The Impact of Engineering Curriculum Units on Students' Interest in Engineering and Science

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Abstract

In this report we describe the analysis of a survey of engineering and science interest given as part of a larger study aimed at evaluating the *Engineering is Elementary* (EiE) curriculum. Students were presented with a number of statements addressing their interest in science and engineering as well as their understanding of science and engineering careers. Using hierarchical linear modeling (HLM) and hierarchical ordinal logistic regression, we found that for two scales and several individual statements, demographics (gender, race/ethnicity, Individualized Education Program (IEP) status, and others) had no significant effect on student responses and answers from students participating in EiE did not differ significantly from those of students in the control group. However, for statements pertaining to interest in and understanding of engineering, EiE student responses became more positive after participation in EiE as compared to the control group. Additionally, although males were initially more likely than females to be interested in engineering as a career, female interest increased after participation in EiE. Finally, we found that females showed more interest in jobs that relate to helping people and the environment, while males were more interested in jobs that would allow them to figure things out and to invent things.

Introduction

Engineering is a rapidly growing field; however, the number of American citizens pursuing engineering as a career has decreased to the point where we may not be able to meet the growing demand for new engineers (Stine & Matthews, 2009). Additionally, women and other minority groups are historically underrepresented in engineering at postsecondary levels (Burke & Mattis, 2007). There is evidence to suggest that individuals who have pursued careers in science and engineering developed their interest in these fields during elementary school (Maltese & Tai, 2010). Additionally, research suggests that student interest in science tends to decline after elementary school (Brotman & Moore, 2008; Catsambis, 1995; Clewell & Braddock, 2000; Reid & Skryabina, 2003), a problem that is particularly true for girls and minority students (Catsambis, 1995). It has been suggested that introducing engineering to children at an early age can encourage them to enroll in the necessary science and math courses in middle and high school and to consider engineering as a future career (Katehi, Pearson, & Feder, 2009; Wicklein, 2003). Thus, it is imperative that children engage in high-quality engineering activities at an early age in order to promote and maintain their interest in the field of engineering.

The *Engineering is Elementary* (EiE) curriculum, a program designed to introduce elementary school-aged children to engineering and technology concepts, is committed to attracting and engaging all students, especially those who are typically underrepresented in STEM, and is designed to be maximally inclusive. EiE utilizes a number of design principles drawn from research and prior experience—setting learning in a real-world context, providing design challenges that are authentic to engineering practice, and demonstrating that everyone can and does engineer—in order to engage *all* students in the process of engineering.

In this report, we will examine students' interest in engineering and science. Our research questions are:

1) How does participation in an EiE unit affect students' interest in science and engineering as compared to a control group who did not participate in EiE?
2) How is interest affected by demographics (girls, students from low-income households, etc.)? Does participation in EiE affect the interest of students from these various demographic groups?

Theoretical Framework

The EiE curriculum is designed to engage elementary school students in engineering design challenges that require the application of scientific concepts. Each EiE curriculum unit is designed to be taught in conjunction with a particular science concept, and to take approximately 6-8 hours of instructional time. Students work in collaborative groups with hands-on materials on open-ended design challenges, iteratively refining their designs to improve them (Cunningham & Hester, 2007).

EiE units are set in a real-world context using a narrative story about a child who solves a problem using the engineering design process. Students then solve the same or a similar problem in the classroom. Their activity is framed for students as engineering, and explicit scaffolding supports students in the use of the engineering design process. EiE was designed in this way to help students think of themselves as learning a disciplinary practice. When students are productively engaged in appropriately complex disciplinary practices, they learn better how and when to apply what they are learning (Duschl, 2008; Duschl & Grandy, 2008; Engle & Conant, 2002; Sawyer, 2006). When students are immersed in a rich environment where learning increases their ability to act and be effective in the world, students are more likely to be motivated to participate (Blumenfeld, Soloway, Mark, Krajcik, Guzdial, & Palincsar, 1991; Roth & Lee, 2007). Motivation increases engagement and learning (Edelson, 2001; Krajcik & Blumenfeld, 2006).

We theorize that positive experiences and exposure to disciplinary practices and concepts leads to increased interest in the discipline as a future career. In this paper, we examine students' interest in engineering after participation in EiE.

Methods

Study Design

Data was collected over 5 years from field test classrooms implementing draft versions of a variety of EiE curriculum units, each in conjunction with a related science unit, as well as from control classrooms implementing only the related science content. Teachers volunteered to participate, and were not randomly assigned to treatment or control conditions—control data was collected as part of a separately funded project. Most teachers who submitted control data from their classrooms did so as a condition for receiving EiE professional development and classroom implementation materials after data collection. Teachers came from a variety of locations distributed across the United States.

The “Engineering Interests” survey was collected in addition to content assessments. Results of analysis of content assessments are reported elsewhere (Jocz and Lachapelle, 2012; Lachapelle, Cunningham, Jocz, Kay, Phadnis, Wertheimer, & Arteaga, 2011; Lachapelle, Cunningham, Jocz, Phadnis, Wertheimer, & Arteaga, 2011). Students were surveyed twice—once before beginning the science curriculum and/or related *Engineering is Elementary* unit(s), and once after instruction was completed—allowing for a test-retest analysis. The completed assessments were digitized using an OMR scanner and then imported into a Microsoft Access database. This data was then exported to SPSS Statistics version 19.0, together with student demographic data, for initial analysis.

Instrument

We designed an instrument utilizing Likert scales to determine each student’s attitudes towards a series of statements. The Engineering Attitudes survey consists of twenty statements with the option of choosing “Strongly Disagree”, “Disagree Somewhat”, “Not Sure”, “Agree Somewhat”, or “Strongly Agree” for each statement. The students are instructed to select the one that corresponds most closely to their feelings about a statement.

