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Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA,
IRVINE

Cultural Values and Cross-National Differences in Educational Choices and Performance

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Education

by

Suhang Jiang

Dissertation Committee:
Professor Jacquelynne Sue Eccles, Chair
Professor Mark Warschauer, Co-Chair
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2018

DEDICATION

To

World Peace

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ABSTRACT OF THE DISSERTATION

Cultural Values and Cross-National Differences in Educational Choices and Performance

By

Suhang Jiang

Doctor of Philosophy in Education

University of California, Irvine, 2018

Professor Jacquelynne Sue Eccles, Chair

Professor Mark Warschauer, Co-Chair

This dissertation explores how country-level cultural values are associated with gender differences in the enrollment in and completion of science, technology, engineering, and mathematics (STEM) Massive Open Online Courses (MOOC), national achievement in mathematics and science, and students' science achievement.

Study 1 explored how gender-equal culture and economic development moderate the gender differences in STEM MOOC enrollment and completion across countries. This study provides evidence supporting MOOC democratization. Using multilevel logistic regression on the HarvardX-MITx Person-Course de-identified dataset, this study found that while females were less likely than males to enroll in STEM MOOCs, they were equally likely to complete them. Further, a higher probability to enroll in STEM MOOCs and smaller gender gaps in STEM MOOC enrollment and completion were found in less gender-equal and less economically developed countries.

Study 2 investigated the relationship between cultural values and national achievement in mathematics and science. Using cluster analysis and Analysis of Covariance (ANCOVA) on the Programme for International Student Assessment (PISA) 2015 and World Value Survey (WVS) wave 6 datasets, study 2 found that country-level valuing science and technology and thriftiness were positively associated with while worrying about the availability of education and trying to make parents proud were negatively associated with national achievement in mathematics and science. Four cultural value profiles were identified and the highest achieving cultural value profile was high in valuing science and technology and thriftiness, low in trying to make parents proud, and about average in worrying about the availability of education.

Study 3 explored the relationship between country-level cultural value profiles, gender, self-concept of science ability, utility value of science, and individual student's science achievement. Using Hierarchical Linear Modeling (HLM) on TIMSS 2015 8th grade and WVS wave 6 datasets, study 3 found that country-level cultural value profile was significantly associated with individual student's science achievement and country profile moderated gender differences in students' science achievement, females and males performed equally well in science, and self-concept of science ability and utility value of science are positively associated with students' science achievement.

INTRODUCTION

We are in an age of unprecedented globalization that is characterized by a shift to knowledge-driven economies. Economic development has become more reliant on intellectual capabilities rather than on physical and natural resources (Hanushek & Wößmann, 2008) . In addition, knowledge-driven economies are largely based on technological advancement. Technology is essential for countries to compete and prosper in the globalized world (e.g., National Science Board, 2016). Educating a large pool of high-skilled technology-savvy professionals who have expertise in Science, Technology, Engineering, and Mathematics (STEM), as well as educating citizens in order to provide a general mastery of mathematics and science, is critical for a country's innovation and global competitiveness. Moreover, STEM professionals can benefit the world as a whole and push the progress of humanity, as evidenced in the invention of electricity, computers, and the Internet. Therefore, STEM education is of crucial importance in the contemporary world.

However, not all countries are achieving a high level of academic performance in mathematics and science. Cross-national differences in mathematics and science achievement have been studied since the 1960s (Husen, 1967; Wiersma, 1969). Adolescents in the United States were found to lag behind in mathematics development compared to their international counterparts from 11 other industrialized countries in the first large-scale multinational assessment (Husen, 1967). More recent international assessments such as Trends in International Mathematics and Science Study (TIMSS) and Programme for International Student Assessment (PISA) showed a persistent achievement gap between countries over the past 20 years (Martin, Mullis, Foy, & Hooper, 2016). For instance, Asian countries such as Singapore, China, Korea,

and Japan usually topped the TIMSS and PISA mathematics and science rankings (Mullis, Martin, Foy, & Hooper, 2016; OECD, 2016b).

Therefore, in order to improve national and global education quality, it is not only important to understand achievement gaps within a country, but also the academic achievement differences between countries (Stevenson & Stigler, 1994). First, the international perspective on academic achievement is valuable in providing a unique angle and approach to examine and improve educational quality. Students, parents, teachers, researchers, and education stakeholders are living in a particular cultural context. Without taking a step back from the culture one is exposed to, it is difficult to gain a clear picture of one's own approaches to learning. Second, identifying the characteristics of high-achieving countries allows educators, researchers, and policy makers to have a deeper understanding of country-level variables that may play a role in influencing educational achievement. Specifically, cross-national studies provide opportunities to examine how culture guides the socialization of academic achievement, i.e., how national characteristics and cultures are associated with individual beliefs, values, behaviors, and ultimately academic achievement in a larger international context.

A number of theories and approaches have been proposed to explain cross-national differences in academic achievement. Cross-national differences are mainly explained from two perspectives, i.e., genetic differences and socio-cultural influences. The genetic perspective emphasizes the role of genes in determining individuals' attributes such as personality and intelligence (Jensen, 1998; Herrnstein & Murray, 2010). The genetic explanation holds that certain races have genetic superiority and are innately more intelligent than others (Lynn, 1982; Vernon, 1982; Lynn, 1987). A general intelligence factor has been identified and measured in global intelligent quotient (IQ) tests (Lynn & Vanhanen, 2002; Lynn & Vanhanen, 2006). Lynn

and colleagues (2007) stated that national IQs predicted academic achievement differences in 67 countries.

Nevertheless, explaining national differences in academic achievement as genetic difference is disputable. It is circular reasoning to argue that different races achieve different IQ test scores because they are different races. There is no sufficient evidence to suggest that the IQ test score differences are primarily genetically determined, and Lynn (1987) did not control for environmental influences. Nisbett (2009) rebutted the view that genes determine intelligence with a collection of empirical evidence and argued that schools and cultures count for the primary forces influencing intelligence. One example is that a higher percentage of Chinese Americans entered high-status occupations compared with Whites, though the two groups started with the same scores on IQ tests (Nisbett, 2009). Similarly, Flynn (1991) found that Asian Americans' occupational achievements go beyond their IQ, and that non-IQ factors such as family, work ethic, and educational traditions are important for explaining the group's achievement differences. Dandy and Nettelbeck (2002) found that students from Asian cultures (Chinese and Vietnamese Australian) in Australia achieved higher scores in mathematics, even compared with their Anglo-Celtic peers who had the same IQ levels. This indicates that some other factors beyond genes and IQ influence students' achievements in mathematics, which leads us to socio-cultural influences on national mathematics and science achievement.

The socio-cultural perspective considers environmental influences on individuals' behaviors, psychological development, and educational achievement, such as family, school, and cultural values (Eccles, 1983; Bronfenbrenner, 1994). A considerable amount of work has explored how sociocultural factors are associated with cross-national achievement differences. For example, some studies attributed the cross-national differences to different school systems;

such as the time students spend in school, class size, teaching practices, and curriculum (Stevenson & Stigler, 1994; Schmidt et al., 2001). Previous studies showing that Asian Americans who received the same education as their peers in the U.S. still tended to have higher academic achievement (Sue & Okazaki, 1990) suggests that the educational system is not a sufficient explanation for the national differences in educational achievement, and that cultural values and beliefs may play an important role.

A body of work explored the role of cultural values in influencing national differences in academic achievement. Stevenson and colleagues (1993) argued that the cultural belief of the importance of hard work contributed to the higher academic performance of Asian students, compared with their American peers. Guiso and colleagues (2008) found that increased country-level gender equality was associated with a reduced gender gap favoring boys in mathematics achievement.

Nevertheless, previous empirical studies suffer from several limitations. First, in general, only a few countries were sampled for cross-national comparisons and the majority of the empirical studies compared students from Asian countries and the United States. It is unclear whether the patterns identified also apply to other countries. Second, the majority of studies did not explicitly measure country-level cultural factors and include them in data analysis; instead, they mainly speculated on the potential influence of cultural forces. Third, previous studies mainly used general and broad values to explain the achievement differences, such as the valuing of efforts. However, no studies have explored how domain-specific cultural values, such as valuing science and technology, are associated with the achievement differences in mathematics and science. Fourth, limited empirical studies identified the different combinations of cultural

values and how cultural value profiles are associated with national achievement in mathematics and science.

This dissertation aims to fill these gaps with the following three empirical studies. Study 1 used the HarvardX-MITx Person-Course de-identified dataset from the 2012-2013 academic year (MITx and HarvardX, 2014) to explore how gender-equal culture and national economic development moderate the gender differences in the enrollment in and completion of STEM MOOCs. We found that while females were less likely than males to enroll in STEM MOOCs, females and males are equally likely to complete STEM MOOCs. In addition, smaller gender gaps in STEM MOOC enrollment and completion were found in less gender-equal and less economically developed countries.

Study 2 used the PISA 2015 public datasets and the World Values Survey (WVS) wave 6 (2010-2014) dataset to investigate how general cultural values (e.g., thriftiness, making parents proud, and worrying about education) and the domain-specific cultural value (e.g., the importance of science and technology) are associated with the average nationwide mathematics and science scores by adopting cluster analysis and ANCOVA. We found that valuing science and technology, thriftiness, and GDP per capita were positively associated with national achievement in mathematics and science while trying to make parents proud and worrying about education were negatively associated with mathematics and science achievement. Countries were grouped into four clusters based on the above-mentioned four cultural values. The highest achieving country profile was high in valuing science and technology and thriftiness, low in collectivism, and about average in worrying about the availability of education.

Study 3 used the TIMSS 2015 8th grade dataset and the WVS wave 6 to examine the association between country-level cultural value profile, gender, self-concept of science ability,

utility value of science and individual student's science achievement, and whether broad cultural value profile and economic development level moderate the gender differences in science achievement. Using HLM, we found that country-level cultural value profile is significantly associated with students' science achievement, females and males performed equally well in science achievement, and students' self-concept of science ability and utility value of science are positively associated with students' science achievement. In addition, cultural value profile and GDP per capita moderated the relationship between gender and science achievement.

Conceptual Framework

This dissertation adopts the expectancy-value theory proposed by Eccles and colleagues as the guiding framework (Eccles, 1983; Wigfield & Eccles, 2000; Eccles & Wigfield, 2002). Expectancy-value theory acknowledges socio-psychological influences on individuals' choices and persistence, and posits that individuals' expectancies and task value beliefs directly influence educational choices, persistence, and performance (Wigfield & Eccles, 2000). According to the expectancy-value model, expectancies and subjective task values are influenced by children's goals and their perceptions of their abilities and of task difficulty, which are in turn influenced by children's perception of socializers'-parents, teachers, etc.-beliefs, expectations, and attitudes, and their interpretation of their experiences. The broad cultural milieu directly influences socializers' beliefs, and both of them directly influence children's perception of socializers' beliefs and activity stereotypes (Wigfield & Eccles, 2000; Eccles & Wigfield, 2002).

This dissertation mainly focuses on the value and cultural milieu components of expectancy-value theory. Subjective task values refer to individuals' perceptions of their own values for a certain task, and have four components: attainment value, intrinsic value, utility

value, and cost (Eccles, 2005). Attainment value is defined as the personal importance of doing well on a task and denotes the extent to which individuals confirm or disconfirm their self-schema with the task; intrinsic value refers to the inherent enjoyment individuals obtain from performing certain activities and is similar to the intrinsic motivation proposed in intrinsic motivation theory (Deci & Ryan, 1985); utility value refers to the usefulness of the task for individuals; cost refers to the negative aspect of engaging in the activity (Wigfield & Eccles, 1992; Eccles, 2005).

In general, expectancy-value theory takes the individual as the unit of analysis. We extend the value component of the theory and examine whether it also applies to country-level analysis in Study 2. As country-level analysis aggregates representative individual-level variables, we expect that expectancy-value theory still holds true for country-level analysis. We expect that countries that have high values for science and technology achieve higher scores in international assessments of mathematics and science.

CHAPTER 1

Study 1: Cross-National Comparison of Gender Differences in the Enrollment in and Completion of STEM MOOCs

MOOCs have attracted tens of millions of learners around the world. Theoretically, anyone with an Internet connection is able to freely access these online courses, which are often provided by professors from elite universities. Similar to previous technological advancements in broadcast media, such as radio and television, MOOCs were expected to transform education by providing learning opportunities for those who otherwise would not have access to them (Eccles, Wigfield, & Schiefele, 1998). The growing MOOC movement stems from the beliefs that knowledge should be freely shared and people have the right to learn regardless of their social and economic backgrounds (Yuan & Powell, 2013). MOOC proponents argue that MOOCs can democratize higher education and provide learning opportunities not only for traditionally underserved populations but also for college-educated populations, since both may improve their employment opportunities through the extra coursework provided (Koller, 2013).

However, the optimistic expectation that MOOCs will promote educational equity has been dampened by studies describing the demographics of individuals who enroll in and complete MOOCs (Christensen et al., 2013; Hansen & Reich, 2015; Ho et al., 2015). Statistics show that the majority of MOOC learners are young, well-educated males from developed countries (Christensen et al., 2013). In the United States, for example, individuals of higher socioeconomic status (SES) are much more likely to enroll in MOOCs than people of lower SES (Hansen & Reich, 2015). Based on these demographics, critics argue that MOOCs are failing to reach disadvantaged individuals, such as those without access to higher education in developing countries (Emanuel, 2013). This critique implicitly assumes that those in developing countries

who have already earned a college degree should not be considered disadvantaged. However, compared to their peers from developed countries, those in developing countries who already have a college degree are still at a disadvantage in terms of accessing both high-quality education from elite universities and high-quality jobs that often result from such an elite education.

