Impact of Self-Efficacy and Outcome Expectations on First-Year Engineering Students' Major Selection

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Abstract

Deciding on a major is one of the critical decisions first-year students make in their undergraduate study. Framed in Social Cognitive Career Theory, this work investigates differences between measures of self-efficacy and outcome expectations by students intending to pursue different engineering majors. Our results show that tinkering self-efficacy, experimental self-efficacy, and professional outcome expectations are statistically significantly different for students intending to pursue different majors. Students from Biomedical Engineering, Chemical & Biomolecular Engineering, Computer Engineering, Computer Science, Electrical Engineering, and Mechanical Engineering have different average scores from at least one other group of students on at least one construct. Differences by gender are also explored, as well as student major changes, confidence in major choice, and the importance of both professional and lifestyle outcome expectations.

Introduction

One of the most important decisions first-year undergraduate students make is choosing their major. Many universities offer first-year engineering programs that allow students to pre-select into engineering while delaying commitment to a specific engineering major until the conclusion of the first-year program. Even institutions that do not offer first-year programs often include a common first-year sequence that allow students to switch their engineering major without a delay to graduation. Understanding how students make their major selection can allow for enhanced advising and fewer major changes after the first year. The research question this work will address is: How do self-efficacy and outcome expectations vary among first-year engineering students as they prepare to select an engineering major?

Additionally, there are studies that document student movements throughout their engineering careers that show a substantial number of students remain in engineering, but switch their major within engineering [1], [2]. The amount of switching can vary based on the engineering program attended and whether the institution uses a common, first-year engineering program that allow students to freely switch engineering majors with delayed timelines to graduation. These types of programs have been found to help retain students in engineering [3] and in their first choice engineering major [4].

Literature Review

Normally, before students decide to pursue an engineering major, students first must decide that they want to major in engineering at large. The factors that attract students to the field of engineering have been explored with largely consistent results. Among the most prevalent factors for students are their abilities in math and science [5]–[8]. However, some students choose to major in engineering because they are aware of the difficulty of transferring into engineering after beginning their undergraduate studies [4], [9], [10].

The impacts of an engineering degree are also important considerations for many students when choosing to major in engineering. Engineering students often discuss their future ability to have impacts on society and the ability to address the problems facing the world upon graduation, especially among students majoring in civil and environmental engineering [7], [11]. Students also consider the availability of career options because some students are more focused on "making a career choice than an educational choice" [12]. Salary is also an important consideration for students [6], [13] and one of the reasons parents believe engineering is a good career choice for their children [5].

As expected, not all students that begin in engineering remain and graduate with an engineering degree. However, engineering has one of the highest rates of persistence at approximately 57% [10]. Despite the higher rate of persistence, recruitment is a considerable issue for engineering. Of all engineering students in their eighth semester, 90% began in engineering; this proportion is considerably higher than any other group of majors [10]. These statistics are also concerning because even though persistence in engineering is high, there can be high fluctuation in the number of students graduating with an engineering degree; for example, more students graduated with engineering degrees in 1985 than in 2010 [14].

Seymour and Hewitt have reported that many students who are capable of earning engineering degrees (and other math and science degrees) leave their degree programs [15]. The Persistence in Engineering (PIE) survey has been used to help identify some of the differences between students who do and do not persist in engineering degrees – sources of motivation, confidence in math and science skills, and financial concerns [8]. In that study, more non-persisting students were motivated by their family while students who persisted were motivated by a high school mentor. Confidence in math and science skills were also a differentiating factor; students who persist are more confident in those skills than students who do not persist. While there are some differences between these two groups of students, many of the factors in the survey instrument were not significantly different for students who did and did not persist in engineering [8]. This conclusion is consistent with Seymour and Hewitt's conclusion that the differences between students cannot be identified by "high school preparation, performance scores or effort expended" [15].

Another of Seymour and Hewitt's conclusions is that interest in the discipline and the careers that follow is "conducive to persistence" [15]. Additionally, for engineering educators to foster a learning environment to engage students, the factors that influence major selection are important [7]. The work to identify these factors is underway and includes understanding the perceptions that students have of the engineering disciplines. Research has shown that first-year engineering students consistently identify many important topics that are familiar to all engineering disciplines, such as maintenance, research, and processes [16]. Additionally, students ascribed mechanical engineering as having the most "options;" this may be due to the marketing of the major, its general perception as a "broad discipline," or the type of work that many mechanical engineers perform. This study found that while some perceptions were broadly held, the disciplines were perceived differently based on the students' majors and the institution they attended [16].

