Gender and Discipline Specific Differences in Mathematical Self-Efficacy of Incoming Students at a Large Public University

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*This study investigates differences in mathematical self-efficacy and outcome expectations of 3107 incoming students enrolled in introductory level mathematics or statistics courses at a land grant university in the Midwest. Students were grouped by discipline (STEM (**S**cience, **T**echnology, **E**ngineering and **M**athematics), Social Sciences and Arts & Humanities) and by gender within each discipline. All students enrolled in an introductory mathematics or statistics course during their first semester at the institution were surveyed about their perceived mathematical self-efficacy and outcome expectations at the beginning of that semester. Our results suggest that discipline specific differences are dependent on the definition of STEM majors, namely distinguishing between math intensive and non-math intensive STEM majors. After accounting for this distinction gender differences in mathematical self-efficacy and outcome expectations disappear.*

Key words: Mathematics, Self-Efficacy, Gender, Social Sciences, and STEM

Introduction

The gender gap in the STEM sciences continues to afflict the U.S.'s economic and social prosperity. For the U.S., as a nation, to remain innovative, competitive and at the forefront economically and technologically, the country needs to continue growing the number of baccalaureates in the STEM sciences and provide diverse opportunities for individuals to pursue STEM related career paths. The National Science Board (NSB-2015-10) published in a recent, up to date, report that "policymakers, scholars, and employers have come to recognize that science, technology, engineering, and mathematics (STEM) knowledge and skills are critical to an extensive portion of the entire U.S. workforce and that a broad range of STEM-capable workers contribute to economic competitiveness and innovation."

In addition to unrecognized pathways, one of the recognized reasons for the existing shortage is the systematic exclusion of parts of the population due to the underrepresentation of women and minorities pursuing STEM or STEM-related degrees, a trend that has been challenging to reverse or to even slow down. Although much research has been devoted to understanding reasons for the shortage of women and other minorities in the STEM sciences (e.g., Betz & Hacket, 1983; Blickenstaff, 2005; Eccles et al., 1983; Else-Quest, Hyde, & Linn, 2010; Gainor & Lent, 1998; Hacket et al., 1992; Lent, Lopez & Bieschke, 1991, 1993; Lent, Brown, & Larkin, 1984, 1986; Wigfield & Eccles, 1992;) it is still not fully understood why these groups choose STEM careers at significantly lower rates than non-minority men. Contributing factors include gender differences in STEM science self-efficacy (Eccles et al., 1993; Jacobs, Davis-Kean, Bleeker, Eccles, & Malanchuk, 2005), lack of role models (Betz & Fitzgerald, 1987; Blickenstaff, 2005) or societal norms and expectations Eccles, 1987, Raty et al., 2002). Additionally, the complexity of the associations among these factors adds another layer of complicatedness to the phenomenon. For a more recent and complete review of the literature we refer to Wang & Degol (2013).

The primary focus of this research is on introductory mathematics and statistics classes taken at the beginning of college motivated by the fact that the mathematical and statistical sciences are seen as gate keepers (Gainen, 1995) to the STEM sciences. Without successful completion of calculus or differential equations continuing in many STEM science majors is difficult if not impossible. While research has explored gender differences in mathematical self-efficacy at the middle and high school level or at the college level within specific STEM disciplines, less is known about the critical transition period from high school to college. For students enrolling into STEM majors or interested in pursuing a STEM major introductory mathematics and statistics classes are commonly among the classes taken during their first semester at college. This motivates the question whether students' experiences in these classes contribute or are related to the gender gap. To provide at least partial insight into this question we investigate the levels of mathematical (and statistical) self-efficacy of incoming students at a large public state university.