In addition to the critique that MOOCs do not reach disadvantaged individuals, concerns have been voiced about whether MOOCs increase the participation of females in STEM fields (Ho et al., 2015). Gender disparity is prevalent in MOOCs, especially in STEM subjects. On average, only 1 in 5 learners in a STEM MOOC is female (Ho et al., 2015). As females have been traditionally underrepresented in STEM fields, we are particularly interested in females' enrollment and performance in STEM MOOCs. For example, females constitute 29% of those employed in science and engineering occupations in the United States (Beede et al., 2011), 12.8% in the United Kingdom (Arnett, 2015), 16% in Australia (Office of the Chief Scientist, 2016), and 13.8% in Japan (Homma, Motohashi, & Ohtsubo, 2013). Increasing female participation in STEM fields is crucial for strengthening the STEM workforce and a country's global competitiveness (Beede et al., 2011). Though females are generally underrepresented in STEM MOOC participation, it is unclear whether the gender disparity differs across countries and, if so, how. No studies have explored how country-level characteristics (e.g., gender equality and economic development level) may moderate the relationship between gender and the enrollment in and completion of STEM MOOCs. Investigating the moderating effect of country-level characteristics would provide evidence either for or against the claim that MOOCs are democratizing higher education across the world.

Therefore, this paper aims to explore the question of MOOC global democratization by examining the cross-national differences of females' enrollment in and completion of STEM

MOOCs and exploring whether and how the size of the gender gap in STEM MOOC enrollment and completion varies by country-level characteristics (e.g., gender equality and economic development level). We specifically examine enrollment and completion separately because MOOCs are notorious for having very low completion rates (Ho et al., 2015). Additionally, different factors may be associated with whether an individual decides to enroll in a STEM MOOC and whether that individual actually completes it.

Related Work

Our analytical framework is guided by the Eccles' Expectancy-Value Model of Achievement-Related Choices (Eccles, 1983, 1994; Wigfield, Tonks, & Eccles, 2004). This model accounts for individuals' choices of and performance in activities (Wigfield et al., 2004). It suggests that social context and cultural forces contribute to gendered educational choices (Eccles, 1994; Wigfield et al., 2004). Gender role stereotypes and cultural stereotypes of subject matter and occupational characteristics influence individuals' achievement choices through the socialization process (Wigfield, Eccles, Schiefele, Roeser, & Davis-Kean, 2007). In addition, we consider the impact of economic development level on females' educational choices because economic development has been found to be associated with less gender segregation and more gender equality in education (Baker & Jones, 1993; Hannum, 2005). We reviewed the literatures on cross-national differences in STEM education enrollment and performance, gender differences in using the Internet, and gender differences in online education performance. Based on the review, we proposed hypotheses about the direction of the gender differences and the potential influence of country-level characteristics on gender differences in the enrollment in and completion of STEM MOOCs.

Cross-National Differences in STEM Enrollment and Performance

One strand of previous empirical studies suggests that gender-equal cultures are associated with higher levels of female representation in STEM choices and smaller gender differences in STEM performance. Van Langen and Dekkers (2005) found that females from countries that were more gender conscious and advanced in females' emancipation (e.g., Sweden) considered STEM courses more attractive. In terms of STEM performance, previous studies showed that there were smaller gender differences in math performance in more gender-equal cultures (Guiso et al., 2008; Hyde & Mertz, 2009). On the other hand, conservative social norms and cultural expectations may both decrease the likelihood that females will choose STEM courses and undermine their performance in STEM. Nosek and colleagues (2009) found that national-level implicit gender stereotypes are positively associated with a national-level male-favoring gender gap in 8th grade science and math achievement. McDaniel (2010) found that the male-favoring gender gap in STEM career expectation became larger in countries with more traditional gender ideologies. If this pattern were the norm, we would expect the gender gap in STEM MOOC enrollment and completion to decrease as the level of gender equality in a country increases.

Another strand of empirical studies found that economic development is negatively associated with females' participation in STEM field (Bradley, 2000). Bradley (2000) found that the proportion of females in engineering was higher in the less economically developed countries than in more economically developed countries. For instance, Mexico had the highest percentage of tertiary computing degrees awarded to females in 2011 among countries that are OECD members (Khazan, 2014). In addition among 44 countries, Finland was found to have the highest

level of gender segregation in different fields of study (Charles & Bradley, 2009). The pronounced gender segregation in economically developed countries may be accounted for by the varying opportunities to express a gendered identity and the cultural beliefs that males and females are fundamentally and innately different (Charles & Bradley, 2009). Females from developed countries may feel that it is legitimate to express their aversion to math or STEM-related courses, which reinforces their inclination to avoid STEM fields. If this were the case, we would expect more gender segregation in STEM MOOC enrollment and completion in more economically developed countries than in other countries.

When it comes to developing countries, lack of access to high-quality STEM courses has been one of the factors that has hindered students' enrollment in traditional STEM fields (van Langen & Dekkers, 2005), and this may be especially true for females from developing countries. In addition to local programs to promote STEM education in developing countries (Bojic, Podobnik, Arratia, & Grgic, 2016), the free and easy access to online courses provided by elite universities may spark the interest of learners in developing countries to pursue STEM education. Research shows that internet users, especially females from developing countries, were more interested in working in STEM fields than their peers in developed countries (Penn, 2015). For instance, 77% of female respondents from developing countries stated that they felt encouraged to work in STEM fields while only 46% of female respondents from developed countries felt the same way (Penn, 2015). Based on this, we may expect smaller gender differences in STEM MOOC enrollment and completion in less developed countries compared to developed countries.

Gender Differences in Using the Internet

The male-favoring gender differences in the use of computers, mobile devices, and the Internet still exist in most parts of the world, especially in developing countries (Antonio & Tuffley, 2014; J. Cooper, 2006; Joel Cooper & Weaver, 2003; International Telecommunication Union, 2013; Kennedy, Wellman, Klement, & Klement, 2003). For instance in 2013, it was reported that the male-favoring gender gap was larger in developing countries, where 16% fewer females than males used the Internet while only 2% fewer females than males did so in developed countries (International Telecommunication Union, 2013). In 2016, the regional gender gap was largest in Africa (23%) and smallest in the Americas (2%) (International Telecommunication Union, 2016). Hilbert found that fewer females accessed and used Information and Communication Technology (ICT) than did males in developing countries (2011). Another report showed that in developing countries females were 50% less likely to access the Internet than were males in the same age group with similar levels of education and household income (Web Foundation, 2015). Based on this, we may expect that both females are less likely than males to enroll in STEM MOOCs and that larger male-favoring gender differences in STEM MOOC enrollment exists in less developed countries compared to developed countries.

Gender Differences in Online Education Performance

Previous studies show that females perform as well as, if not better than, males in online learning settings. For instance, Yukselturk and colleagues (2009) did not find significant differences in programming achievement with respect to gender in a self-regulated online learning environment in Turkey. Wladis and colleagues (2015) found that females and males had similar success rates in online STEM courses provided by an urban community college in the

United States. Price (2006) reported that females studying online are confident and independent learners who may outperform their male counterparts in an online undergraduate course provided by Open University. Chyung (2007) found that females scored higher than males in a graduate-level online course provided by a mid-sized university in the United States. Xu and Jaggars (2013) found that females outperformed males in online courses provided by 34 community and technical colleges in Washington State. Based on this, we may expect that once females enroll in STEM MOOCs, they may be equally or more likely than males to complete them.

In summary, previous studies suggest possible gender differences in STEM MOOC enrollment and completion as well as varying gender differences associated with country-level characteristics (e.g., gender equality and economic development level). We ask the following research questions: What are the directions of gender differences in STEM MOOC enrollment and completion? How do country-level characteristics (e.g., gender equality and economic development level) moderate the relationship between gender and the enrollment in and completion of STEM MOOCs? If MOOCs were to hold the promise to democratize and empower the traditionally disadvantaged females, the potential gains would be much larger in less gender-egalitarian and less economically developed countries.

Methods

To address our research questions, we used the HarvardX-MITx Person-Course de-identified dataset from the 2012-2013 academic year (Fall 2012, Spring 2013, Summer 2013) (MITx and HarvardX, 2014), which included 16 HarvardX and MITx courses on the edX platform. This dataset is the most comprehensive publicly available dataset on MOOCs. In total, 13 MOOCs were labeled as STEM MOOCs and three MOOCs were labeled as non-STEM.

Table 1.1 presents the description of the courses in the dataset. Courses in Biology, Computer Science, Engineering and Mechanics, Mathematics and Statistics, Physics, Chemistry, and Environmental Studies were labeled as STEM MOOCs because these fields are included in the STEM Designated Degree Program List (Department of Homeland Security, 2016). Learners in these online courses came from all over the world. The dataset included self-reported variables such as gender, age, highest level of education, country, and information about the courses that learners enrolled in and whether they have completed those courses. There were 641,138 person-course observations in the original dataset. We aggregated the dataset and obtained 476,532 unique students' observations. After removing those who did not report specific country names such as "other Europe" and personal information such as age, gender, and highest level of education and those who reported age under 10, we obtained 269,263 student observations from 25 countries for data analysis. The dependent variable STEM MOOC enrollment was set to 1 if a learner took at least one STEM MOOC and 0 otherwise. The dependent variable STEM MOOC completion was set to 1 if a STEM MOOC enrollee completed least one STEM MOOC and 0 otherwise.

Table 1. 1
Course Description

Institution	Course Title	STEM MOOC
HarvardX	The Ancient Greek Hero	No
HarvardX	Introduction to Computer Science I	Yes
HarvardX	Justice	No
HarvardX	Health in Numbers: Quantitative Methods in Clinical & Public Health Research	Yes
HarvardX	Human Health and Global Environmental Change	Yes
MITx	The Challenges of Global Poverty	No
MITx	Elements of Structure	Yes
MITx	Introduction to Solid State Chemistry 01	Yes
MITx	Introduction to Solid State Chemistry 02	Yes
MITx	Circuits and Electronics 01	Yes
MITx	Circuits and Electronics 02	Yes
MITx	Introduction to Computer Science and Programming 01	Yes
MITx	Introduction to Computer Science and Programming 02	Yes
MITx	Introduction to Biology – The Secret of Life	Yes
MITx	Electricity and Magnetism	Yes
MITx	Mechanics Review	Yes

We used the Gender Gap Index (GGI) created by the World Economic Forum to measure a country's gender equality level (World Economic Forum, 2012). The GGI is composed of the country's health index, educational attainment index, economic participation index, and political empowerment index. The health index refers to the sex ratio at birth and the gap between females' and males' healthy life expectancies. The educational attainment index reflects the ratios of females to males in primary-, secondary-, and tertiary-level education. The economic participation index reflects the gap between females' and males' labor force participation rates, wage equality, and the ratio of females to males among professional workers and senior officials. The political empowerment index reflects the gender gap at the highest-level of political decision-making (World Economic Forum, 2012). GGI ranges from 0 (full inequality) to 1 (full equality) with a higher GGI referring to a more gender-egalitarian environment. The GGI for the 25 countries in the dataset ranges from 0.55 (Pakistan) to 0.78 (Philippines). For this study, we used the grand mean centered GGI as a level 2 variable in the multilevel models.

As GGI does not reflect a country's development level, we included GDP per capita (2012) to measure a country's economic development level the year the data were collected (The World Bank, 2012) and used the grand mean centered log GDP per capita as a level 2 variable in the analysis. The GDP per capita for the countries in the dataset ranged from \$859 (Bangladesh) to \$67,512 (Australia). We also included controls for the learner's age and education using a bachelor's degree as the reference group.

To answer our research questions on the directions of gender differences and how country-level characteristics (e.g., gender-equal culture and economic development level) may moderate the relationship between gender and the enrollment in and completion of STEM MOOCs, we conducted a series of multilevel logistic regression models using R lme4 package to

account for the nesting of an individual within a country. The multilevel framework is an appropriate method for addressing our research questions because it takes into account the nesting of individuals within groups (in our case within countries) (Hox, 2010). These models allow for the examination of how country-level variables (e.g., GGI) are associated with individual's enrollment in and completion of STEM MOOCs as well as with cross-level interaction effects between individuals and country-level variables. The model examining GGI can be written:

Level-1 equation

$$Outcome_{ik} = \beta_{0k} + \beta_{1k}Female_{ik} + \beta_{2k}Age_{ik} + \beta_{3k}Education_{ik} + e_{ik}$$

Level-2 equation

$$\begin{aligned}\beta_{0k} &= \gamma_{00} + \gamma_{01}GGI_k + u_{0k} \\ \beta_{1k} &= \gamma_{01} + u_{1k}\end{aligned}$$

The level 1 equation indicates that the learner's outcome is a linear combination of the intercept for the country where the learner comes from (β_{0k}), the main effect of being female ($\beta_{1k}Female_{ik}$), the main effect of age ($\beta_{2k}Age_{ik}$), the main effect of education ($\beta_{3k}Education_{ik}$), and a residual for the learner (e_{ik}). The level-two equation allows for random variations in intercepts between countries where the country-level intercepts (β_{0k}) are comprised of a grand mean (γ_{00}), a fixed effect for GGI ($\gamma_{01}GGI_k$), and random deviations in intercepts between countries (u_{0k}). Additionally, a random effect for gender was included such that the association between gender and the outcome was allowed to differ between countries as denoted by u_{1k} . For the models examining the relation between GDP per capita and STEM MOOC enrollment and completion, GDP per capita instead of GGI is used in the above-mentioned equations.

