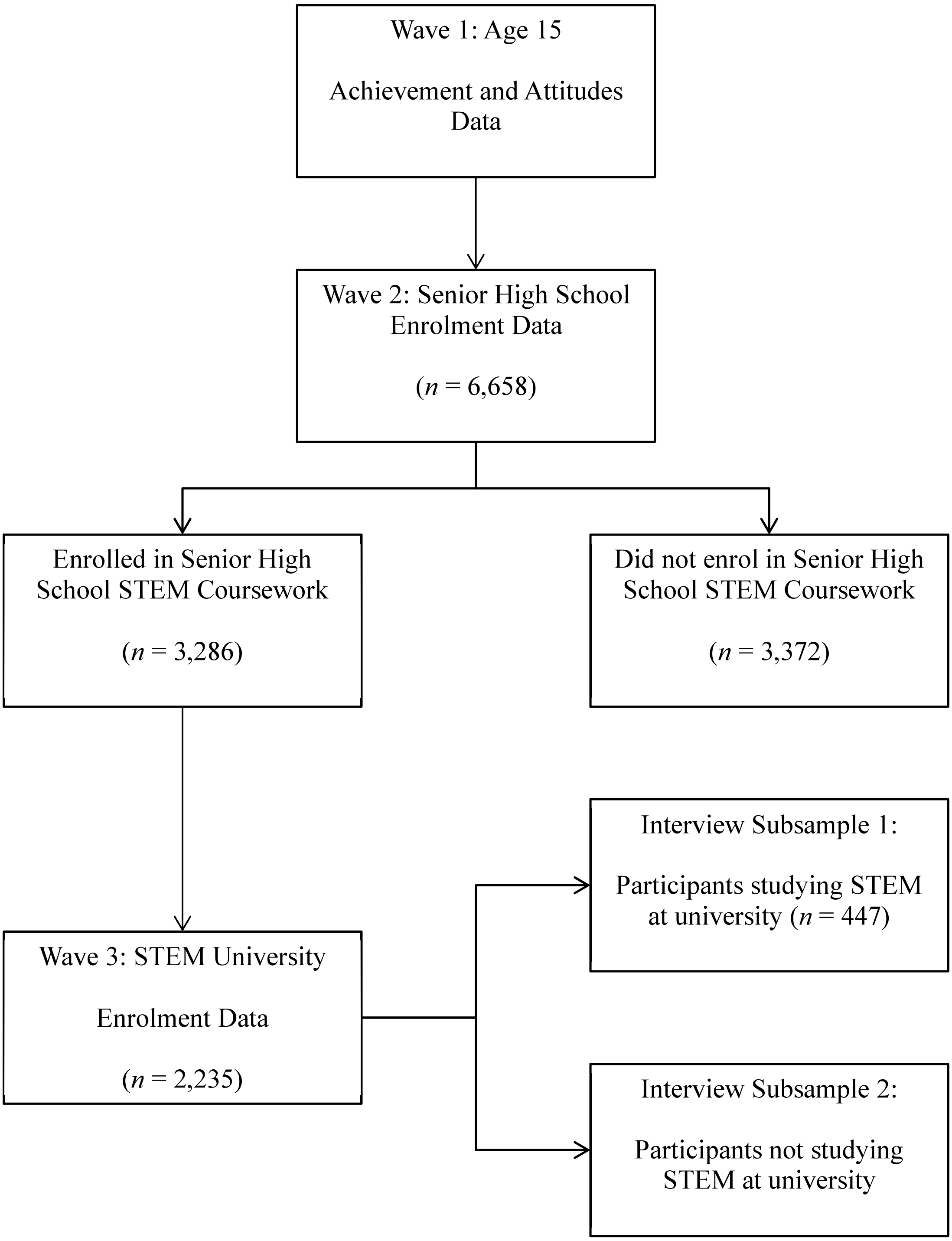

Figure 1. Flow diagram of data collection across time waves for Studies 1 and 2.

Online Supplementary Materials

Section 1. **Summary of the Participants in the Longitudinal Survey of Australian Youth (LSAY)**

Section 2. **Wording of Items to Measure EVT variables**

Section 3. **Classification of Courses Classified as a Life or Physical Science**

Section 4. **Interview Schedule Used To Collect Categorical Outcome Variables for Longitudinal Analysis**

Section 1. Summary of the Participants in the Longitudinal Survey of Australian Youth (LSAY)