Theoretical Framework

The theoretical framework builds on the construct of social cognitive career theory (SCCT; Lent, Brown & Hackett, 1994, 2000). SCCT is based on Bandura's social cognitive theory (Bandura, 1986, 1989, Bussey & Bandura, 1999). At the center of SCCT lies an individual's self-efficacy. Self-efficacy is defined according to Bandura (1986) as 'people's judgments of their capabilities to organize and execute courses of action required to attain designated types of performance' (p. 391). Thus when an individual contemplates a particular career path, the conviction the individual has about his or her ability as well as past, successful experiences plays an important role. With specific regard to a STEM field, if a person perceives that ultimately, he or she is not likely to be successful and has had what can be thought of as less than successful experiences, the likelihood that this person will choose that particular career path decreases. Self-efficacy is only one of three components of SCCT. The other two components are outcome expectations and personal goals. Outcome expectations refer to the belief about what outcomes are possible based upon specific courses of actions or experiences. An individual considers the question about what will happen if a course of action is completed. Environmental factors are often perceived as controllable and influential on the outcome, more than the individual's own behavior (Gro, 2008). Self-Efficacy and Outcome Expectations as the two primary pillars of SCCT are important when considering success of underrepresented groups, in particular females, in STEM career choices.

Research Questions and Research Hypotheses

The main research question of interest focuses on the levels of mathematical (and statistical) self-efficacy and outcome expectations of incoming students at a large public university such as Iowa State University. In order to obtain information related to gender gap issues in the STEM sciences, we group incoming students according to gender and discipline of declared major. We categorized declared major into STEM majors (distinguishing between math-intensive STEM and non math-intensive STEM majors), social sciences and arts and humanities. A student was considered as pursuing a STEM degree if the first or second declared major was in a STEM field.

Research Question

What is the level of mathematical or statistical self-efficacy and of outcome expectations of students entering a large public university, such as Iowa State University?

In order to obtain information related to the gender gap in the STEM sciences, incoming students will be grouped according to

(1) gender

(2) declared discipline, i.e. STEM, social sciences, arts and humanities.

Thus, our research question is aimed at baseline information, summarizing academic self-efficacy in mathematics and statistics courses.

Hypotheses

H1.1 *Self-efficacy, mathematical self-confidence and outcome expectations of incoming students are, on average, significantly higher in students with STEM majors compared to students with a social science or an arts and humanities major.*

H1.2 *Within each of the three groups, self-efficacy, and mathematical self-confidence and outcome expectations is comparable for women and men.*

Data and Statistical Analyses

Data for this study stem from a larger parent study, which collected data on 15,960 students enrolled into an introductory mathematics or statistics course during the semesters of Spring and Fall 2012 and Spring 2013. Of these students, 3107 students were described as *an incoming student*, for which we also had complete background data on ACT scores, high school credits in mathematics and natural sciences, as well as high school rank and GPA. Incoming students are defined, as students who entered the university directly from high school, were actively degree seeking, had U.S. residence status and enrolled into an introductory level mathematics or statistics course during their first college semester. Of the 3107 students 1868 completed a pre-survey on mathematical or statistical self-efficacy during week three of the semester. The survey instrument is based on an existing 36-item instrument called the "Survey on Attitudes Toward Statistics" (SATS-36) (Schau et al., 1995 and Schau, 2003). Schau's SATS-36 survey consists of six subscales measuring *Affect*, *Interest*, *Difficulty*, *Cognitive Competence*, *Effort* and *Value*, respectively. Although the survey is well known among statistics educators and has been utilized extensively since its introduction in the literature, the authors were not able to confirm the six dimensional structure but rather that items measuring Affect, Cognitive Competence and Difficulty loaded onto a single factor. This single factor reflects what is generally defined as perceived mathematical/statistical self-efficacy. Our finding is supported by VanHoof, S., et al. (2011). Some items not loading onto any factor motivated additional changes to individual items. These changes, most of them minor, and adapting the survey to mathematics students were made in consultation with a survey expert from the Center of Survey Statistics and Methodology (CSSM) at Iowa State University. In accordance with Lent's Social Cognitive Career Theory (Lent, Brown & Hackett, 1994, 2000) we further added six questions to measure outcome expectations, as outcome expectations are the second pillar in the SCCT framework in addition to self-efficacy.

We used exploratory factor analysis to estimate the latent factor structure (self-efficacy, value, effort, interest and outcome expectations) and evaluated each factor calculating Cronbach's alpha. The levels of Cronbach's alpha (standardized) are 0.87 (self-efficacy), 0.90 (value), 0.76 (effort), 0.61 (interest) and 0.87 (outcome expectations). Subsequently, we obtained the corresponding factor scores for each student and calculated numerical summaries of the factor scores and conducted corresponding two-sample t-tests according to the groupings defined in the Research Question.