We tested all of our models for the inclusion of random slopes and random intercepts. Using the likelihood ratio test, we found that random slope models performed significantly better

when a random slope was included for female. Therefore we report results from models where slopes were able to vary randomly for female. To examine the degree to which learners from different countries differ in their propensity to choose and complete STEM MOOCs, we calculated the intraclass correlation coefficient (ICC) to determine if there was sufficient country-level variance to model (Snijders & Bosker, 2011). The ICC is 0.2 for enrollment and 0.13 for completion, indicating that about 20% and 13% of the variation in STEM MOOC enrollment and completion, respectively, can be attributed to differences in learners' country of origin. We first ran multilevel logistic regression models for STEM MOOC enrollment, and then examined only those learners who took at least one STEM MOOC and modeled their STEM MOOC completion.

Results

Descriptive Analysis

Figure 1.1 displays the number of female and male learners who took at least one STEM MOOC in each country. Across all countries, 54,214 female learners chose to enroll in at least one STEM MOOC, which comprised 24.16% of STEM MOOC learners ($n = 224,318$) in the dataset (see Figure 1.1). By country, the percentage of female STEM MOOC learners ranged from 5% in Bangladesh to 38.92% in the Philippines (see Figure 1.1). It is worth noting that the top two countries with the highest female representation were developing countries (the Philippines and Indonesia). Figure 1.2 shows the percentage of all MOOC learners in each country who enrolled in at least one STEM MOOC, by gender. Across all countries, 72.35% of female and 87.53% of male MOOC learners enrolled in at least one STEM MOOC (see Figure 1.2). The percentage of female MOOC learners taking one or more STEM MOOCs ranged from

17.33% in Japan to 96.93% in Portugal (see Figure 1.2). In several countries (including Portugal, Egypt, and Nigeria), female learners took STEM MOOCs at nearly the same rate as males. For example, 96.38% of female and 98.19% of male MOOC learners from Egypt chose to enroll in at least one STEM MOOC (see Figure 1.2). This shows that while a lower percentage of female MOOC students overall enrolled in STEM MOOCs, the gender differences varied considerably by country.

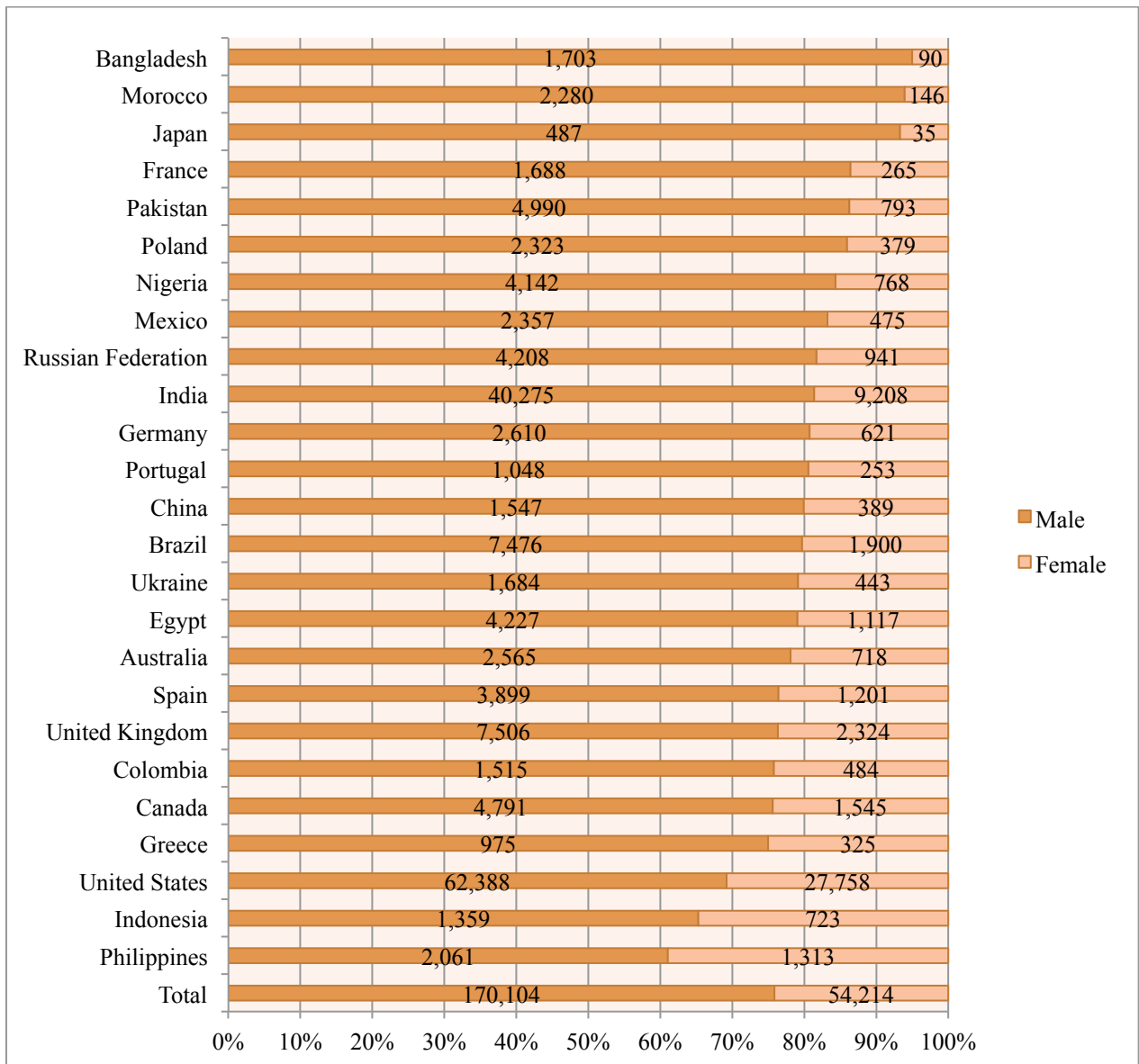


Figure 1. 1. Number of males and females who enrolled in one or more STEM MOOCs in each country

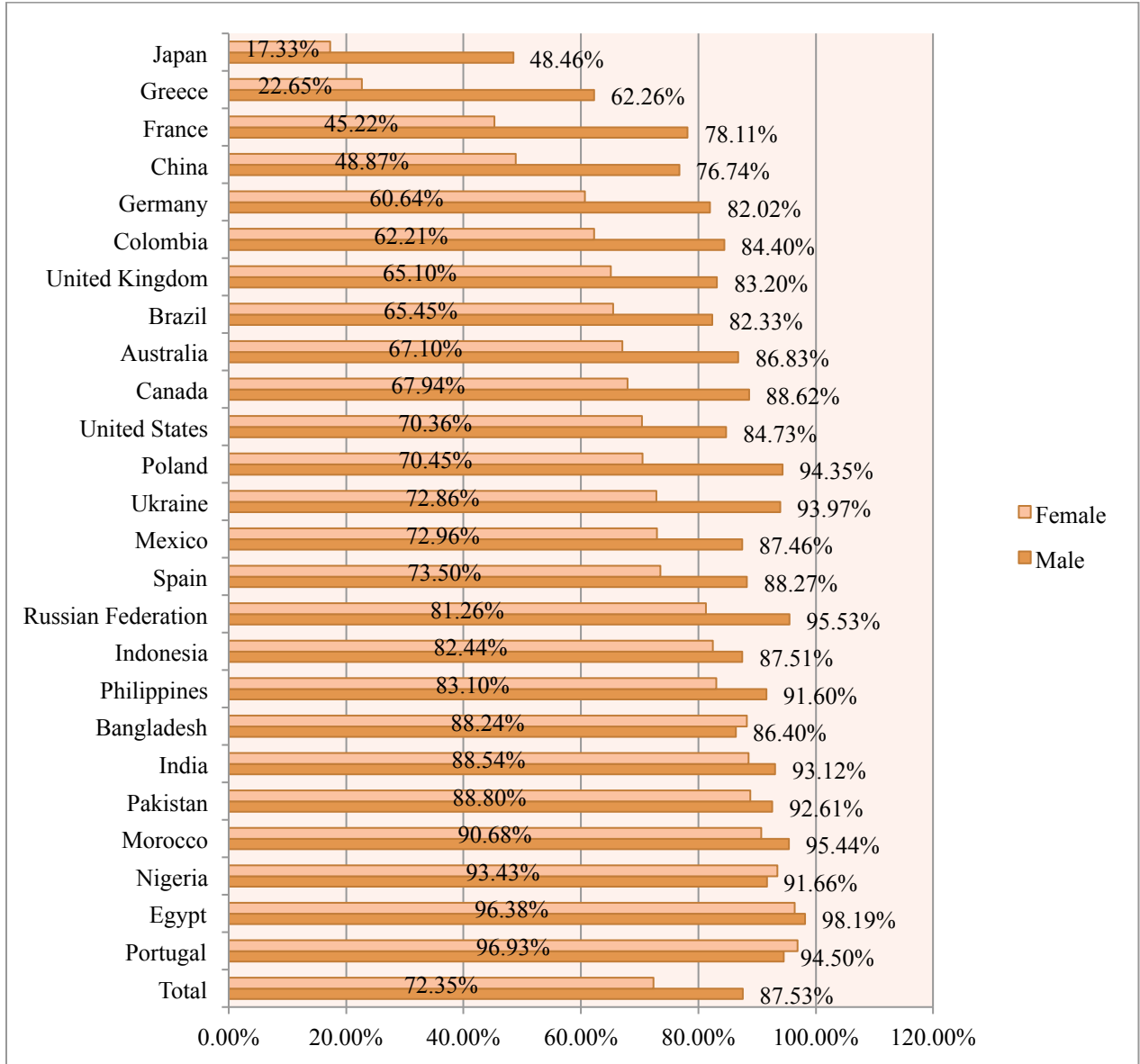


Figure 1. 2. Percentage of all MOOC enrollees in each country who enrolled in one or more STEM MOOCs, by gender

When it comes to completion of STEM MOOCs (Figure 1.3), only 1,659 female and 5,294 male STEM MOOC learners completed at least one STEM MOOC. On average, 23.86% of STEM MOOC learners who completed a MOOC were female, but this varied greatly by country. As shown in Figure 1.3, Indonesia, China, and the Philippines had the highest rate of females completing at least one STEM MOOC, with 52.78%, 50%, and 31.03%, respectively.

When examining the STEM MOOC completion rate by gender alone (see Figure 1.4 Total), only 3.06% of females and 3.11% of males who enrolled in STEM MOOCs actually completed at least one STEM MOOC. This suggests that both males and females had low STEM MOOC completion rates while these rates varied across countries.

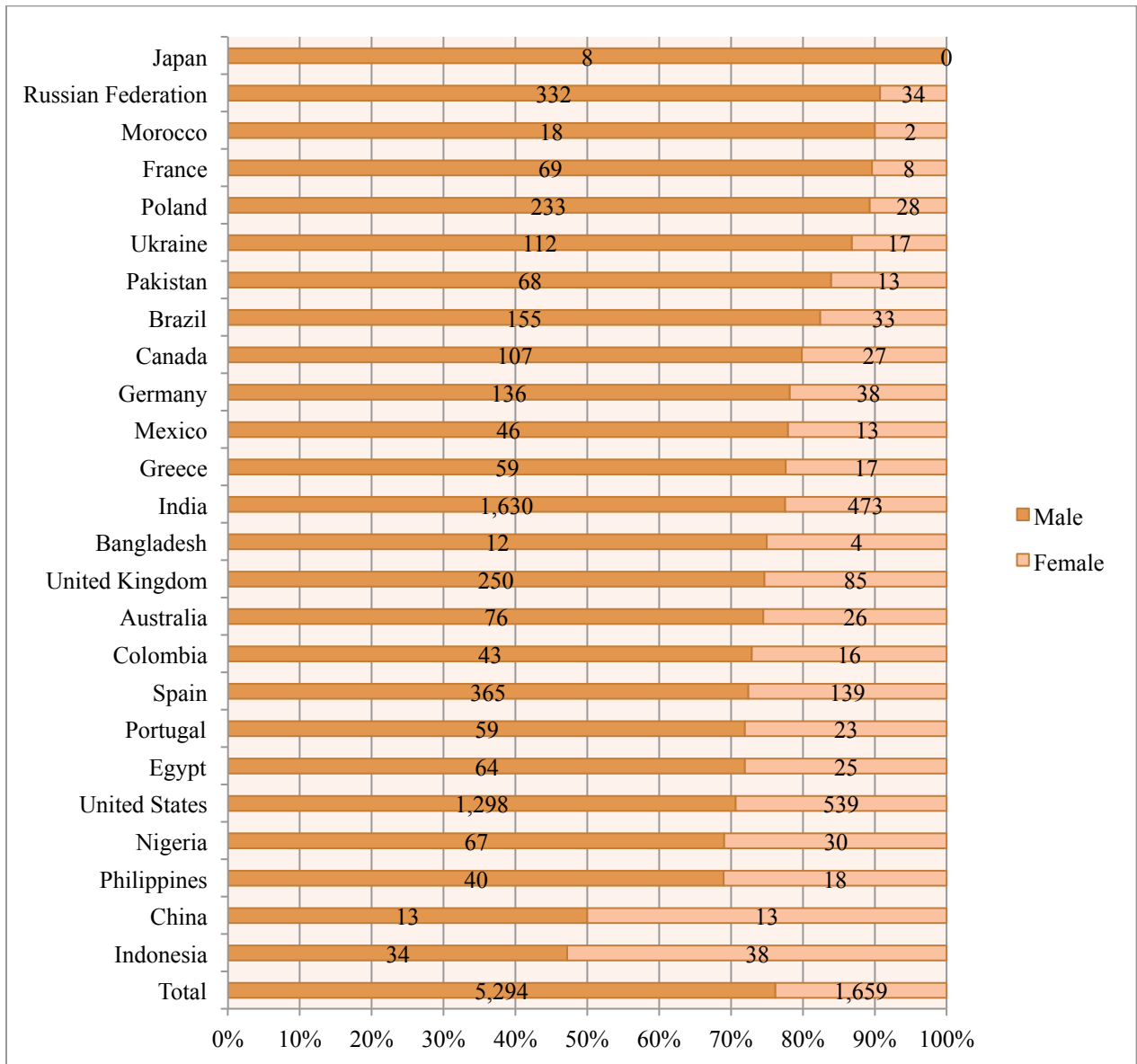


Figure 1. 3. Number of males and females who completed one or more STEM MOOCs in each country