The survey includes a variety of statements intended to measure students’ interest in scientific and engineering skills and jobs as well as some of their attitudes towards science, math, scientists, and engineers (see

Table 1). Students are asked to mark how strongly they agree or disagree with each statement on a scale of 0-4, where 0 is “Strongly Disagree” and 4 is “Strongly Agree”.

Table 1. Engineering Attitudes Student Survey Questions (Text)

Statement #	Category	Statement
1	Science as a career	I would enjoy being a scientist when I grow up.
2	Engineering as a career	I would enjoy being an engineer when I grow up.
3	Inventing jobs	I would like a job where I could invent things.
4	Inventing jobs	I would like to help plan bridges, skyscrapers, and tunnels.
5	Inventing jobs	I would like a job that lets me design cars.
6	Helping jobs	I would like to build and test machines that could help people walk.
7	Helping jobs	I would enjoy a job helping to make new medicines.
8	Helping jobs	I would enjoy a job helping to protect the environment.
9	Science in real life	Science has nothing to do with real life.
10	Math in real life	Math has nothing to do with real life.
11	Figuring things out	I would like a job that lets me figure out how things work.
12	Figuring things out	I like thinking of new and better ways of doing things.
13	Figuring things out	I like knowing how things work.
14	Self efficacy	I am good at putting things together.
15	Attitudes towards scientists	Scientists cause problems in the world.
16	Attitudes towards engineers	Engineers cause problems in the world.
17	Attitudes towards scientists	Scientists help make people’s lives better.
18	Attitudes towards engineers	Engineers help make people’s lives better.
19	Self-reported knowledge	I think I know what scientists do for their jobs.
20	Self-reported knowledge	I think I know what engineers do for their jobs.

Scale Construction

Scales were constructed after completion of the post-surveys. The sample for pre-test reliability analysis consisted of 407 students who had returned both a pre- and a post-test. We constructed a raw score which was the sum of all answers on all items. Note that responses to statements 9, 10, 15, and 16 (see

Table 1 above) were reversed so that positive answers to all questions will result in higher scores. The All score (which includes all statements) was tested for internal reliability and was found to have a Cronbach's alpha of .739 (n=332) for the pre-survey (PreAll). For the post-survey (PostAll), we found a Cronbach's alpha of .798 (n=327).

Since our survey consists of statements that measure different aspects of attitude (towards science, math, and engineering, towards scientists and engineers, and towards skills and careers associated with engineering, see

Table 1), we decided to analyze these different categories separately. Questions 1, 2, 9, 10, 11, 12, 13, 19, and 20 were analyzed individually since they do not group with any other questions addressing the same aspect of attitude. Questions 15-18 were not analyzed or included in subscales because, on reflection, we felt these statements were too ambiguous to accurately test students' attitudes towards scientists and engineers, and therefore without validity. We also dropped Question 14 from the analysis as it was the only statement measuring students' feeling of self-efficacy, and we felt a variety such statements are needed to get an accurate sense of students' self-efficacy in engineering.

The remaining nine statements all address jobs and activities related to engineering and science, although they do not name these specific career fields (making them different from statements 1 and 2). Scales were constructed using these nine statements after completion of the post-surveys. The sample consisted of 407 students who had returned both a pre- and a post-survey. We constructed a raw score which was the sum of all answers on these nine items. This scale was tested for internal reliability and was found to have a Cronbach's alpha of .719 (n=366) for the pre-scale (PreJobs). For the post-scale (PostJobs), we found a Cronbach's alpha of .680 (n=217) for the control group and .811 (n=152) for the test sample. Principal components factor analysis (PCA) with direct obilimin rotation revealed a pattern of three components, each corresponding to a different job category: inventing, helping, and figuring things out.

Based on the results of the PCA, we decided to form two additional subscales, which are summarized in Table 2. Both scales had a Cronbach's alpha of slightly more than .5 for the pre-assessment; higher for the test group on the post-assessment. Student responses were summed to create scores for each of the subscales, which were then used in the analysis.

Table 2. Summary of Engineering Attitudes Subscales

Scale	Statements	Content Assessed	Pre-Survey Reliability: α (N)	Post-Survey Reliability (Cronbach's α)	
				Control	Test
Invent	3-5	Interest in jobs and activities that involve inventing and building/designing cars and buildings	.515 (n=393)	.516 (n=235)	.555 (n=158)
Help	6-8	Interest in jobs and activities that involve helping people and the environment	.525 (n=396)	.535 (n=230)	.650 (n=160)

Analytic theory

The instrument utilized Likert scales to determine students' level of interest in engineering. Likert scales yield ordinal categorical data for individual items, which cannot be analyzed using techniques such as linear modeling, due to both boundary effects and to the non-interval nature of the data. Therefore, hierarchical ordinal logistic regression was used to analyze student responses to individual questions. Ordinal logistic regression was used to analyze student responses to individual questions. For a set of predictors, this method runs every combination of every value of the predictors, called cells. The program compares the answers of the students in each cell, using them to assign a cumulative probability to each answer. The log-odds of the cumulative probabilities are then modeled linearly, as a set of parallel lines, with each intercept or threshold corresponding to the log-odds of the cumulative probability of a potential answer, and the slope provided by the coefficients of the predictors, which are assumed to act similarly for each threshold. If a predictor coefficient is positive, it is interpreted to mean that increasing that predictor increases the probability that such a student would more strongly agree with the statement at hand.

This model makes the proportional-odds assumption, that is, that the effect of each predictor will be the same across all of the categories. For example, it assumes that the treatment changed every student's answer by the same amount, even though it may be that the treatment had a large effect on the students who answered "Strongly Disagree" on the pre-assessment, but not on those who answered "Not Sure" on the pre-assessment.

For each statement we have computed a table of probabilities for each answer. The probabilities are computed by first exponentiating the log odds to get an odds ratio and then converting that to a cumulative probability. We then computed the predicted probability for each answer by taking the difference between consecutive cumulative probabilities. The error bars were computed by utilizing the same process on the upper and lower bounds of the 95% confidence intervals of the coefficients. Finally, we used these probabilities in a weighted average to calculate our models' expected answers for students with different attributes.