Results

We will summarize the results in tabular form for each hypothesis. We begin with H1.1: Although the primary focus is on mathematical self-efficacy and outcome expectations we also include the results for students' perceived value and interest in mathematics. H1.1 hypothesizes that mathematical self-efficacy and outcome expectations of incoming students are, on average, significantly higher in students with STEM majors compared to students with a social science or an arts and humanities major.

Contrary to hypothesis H1.1 we were not able to identify significant discipline specific differences among the incoming student that participated in our study (see Tables 1 and 2).

Table 1
STEM Sciences versus Social Sciences (Soc. Science)

Dimension	Mean STEM	Mean Soc. Science	t-statistic	df	p-value	95% Confidence Interval for difference in means
Self-Efficacy	0.154	-0.084	2.049	72.3	0.0441	(0.006, 0.472)
Value	**0.352**	**-0.371**	**5.80**	**70.5**	**<0.0001**	**(0.475, 0.972)**
Interest	0.028	0.044	-0.139	72	0.8898	(-0.240, 0.209)
Outcome Expectations	0.075	-0.135	2.070	76	0.0419	(0.008, 0.412)

Table 2
STEM Sciences versus Arts & Humanities (Arts & Hum)

Dimension	Mean STEM	Mean Arts & Hum	t-statistic	df	p-value	95% Confidence Interval for difference in means
Self-Efficacy	0.154	-0.126	2.103	56.8	0.0399	(0.013, 0.547)
Value	**0.352**	**-0.550**	**6.402**	**55.8**	**<0.0001**	**(0.620, 1.185)**
Interest	0.028	-0.052	0.713	57.8	0.4789	(-0.145, 0.306)
Outcome Expectations	0.075	-0.117	0.858	60	0.3944	(-0.124, 0.309)

Both, mathematical self-efficacy and outcome expectations are comparable although based on the observed p-values less than 0.05 one may suggest a week tendency[1]. The same result holds for interest suggestion no significant differences between the disciplines. Highly significant, however, is the difference in how students in different disciplines value mathematics. A possible explanation based on the items belonging to the interest dimension is that students in STEM majors directly experience and appreciate the need for foundational mathematics knowledge in order to succeed in their downstream courses while for many social science and arts and humanities majors degree requirements often consist of no more than one class. Regarding the somewhat unexpected results for self-efficacy and outcome expectations we theorize that a possible explanation for this result lies in the definition itself of what majors are considered STEM majors. In recent years several majors such as economics, psychology or food sciences,

[1] Because of the large number of hypotheses tests, we do not use the usual cut-off value of 0.05 for the level of significance but in an effort to adjust for the multiple testing procedures consider p-values of 0.001 or less as statistically significant.

for example, have been grouped more frequently with the STEM sciences in an effort to provide a more inclusive definition of STEM and because many of these majors frequently include STEM related tasks or knowledge. Different majors within STEM, nevertheless have substantially different mathematical prerequisites, which prompted us follow up our analysis by distinguishing between so-called math intensive STEM majors and those that are not math intensive. For a major to be considered math intensive the major's degree requirement had to include science/engineering Calculus I, or equivalent. Table 6 provides the updated results displaying differences in mathematical self-efficacy and outcome expectations for students when distinguishing between math intensive and non-math intensive STEM majors. All four factors show a significant difference between both groups with students in math intensive STEM majors exhibiting higher levels of self-efficacy, value, interest, and outcome expectations. The same distinction further explains gender differences in mathematical self-efficacy and value originally observed in Table 3 for students in the STEM sciences. When accounting for the type of STEM major (math intensive or not) Tables 7 and 8 show that gender differences within each group disappear and can likely be attributed to random variation. Tables 4 and 5 support our second hypothesis H1.2 showing no gender differences in the social sciences and the arts and humanities.