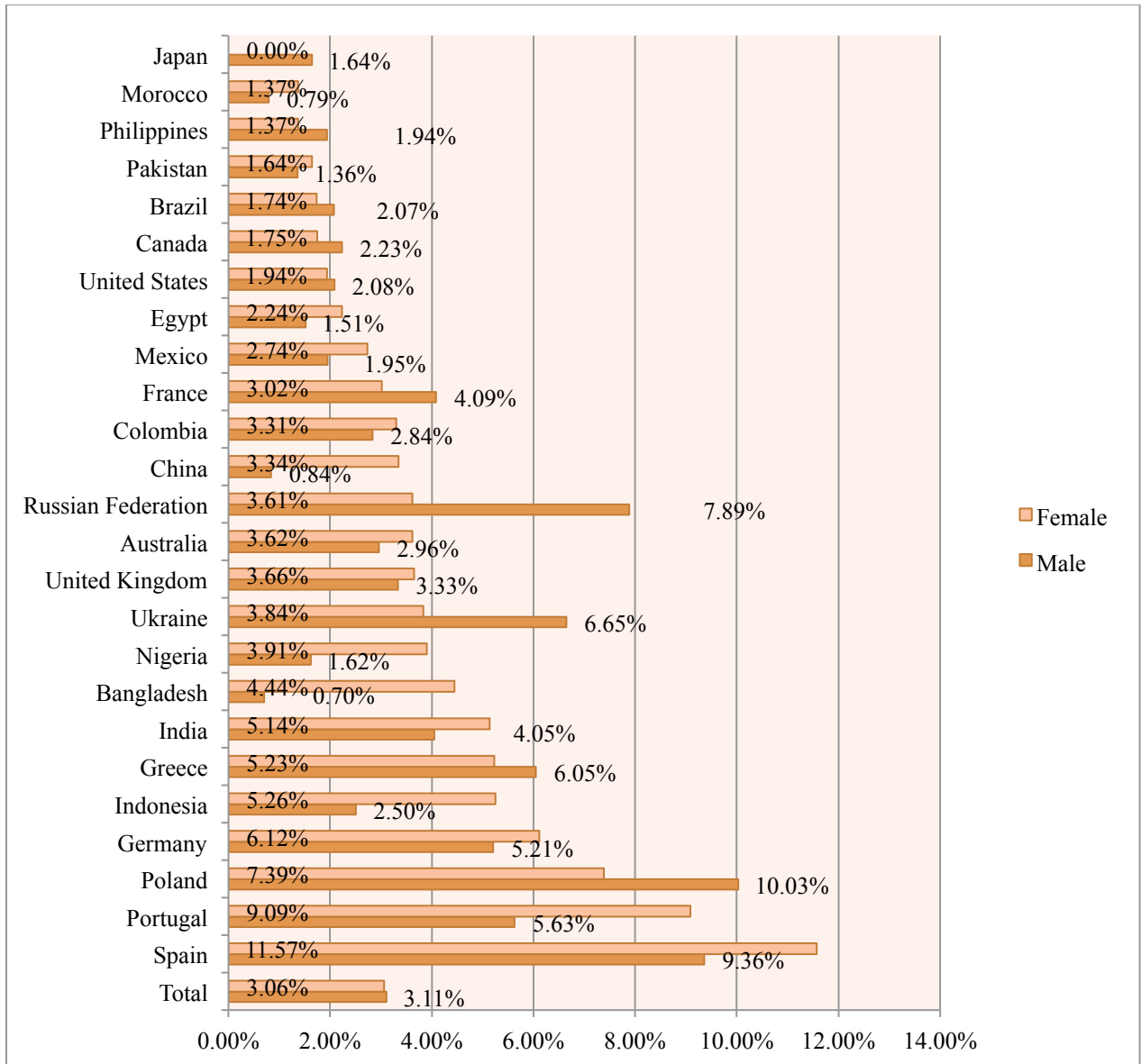


Figure 1. 4. Percentage of STEM MOOC enrollees in each country who completed one or more STEM MOOC, by gender

Statistical Analysis

Table 1.2 shows the results from the multilevel logistic regression models used to assess the relationship between gender and STEM MOOC enrollment, and the moderation effect of country-level characteristics (e.g., GGI and GDP per capita). Seven models are presented each with an increasing number of covariates (the same models were conducted for STEM MOOC

completion, see Table 1.3). Model 1 tested the raw effect of being female on the enrollment in STEM MOOCs. Model 2 controlled for age and Model 3 controlled for both age and education level. Based on Model 3, Model 4 controlled for GGI and Model 5 included the interaction term between female and GGI. Model 6 controlled for log GDP per capita, and Model 7 controlled for the interaction term between female and log GDP per capita. Across the entire sample, a female's probability of enrolling in at least one STEM MOOC was 12% lower than that of a male, when controlling for the individual's age and highest level of education, as shown by Model 3 in Table 1.2. Model 3 in Table 1 also shows that age was negatively related to enrollment in STEM MOOCs ($r = -0.003$, $p < 0.001$). Learners with a less than secondary degree ($r = -0.01$, $p < 0.1$), a master's ($r = -0.03$, $p < 0.001$), or a Ph.D degree ($r = -0.01$, $p < 0.001$) were less likely than those with only a bachelor's degree to enroll in STEM MOOCs while learners with a secondary education ($r = 0.03$, $p < 0.001$) were more likely than those with a bachelor's degree to enroll in STEM MOOCs (see Model 3 in Table 1.2). GGI ($r = -0.51$, $p < 0.001$) was negatively significantly associated with enrollment in STEM MOOCs (see Model 4 and 5 in Table 1.2). The negative interaction term between female and GGI ($r = -0.42$, $p < 0.001$) was significant, which indicates that higher gender equality was related to an increased gender gap in STEM MOOC enrollment (see Model 5 in Table 1.2). More specifically, a 0.1 increase of GGI is associated with a 5.1% decrease in an enrollee's probability and an additional 4.2% decrease in a female's probability to enroll in STEM MOOCs. GDP per capita was negatively associated with STEM MOOC enrollment ($r = -0.03$, $p < 0.001$) (see Model 7 in Table 1.2). In addition, higher GDP per capita is associated with an increased gender gap in STEM MOOC enrollment when controlling for age and the highest level of education, as shown by Model 7 in Table 1.2. More specifically, a 1% increase in GDP per capita is associated with a 3% decrease in an

enrollee’s probability and an additional 3% decrease in a female enrollee’s probability of STEM MOOC enrollment. The findings suggest that the male-favoring gender differences in STEM MOOC enrollment were smaller in less gender-equal and less economically developed countries.

Table 1. 2
Multilevel Logistic Regression on Whole Sample for Enrolling in STEM MOOCs

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Female	-0.13 ^{***} (0.02)	-0.13 ^{***} (0.02)	-0.12 ^{***} (0.02)	-0.12 ^{***} (0.02)	-0.12 ^{***} (0.02)	-0.12 ^{***} (0.02)	-0.12 ^{***} (0.00)
Age		-0.004 ^{***} (0.00)	-0.003 ^{***} (0.00)	-0.003 ^{***} (0.00)	-0.003 ^{***} (0.00)	-0.003 ^{***} (0.00)	-0.003 ^{***} (0.00)
< Secondary			-0.01 ⁺ (0.01)	-0.01 ⁺ (0.01)	-0.01 ⁺ (0.01)	-0.01 ⁺ (0.01)	-0.01 ⁺ (0.01)
Secondary			0.03 ^{***} (0.00)	0.03 ^{***} (0.00)	0.03 ^{***} (0.00)	0.03 ^{***} (0.00)	0.03 ^{***} (0.00)
Master			-0.03 ^{***} (0.00)	-0.03 ^{***} (0.00)	-0.03 ^{***} (0.00)	-0.03 ^{***} (0.00)	-0.03 ^{***} (0.00)
PhD			-0.01 ^{***} (0.00)	-0.01 ^{***} (0.00)	-0.01 ^{***} (0.00)	-0.01 ^{**} (0.00)	-0.01 ^{**} (0.00)
GGI				-0.38 ⁺ (0.20)	-0.51 ^{***} (0.08)		
Female*GGI					-0.42 ^{***} (0.06)		
Log GDP per capita						-0.03 (0.02)	-0.03 [*] (0.02)
Female*log GDP per capita							-0.03 [*] (0.01)
N	269,263	269,263	269,263	269,263	269,263	269,263	269,263
Marginal R ²	0.04	0.06	0.06	0.08	0.10	0.09	0.12
Conditional R ²	0.24	0.26	0.26	0.26	0.27	0.25	0.27

Note. Standard errors in parentheses. Coefficients are average marginal effects. The R² given above is Nakagawa and Schielzeth’s R² (2013). ^{***} p < 0.001, ^{**} p < 0.01, ^{*} p < 0.05, ⁺ p < 0.1

Table 1.3 shows the results of using multilevel logistic regression models to assess the relationship between being female and STEM MOOC completion, and the moderation effect of country-level characteristics (e.g., GGI and GDP per capita). We found that females and males were equally likely to complete STEM MOOCs, after controlling for age, highest level of education, country-level characteristics, and the interaction term between female and country-

level variables (see Model 1-7 in Table 1.3). Furthermore, increased gender equality (GGI) ($r = 0.17$, $p < 0.01$) was positively associated with the completion of STEM MOOCs (see Model 5 in Table 1.3), i.e., 0.1 increase of GGI increase the probability to complete STEM MOOCs by 1.7%. The interaction term between gender and GGI ($r = -0.11$, $p < 0.001$) was negatively associated with completion of STEM MOOCs, indicating that a 0.1 increase of GGI is associated with a 1.1% decrease in a female's probability to complete STEM MOOCs (see Model 5 in Table 1.3). GDP per capita was positively associated with learners' completion of STEM MOOCs ($r = 0.01$, $p < 0.5$) and reduced female advantage in completing STEM MOOCs ($r = -0.005$, $p < 0.1$) (see Model 7 in Table 1.3). Precisely, a 1% increase in GDP per capita increases the probability to complete STEM MOOCs by 1% and decreases females' probability to complete STEM MOOCs by 0.5%, as shown by Model 7 in Table 1.3. The findings suggest that the gender difference in STEM MOOC completion is smaller in in less gender-egalitarian and economically developed countries.

Table 1. 3
Multilevel Logistic Regression for Completing Conditional on STEM MOOC Enrollment

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Female	0.002 (0.00)	0.002 (0.00)	0.002 (0.00)	0.002 (0.00)	0.001 (0.00)	0.002 (0.00)	0.001 (0.00)
Age		-0.00 ⁺ (0.00)	-0.00 ^{***} (0.00)	-0.00 ^{***} (0.00)	-0.00 ^{***} (0.00)	-0.00 ^{***} (0.00)	-0.00 ^{***} (0.00)
< Secondary			0.01 [*] (0.00)	0.01 [*] (0.00)	0.01 [*] (0.00)	0.01 [*] (0.00)	0.01 [*] (0.00)
Secondary			0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Master			0.01 ^{***} (0.00)	0.01 ^{***} (0.00)	0.01 ^{***} (0.00)	0.01 ^{***} (0.00)	0.01 ^{***} (0.00)
PhD			0.03 ^{***} (0.00)	0.03 ^{***} (0.00)	0.03 ^{***} (0.00)	0.03 ^{***} (0.00)	0.03 ^{***} (0.00)
GGI				0.11 ^{***} (0.03)	0.17 ^{**} (0.06)		
Female*GGI					-0.11 ^{***} (0.03)		
Log GDP per capita						0.01 ⁺	0.01 [*]

						(0.00)	(0.00)
Female*log GDP per capita							-0.005 ⁺
							(0.00)
N	224,318	224,318	224,318	224,318	224,318	224,318	224,318
Marginal R ²	0.001	0.001	0.01	0.02	0.03	0.02	0.03
Conditional R ²	0.13	0.13	0.13	0.12	0.13	0.12	0.12

Note. Standard errors in parentheses. Coefficients are average marginal effects. The R² given above is Nakagawa and Schielzeth's R² (2013). *** p < 0.001, ** p < 0.01, * p < 0.05, + p < 0.1

Discussion

This study complements previous work investigating the democratization of MOOCs in the United States (Hansen & Reich, 2015) by suggesting that MOOCs have the potential to democratize education across the world and provide STEM learning opportunities for learners, particularly female learners from less gender-equal and less economically developed countries. This study demonstrates that while females were less likely than males to enroll in STEM MOOCs, females and males were equally likely to complete them. A higher probability to enroll in STEM MOOCs and smaller male-favoring gender gaps in STEM MOOC enrollment and completion were found in less gender-egalitarian and less economically developed countries.