The sample was taken from the 2003/Y03 cohort of LSAY (N = 10, 370; 50.82% male). Starting with the Australian PISA data, LSAY follows large nationally representative samples of Australian youth from the age of 15 every year until their mid-twenties. The sample was largely comprised of Australian-born students (78%), with 11% of students as first generation immigrants, and 9% second-generation immigrants. Six percent of the sample also identified as Indigenous Australians. Forty percent of the young people surveyed had at least one parent with a university level education. The average socio-economic index of participants on the International Socio-economic Index was 52.84 (*SD* = 15.93), which is substantially higher than the OECD average (OECD, 2010). Data for achievement, self-beliefs, and attitudes came from Wave 1 of data collection for which participant mean age was 15.69 years (*SD* = .29; *Range* = 15-16). Educational attainment data was based on senior high school course selection, where participants were in Grade 12 at age 18 (*n* = 6,658), and on university STEM course enrolment at age 19 (*n* = 2,235). Importantly, participants in our final data wave at age 19 were a subsample of the larger database, whereby only students who enrolled in senior high school STEM courses were asked follow-up questions regarding whether or not they continued their STEM studies at university (see Figure 1 for a visual representation). Importantly, readers should note that the Australian school system differs from the US educational system, whereby STEM courses are not compulsory for senior high school students, and more like the German system (Nagy, et al., 2006) where high school students are forced to make early decisions about specialization so that high school coursework selection is a precursor of university coursework selection.

Out of the 6,658 students who provided data for course selection, 49.4% (*n* = 3,286) had enrolled in a senior STEM course during the last two years of high school (noting that in Australia, all students are required to take mathematics and science courses during the first four years of high school, but not in the last two years of high school). In general, it is these students who completed STEM coursework in the last two years of high school who are eligible to major in a STEM subject at university (see earlier discussion). At the fifth wave of data collection 2,235 of these students who had studied a STEM course at the end of high school provided responses as to whether or not they had continued their STEM education into university. From this subsample of participants (*n* = 1,221, 54.6% of the young people surveyed) reported that they were currently studying a science, engineering, mathematics, or IT course at university.

Data Analysis with the Longitudinal Survey of Australian Youth (LSAY)

The first time wave of LSAY utilizes the responses of the Program for International Student Assessment (PISA) participants on mathematics, reading, and science achievement tests, as well as attitudes towards mathematics. To measure achievement, the PISA survey provides five plausible values for each domain of achievement (e.g., mathematics, science, and reading). Thus, our study contained five separate data-sets, each containing one of five possible plausible values for mathematics, reading, and science achievement. We used the formulas provided by Rubin (1987), whereby analyses were run on each dataset separately, and parameter estimates were generated from the average estimates across the five datasets with standard errors corrected for the between plausible value variance.

LSAY is a large, complex database, and thus there are a number of recommendations provided to researchers who plan on analysing the data (see the website provided by the National Centre for Vocational Education Research, 2017). A critical issue in a large longitudinal database is attrition of participants. LSAY recommends that to counteract this issue researchers use attrition weights provided in the database to account for the effect of participant drop out. LSAY also recommends the use of sample weights which are included in the data provided to researchers. LSAY's sample weights ensure that the sample matches the population distribution. Using sample weights helps to ensure that any conclusions drawn from analyses are not altered by oversampling or under sampling of parts of the population. Finally, in order to be able to compare the estimates in our regression across different variables, we standardised the scales included in our analyses ($M = 0$; $SD = 1$).

Section 2. Wording of Items to Measure EVT variables

The index of mathematics self-concept asks students to rate the extent to which they strongly agreed, agreed, disagreed, or strongly disagreed with the following statements:
I am just not good at mathematics. (R)
I get good grades in mathematics.
I learn mathematics quickly.
I have always believed that mathematics is one of my best subjects.
In my mathematics class, I understand even the most difficult work.
R = Reverse scored item

PISA self-efficacy items
The index of mathematics self-efficacy asks students to rate the extent to which they feel very confident, confident, not very confident, and not confident about doing the following tasks:
Using a train timetable to work out how long it would take to get from one place to another.
Calculating how much cheaper a TV would be after a 30% discount.
Calculating how many square meters of tiles you need to cover a floor.
Understanding graphs presented in newspapers.
Solving an equation like $3x + 5 = 17$.
Finding the actual distance between two places on a map with a 1:10,000 scale.
Solving an equation like $2(x + 3) = (x + 3)(x - 3)$.
Calculating the petrol consumption rate of a car.