HLM, or hierarchical linear modeling (also known as mixed-effect modeling) was used to model students' responses for the two scales. This is a common technique used with continuous data of a hierarchical or nested structure (in this case, students nested within classrooms). As the name suggests, it is a method of multivariate linear regression that takes into account the hierarchical nature of the data, by allowing each student-level coefficient to be modeled by classroom-level predictors, including random coefficients that can be tested for significance. HLM models assume that the data is multivariate normal, and the model specification is checked by ensuring that the residuals are not correlated with any predictors used. Both of these assumptions were checked and found to hold.

Analysis

The data was cleaned in SPSS, then exported to the SuperMix 1.2 (Hedeker, Gibbons, du Toit, & Patterson, 2009) or HLM 6 (Raudenbush, Bryk, Cheong, Congdon, & du Toit, 2004) software packages for analysis. In both cases, the analysis was done using a backwards stepwise regression method, with the variables entered in clusters. First the level-1 (student level) independent variables and their treatment interactions were entered, and those with $p>.01$ were removed in descending order of significance. Once only significant level-1 variables remained, level-2 variables were entered, along with any interactions.

The level-1 independent variables used were Gender, limited English proficiency (LEP), participation in the National Free and Reduced-Price Lunch Program (FRL), Black, and Hispanic. The treatment interaction for each variable, calculated by multiplying the level-1 variable by the treatment indicator variable, was entered simultaneously in order to detect any divergent treatment slopes, i.e., if one predictor correlated positively with the dependent variable in the treatment group but negatively in the control group. None of these variables were centered.

The level-2 independent variables used were ClassSize, overall teacher experience (NumberOfYearsTeaching), Grade_4, Grade_5, the number of EiE units the teacher had taught in prior years (PriorUnits), whether the EiE units taught had content typically associated with women or not associated with gender (FemaleUnits and NeutralUnits), and finally the treatment indicator variable. ClassSize and NumberOfYearsTeaching were both grand-mean centered. However, PriorUnits, FemaleUnits and NeutralUnits were not centered, as we wished to be able to interpret our baseline results in the context of an average teacher who had not taught EiE before, and who was teaching content stereotypically associated with males. Each of the first four level-2 variables (ClassSize, NumberOfYearsTeaching, Grade_4, Grade_5) was also simultaneously entered with its treatment interaction, again calculated by multiplying the variable by the treatment indicator variable. PriorUnits, FemaleUnits and NeutralUnits did not have treatment interactions, as they were already only nonzero for test classes. However, the FemaleUnits and NeutralUnits variables were tested for gender interactions, to see if the gender association of the content had any effect on the gender difference of boys' and girls' attitudes towards engineering.

Since our data set was large enough to allow it, we randomly split our data set so we could cross-validate our models (Cohen, Cohen, West, & Aiken, 2003). We used SPSS to randomly select half of the classrooms, and used this half of the data set to build our models, using an alpha level of .01. We then ran these models on the second half of the data set, noting which variables stayed significant at the .01 level and which did not achieve significance. Only those that stayed significant when tested on the second half were incorporated into our final models, which were run on the full data set in order to obtain the most precise coefficients possible. We found that none of the variables which were significant at the $p<.05$ but $p>.01$ level remained in the model after cross-validation, confirming our decision to use the p<.01 level of significance for building our model.

We used this method to analyze the individual questions, using hierarchical ordinal logistic regression implemented in SuperMix, as well as to analyze the Invent and Help scales using hierarchical linear modeling implemented in HLM.

Results

Sample

The full sample of collected data for the Engineering Attitudes Survey included 7518 students in grades 3 to 5. Of this full sample, 26.0% (n=1959) were excluded due to missing pre- or post-surveys. Additionally, 1609 students across the sample were dropped due to missing demographic information. The final dataset used for analysis included 3950 students in 210 classrooms, with a mean cluster size of 18.8 students per classroom (SD=6.249). The samples included somewhat fewer grade 3 students than the other grades – see Table 3.

Table 3. Grade Distribution

Treatment	Grade			Total
	3	4	5	
Control	210	294	295	799
Test (EiE)	851	1088	1212	3151
Total	1061	1382	1507	3950

Males made up slightly less than half of both control and test groups (see Table 4). Compared to the test group, the control group had a larger proportion of students receiving free or reduced-price lunch (FRL) from the National School Lunch Program and students with limited English proficiency (LEP) (see Table 4). The treatment group also had fewer racial minorities and more white students (see Table 5). As Asian students and those with racial designation marked "other" had such small sample sizes, these demographic variables were not included in the analytic models.

Table 4. Proportions for Demographic Variables

Treatment	Gender: Male	FRL	LEP
Control	396 (49.6%)	457 (57.2%)	168 (21.0%)
Test (EiE)	1571 (49.9%)	981 (31.1%)	313 (9.9%)
Total	1967 (49.8%)	1438 (36.4%)	481 (12.2%)

Table 5. EA Proportions for Demographic Variables – Race

Treatment		White	Asian	Black	Hispanic	Other
Control	Proportion	37.9%	10.6%	14.6%	33.0%	3.8%
	N	303	85	117	264	30
Test (EiE)	Proportion	71.3%	6.6%	8.7%	9.3%	4.1%
	N	2248	209	273	292	129
Total	Proportion	64.6%	7.4%	9.9%	14.1%	4.0%
	N	2551	294	390	556	159

Jobs Scales

Two outcome variables, one for each of the subscales described in Table 2, were used to test for treatment effects on the performance of students in grades 3 through 5 on the survey. The outcome variable PostInvent, which measures students' interest in jobs and activities related to building and inventing things (see Table 2), had a possible range of 0 to 12. Both the PreInvent and PostInvent mean scores were higher for the control group as compared to the test group (see Table 6).