Considering that females are generally less likely than males to enroll in STEM MOOCs and only consisted of about 24% of STEM MOOC learners, more studies should be conducted to explore the factors influencing females' enrollment in STEM MOOCs. Currently, it is unclear whether females' underrepresentation in STEM MOOC enrollment is due to the lack of Internet access (International Telecommunication Union, 2013), gender stereotypes related to STEM field (Charles & Bradley, 2009), not being aware of online STEM learning opportunities, or other factors. Knowing the underlying cause of female underrepresentation in enrollment would allow for targeted corrective action. Corresponding actions can be taken to increase females' enrollment in STEM MOOCs based on the underlying reasons. For instance, if females' low

participation is due to the fact that they are not aware of free online STEM courses or the opportunities and financial rewards that could result from taking these courses (Chen et al., 2015; Eccles, 1994), additional outreach could promote such awareness.

The smaller male-favoring gender gaps in STEM MOOC enrollment and completion in less gender-egalitarian and less economically developed countries indicate that MOOCs might offer broad country-level social benefits for less socially and economically developed countries. Free and easy access to MOOCs in developing countries allows females to try out STEM courses that are not easily available to them in their local communities. This finding also aligns with the educational-gender-equality paradox found by Stoet and Geary, i.e., the gender differences in the magnitude of relative academic strengths and pursuit of STEM degrees rose with increases in national gender equality (Stoet & Geary, 2018). These phenomena can be explained by the expectancy value theory (Eccles, 1983). The life-quality pressures in less gender-equal and less economically developed countries may increase females' utility value of pursuing a STEM education and career, which in turn promotes females' STEM engagement (Banerjee, Schenke, Lam, & Eccles, 2018). Pursuing a STEM education and career may be more appealing to females from less socially and economically developed countries, because STEM occupations are usually well paid and can provide economic security. On the other hand, the cost for females from more socially and economically developed countries to forgo a STEM career is relatively small, since there may be a higher level of social and economic security (Stoet & Geary, 2018). At the same time, females from more developed countries may be more influenced by gender essentialist ideology (Bradley, 2000; Charles & Bradley, 2009), which in turn reduces their interest and engagement in STEM. We suggest that future studies be conducted to understand females' decision-making process to enroll in and complete STEM MOOCs.

This study has certain limitations. First, the fact that the pseudo-R squareds are small (see Table 1.2-1.3) implies that the variables in the model only explain a portion of the overall variance in STEM MOOC enrollment and completion. Though this is a limitation, the paper focuses on the narrower question of the moderating effect of country-level characteristics on the relationship between gender and enrollment or completion of STEM MOOCs. In that sense, the pseudo-R squareds, though small, are still scientifically valid for identifying the moderator.

Secondly, the datasets were collected in 2012-2013 and thus do not reflect more recent trends in MOOC enrollment and completion. This is due to the nature of MOOC data that has been made publicly available so far. As additional MOOC data becomes available, future research should investigate whether and how the patterns of results identified in our study might change.

CHAPTER 2

Study 2: Cultural Value Profiles and Cross-National Differences in Mathematics and Science Achievement

Persistent and significant national differences in mathematics and science achievement have been observed in the past decades (Husen, 1967; Mullis et al., 2016). How might national-level mathematics and science achievement be related to pervasive cultural values? The answer to this question is explored in this study focusing on different cultural profiles and their relationships with national-level educational achievement in mathematics and science.

Culture is the shared mental programming (e.g., patterns of thinking, feeling, and acting) that distinguishes members of one group from another (Hofstede, 1991; Schwartz, 1997). Values, i.e., the ideas about what is good, right, and desirable, are central features of culture and important sources of motivation (Schwartz, 1997). Expectancy value theory explicates the relationship between individuals' values and their educational choices, achievement, and persistence (Eccles, 1983; Wigfield & Eccles, 2000). Previous empirical studies found that students are more likely to engage in and perform better in science activities when they attach high subjective value to science (Hulleman & Harackiewicz, 2009). International assessments also showed strong positive relationships between students' subjective values (e.g., interest value and utility value) of science and their science achievement exist within country (e.g., Mullis, Martin, Foy, & Arora, 2012; Abu-Hilal et al., 2014; Wang & Liou, 2017). However, it is unclear how country-level value of science and technology varies across countries. In addition, no studies have examined the associations between country-level value of science and technology and national achievement in mathematics and science. Based on expectancy-value theory, we

expect that country-level value of science and technology will be positively associated with national achievement in science and technology.

In addition to national value of science and technology, we speculate that thriftiness, worrying about the ability to provide for one's children's education, and the desire to make parents proud might also be related to national educational achievement in mathematics and science.

Thriftiness, i.e., saving money and things, reflects a long-term and future orientation (Hofstede, 1991) and a tendency for delayed gratification (Mischel, Shoda, & Rodriguez, 1989). Previous studies found that long-term orientation was positively correlated with TIMSS 1999 math score with $r = .58^*$ for fourth grade and $r = .72^{**}$ for eighth grade but was not associated with science scores (Hofstede & Hofstede, 2001). We may expect that countries that value thriftiness may have higher achievement in mathematics and science because they value the long-term investment in studying mathematics and science.

The extent one worries about providing good education to one's children indicates the value one attaches to education, perceived important role that education plays in upward social and economic mobility (Chen & Uttal, 1988; Sue & Okazaki, 1990b), as well as whether there are sufficient educational resources and quality teachers readily available in the local community (Eggerman & Panter-Brick, 2010). A high score on this construct could represent both valuing education and being concerned about its inaccessibility. Countries that have high average values on this measure may be at the brink of upward mobility.

The desire to make parents proud reveals a social oriented motivation that is usually observed in traditional societies. Chen and Uttal (1998) speculated that Chinese students' high achievement was due to the fact that education was considered a collective effort of the family

and the community. On the other hand, Stankov (2009) found that collectivism, which is an indicator of conservatism, was negatively associated with intelligence. If this were the case, we may expect that trying to make parents proud is negatively associated with national mathematics and science achievement.

Present Study

Previous studies suffered from several limitations. First, the relationship between country-level value of science and technology and national achievement in mathematics and science has not been empirically tested. Second, most of previous studies used a variable-centered approach (e.g., univariate analysis) to identify the unique associations of cultural values with national level educational achievement (e.g., Hofstede & Hofstede, 2001). Few studies employed a pattern-centered approach to explore the combinations of cultural values and their relationship with national educational achievement (e.g., Meyer & Schiller, 2013). Third, few studies controlled for economic development levels when investigating the cultural value effect on educational achievement (e.g., Chiu & Klassen, 2010). It is unclear whether the proposed cultural value effect will hold when controlling for economic growth.

To fill the above-mentioned research gap, in this study we aim to answer the following research questions, 1) to what extent are the proposed cultural values associated with national achievement in mathematics and science? 2) what are the cultural profiles that are related to national achievement in mathematics and science? 3) do national achievement in mathematics and science vary by the cultural profiles after controlling for economic development levels?

Methods

Datasets

This study used the WVS wave 6 (2010-2014) dataset (Inglehart et al., 2014) to measure cultural values for each country. The WVS data were collected from 60 countries by conducting face-to-face interviews with the sampled participants. At least 1,000 participants were sampled in each country. The participants were asked a series of questions about their values and beliefs. The results of the WVS are assumed to represent the prevailing cultural values and beliefs of each country.

In addition, this study used the PISA 2015 dataset (OECD, 2016) to measure national-level achievement in mathematics and science. PISA focuses on assessing how 15-year-old students can apply what they have learned in school to real-life situations. PISA 2015 has 72 participating countries and economies. This study used country as the unit of analysis.

Dependent Measures

Average national PISA mathematics score. PISA 2015 mathematics scores were used to measure a country's mathematics achievement (OECD, 2016). Singapore, Hong Kong SAR, Macao, Chinese Taipei, and Japan are the top five achievers in PISA mathematics.

Average national PISA science score. PISA 2015 science scores were used to measure a country's science achievement (OECD, 2016). Singapore, Japan, Estonia, Chinese Taipei, and Finland are the top five achievers in PISA science.

Independent Measures

National Utility Value of Science and Technology. This variable was measured by four questions in the WVS wave 6 dataset. The survey participants were asked to rate how much they

agree or disagree with the following statements on a scale of 1-10. The reliability of the importance of science and technology measure was Cronbach's $\alpha = 0.73$ in the dataset. We calculated the weighted average for each of the four questions for each country and used the average of the four questions to represent the national utility value of science and technology.

- a. "Science and technology are making our lives healthier, easier, and more comfortable" (V192). The answer "completely disagree" is labeled as 1 and "completely agree" is labeled as 10.
- b. "Because of science and technology, there will be more opportunities for the next generation" (V193). The answer "completely disagree" is labeled as 1 and "completely agree" is labeled as 10.
- c. "It is not important for me to know about science in my daily life"(V196). The answer "completely disagree" is labeled as 10 and "completely agree" is labeled as 1.
- d. "All things considered, would you say that the world is better off, or worse off, because of science and technology?" (V197). The answer "the world is a lot worse off" is labeled as 1 and the answer "the world is a lot better off" is labeled as 10.

Thriftiness. Thriftiness reflects an orientation toward the future, delay of gratification, and is an indicator of long-term orientation. The WVS measures thriftiness with the following survey item: "Here is a list of qualities that children can be encouraged to learn at home. Which, if any, do you consider to be especially important?: Thrift, saving money and things " (V17). A response of 1 indicates thrift is important for the respondent while a response of 0 indicates it is not important. We calculated the weighted average of this question for each country to measure thriftiness.

Worrying about the Availability of Education. Worrying about the availability of education was measured by the question “To what degree are you worried about the following situations? Not being able to give my children a good education”(V182). The level of agreement ranges from 1 to 4. Originally, the WVS dataset labeled the answer “very much” as 1, “a great deal” as 2, “not much” as 3, and “not at all” as 4. We reversed the coding of the answer so that a higher value indicates more agreement with worrying about education. We used the weighted average of this question for each country to measure this variable.

Making Parents Proud. This variable is measured by the extent of the agreement with the statement “One of my main goals in life has been to make my parents proud” (V49). The WVS labeled the answer “strongly agree” as 4, “agree” as 3, “disagree” as 2, and “strongly disagree” as 1. We calculated the weighted average of this question for each country to measure this variable.

GDP per capita. GDP per capita in 2015 was included for measuring a country’s economic development level. GDP per capita is the gross domestic product divided by midyear population (The World Bank, 2015). It is necessary to separate the economic effect from cultural factors.

Data Analysis

We merged the WVS wave 6 dataset with the PISA 2015 dataset and obtained 35 countries that have both cultural values and PISA scores. Mahalanobis distance (using a $p < .01$

criterion) was used to identify multivariate outliers: Qatar was the only outlier. Since outliers may have significant impacts on the results, Qatar was removed from the data analysis. As a result, we had 34 countries in the dataset for data analysis.

Zero-order correlations were conducted to identify the correlation between independent and dependent variables. Cluster analyses were employed to explore the national cultural profiles. The independent variables were standardized prior to the cluster analyses as they have different scales. Cluster analysis is a tool to organize observed data into groups that maximizes the similarity within each group, while maximizing the dissimilarity between groups (Hastie, Tibshirani, & Friedman, 2009). In this study, cluster analyses were performed on four independent variables (i.e., utility value of mathematics and science, thriftiness, worrying about education, and making parents proud) to identify different cultural profiles in the PISA dataset. Hierarchical agglomerative cluster analysis using Ward's method was conducted to identify clusters applying average squared Euclidean distance as a measure of similarity. K-means relocation clustering was conducted subsequently using the Ward cluster solution as start values to relocate each case to the optimal cluster (Bergman, Magnusson, & Khouri, 2003).

ANCOVA was conducted separately on PISA mathematics and science to explore whether the national average PISA mathematics and science achievement is the same for different types of cultural profiles, while controlling for GDP per capita. Levene's test for homogeneity of variances and homogeneity of regression slopes assumption were tested and the assumptions met for PISA mathematics achievement. The homogeneity of regression slopes assumption was violated for PISA science achievement. *Post hoc* analyses were conducted to evaluate pair-wise comparison of adjusted means of different cultural profiles.

Results

Table 2.1 presents the summary statistics of both independent and dependent variables in the merged dataset. Table 2.2 presents the zero-order correlation between the independent and dependent variables. It shows that national utility value of science is positively associated with PISA mathematics ($r = 0.44$, $p < 0.01$) and science scores ($r = 0.41$, $p < 0.05$). Thriftiness is positively associated with both PISA mathematics ($r = 0.66$, $p < 0.001$) and science scores ($r = 0.62$, $p < 0.001$). Worrying about the availability of education is negatively associated with PISA mathematics ($r = -0.52$, $p < 0.01$) and science scores ($r = -0.52$, $p < 0.01$). Trying to make parents proud is also negatively associated with PISA mathematics ($r = -0.78$, $p < 0.001$) and science scores ($r = -0.80$, $p < 0.001$). GDP per capita are positively associated with both PISA mathematics ($r = 0.67$, $p < 0.01$) and science score ($r = 0.70$, $p < 0.001$). PISA mathematics and science scores are highly correlated with ($r = 0.98$, $p < 0.001$).