Factors that have been identified as important for major selection include outcomes expectations and self-efficacy [17]. These factors are part of Social Cognitive Career Theory [18], [19] and represent the anticipated results from completing a task and the confidence in ability to complete tasks, respectively. Performance outcomes, a source of self-efficacy, were the most significant factor for students in each of the five engineering departments studied. Students intending to major in Civil and Environmental Engineering had the highest proportion of responses including outcomes expectations which the authors note could be due to the perceived possibility of societal impact after graduation [17].

Another study has used a single-item measure of confidence in major choice and found significant results between that item and students staying in or changing from their intended engineering major at admission to their actual, degree-granting major one year later after completing a first-year engineering program [20]. While this item was found to be predictive of major changes within engineering, it is not predictive of remaining or leaving engineering at large [20]. These results were consistent with a previous study that found that students who graduated in the same engineering major as they entered had the highest levels of confidence [21]. Additionally, among first-year female engineering students, confidence in engineering at large and in their choice of engineering major increases over the course of their first semester [22].

Theoretical Framework

This study was framed using Social Cognitive Career Theory (SCCT), especially the self-efficacy and outcomes expectations constructs [18], [19]. Even though this theory is named a career development theory, the authors note that it also explains academic development. The theory seeks to explain the interdependence of people and their environment. In addition to self-efficacy and outcome expectations, the theory also uses goals as a significant factor with models incorporating interests, choice, and performance [18], [19].

Self-efficacy is the confidence people have about their perceived ability to complete a task. Upon successful completion of a task, self-efficacy generally increases but decreases after an unsuccessful attempt. There are four primary sources of self-efficacy: performance accomplishments, vicarious experiences, verbal persuasion, and emotional arousal [23]. Outcome expectations are the perceived consequences of completing a task, both positive and negative. Outcome expectations can be informed by the anticipation of rewards and pride in completing the task. Self-efficacy and outcomes expectations can be summarized, respectively, with these questions: "Am I capable of completing this task?" and "What will happen if I complete this task?" [18], [19].

Methods

Population and Context

This study was conducted at a large, public, research university in the southeastern United States. The target population includes first-year engineering students who enroll in a sequence of required, common first-year engineering courses but are admitted to degree-granting majors; the institution is categorized as DMa (direct matriculation with required engineering course for all majors) by the Chen *et al.* taxonomy [24]. The required first-year courses allow students to switch engineering majors anytime during the first year without delaying graduation.

The survey instrument was distributed one time, six weeks into the Fall 2019 semester. The survey distribution was approximately one week after the college's primary major exploration event. The event allows students to interact with the engineering majors available at the university through presentations and informal discussions.

The sample of the population used in this study is described in Table 1. The sample is 33% female while the undergraduate population in the college of engineering, according to the university website, is 22% female. The national engineering enrollment in 2018 was 26.3% female at the undergraduate level [25].

Table 1. Summary statistics of the sample in this study by intended engineering major and gender. The table is sorted by decreasing totals of intended enrollment.

	Female	Male	Non-binary	No response	TOTAL
Biomedical	26	23	1	1	51
Mechanical	10	39	0	2	51
Computer Science	7	26	1	0	34
Aerospace	7	21	1	1	30
Chemical	12	15	0	1	28
Civil	11	12	0	3	26
Computer	3	13	0	1	17
Electrical	1	15	0	0	16
Industrial & Systems	8	6	0	2	16
Nuclear	6	9	1	0	16
Materials Science	2	5	0	0	7
Biosystems	3	1	0	1	5
Other	6	5	0	0	11
TOTAL	102	190	4	12	308

Race and ethnicity data were also collected. The sample is 59% White, 11% Asian, 8% Black or African American, 4% Hispanic or Latinx, and less than 2% each of Middle Eastern or North African and Native Hawaiian or Other Pacific Islander. 10% of students in the sample reported two or more racial and / or ethnic identities and 4% did not report their racial and / or ethnic identity. The undergraduate population in the college of engineering, according to the university website, is 74% White. This difference is the result of survey response rates; actual demographics only vary marginally from class-to-class and year-to-year.