Table 6. EA Descriptive Statistics: PreInvent and PostInvent Scores by Treatment and Gender

	PreInvent				PostInvent			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Control	6.16	3.009	0	12	6.31	3.078	0	12
Test (EiE)	5.67	3.035	0	12	5.87	3.098	0	12
Female	5.07	2.888	0	12	5.02	2.864	0	12
Male	6.49	3.015	0	12	6.90	3.041	0	12

No treatment effect was found for this scale; however, we did find a large standardized effect size (Cohen's *d*=0.481) for male students. Thus, regardless of treatment, boys had more positive attitudes than girls toward jobs and activities having to do with inventing and building things (see Level-1 Model:

$$\mathrm{PostInvent} = \beta_0 + \beta_1(\mathrm{Gender}) + \beta_2(\mathbf{PreInvent}) + \mathrm{r}$$

Level-2 Model

$$\beta_0 = \gamma_{00} + \gamma_{01}(\mathrm{Pr}\,\mathit{eInventMean}) + \mathrm{u}_0$$

$$\beta_1 = \gamma_{10}$$

$$\beta_2 = \gamma_{20} + \mathrm{u}_2$$

BOLD indicates group mean centered.
ITALICIZED indicates grand mean centered.

Table 7).

Level-1 Model:

$$\text{PostInvent} = \beta_0 + \beta_1(\text{Gender}) + \beta_2(\textbf{PreInvent}) + \text{r}$$

Level-2 Model

$$\beta_0 = \gamma_{00} + \gamma_{01}(\mathit{PreInventMean}) + \text{u}_0$$

$$\beta_1 = \gamma_{10}$$

$$\beta_2 = \gamma_{20} + \text{u}_2$$

BOLD indicates group mean centered.

ITALICIZED indicates grand mean centered.

Table 7. PostInvent Scale Conditional Model – Final Estimation of Fixed Effects (with robust standard errors)

Fixed Effect	Coefficient	Standard Error	T-ratio	Approx. df	P-value
For Intercept 1, β_0					
Intercept 2, γ_{00}	5.320	0.076	70.193	208	<0.001
Class PreInventMean, γ_{01}	0.474	0.063	7.517	208	<0.001
For Gender slope, β_1					
Intercept 2, γ_{10}	1.271	0.093	13.720	3529	<0.001
For PreInvent (Group mean centered) slope, β_2					
Intercept 2, γ_{30}	0.434	0.017	25.285	209	<0.001

Table 8. PostInvent Scale Conditional Model – Final Estimation of Variance Components

Random Effect	Standard Deviation	Variance Component	df	Chi-square	P-value
Intercept 1, u_0	0.563	0.317	208	396.903	<0.001
PreInvent, u_2	0.114	0.013	209	273.908	0.002
level-1, r	2.568	6.595			

Table 9. PostInvent Scale Unconditional Model – Final Estimation of Variance Components

Random Effect	Standard Deviation	Variance Component	df	Chi-square	P-value
Intercept 1, u_0	0.624	0.390	209	375.556	<0.001
level-1, r	3.035	9.214			

Figure 1: Engineering Jobs for Inventing, Infrastructure, and Cars—Gender Effects.

The outcome variable PostHelp, which assesses students' interest in jobs that help people and the environment, had a possible range of 0 to 12. The PostHelp scores were somewhat higher for the test group as compared to the control group (see Table 10).

Table 10. EA Descriptive Statistics: PreHelp and PostHelp Scores by Treatment

	PreHelp				PostHelp			
	Mean	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
Control	6.77	3.086	0	12	7.06	3.159	0	12
Test	6.31	3.088	0	12	6.51	3.132	0	12
Female	6.89	2.947	0	12	7.03	3.045	0	12
Male	5.91	3.159	0	12	6.21	3.193	0	12

Again, this model shows no treatment effect, however it shows a gender effect with a Cohen's *d* effect size of -0.125, indicating that girls were more likely to express interest in "helping" jobs than boys.

Level-1 Model:

$$\text{PostHelp} = \beta_0 + \beta_1(\text{Gender}) + \beta_2(\textbf{PreHelp}) + \text{r}$$

Level-2 Model

$$\beta_0 = \gamma_{00} + \gamma_{01}(\textit{PreHelpMean}) + \text{u}_0$$

$$\beta_1 = \gamma_{10}$$

$$\beta_2 = \gamma_{20}$$

BOLD indicates group mean centered.

ITALICIZED indicates grand mean centered.

Table 11. PostHelp Scale Conditional Model – Final Estimation of Fixed Effects (with robust standard errors)

Fixed Effect	Coefficient	Standard Error	T-ratio	Approx. df	P-value
For Intercept 1, β_0					
Intercept 2, γ_{00}	6.783	0.077	87.799	208	<0.001
Class PreHelpMean, γ_{01}	0.587	0.055	10.753	208	<0.001
For Gender slope, β_1					
Intercept 2, γ_{10}	−0.341	0.096	−3.561	3738	<0.001
For PreHelp (Group mean centered) slope, β_2					
Intercept 2, γ_{30}	0.478	0.016	30.141	3738	<0.001

Table 12. PostHelp Scale Conditional Model – Final Estimation of Variance Components

Random Effect	Standard Deviation	Variance Component	df	Chi-square	P-value
Intercept 1, u_0	0.563	0.317	208	383.977	<0.001
level-1, r	2.674	7.148			

Table 13. PostHelp Scale Unconditional Model – Final Estimation of Variance Components

Random Effect	Standard Deviation	Variance Component	df	Chi-square	P-value
Intercept 1, u_0	0.79657	0.63453	209	479.95733	<0.001
level-1, r	3.04424	9.26739			

Figure 2: Engineering & Science Jobs to Help People & Society—Gender Effects.

Analysis of Individual Statements

A number of questions needed to be analyzed individually as there were no other questions on the survey addressing the same aspect of attitude. For these questions (questions 1, 2, 9, 10, 11, 12, 13, 19 and 20) we used ordinal logistic regression to analyze student responses to each statement.