Table 2. 1
Summary Statistics of the Merged PISA and WVS Dataset

	Count	Mean	SD	Min	Max
Value of Science & Tech	34	7.07	0.36	6.46	8.10
Thriftiness	34	0.38	0.14	0.13	0.77
Worrying about Education	34	2.77	0.51	1.83	3.74
Making Parents Proud	34	3.16	0.32	2.67	3.85
GDP per capita	34	21270.90	16947.72	3764.60	56554.00
PISA Math	34	459.56	60.16	360.00	564.00
PISA Science	34	465.74	53.60	376.00	556.00

Table 2. 2
Correlation Tables of Independent and Dependent Variables at the Country Level

	1	2	3	4	5	6	7
Value of Science & Tech	1.00						
Thriftiness	0.39*	1.00					
Worrying about Education	-0.16	-0.15	1.00				
Making Parents Proud	-0.24	-0.37*	0.57***	1.00			
GDP per capita	0.18	0.17	-0.66***	-0.64***	1.00		
PISA Math	0.44**	0.66***	-0.50**	-0.78***	0.67***	1.00	

PISA Science 0.41* 0.62*** -0.52** -0.80*** 0.70*** 0.98*** 1.00

Note. + p<0.1 * p<0.05 ** p<0.01 *** p<0.001

A four-cluster solution was selected after comparing different cluster solutions with different numbers of clusters. The four-cluster solution accounted for 61.33% of the variance. Table 2.3 presents the means of the standardized variables, the homogeneity coefficient for each of the clusters, and the countries included in each cluster. Figure 2.1 shows the visualization of the four clusters. Countries in Cluster 1 are relatively high in the importance of making their parents proud, but relatively low in thriftiness, and slightly above the average in worrying about providing good education to their children and valuing science and technology. Countries in Cluster 2 are relatively high in worrying about the availability of education, and are relatively low in valuing science and technology and thriftiness, and slightly above the average in the importance of making their parents proud. Countries in Cluster 3 are relatively low in worrying about the availability of education and the importance of making their parents proud, and slightly above the average in valuing science and technology and thriftiness. Countries in Cluster 4 are high in valuing science and technology and thriftiness, but are low in the importance of making one’s parents proud, and slightly above the average in worrying about the availability of education. Figure 2.1 presents the visualization of country clusters.

Table 2. 3
Summary of Country Clusters

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Value of Science & Tech	0.38	-1.09	0.29	0.87
Thriftiness	-0.59	-0.61	0.11	1.25
Worrying about Education	0.43	0.50	-1.21	0.14
Making Parents Proud	1.39	0.26	-1.05	-0.53
Homogeneity Coefficient	0.77	0.98	0.57	1.02
Cluster Size	7	11	8	8
Counties	Algeria, Cyprus, Georgia, Jordan,	Argentina, Brazil, Chile, Colombia,	Australia, Germany, Hong Kong, Netherlands,	B-S-J-G (China), Estonia, Japan, Poland,

Trinidad and Tobago, Tunisia, Turkey	Lebanon, Mexico, Peru, Romania, Spain, Thailand, Uruguay	New Zealand, Slovenia, Sweden, United States	Russia, Singapore, South Korea, Chinese Taipei
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Note. B-S-J-G (China) refers to the four PISA-participating China provinces: Beijing, Shanghai, Jiangsu and Guangdong.

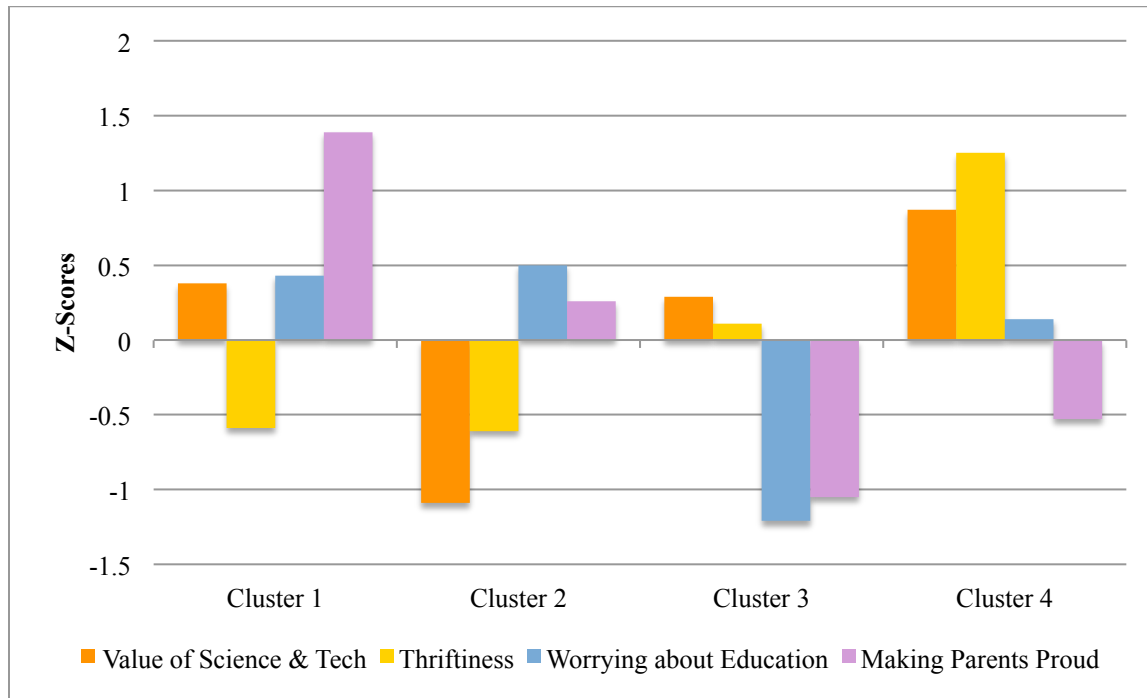


Figure 2. 1. Visualization of country clusters

Table 2.4 presents the average PISA mathematics and science scores and GDP per capita for each cluster. When it comes to educational achievement, countries in Cluster 4 have the highest achievement in PISA mathematics (mean = 526.38) and science (mean = 522.75), followed by Cluster 3 (mathematics mean = 503.63, science mean = 508.25) and Cluster 2 (mathematics mean = 418.18, science mean = 429.27). Countries in Cluster 1 have the lowest average achievement in PISA mathematics (mean = 397.86) and science (mean = 409.29). In terms of economic development levels, countries in Cluster 3 have the highest economic development level (mean = \$43,762.36), followed by Cluster 4 (mean = \$23,098.66) and Cluster

2 (mean = \$11,011.3). Countries in Cluster 1 have the lowest average GDP per capita (mean = \$9,599.71).

Table 2. 4
Average PISA Math and Science Scores and GDP per capita for Each Cluster

	PISA Math		PISA Science		GDP per capita	
	Mean	SD	Mean	SD	Mean	SD
Cluster 1	397.86	29.24	409.29	21.25	9,599.71	7,859.79
Cluster 2	418.18	32.84	429.27	32.66	11,011.3	5,888.29
Cluster 3	503.63	22.28	508.25	9.63	43,762.36	11,559.90
Cluster 4	526.38	21.74	522.75	21.94	23,098.66	15,309.24

The one-way ANCOVA results show that there was a significant difference in PISA mathematics [F (3, 29) = 25.68, $p < 0.000$] and science [F (3, 29) = 26.84, $p < 0.000$] achievement between cultural profiles after adjusting for GDP per capita. The cultural profile effect size (measured by partial eta squared) is 0.72 and 0.74 for PISA mathematics and science respectively.

Post hoc analysis shows that Cluster 1 and Cluster 2 are not significantly different in PISA mathematics and science achievement, and all the other pairwise cluster comparisons are statistically significant. Table 2.5 presents both the raw and adjusted mathematics and science achievement means for each cluster. Comparing the estimated adjusted means shows that countries in Cluster 4 have the highest achievement in mathematics (mean = 519.48) and science (mean = 516.26), followed by countries in Cluster 3 (mathematics mean = 472.96, science mean = 479.41). Countries in Cluster 2 (mathematics mean = 431.21, science mean = 441.56) and Cluster 1 (mathematics mean = 420.25, science mean = 430.36) have the lowest achievement in mathematics and science. Table 2.5 also shows that after controlling for GDP per capita, the average PISA mathematics and science scores for Cluster 1 and Cluster 2 increased while the scores for Cluster 3 and Cluster 4 decreased, which indicates that the economic development level can level up a country's average achievement in mathematics and science.

Table 2. 5
Raw and Adjusted Achievement Means for Each Cluster

	Raw PISA Math		Adjusted PISA Math		Raw PISA Science		Adjusted PISA Science	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Cluster 1	397.86	29.24	420.25 ^a	9.80	409.29	21.25	430.36 ^a	8.14
Cluster 2	418.18	32.84	431.23 ^a	7.28	429.27	32.66	441.56 ^a	6.05
Cluster 3	503.63	22.28	472.96 ^a	10.55	508.25	9.63	479.41 ^a	8.77
Cluster 4	526.38	21.74	519.48 ^a	7.91	522.75	21.94	516.26 ^a	6.58

Note. a. Covariates appearing in the model are evaluated at the following value: log of GDP per capita = 9.63.

Discussion

To explore the impact of cultural values on national achievement in mathematics and science, this study investigated the unique effect of different cultural values, identified different cultural value profiles, and revealed that national achievement in mathematics and science differed by different cultural value profiles after controlling for GDP per capita.

This study provides evidence that expectancy-value theory can explain country-level differences in academic achievement. Specifically, the results show that the national level utility value of science and technology is positively associated with PISA mathematics and science achievement. Countries that have high values of science and technology tend to perform higher in national mathematics and science.

This study also provides evidence that thriftiness is positively associated with national achievement in mathematics and science. Thriftiness is an important indicator of long-term orientation and delayed gratification. In long-term oriented cultures, people tend to save money and goods, and they neither value leisure time nor expect immediate gratification of their desires, and they are tenacious when pursuing goals (Hofstede & Minkov, 2010). This finding aligns with the previous studies, which show that the ability to postpone immediate gratification for the sake of more long-term gains fosters educational achievement, social and cognitive competencies, and stress tolerance (Figlio, Giuliano, Özek, & Sapienza, 2016; Mischel, Shoda, & Peake, 1988;

Mischel et al., 1989) and a long-term orientation is positively associated with the long-term investment in schooling (e.g., years of schooling) (Galor & Özak, 2014)

Worrying about the availability of education was found to be negatively associated with the national mathematics and science achievement. This may be due to that people from countries that have inadequate educational provision and limited opportunities to receive education that leads to better-paying jobs tend to place more value on education and express more anxiety towards education than those from countries that have readily available education resources for all.

This study shows that trying to make parents proud is negatively associated with the national average achievement in mathematics and science. This finding aligns with previous studies which show that conservatism (a variable that included collectivism) was correlated negatively with measures of intelligence and achievement (Stankov, 2009; Khine & Areepattamannil, 2016). A number of high-achieving Asian countries and economies (e.g., Japan, Singapore, South Korea, and Chinese Taipei) have relatively low values of trying to make parents proud, compared with countries in Cluster 1 and 2 (e.g., Georgia, Brazil, and Mexico). This may be due to that collectivism declined over time in Asian countries. This finding aligns with studies showing that Chinese adolescents expressed more individual than social goals in the domain of learning (Li, 2006).

The cluster analyses results presented a four-cluster solution of different cultural value profiles. We found that countries that are high in national value in science and technology and thriftiness and low in the importance of making one's parents proud, and about average in worrying about the availability of education (i.e., countries in Cluster 4) have the highest national achievement in mathematics and science when controlling for economic development

levels. Countries that are relatively low in worrying about the availability of education and the importance of making their parents proud and slightly above the average in valuing science and technology and thriftiness (e.g., countries in Cluster 3) have the second highest achievement in mathematics and science. Countries that tend to hold a traditional view (e.g., trying to make parents proud) and do not value long-term orientation (e.g., countries in Cluster 1) and countries that do not value science and technology and long-term orientation (e.g., countries in Cluster 2) have the lowest mathematics and science achievement.

The results demonstrate that national domain-specific value of science and technology coupled with the general value of thriftiness, which is an indicator of long-term orientation and delayed gratification, accessible educational resources, and attitudes associated with modern societies, such as autonomy, one's right to shape their future, and strive for upward mobility (Meyer & Schiller, 2013) are important contributors to a nation's high mathematics and science achievement. The long-term orientation may help students recognize the importance of studying mathematics and science in the long run and help them maintain effort and commitment, and persevere when experiencing failures, adversities, and difficulties in technology and science related activities. This finding also suggests that the direction and duration of effort are important to educational achievement.

The study demonstrates that cultural profiles can largely explain national differences in mathematics and science achievement, as the variance in national achievement explained by the cultural profile is 72% for PISA mathematics and 74% for PISA science achievement, after controlling for GDP per capita. The results provide an important contribution to understanding the relationship between cultural values and the national achievement in mathematics and science. However, this study only identified a correlational instead of a causal relationship. More

empirical studies should be conducted to explore the processes and mechanisms through which national values influence educational achievement.

CHAPTER 3

Study 3: Predicting Students' Science Achievement Using Gender, Cultural Value Profile, Self-Concept of Ability, and Utility Value of Science

Expectancy value theory proposes that the broad culture milieu influences individuals' domain-specific self-concept of ability, expectancies for success, and task-specific values, which in turn influence their persistence and performance on the task (Eccles, 1983; Wigfield & Eccles, 1992, 2000). A large body of empirical studies have tested and supported that self-concept of ability, expectancies for success, and subjective task values related to various educational achievements (Abu-Hilal et al., 2014; Chiu & Klassen, 2010; House, 1995; Safavian & Conley, 2016; Trautwein et al., 2012). However, most of the empirical studies were conducted within countries and did not explore how country-level cultural values might be associated with individual student's educational achievement. Only a handful of studies empirically examined the association between country-level cultural values and educational achievement (Chiu & Klassen, 2010; Liou, 2017; Nagengast et al., 2011; Schütte, 2015). Nevertheless, the cultural values tested in previous studies were mainly general cultural values, e.g., egalitarian and individualism (Chiu, 2007). No empirical studies explored how country-level cultural value profiles derived from both general and domain-specific cultural values (e.g., value science and technology) might be associated with science achievement.