Table 3
Gender Differences in the STEM Sciences

Dimension	Mean Female	Mean Male	t-statistic	df	p-value	95% Confidence Interval for difference in means
Self-Efficacy	**0.032**	**0.201**	**-2.921**	**572.1**	**0.0036**	**(-0.282, 0.055)**
Value	**0.140**	**0.433**	**-5.485**	**551.9**	**<0.0001**	**(-0.398, -0.188)**
Interest	-0.042	0.055	-1.838	620	0.0666	(-0.200, 0.007)
Outcome Expectations	0.071	0.076	-0.085	631.5	0.9323	(-0.121, 0.111)

Table 4
Gender Differences in the Social Sciences

Dimension	Mean Female	Mean Males	t-statistic	df	p-value	95% Confidence Interval for difference in means
Self-Efficacy	-0.093	-0.047	-0.150	16	0.8829	(-0.689, 0.598)
Value	-0.347	-0.484	0.348	13.6	0.7333	(-0.713, 0.988)
Interest	0.094	-0.186	1.006	16.7	0.3290	(-0.309, 0.870)
Outcome Expectations	-0.111	-0.244	0.424	13.7	0.6779	(-0.367, 0.488)

Table 5
Gender Differences in the Arts & Humanities

Dimension	Mean Females	Mean Males	t-statistic	df	p-value	95% Confidence Interval for difference in means
Self-Efficacy	0.004	-0.277	1.078	51.5	0.2859	(-0.119, 0.740)
Value	-0.549	-0.552	0.012	49.1	0.9903	(-0.567, 0.574)
Interest	-0.013	-0.098	0.387	52	0.7007	(-0.357, 0.527)
Outcome Expectations	0.003	-0.041	0.204	45	0.8393	(-0.280, 0.486)

Table 6
Math intensive (MI) versus non-math intensive (NMI) STEM Sciences

Dimension	Mean MI	Mean NMI	t-statistic	df	p-value	95% Confidence Interval for difference in means
Self-Efficacy	**0.192**	**-0.019**	**-2.847**	**287**	**0.0047**	**(-0.357, -0.065)**
Value	**0.523**	**-0.443**	**-15.441**	**280.4**	**<0.0001**	**(-1.089, -0.843)**

Interest	**0.070**	**-0.164**	**-3.527**	**300**	**0.0005**	**(-0.407, -0.104)**
Outcome Expectations	**0.120**	**-0.136**	**-3.326**	**295.4**	**0.0010**	**(-0.356, -0.092)**

Table 7
Gender Differences in the math intensive STEM Sciences

Dimension	Mean Female	Mean Male	t-statistic	df	p-value	95% Confidence Interval for difference in means
Self-Efficacy	0.110	0.212	-1.553	312.8	0.1215	(-0.214, 0.027)
Value	0.546	0.517	0.581	331.7	0.5617	(-0.070, 0.128)
Interest	0.086	0.066	0.333	333	0.7393	(-0.098, 0.138)
Outcome Expectations	0.193	0.102	1.447	372.6	0.1487	(-0.033, 0.214)

Table 8
Gender Differences in the Non-math intensive STEM Sciences

Dimension	Mean Female	Mean Male	t-statistic	df	p-value	95% Confidence Interval for difference in means
Self-Efficacy	-0.082	0.089	-1.210	179.5	0.2279	(-0.387, 0.101)
Value	-0.455	-0.423	-0.253	158	0.8007	(-0.280, 0.216)
Interest	-0.228	-0.054	-1.355	166.1	0.1722	(-0.427, 0.079)
Outcome Expectations	-0.107	-0.185	0.549	188.7	0.5839	(-0.204, 0.362)

Discussion and Conclusions

Although we did not test for significant differences between math intensive STEM majors and the social sciences and arts and humanities, respectively it is possible to conclude that the statistically significant differences found between math intensive and non-math intensive STEM majors will extend to statistically significant differences between math intensive STEM majors and the social sciences and arts and humanities as the sample means for math intensive STEM majors only increased from those of all STEM majors combined. Under the theoretical framework of Social Cognitive Career Theory with self-efficacy and outcome expectations as its two cornerstones the existing differences imply that the shortage of a strong STEM workforce as well as limitations on the number of pathways leading to a workforce will continue rather than beginning to embrace the STEM sciences. Our results were encouraging, however, in the sense that within each of the disciplines gender differences have subsided or continue to no longer present.

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