Some statements on the survey revealed no significant differences between demographic groups and no significant change in student response after participation in EiE. These included statements pertaining to interest in and understanding of science and the work of scientists ("I would enjoy being a scientist when I grow up", "Science has nothing to do with real life", and "I think I know what scientists do for their jobs") as well as statements concerning interest in improving things and knowing how things work ("I like thinking of new and better ways of doing things", "I like knowing how things work"). Thus, it appears that all students, regardless of demographics, have similar feelings regarding these statements, and these feelings are not changed through participation in EiE. The remaining statements did reveal either demographic differences or differences based on treatment and are described in detail below.

Statement 2: "I would enjoy being an engineer when I grow up"

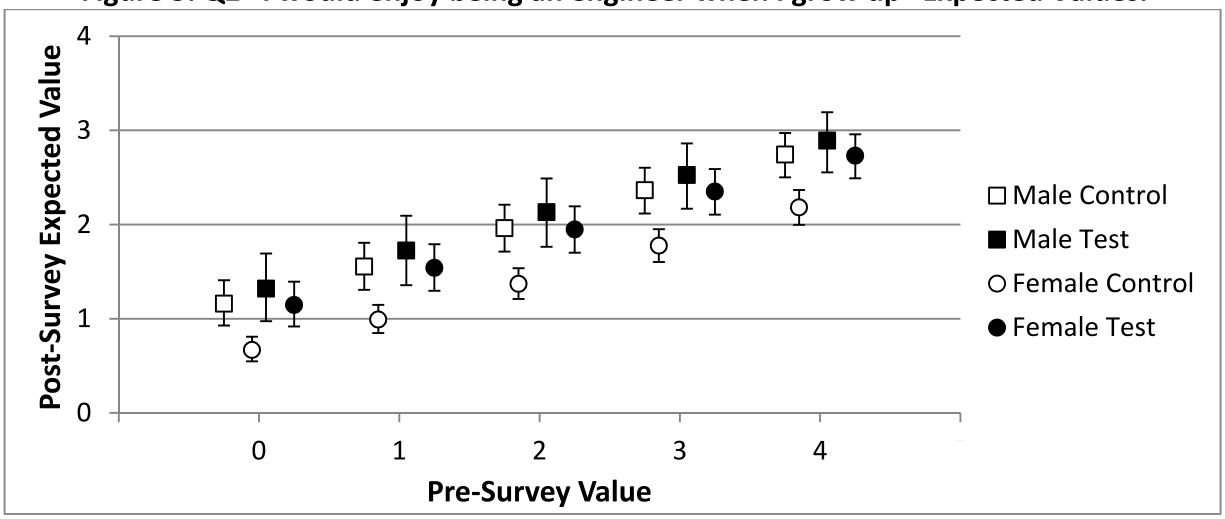
The model for statement 2 is shown in Table 14 below. Besides Gender (male), no demographic variables (IEP, LEP, Free or Reduced Lunch, and race/ethnicity) were found to be significant predictors of the students' answers. Boys were more likely than girls to answer on the post-assessment that they would like to be an engineer when they grow up. However, this difference was strongly modified by treatment, so that both boys and girls were more likely than control to answer positively, and the difference between boys and girls shrank significantly (see

Table 1 and Figure 3). The treatment effect was stronger than the effect of the pre-survey on post-survey responses.

Table 14: Q2 "I would enjoy being an engineer when I grow up" Model.

Parameter	Estimate	Standard Error	z Value	P Value
Threshold1	-0.7912	0.1247	-6.3458	<.0001
Threshold2	0.1365	0.1242	1.0995	0.2716
Threshold3	1.5852	0.1266	12.5244	<.0001
Threshold4	3.0106	0.1340	22.4706	<.0001
Treatment	0.8686	0.1347	6.4492	<.0001
Gender (Male)	0.8887	0.1372	6.4758	<.0001
Gender by Treatment Interaction	-0.6143	0.1518	-4.0470	.0001
Pre-Survey Score	0.6110	0.0307	19.8991	<.0001

Figure 3: Q2 "I would enjoy being an engineer when I grow up" Expected Values.



Question 10: "Math has nothing to do with the real world"

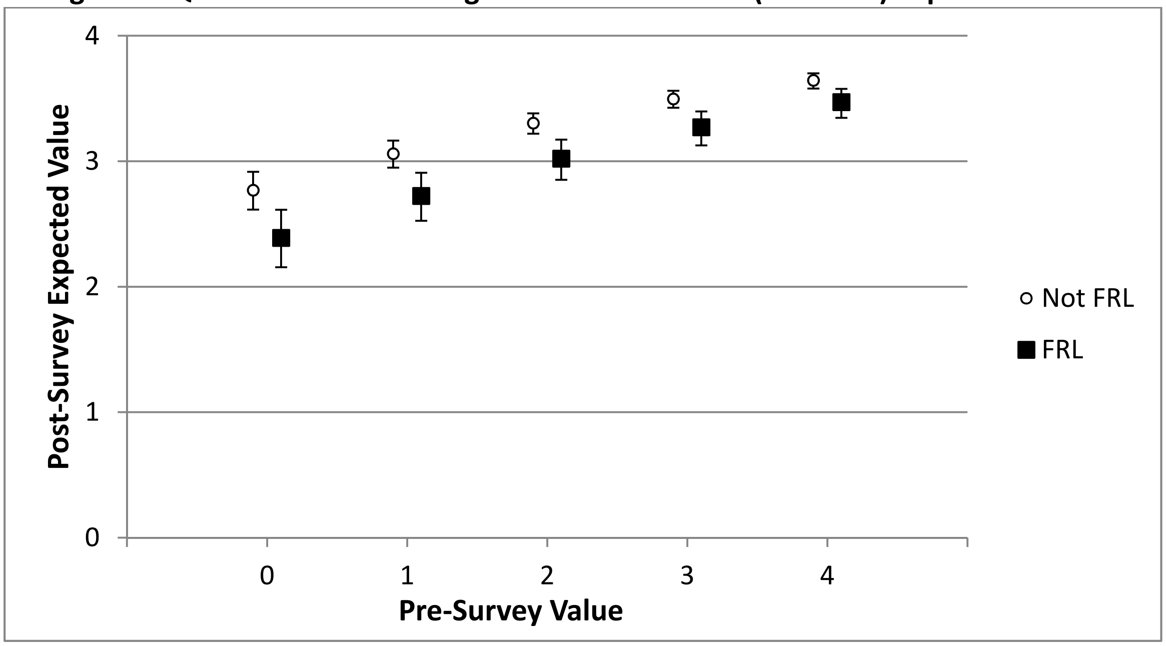
Question 10 on the survey is "Math has nothing to do with the real world". The scores for this item were reversed so that a larger number would be a positive response. Once reduced, our model showed a significant effect for students receiving free or reduced-price lunch from the National School Lunch Program. FRL students were more likely to agree with this statement (more likely to be negative about the role of math in the real world) than other students; this relationship was not moderated by treatment. These results are summarized in Table 15 and Figure 4.