PISA intrinsic motivation items
The index of intrinsic motivation to learn mathematics asks students to rate the extent to which they strongly agreed, agreed, disagreed, or strongly disagreed with the following statements:
I enjoy reading about mathematics
I look forward to my mathematics
I do mathematics because I enjoy it
I am interested in the things I learn in mathematics

PISA instrumental motivation items
The index of instrumental motivation to learn mathematics asks students to rate the extent to which they strongly agreed, agreed, disagreed, or strongly disagreed with the following statements:
Making an effort in mathematics is worth it because it will help me in the work that I want to do later on
Learning mathematics is worthwhile for me because it will improve my career prospects
Mathematics is an important subject for me because I need it for what I want to study later on
I will learn many things in mathematics that will help me get a job

PISA anxiety items
The index of mathematics anxiety asks students to rate the extent to which they strongly agreed, agreed, disagreed, or strongly disagreed with the following statements:
I often worry that it will be difficult for me in mathematics classes
I get very tense when I have to do mathematics homework
I get very nervous doing mathematics problems
I feel helpless when doing a mathematics problem
I worry that I will get poor grades in mathematics

All items are provided by the PISA 2003 Data Analysis Manual (OECD)
OECD (2005). *PISA 2003 Data Analysis Manual: SPSS users.*

Section 3. Classification of Courses Classified a Life and Physical Science

Field of study classifications

Coursework selection in high school
Life science
Biology (biological science)
Human Biology
Life science
Psychology
Environmental science
Marine Studies (Marine and Aquatic practices)
General Science (multi-strand science, Science life skills)
Physical science
Physics
Chemistry
Physical science
Earth science
Geology

University enrolment in STEM
Physical science
Mathematics (mathematical science)
Statistics
Physics (e.g., physics, astronomy)
Chemistry (e.g., Organic chemistry, inorganic chemistry)
Earth science (e.g., Geology, Geophysics, Geochemistry, Soil Science, Hydrology, Oceanography)
Computer Science (e.g., Programming, Algorithms, Systems Analysis and Design, Artificial Intelligence, Algorithms, Data Structures)
Engineering (e.g., Industrial Engineering Science, Mechanical Engineering, Mining Engineering Science, Chemical Engineering Science, Civil Engineering)

Life science
Biological science (e.g., Biochemistry and Cell Biology, Botany, Marine Science, Genetics, Human Biology)
Medicine science (e.g., General Medicine, Psychiatry, Paediatrics, Dental Science, Pharmacy, Nursing, Veterinary Science)
Health Sciences (e.g., Audiology, Naturopathy, Podiatry, Nutrition and Dietetics)
Agricultural Science (e.g., Agriculture, Wool Science, Horticulture, Forestry, Aquaculture)

Section 4. Interview Schedule Used To Collect Categorical Outcome Variables for Longitudinal Analysis (Adapted From The LSAY Y03 Questionnaire And Codebook; National Centre For Vocational Education Research, 2017, P. 31)

C104. In previous interviews we recorded that you did science, or mathematics subjects in Yr 12. Are you currently studying a science, engineering, mathematics or IT-related course?

1. Yes (Go to C105)
2. No (Go to C107)

C105. How important was each the following in your decision to study science, engineering, maths or IT:
a You were good at science, engineering, maths or IT.
b You wanted to pursue a career in science, engineering, maths or IT.
c You were influenced by career advice provided by your teachers or career advisers.
d You were influenced by having good science or maths teachers in high school.
e You were influenced by your parents.
f You were influenced by one or more science related 'experiences' at high school.
g You have an employer who supports your study in this field.
h The course you are doing provides a good basis for employment in areas you like.

Was it….(READ OUT)
1 Very Important
2 Important
3 Neither Important or unimportant
4 Not Important
5 Not at all important
6 DON'T KNOW/CAN'T SAY

PRE 105a IF C105e = 1,2, CONTINUE
ELSE GO TO C106
C105a. Do you have a parent or close relative with a career in this field?
1. Yes
2. No

C106. What other factors (if any) influenced your decision to study science, engineering, maths or IT? (PROBE FULLY – RECORD VERBATIM)

C107. How important was each of the following in your decision NOT to study science, engineering, mathematics or IT after leaving school:
a You had no desire to work in science, engineering, maths or IT
b You thought those fields would not get you a well-paid job
c You were influenced by advice from teachers and career advisers to consider other careers.
d Your parents influenced you to do other things.
e Science and maths teachers didn't inspire you enough to consider careers in science, engineering, maths or IT.
f Your friends did not study science, engineering, maths or IT.
g You were influenced against science, engineering, maths or IT by the negative image of them in the community.

Was it….(READ OUT)
1 Very Important
2 Important
3 Neither Important or unimportant
4 Not Important
5 Not at all important
6 DON'T KNOW/CAN'T SAY

PRE 107a IF C107g =1, 2 ASK C107a
ELSE GO TO C108
C107a Can you describe the image that you found off-putting?
(PROBE FULLY – RECORD VERBATIM)
C108. What other factors (if any) influenced your decision not to study science, engineering, maths or IT?

(PROBE FULLY – RECORD VERBATIM)
C109. What would need to change for you to consider choosing to study science, engineering, maths or IT?
(PROBE FULLY – RECORD VERBATIM)