When analysis is performed by intended engineering major, students who selected Biosystems Engineering, Materials Science and Engineering, a major outside engineering (Other), or did not respond were excluded from analysis due to our inability to draw conclusions based on that sample. Similarly, when analysis is performed by gender, students who selected a non-binary gender option or who chose not to report their gender were excluded from analysis due to our inability to draw conclusions based on that sample.

Survey Instrument

The survey instrument used in this study uses two existing instruments in addition to some items written for this study. The first published instrument [26] is based in SCCT and contains scales measuring self-efficacy of choice as well as professional and lifestyle outcome expectations. This instrument was originally developed for use with first-year medical school students so words and phrases were edited to be consistent with language first-year engineering students would expect, as previously described [27]. Choice self-efficacy items ask students about their confidence in selecting a major; for example, "How confident are you that you can…choose a major that will fit your interests and abilities." The professional and lifestyle outcome expectations items ask students about their perceived outcomes based on the major they are most likely to pursue. For example, for professional outcome expectations, students are asked, "How much do you expect your choice of major will…allow you to achieve your desired professional success" and for lifestyle outcome expectations, students are asked, "How much do you expect your choice of major will…allow you to pursue leisure time activities/interests that you like" [26].

The second published instrument [28] was selected because it expands self-efficacy into four factors: general engineering self-efficacy, experimental self-efficacy, tinkering self-efficacy, and design self-efficacy. The general engineering self-efficacy items ask students about their confidence in engineering coursework; for example, "I can learn the content taught in my engineering-related courses." The experimental, tinkering, and design self-efficacy items ask students about their confidence in tasks relevant to those skills. For example, in experimental self-efficacy, "I can analyze data resulting from experiments;" for tinkering self-efficacy, "I can build machines;" and for design self-efficacy, "I can evaluate a design" [28].

In addition to using the self-efficacy and outcome expectations constructs from SCCT, items were added to ask respondents if the potential outcomes were important to them as well as how much they believe their engineering major will allow for each potential outcome. Additionally, students were asked to report their major at admission, their current major, and the major they intend to pursue. At the time of the survey, the major at admission was retrospective and intended major was prospective. Finally, students were asked a single-item measure of confidence in their prospective choice of the major [20].

Confirmatory Factor Analysis

Because the first instrument [26] included in our survey was originally intended for use with first-year medical students, a confirmatory factor analysis (CFA) was conducted to confirm that the reworded items were appropriate for first-year engineering students. Although it was designed for use with engineering students, a CFA was also conducted on the second instrument [28] included in our survey to be sure it behaved as expected. These analyses were conducted with all students who intend to pursue an engineering major (n = 297) which is approximately equal to the minimum suggested sample sizes of 300 [29] and exceeds the minimum recommendation for good fit [30]. There are four factors on each scale with the number of items included in Table 3; the fourth scale from Rogers, Searle, & Creed instrument, goals, was included in the survey instrument, but not used in this study and does not appear in Table 3. The goals scale has 6 items.

Four indices of fit were computed for the CFA on each instrument. Chi-squared is indicative of a good fit when the statistic is smaller and the corresponding p-value is greater than 0.05; this is commonly problematic with large samples [31], [32]. The Comparative Fit Index (CFI) is indicative of good fit at values of 0.97 and higher with values higher than 0.95 being acceptable [32]; however, values higher than 0.90 are sometimes considered acceptable [31]. Root Mean Square Error of Approximation (RMSEA) is indicative of good fit at values below 0.05, adequate fit between 0.05 and 0.08, mediocre fit between 0.08 and 0.10, and unacceptable above 0.10 [32]. Finally, Standardized Root Mean Squared Residual (SRMR) indicates a good fit at values less than 0.05 and an acceptable fit at values less than 0.10 [31], [32].

We also checked internal consistency using Cronbach’s alpha and comparing the values from our survey distribution to the values published with the original instruments.