Table 15: Q10 "Math has nothing to do with real life" (reversed) Model.

Parameter	Estimate	Standard Error	z Value	P Value
Threshold1	−2.6300	0.0887	−29.6638	<.0001
Threshold2	−2.1479	0.0808	−26.5888	<.0001
Threshold3	−1.2722	0.0723	−17.5859	<.0001

Threshold4	−0.8229	0.0702	−11.7295	<.0001
FRL	−0.4646	0.0902	−5.1517	<.0001
Pre-Survey Score	0.4045	0.0309	13.1002	<.0001

Figure 4: Q10 "Math has nothing to do with real life" (reversed) Expected Values.



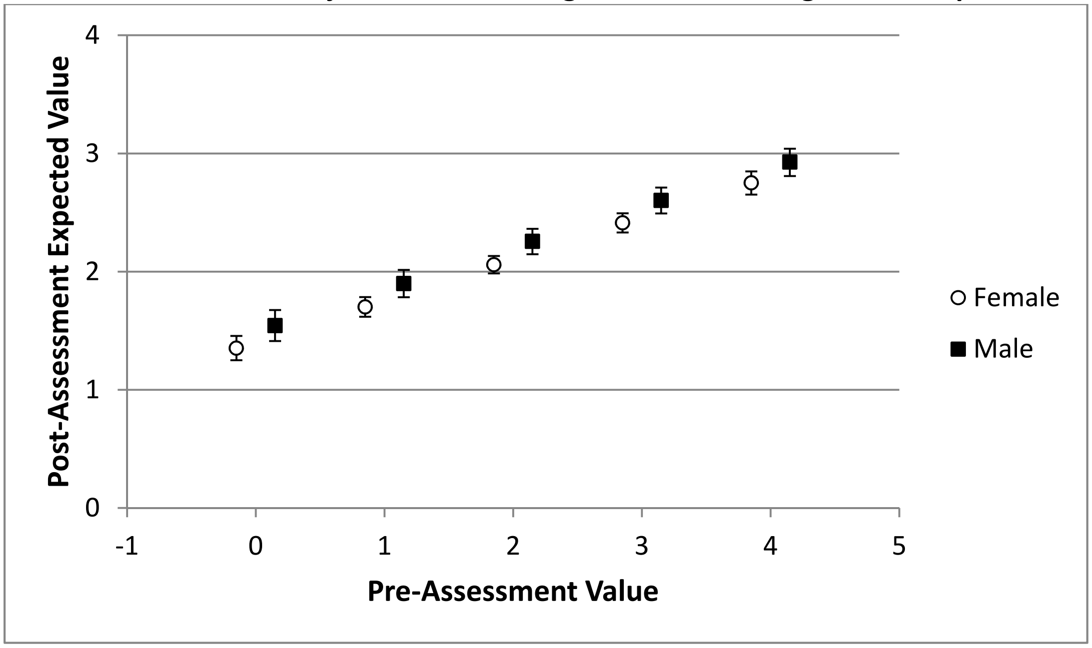
Question 11: "I would like a job that lets me figure out how things work"

Males were significantly more likely than females to agree with the statement "I would like a job that lets me figure out how things work". This relationship was not moderated by treatment.

Table 16: Q11 "I would like a job that lets me figure out how things work" Model.

Parameter	Estimate	Standard Error	z Value	P Value
Threshold1	-1.8324	0.0608	-30.1299	<.0001
Threshold2	-0.8375	0.0515	-16.2734	<.0001
Threshold3	0.6078	0.0505	12.0289	<.0001
Threshold4	1.7626	0.0581	30.3569	<.0001
Gender	0.2892	0.0586	4.9380	<.0001
Pre-Survey Score	0.5234	0.0283	18.4797	<.0001

Figure 5: Q11 "I would like a job that lets me figure out how things work" Expected Values.