In addition, we are particularly interested in the extent to which gender differences in science achievement may vary across countries and cultures, as increasing female participation in STEM fields is crucial for strengthening the STEM workforce (Beede et al., 2011). It is possible that the relationship may be weakened or strengthened due to the broad culture milieu and socio-economic environment. Previous studies mainly focused on the association between

gender-equal culture and gender differences in educational achievement (Guiso et al., 2008; Hyde & Mertz, 2009). Nevertheless, it is unclear the extent to which gender differences in educational achievement may differ across country-level cultural profiles and economic development levels (Wigfield et al., 2004).

This study therefore aims to fill the gap and empirically test expectancy value theory from a cross-cultural perspective (Wigfield et al., 2004). We reviewed literature in the relationship between cultural values, ability self-concept, utility values, gender and educational achievement in the following sections and proposed hypotheses accordingly.

Cultural Values

Cultures play an important role in shaping individuals' motivation. Expectancy value theory suggests that cultures influence individuals' educational achievement through a number of social and psychological constructs (Eccles, 1983; Wigfield & Eccles, 1992, 2000). It is possible that cultural socialization influences the values that individuals develop and the opportunities to try different activities may vary across cultures and countries, which lead to between and within-group differences in ability self-concepts, task values, and educational achievement (Wigfield et al., 2004). However, no large-scale empirical studies were conducted to explore the extent to which country-level domain-specific cultural values are associated with individual student's science achievement and how the strength of the association may vary across cultures. Given that cultural value profiles can largely explain national differences in mathematics and science achievement (see Study 2), we expect that the proposed cultural value profiles would be able to explain individual student's achievement in mathematics and science as well.

Academic Self-Concept

Academic self-concept refers to individuals' perceptions of themselves in particular school subjects (Marsh, 1993; Shavelson & Bolus, 1982). Previous studies show that domain-specific academic self-concept is a strong predictor of educational achievement and vice versa (Chiu & Klassen, 2010; Liou, 2017). For instance, Chiu and Klassen (2010) found that mathematics self-concept is positively associated with PISA mathematics scores.

Mohammadpour and colleagues (2015) found that students scored higher when they had more self-confidence in learning science using TIMSS 2017 dataset. Liou (2017) found that self-concept is the most predictive motivational belief to TIMSS 2011 science achievement. We expect that the self-concept of science ability will predict TIMSS 2015 science achievement as well.

In addition, previous studies show that the magnitude of the relationship between self-concept and educational achievement varies by countries. For instance, Chiu and Klassen (2010) found that students' mathematics self-concept was more strongly linked to mathematics achievement in countries that were wealthier, more egalitarian, more tolerant of uncertainty, or more flexible regarding gender roles. There is a need to examine how this relation may vary across domain-specific cultural profiles.

Utility Value

Utility value refers to how a task fits into an individual's current and future plans (Wigfield & Eccles, 2000; Eccles, 2005), for instance, enrolling in a science course to achieve one's long-term goal of being a scientist. A considerable amount of work shows that valuing science is related to higher achievement in science. Within countries, a positive relationship

between students' subjective values (e.g., interest value and utility value) of science and their science achievement has been consistently observed in TIMSS assessments (e.g., Mullis, Martin, Foy, & Arora, 2012; Abu-Hilal et al., 2014; Wang & Liou, 2017). The eighth grade students in general science countries who reported that they valued science had higher average achievement than students who only reported valued science somewhat, and those who reported valued science somewhat had higher achievement than students who did not value science (Martin, Mullis, Foy, & Stanco, 2012). We expect that utility value of science will be positively associated with individual's science achievement. Given that the strength of the correlation between utility value and science achievement varies across countries, we expect that the relation will vary across cultural value profiles as well.

Gender Differences

Previous studies showed that gender differences in educational achievement vary across countries. For instance, Stoet and Geary (2018) found that females performed similarly to or better than males in science in two of every three countries. TIMSS 2015 report showed that females outperformed males in Biology in 24 countries, in Chemistry in 26 countries, in Physics in eight countries, and Earth Science in eight countries, while males outperformed males in Physics in 17 countries and Earth Science in 18 countries (Martin, Mullis, Foy, et al., 2016). Else-Quest and colleagues (2010a) found that a gender gap in mathematics exist in some countries but not in others. A number of studies revealed that females and males performed about equally well in mathematics and science achievement (Else-Quest et al., 2010a; Hyde, Lindberg, Linn, Ellis, & Williams, 2008).

In addition, we expect that gender differences in science achievement vary across cultural value profiles. We identified four country-level cultural value profiles (based on valuing science and technology, thriftiness, making parents proud, worrying about education) and that predict national achievement in mathematics and science in Study 2. Countries in Cluster 4 that are high in valuing science and technology and thriftiness outperformed countries with other cultural value profiles in mathematics and science. Considering that thriftiness is a reflection of delayed gratification and gender differences exist in delayed gratification (Silverman, 2003) and attitudes towards science (Jones, Howe, & Rua, 2000), we expect that gender differences in science achievement vary across cultural value profiles.

Present Study

This study aims to answer the following questions. 1) is there a relationship between cultural value profile and individual student's science achievement? 2) is there a relationship between students' self-concept of science ability and their science achievement? 3) is there a relationship between students' value of science ability and their science achievement? 4) are there gender differences in science achievement? 5) If so, do gender differences in science achievement vary by cultural value profiles and economic development levels?

Methods

Datasets

This study used the TIMSS 2015 8th grade dataset and the country cluster membership that was derived from WVS wave 6 dataset (see Study 2 cluster analysis result for detail) to address the above-mentioned research questions. The TIMSS 2015 8th grade dataset includes a

student questionnaire that gathered information about students' demographics, their value of science, and perceptions of the utility value of science. The country cluster membership dataset includes 34 countries, which were categorized into four clusters based on four cultural values (e.g., national value of science and technology, thriftiness, worrying about the availability of education, and trying to make parents proud). This cluster membership was adopted as it incorporates different patterns of country profiles.

Dependent Measures

Individual Student's Science Achievement. We used the average of the five plausible values of students' science scores to measure their science achievement. TIMSS administered a limited number of assessment items to each student to keep student burden to a minimum. Since students were not administered all of the available cognitive items, five plausible values were randomly drawn from a distribution of ability estimates representing each student's ability. Each random draw is considered a representative value from the distribution of potential scale scores for all students with similar response patterns and background characteristics in the sampled population (Martin, Mullis, & Hooper, 2016).

Independent Measures

Student-Level Measures

Individual Student's Self-Concept of Science Ability. This construct is measured by seven 4-Likert scale questions. The survey participants were asked to rate how much they agree with the following statements about science. Statements expressing negative sentiment

were reverse coded during the scaling. TIMSS created a variable Student Confident in Science derived from the following statements. Therefore we use the variable Student Confident in Science to represent an individual's self-concept of science ability. We included the group mean centered students' self-concept of science ability as a student-level variable.

- a. I usually do well in science (BSBS23A).
- b. Science is more difficult for me than for many of my classmates (BSBS23B).
- c. Science is not one of my strengths (BSBS23C).
- d. I learn things quickly in science (BSBS23D).
- e. I am good at working out difficult science problems (BSBS23E).
- f. My teacher tells me I am good at science (BSBS23F).
- g. Science is harder for me than any other subject (BSBS23G).

Individual Student's Value of Science. The utility value of science is measured by six 4-level Likert scale questions. The survey participants were asked to rate how much they agree with the following statements about science. TIMSS created a variable Student Value Science derived from the following statements. Therefore we use the variable Student Value Science to represent an individual's utility value of science. We included the group mean centered students' value of science as a student-level variable.

- a. I think learning science will help me in my daily life (BSBS24A).
- b. I need science to learn other school subjects (BSBS24B).
- c. I need to do well in science to get into the <university> of my choice (BSBS24C).
- d. I need to do well in science to get the job I want (BSBS24D).
- e. It is important to learn about science to get ahead in the world (BSBS24F).
- f. Learning science will give me more job opportunities when I am an adult (BSBS24G).

- g. My parents think that it is important that I do well in science (BSBS24H).
- h. It is important to do well in science (BSBS24I).

Gender. Females are coded as 1 and males are coded as 0.

Country-Level Measures

Cultural Value Profile. This is a categorical variable indicating a country's cluster membership. This study used the 4-cluster solution from Study 2 result. Thirty four countries were categorized into four groups based on four standardized cultural values. Countries in Cluster 1 to 4 were labeled as 1 to 4 respectively. We used Cluster 4 as the reference group in the data analysis, as countries in Cluster 4 were found to have the highest educational achievement in Study 2.

GDP per capita. GDP per capita in 2015 was included for measuring a country's economic development level. GDP per capita is the gross domestic product divided by midyear population (The World Bank, 2015). We use the grand-centered country mean GDP per capita as a country-level variable.

Data Analysis

After merging the TIMSS 8th grade dataset and the country cluster data derived from Study 2, we obtained 101,047 students from 17 countries and economies. Since students from Georgia, Lebanon, Russian Federation, Slovenia and Sweden did not answer questions related to self-concept of science ability, we removed students from the above-mentioned countries from the dataset and obtained 80,012 observations from 12 countries afterwards. We used list-wise

deletion to handle missing values, as the percent of missing data for each variable is less than 2%. We obtained 78,337 students from 12 countries for the data analysis.

We used two-level HLM models, i.e., student and country cluster levels, to estimate the relationship between student-level and country-level variables and science achievement. The student house sampling weight HOUWGT was used in the HLM models. House weight is based on the total sample size of each country and is used when estimates across countries are computed or significance tests performed (Laukaityte & Wiberg, 2017). In the first stage, this study used HLM to explore whether students' science achievement varies across countries. We ran an unconditional model and calculated the intraclass correlation coefficient (ICC). ICC indicates how much of the variance in students' science achievement varies across country clusters. In the second stage, we included the independent variables in the HLM random slope models to examine its respective association with students' science achievement. In the third stage, we included the interaction term between gender and cultural value cluster membership and the interaction term between gender and GDP per capita to examine whether cultural value profiles and GDP per capita moderate the relationship between gender and students' science achievement.

Results

Table 3.1 presents the descriptive statistics of students' gender, self-concept of science ability, utility value of science, GDP per capita, cultural value cluster membership, and the 5 plausible values of science achievement. Table 3.2 presents the weighted means of the independent and dependent variables in each country. Table 3.3 presents the zero-order correlations between the independent and dependent variables. Gender is not significantly

correlated with science achievement. Students' self-concept of science ability, utility value of science, GDP per capita, and cultural value cluster membership are all positively associated with science achievement. The ICC for the science achievement is 0.3, which indicates that 30% of the variance in the science achievement is attributed to country cluster level characteristics.

Table 3. 1
Descriptive Statistics of Independent and Dependent Variables

	Count	Mean	SD	Min	Max
Female	78337	0.51	0.50	0.00	1.00
Self-Concept of Science Ability	78337	9.72	2.19	2.82	15.30
Valuing Science	78337	9.87	2.01	4.15	13.16
GDP per capita	78337	32550.56	19747.18	4096.10	56554.00
Cultural Profile	78337	2.79	1.03	1.00	4.00
Science Score Plausible Value 1	78337	519.09	96.82	70.72	848.32
Science Score Plausible Value 2	78337	518.73	96.60	14.14	835.26
Science Score Plausible Value 3	78337	519.83	95.75	72.79	819.36
Science Score Plausible Value 4	78337	518.76	97.37	29.10	860.12
Science Score Plausible Value 5	78337	519.71	96.54	54.05	837.61

Table 3. 2
Weighted Means of the Variables for Each Country

Country	Cluster	Female	Self-Concept	Value Science	GDP per capita	PV1	PV2	PV3	PV4	PV5
Australia	3	0.52	9.67	9.42	56554.00	513.86	513.76	514.87	513.47	514.68
Chile	2	0.48	9.81	9.71	13653.20	454.56	454.10	456.10	454.46	456.36
Hong Kong	3	0.48	9.44	9.44	42351.00	546.23	545.66	546.44	546.23	546.48
Japan	4	0.51	8.56	8.64	34474.10	570.61	570.52	571.56	571.05	571.24
Jordan	1	0.51	10.66	11.35	4096.10	431.49	430.53	432.81	429.80	431.44
New Zealand	3	0.52	9.66	9.71	38201.90	514.24	513.72	514.08	513.66	514.76
Singapore	4	0.49	9.66	10.24	53629.70	596.89	596.27	596.22	597.40	596.92
South Korea	4	0.47	8.66	8.96	27105.10	554.74	555.57	555.83	556.14	556.04
Taipei	4	0.49	8.63	8.57	22541.00	569.76	569.26	569.21	569.07	570.72
Thailand	2	0.54	9.32	10.75	5814.90	456.25	456.60	457.28	454.78	456.52
Turkey	1	0.48	10.68	10.41	10979.50	493.91	494.92	494.84	493.37	494.42
US	3	0.50	10.52	10.07	56207.00	532.16	530.94	532.44	531.52	532.51

Note. PV refers to plausible value of science achievement.