Analysis of Variance and Tukey’s Statistic

Analysis of Variance (ANOVA) tests are used to determine if there are differences in the mean response of a quantitative variable with respect to many groups, divided by different levels of a categorial variable. In this work, the mean response variables are the scores on each of the self-efficacy subscales as well as the outcome expectations scales. The categorical variables most frequently used to divide students into groups were the students’ intended engineering majors, but gender is also used in some tests. ANOVA tests can be one- or two-way depending on the number of different sets of categorial variables used in the test. Most of the tests in this study are one-way tests, but two two-way tests are used.

When data are unbalanced, corrective measures are necessary. Because the data in our study are unbalanced, we used a Type III sum of squares on each one-way and two-way ANOVA test. The Type III sum of squares tests for significance of each main effect after accounting for any other main effects and their interactions, in a two-way ANOVA. The results of a Type III test are the significance of a factor after accounting for all other factors [33].

The results of an ANOVA test allow for the determination of if a difference exists between any groups in the test, but it does not specify which groups are different. Tukey's statistic [34] allows for these differences to be calculated and reported. This statistic will be used as a post-hoc analysis to determine which groups of students have differences.

Results with p-values less than or equal to 0.001 are considered to provide very strong evidence of significance; p-values greater than 0.001 and less than or equal to 0.05 are considered to provide strong evidence of significance. Results with a p-value greater than 0.05 and less than or equal to 0.10 are considered to provide moderate evidence of significance; p-values greater than 0.10 are considered to provide weak evidence of significance. Post-hoc analyses are reported for ANOVA tests that provide at least moderately strong evidence of significance.

Results and Discussion

Instrument Validation

To make sure that the items in the Rogers, Creed, and Seale [26] instrument were appropriate for use with our population, we conducted a confirmatory factor analysis. The values calculated from the CFA on each of the two instruments included in this study are included in Table 2. All of the reported values are acceptable for using the instruments and their constructs in this study.

Table 2. Indices of fit for CFA of instruments included in this study.

Statistic	Rogers, Creed, & Searle	Mamaril et al.
Chi-squared, df, p-value	656.1, 269, <0.001	351.9, 113, <0.001
CFI	0.905 (acceptable)	0.937 (acceptable)
RMSEA	0.072 (adequate)	0.087 (mediocre)
SRMR	0.067 (acceptable)	0.045 (good)

Additionally, we computed Cronbach's alpha values as a measure of internal consistency for each of the scales of interest in this study. The alpha values published with the original instruments and the values calculated from our population are included in Table 3. All our Cronbach's alpha values are in the good to excellent range and generally agree with values from the source papers.

Table 3. Comparison of Cronbach's alpha between source papers and this study.

Source Paper	Scale†	Number of Items	Alpha from Source	Alpha from This Study
Rogers, Creed, & Searle	Choice SE	7	0.86	0.91
	Professional OE	8	0.84	0.82
	Lifestyle OE	4	0.89	0.88
Mamaril et al.	General Engr SE	5	0.89	0.91
	Experimental SE	4	0.79	0.90
	Tinkering SE	4	0.87	0.89
	Design SE	4	0.90	0.94

† Abbreviations: SE = self-efficacy; OE = outcome expectations

Choice Self-Efficacy and Student Major Changes

Students' self-reported majors at admission (Figure 1, left column), six weeks into the Fall semester (Figure 1, center column), and the major they are most likely to pursue (Figure 1, right column) were analyzed to visualize trends in student majors. Over 71% of all students indicated their major was and would be the same at each of the three time points (n = 219), but there are still many students who indicate a change in major or a planned change in major (n = 89).

Confidence in the choice of an engineering major has previously been found to be a significant predictor of whether a student matriculates into that engineering major [20], [21]. While all the data was collected using one survey distribution and is cross-sectional, students who report the same engineering major for each time point (no previous change and no intended change) have a higher choice self-efficacy of 3.96 on a 5-point scale, on average. Students who have changed and / or intend to change their major have an average choice self-efficacy of 3.71. This result is similar to the results with the single-item measure of confidence in their intended major choice. Students who report the same engineering major for each time point have a higher confidence in their choice of the major of 7.67 on a 10-point scale, while students who have had a change and / or intend to make a change of major have a confidence in their choice of 6.87. Using Welch's t-tests, there is very strong evidence that both differences are significantly different ($p < 0.001$).