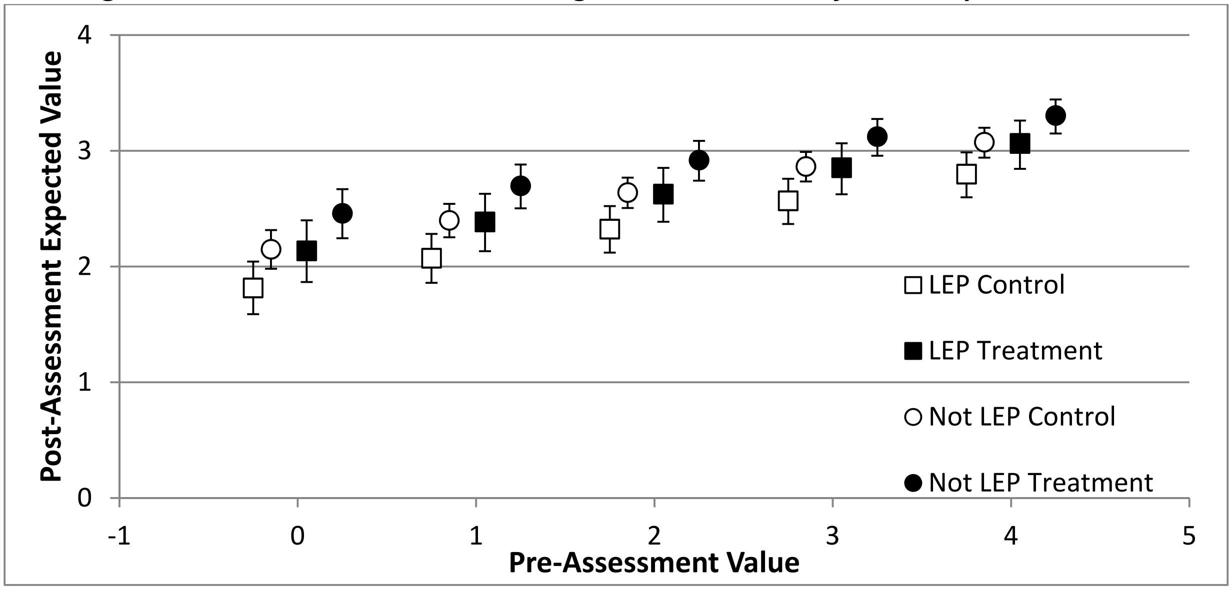
Question 20: "I think I know what engineers do for their jobs"

Question 20 on the survey stated "I think I know what engineers do for their jobs". After participation in EiE, students were more likely to agree with this statement, indicating that they felt that they had a better understanding of what engineers do for their jobs. Although students with limited English proficiency (LEP) were more likely than students in other demographic groups to disagree with this statement, this was true for students in both the test and control groups, thus LEP students participating in EiE were more likely to agree with the statement after participating in EiE than LEP students in the control group. No other demographic variables were found to be significant predictors of student answers. See Table 17 and Figure 6 for a summary of these results.

Table 17: Q20 "I think I know what engineers do for their jobs" Model.

Parameter	Estimate	Standard Error	z Value	P Value
Threshold1	−2.4401	0.1145	−21.3095	<.0001
Threshold2	−1.7969	0.1063	−16.9023	<.0001
Threshold3	−0.3398	0.0993	−3.4219	.0006
Threshold4	0.9541	0.1003	9.5105	<.0001
LEP	−0.4770	0.1061	−4.4955	<.0001
Treatment	0.4572	0.1060	4.3128	<.0001
Pre-Survey Score	0.3655	0.0304	12.0169	<.0001

Figure 6: Q20 "I think I know what engineers do for their jobs"—Expected Values.



Conclusion

For many statements on our engineering and science attitude survey, answers were rarely affected by student demographics or treatment condition. However, for statements dealing specifically with engineering, students participating in EiE showed positive changes in their attitudes compared to control students who were taught only the science content. This result is consistent with our hypothesis that participation in EiE will increase students' interest in engineering.

EiE students were significantly more likely than control students to have improved attitudes towards engineering as careers. Additionally, although boys were initially more likely than girls to answer positively to the statement "'I would enjoy being an engineer when I grow up", girls participating in EiE showed a positive change after participation in EiE such that they were about as likely as boys to agree with this statement on the post-test. Participation in EiE also positively affected students' self-perceived understanding of the work of an engineer. Students participating in EiE were significantly more likely than control students to agree with the statement "I think I know what engineers do for their jobs". This finding is consistent with our prior findings that EiE students performed significantly better on assessments of science and engineering content than control groups studying only the related science (Lachapelle et al., 2011; Lachapelle, Jocz, & Phadnis, 2011). Thus, participation in EiE positively affects students' interest in and understanding of engineering careers.

Interest and attitudes were rarely affected by student demographics; however, we did find that students participating in the National Free or Reduced-price Lunch Program (FRL) were less likely to think that math has anything to do with real life, and we wonder if this is related to the consistently lower math scores of students from lower-SES families, well documented in the literature (e.g. Ladd, forthcoming; Reardon, 2011). Additionally, students with limited English proficiency (LEP) were less likely, overall, to agree that they know what engineers do for their jobs, perhaps indicating a language barrier in knowing and learning about what it means to be an engineer in the United States, and making connections with what they may know about engineering in their primary language and culture.

When asked more specifically about interest in jobs requiring engineering skills and activities, boys and girls showed significantly different patterns of responses. Boys showed more interest than girls in activities having to do with inventing and figuring things out, regardless of treatment group. Girls showed more interest than boys in jobs having to do with helping people and the environment, again regardless of treatment. These findings are consistent with findings in the literature about the science and engineering interests of girls: that girls are interested in "helping" careers, prefer biological sciences to physical sciences and engineering fields, and want to see the social value of science (Baker & Leary, 1995; Buccheri, Gurber, & Bruhwiler, 2011; Dawson, 2000; Drechsel, Carstensen, & Prenzel, 2011; Jones, Howe, & Rua, 2000; Miller, Blessing, & Schwartz, 2006).

References

Baker, D., & Leary, R. (1995). Letting girls speak out about science. *Journal of Research in Science Teaching*, *32*(1), 3–27. doi:10.1002/tea.3660320104

Blumenfeld, P., Soloway, E., Marx, R., Krajcik, J., Guzdial, M., & Palincsar, A. (1991). Motivating Project-Based Learning: Sustaining the Doing, Supporting the Learning. *Educational Psychologist*, *26*(3), 369–398.

Brotman, J. S., & Moore, F. M. (2008). Girls and science: A review of four themes in the science education literature. *Journal of Research in Science Teaching, 45*(9), 971-1002.