Table 3. 3

Zero-Order Correlations between Independent and Dependent Variables

	1	2	3	4	5	6	7	8	9	10
Female	1									
Self-concept	-0.08***	1.00								
Valuing Science	-0.01***	0.49***	1.00							
GDP per capita	-0.01***	-0.00	-0.14***	1.00						
Cultural Profile	-0.02***	-0.23***	-0.31***	0.63***	1.00					
PV1	-0.00	0.19***	0.05***	0.30***	0.43***	1.00				
PV2	-0.00	0.19***	0.05***	0.30***	0.43***	0.92***	1.00			
PV3	-0.00	0.19***	0.05***	0.30***	0.43***	0.92***	0.92***	1.00		
PV4	-0.00	0.19***	0.05***	0.30***	0.44***	0.92***	0.92***	0.92***	1.00	
PV5	-0.00	0.19***	0.05***	0.30***	0.44***	0.92***	0.92***	0.92***	0.92***	1

Note. + $p < 0.1$ * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$. PV refers to plausible value of science achievement

Table 3.4 presents the step-wise regression HLM random slope models of predicting students’ science achievement. It shows that on average females and males did not differ significantly on science achievement (see Model 1 in Table 3.4). Females had higher science achievement than males ($r = 7.01, p < 0.05$) when controlling for self-concept of science and the value of science (see Model 2 and 3 in Table 3.4). The female-favoring gender difference in science achievement still holds true when controlling for country-level cultural value profiles, GDP per capita, and the interaction term between female and GDP per capita (see Model 4-6 in Table 3.4). However, the female-favoring gender differences disappeared when including the interaction term between female and country-level cultural value profiles (see Model 7 and 8 in Table 3.4). The student-level self-concept of science ability ($r = 11.72, p < 0.001$) and value of science ($r = 4.77, p < 0.01$) are consistently positively associated with individual’s science achievement (see Model 3-8 in Table 3.3).

When it comes to country-level variables, the results show that students from countries in cultural value Cluster 1 ($r = -81.07, p < 0.001$), Cluster 2 ($r = -144.52, p < 0.001$), and Cluster 3 ($r = -58.09, p < 0.001$) performed lower in science compared with those from countries in Cluster 4

when controlling for individual-level characteristics, i.e., gender, self-concept of science ability, and value of science (see Model 4 in Table 3.4). A 1% increase of GDP per capita is associated with 24.67 unit increase in science achievement, when controlling for other variables (see Model 5-8 in Table 3.4).

The interaction term between female and GDP per capita is negatively significant ($r = -8.08$, $p < 0.001$) (see Model 6 and 8 in Table 3.4), which reveals that the increase of economic development level is associated with a decrease of female's science achievement. The interaction term between female and cultural value profile is positively significant (see Model 7 and 8 in Table 3.4), which suggests that the female-favoring gender differences are larger in countries in Cluster 1 ($r = 42.16$, $p < 0.001$), Cluster 2 ($r = 12.43$, $p < 0.001$), and Cluster 3 ($r = 5.22$, $p < 0.05$), when compared with those from countries in Cluster 4.

Table 3. 4
HLM Models on Science Achievement

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
(Intercept)	518.31 ^{***} (16.37)	516.08 ^{***} (15.69)	516.10 ^{***} (15.60)	573.07 ^{***} (10.16)	567.63 ^{***} (8.05)	567.62 ^{***} (8.10)	567.69 ^{***} (8.01)	568.02 ^{***} (8.03)
Female	2.51 (4.19)	7.03 [*] (3.12)	7.01 [*] (3.03)	7.01 [*] (3.02)	7.03 [*] (3.03)	6.70 ^{**} (2.36)	-3.82 (3.94)	0.53 (3.38)
Self-Concept		13.56 ^{***} (0.83)	11.72 ^{***} (1.01)	11.71 ^{***} (1.01)	11.71 ^{***} (1.01)	11.70 ^{***} (1.02)	11.70 ^{***} (1.02)	11.71 ^{***} (1.02)
Valuing Science			4.77 ^{**} (1.46)	4.76 ^{**} (1.46)	4.76 ^{**} (1.46)	4.75 ^{**} (1.46)	4.76 ^{**} (1.46)	4.75 ^{**} (1.46)
Cluster 1				-81.07 ^{***} (11.13)	-70.52 ^{***} (18.81)	-69.72 ^{***} (18.82)	-70.13 ^{***} (18.60)	-71.20 ^{***} (18.69)
Cluster 2				-144.52 ^{***} (11.36)	-108.22 ^{***} (16.53)	-109.01 ^{***} (16.54)	-108.34 ^{***} (16.35)	-109.04 ^{***} (16.43)
Cluster 3				-58.09 ^{***} (9.13)	-61.91 ^{***} (9.14)	-61.94 ^{***} (9.15)	-62.17 ^{***} (9.04)	-62.37 ^{***} (9.08)
Log GDP per capita					24.67 [*] (10.00)	24.59 [*] (10.01)	24.86 [*] (9.89)	24.59 [*] (9.94)
Female*log GDP per capita						-8.08 ^{***} (2.00)		-6.31 [*] (2.74)
Female*Cluster 1							42.16 ^{***}	27.83 ^{***}

							(3.20)	(5.22)
Female*Cluster							12.43 ^{***}	-0.33
2							(3.34)	(4.62)
Female*Cluster							5.22 [*]	4.97 [*]
3							(2.63)	(2.52)
R ²	0.0002	0.09	0.09	0.32	0.36	0.34	0.33	0.34

Note. ^{***} p < 0.001, ^{**} p < 0.01, ^{*} p < 0.05. The R² given above is Nakagawa and Schielzeth's R² (2013)

Discussion

This study explored the relationship between country-level cultural value profiles, students' self-concept of science ability, value of science, gender, and student's science achievement, and whether and how country-level cultural value profile and economic development level moderates the gender differences in science achievement. We found that cultural value profile is significantly associated with individual student's science achievement. Specifically, compared to students from countries with a cultural value profile that is high in valuing science and technology and long-term orientation (i.e., Cluster 4), students from countries with other cultural value profiles (Cluster 1-3) on average performed worse in science achievement. This finding is consistent with the finding in Study 2, which revealed that countries that are high in valuing science and technology and thriftiness had the highest mathematics and science achievement, compared to countries with other cultural value profiles. We also found that higher economic development level is associated with higher science achievement. This may be due to the fact that more developed countries are able to provide better and more sufficient learning resources for students.

Consistent with expectancy value theory (Eccles, 1983), individual student's self-concept of science ability and value of science were positively associated with their science achievement. Compared with students who had the average self-concept of science ability and value of science

within country, those who had higher than average self-concept of science ability and value of science had higher science achievement.

In terms of gender differences, the result showed that females and males performed equally well in science. Females performed even better than males in science when controlling for self-concept of science ability and value of science, which suggests that females tended to have lower self-concept of science ability and value of science, compared with males. Increasing females' self-concept of science ability and value of science might further increase their science achievement.

In addition, the interaction term between female and GDP per capita is negatively significant, which suggests that the female-favoring gender differences became smaller in more economically developed countries. This may be that females from economically developed countries were more influenced by the gender-science stereotype than those from less developed countries. It is also possible that females from less developed countries are more interested in learning science due to life pressure, as science-related jobs are usually well-paid (Stoet and Geary, 2018).

The interaction term between female and cultural value profiles are also significant. Compared with gender differences in countries that are high in valuing science and technology and thriftiness (i.e., Cluster 4), the female-favoring gender differences are larger in countries that are relatively low in worrying about the availability of education and the importance of making their parents proud and slightly above the average in valuing science and technology and thriftiness (e.g., countries in Cluster 3) and countries that tend to hold a traditional view (e.g., trying to make parents proud) and do not value long-term orientation (e.g., countries in Cluster 1). This may be due to that the broad cultural milieu of valuing science and technology is also

associated with the gender stereotype that science equals males, which in turn decreases females' self-concept of science ability and value of science.

This study has certain limitations. This study only included 12 countries and most of the countries are high achieving countries in the TIMSS dataset. Empirical studies that include a wider range of countries should be conducted to test whether the results hold.

CONCLUSION

Persistent and significant cross-national differences in educational achievement and gender differences have been observed in the past several decades (Else-Quest, Hyde, & Linn, 2010b; Martin, Mullis, Foy, et al., 2016). Why do educational choices and performance and gender differences vary across countries? This dissertation aims to address this question from a socio-cultural perspective by exploring the relationship between country-level cultural values and STEM educational choices and achievement, both at the individual level and the country level, as well as the moderating effect of broad cultural values and economic development level in gender differences in STEM educational choices and achievement.

The first study examined the gender differences in STEM MOOC enrollment and completion and investigated how country-level gender-equal culture and economic development levels are associated with gender differences in STEM MOOC enrollment and completion. We found that though females were less likely than males to enroll in STEM MOOCs, they are equally likely to complete STEM MOOCs once they enrolled in. A less gender equal culture and a lower economic development level were associated with an increased probability to enroll in STEM MOOCs and a reduced male-favoring gender gap in STEM MOOC enrollment. When it comes to STEM MOOC completion, the decrease of gender equality and economic development level were associated with an decreased probability to complete STEM MOOCs, and an increased probability for females to complete STEM MOOCs.

The second study examined the relationship between four country-level cultural values (e.g., valuing science and technology, thriftiness, making parents proud, and worrying about education) and national achievement in mathematics and science, and explored the different combinations of the four cultural values and the relationship between cultural value profiles and

national achievement in mathematics and science. We used the WVS to measure cultural values and PISA mathematics and science scores to measure national achievement in mathematics and science. We found that valuing science and technology and thriftiness were positively associated with national achievement in mathematics and science, while trying to make parents proud and worrying about the availability of education were negatively associated with national achievement in mathematics and science. We have identified four cultural value profiles using cluster analysis. The cultural value profile that is high in valuing science and technology and thrift, low in valuing trying to make parents proud, slightly above the average in worrying about the availability of education has the highest national achievement in mathematics and science, even after controlling for economic development levels.

The third study investigated the relationship between cultural value profiles, gender, self-concept of science ability, utility value of science, and students' science achievement in TIMSS 2015. We found that the cultural value profile that is high in valuing science and technology, thriftiness, low in trying to make parents proud is positively associated with individual student's science achievement, compared with the other three cultural value profiles (see Study 2 result). Females and males performed equally well in science achievement, and females were found to outperform males in science when controlling for self-concept of science ability and utility value of science. Consistent with expectancy value theory (Eccles, 1983), self-concept of science ability and utility value of science were found positively associated with individual student's science achievement. When it comes to gender differences in science achievement, gender difference is widening in countries that have the cultural value profile that is high in valuing science and technology, thriftiness, and low in making parents proud, when compared to the

other cultural value profiles. GDP per capita was found to be positively associated with science achievement and a widened gender gap in science achievement.

This dissertation tested expectancy value theory from a cross-cultural perspective (Wigfield et al., 2004) and provided empirical evidence that cultural values are related to individual level and national level educational choices and achievement as well as gender differences in educational choices and achievement. Specifically, this dissertation contributed to the existing literature from the following aspects.

First, this dissertation uncovered the gender equality and economic development paradoxes that the increased gender equality and economic development level were associated with students' reduced probability to enroll in STEM MOOCs and widened gender differences in STEM MOOC enrollment and completion, as shown in Study 1. These paradoxes also provide empirical evidence that MOOCs have the potential to democratize education across the world. In addition, the economic development paradox was also corroborated by Study 3, which found that higher economic development levels were associated with an increased male favoring gender gap in science achievement. The gender equality paradox finding is consistent with Stoet and Geary (2018)'s study which found that the gender differences in the magnitude of relative academic strengths and pursuit of STEM degrees rose with increases in national gender equality. The gender equality and economic development paradoxes may be due to the following factors. One potential factor is that females from more gender equal cultures have more freedom to express their gendered self, which reinforces their disinclination to enroll in STEM-related courses and make an effort to study STEM. Another possible explanation is that the cost of females from more developed countries to forgo STEM education and career is less than those from less developed countries, as there may be a high level of social security for citizens in gender equal

and developed countries. Females from less developed countries, on the other hand, may be more interested in taking a STEM path as they have more difficult and less secure living conditions. Therefore, pursuing STEM education and career is more valuable for females from less gender equal and less developed countries, given that STEM related jobs are usually well paid and can provide economic security (Stoet & Geary, 2018).

Second, this dissertation filled the research gap that previous research mainly focused on general cultural values (e.g., collectivism) and tested the relationship between country-level domain-specific cultural value (e.g., valuing science and technology) and national achievement in mathematics and science. The finding that country-level valuing science and technology is positively associated with national achievement in mathematics and science indicates that expectancy value theory can also explain country-level achievement differences.

Third, this dissertation adopted a pattern-centered approach, revealed four different patterns of cultural value profiles, and identified the highest achieving cultural value profile. The combination of high valuing science and technology and thriftiness, which is an indicator of long-term orientation and delayed gratification, and low valuing trying to make parents proud, is a characteristics of high achieving countries in mathematics and science. The domain specific value of science and technology determines the direction of effort. The long-term orientation implies sustained effort towards goals. Not worried about making parents proud implies an autonomy to choose one's goals. Unlike previous studies that mainly identified unique effect of cultural values, this dissertation investigated the combination of important cultural values contributed to high achievement in mathematics and science.

Based on the above-mentioned findings, we suggest that in order to increase females' participation and performance in STEM, changing the academic culture that STEM is masculine,

advocating female STEM role models, and increasing the perceived value of pursuing STEM careers might encourage more females to choose STEM related education. In order to increase individual-level and country-level performance in mathematics and science, the cultural value of valuing science and technology, long-term orientation, delayed gratification, and autonomy should be promoted and encouraged.

Nevertheless, this dissertation suffered from several limitations. First, this dissertation used WVS to measure cultural values and not all TIMSS and PISA participating countries have cultural values in WVS, which limited the sample size for data analysis. Second, this dissertation focused on correlational relationships between cultural values and educational choices and performance, and did not identify causal relationships. Third, this dissertation revealed the relationship between cultural values and educational choices and achievement, but did not explore the mechanisms and processes of how cultural values are shaping individual student's beliefs and behaviors.

Future studies should come up with a more comprehensive world value survey that can be administered to more countries. More studies should be conducted to examine the mechanism of how cultural values are influencing individuals' beliefs, values, and behaviors in cross-national settings.

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