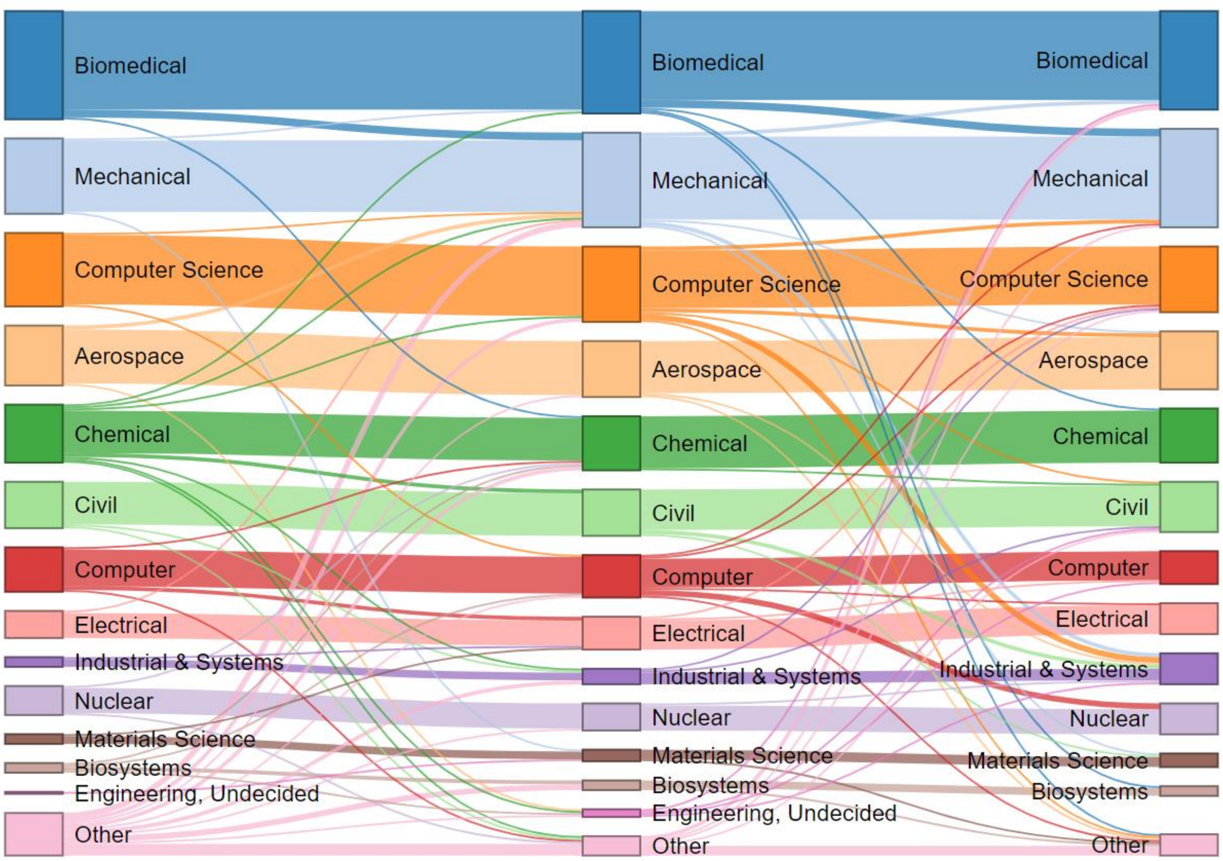

Figure 1. A Sankey diagram representing students' reported majors at admission (left column), six weeks into the fall semester (center column), and the majors they are most likely to pursue (right column). Lines indicate changes to new majors; line thickness represents the number of students following a path. The diagram is sorted by decreasing totals of intended major (right column).

Self-Efficacy and Major Selection

Five different measures of self-efficacy were investigated to determine if any differences existed between students grouped by the engineering major they were most likely going to pursue. Group means are shown in Table 4. Performing an analysis of variance (ANOVA) test in R [35], there is strong evidence that both experimental self-efficacy [$F(9, 270) = 2.51$, $p = 0.009$] and tinkering self-efficacy [$F(9, 270) = 3.30$, $p = 0.019$] are statistically significantly different among students intending to pursue different engineering majors. None of the other three subscales were near any commonly accepted level of significance ($p \geq 0.252$).