Buccheri, G., Gurber, N. A., & Bruhwiler, C. (2011). The Impact of Gender on Interest in Science Topics and the Choice of Scientific and Technical Vocations. *International journal of science education*, *33*, 159–178. doi:10.1080/09500693.2010.518643

Burke, R. J., & Mattis, M. C. (Eds.). (2007). Women and minorities in science, technology, engineering and mathematics: Upping the numbers. Northampton, MA: Edward Elgar Publishing.

Catsambis, S. (1995). Gender, race, ethnicity, and science education in the middle grades. [10.1002/tea.3660320305]. *Journal of Research in Science Teaching, 32*(3), 243-257.

Clewell, B. C., & Braddock, J. (2000). Influences on minority participation in mathematics, science, and engineering. In G. Campbell Jr, R. Denes & C. Morrison (Eds.), *Access denied: Race, ethnicity, and the scientific enterprise* (pp. 89–137). New York: Oxford University Press.

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). *Applied multiple regression/correlation analysis for the behavioral sciences* (3rd ed.). Mahwah, NJ: Lawrence Erlbaum Associates.

Cunningham, C. M., & Hester, K. (2007). *Engineering is Elementary: An engineering and technology curriculum for children*. Paper presented at the ASEE Annual Conference & Exposition, Honolulu, HI.

Dawson, C. (2000). Upper primary boys' and girls' interests in science: have they changed since 1980? *International journal of science education*, *22*(6), 557 – 570.

Drechsel, B., Carstensen, C., & Prenzel, M. (2011). The Role of Content and Context in PISA Interest Scales: A study of the embedded interest items in the PISA 2006 science assessment. *International journal of science education*, *33*(1), 73–95.

Duschl, R. A. (2008). Science education in three-part harmony: Balancing conceptual, epistemic, and social learning goals. *Review of Research in Education, 32*(1), 268-291.

Duschl, R. A., & Grandy, R. E. (2008). *Teaching scientific inquiry: Recommendations for research and implementation*. Rotterdam, The Netherlands: Sense Publishers.

Edelson, D. C. (2001). Learning-for-use: A framework for the design of technology-supported inquiry activities. *Journal of Research in Science Teaching*, *38*(3), 355–385.

Engle, R. A., & Conant, F. R. (2002). Guiding principles for fostering productive disciplinary engagement: Explaining an emergent argument in a community of learners classroom. *Cognition and Instruction, 20*(4), 399-483.

Hedeker, D., Gibbons, A. S., du Toit, S., & Patterson, D. (2009). *Supermix 1.2: A program for mixed-effects models*. Lincolnwood, IL: Scientific Software International.

Jocz, J., & Lachapelle, C. (2012). *The Impact of Engineering is Elementary (EiE) on Students' Conceptions of Technology*. Boston, MA: Museum of Science.

Jones, M. G., Howe, A., & Rua, M. J. (2000). Gender differences in students' experiences, interests, and attitudes toward science and scientists. *Science Education*, *84*(2), 180–192. doi:10.1002/(sici)1098-237x(200003)84:2<180::aid-sce3>3.0.co;2-x

Katehi, L., Pearson, G., & Feder, M. A. (Eds.). (2009). *Engineering in K-12 education: Understanding the status and improving the prospects*. Washington, DC: National Academies Press.

Lachapelle, C. P., Cunningham, C. M., Jocz, J., Kay, A. E., Phadnis, P., Wertheimer, J., & Arteaga, R. (2011). *Engineering is Elementary: An evaluation of years 4 through 6 field testing*. Boston, MA: Museum of Science.

Lachapelle, C. P., Cunningham, C. M., Jocz, J., Phadnis, P., Wertheimer, J., & Arteaga, R. (2011). *Engineering is Elementary: An evaluation of years 7 and 8 field testing*. Boston, MA: Museum of Science.

Lachapelle, C. P., Jocz, J., & Phadnis, P. (2011). *An evaluation of the implementation of Engineering is Elementary in fourteen Minneapolis Public Schools* (p. 53). Boston, MA: Museum of Science. Retrieved from http://www.mos.org/eie/pdf/research/Cargill_Year1_Report.pdf

Ladd, H. F. (forthcoming). Education and poverty: Confronting the evidence. *Journal of Policy Analysis and Management*.

Maltese, A. V., & Tai, R. H. (2010). Eyeballs in the Fridge: Sources of early interest in science. *International Journal of Science Education, 32*(5), 669-685.

Miller, P. H., Blessing, J. S., & Schwartz, S. (2006). Gender Differences in High-school Students' Views about Science. *International journal of science education*, *28*(4), 363 – 381.

Raudenbush, S., Bryk, A., Cheong, Y., Congdon, R., & du Toit, M. (2004). *HLM 6: Hierarchical linear and nonlinear modeling*. Lincolnwood, IL: Scientific Software International.

Reardon, S. (2011). The widening achievement gap between the rich and the poor: New evidence and possible explanations. In G. J. Duncan & R. J. Murnane (Eds.), *Whither Opportunity?: Rising Inequality, Schools, and Children's Life Chances* (pp. 91–116).

Reid, N., & Skryabina, E. A. (2003). Gender and physics. *International journal of science education, 25*(4), 509 - 536.

Roth, W.-M., & Lee, Y.-J. (2007). "Vygotsky's Neglected Legacy": Cultural-Historical Activity Theory. *Review of Educational Research*, 77(2), 186-232.

Sawyer, R. K. (2006). Introduction: The new science of learning. In R. K. Sawyer (Ed.), *The Cambridge Handbook of the Learning Sciences* (pp. 1-16). Cambridge, UK: Cambridge University Press.

Stine, D. D., & Matthews, C. M. (2009). The US science and technology workforce. Washington, DC: Congressional Research Service.

Wicklein, R. C. (2006). Five good reasons for engineering as THE focus for technology education. *The Technology Teacher, 65*(7), 25-29.