Post-hoc analysis was then conducted using Tukey's test [34] to determine the individual differences between the engineering majors. There is strong evidence that students in Electrical Engineering (EE) have significantly higher experimental self-efficacy than students in both Computer Science (CS) ($p = 0.023$) and Biomedical Engineering (BME) ($p = 0.046$). There is moderately strong evidence that students in Mechanical Engineering (ME) have significantly higher tinkering self-efficacy than students in both BME ($p = 0.052$) and CS ($p = 0.053$).

Computer Science, while not always included in colleges of engineering, is included at the institution being studied. The differences found here between CS and two engineering majors may speak to some of the reasons why CS is sometimes organized differently. Additionally, the tinkering self-efficacy differences stand out between ME and BME because while ME is male dominated, BME enrolls the highest proportion of female students in the college and approaches gender parity (female enrollment was 46% in Fall 2019). ME and BME are also hosted in the same department and have a considerable overlap of content and coursework until the senior year of study.

Table 4. Average score for each self-efficacy construct by major students are intending to pursue.

	Choice[†]	General Engineering	Experimental	Tinkering	Design
Aerospace	3.93	4.25	4.48	4.00	4.09
Biomedical	3.77	4.11	4.03[2]	3.78[3]	3.69
Biosystems	3.66	3.60	4.45	4.60	4.45
Chemical	4.07	4.44	4.63	4.12	4.10
Civil	3.88	4.24	4.18	3.96	4.24
Computer	3.59	3.92	4.10	4.60	3.99
Computer Science	3.82	4.17	3.90[1]	3.69[4]	3.74
Electrical	4.04	4.49	4.98[1,2]	4.53	4.27
Industrial & Systems	4.01	4.49	4.52	3.88	4.42
Materials Science	3.92	4.11	4.39	4.50	4.43
Mechanical	3.93	4.27	4.40	4.56[3,4]	4.06
Nuclear	4.09	4.49	4.52	4.19	4.47

[†] Choice self-efficacy was measured using a 5-point scale; all others are 6-point scales.

[1,2] Students intending to major in Electrical Engineering have significantly higher experimental self-efficacy than students in both Computer Science and Biomedical Engineering.

[3,4] Students intending to major in Mechanical Engineering have significantly higher tinkering self-efficacy than students in both Biomedical Engineering Computer Science.

Self-Efficacy and Gender

The five measures of self-efficacy were also investigated to determine if any differences existed between students grouped by gender. Group means are shown in **Table 5**. In this analysis, students who chose not to report their gender or selected a non-binary option were excluded, as explained previously. An ANOVA test provides strong evidence of significant differences between the two genders studied with respect to general engineering self-efficacy [$F(1, 289) = 7.09$, $p = 0.008$] and tinkering self-efficacy [$F(1, 286) = 11.32$, $p = 0.001$]; it also provides moderately strong evidence of a difference in design self-efficacy [$F(1, 285) = 3.27$, $p = 0.072$]. In all cases, males have the higher self-efficacy.

Table 5. Average score for each self-efficacy construct by gender.

	Choice†	General Engineering	Experimental	Tinkering	Design
Female	3.87	4.02*	4.17	3.77*	3.85*
Male	3.91	4.34*	4.37	4.28*	4.12*

† Choice self-efficacy was measured using a 5-point scale; all others are 6-point scales.

* Males have significantly higher general engineering, tinkering, and design self-efficacies than females.

Because tinkering self-efficacy was significantly different by both intended engineering major and gender, follow-up two-way ANOVA tests of intended major and gender were conducted including only students intending to pursue ME or BME and ME or CS majors (the identified differences from the Tukey's test) and who also identified as female or male. For ME and BME students, tinkering self-efficacy is strongly associated with both intended engineering major [$F(1, 91) = 10.78$, $p = 0.002$] and gender [$F(1, 91) = 2.91$, $p = 0.092$]; however, there is strong evidence of an interaction of intended engineering major and gender [$F(1, 91) = 3.96$, $p = 0.050$], which indicates that the relationship between intended engineering major and tinkering self-efficacy depends on gender. Because this interaction effect is significant, it is difficult to interpret the effects of gender and intended engineering major independently. An interaction plot is shown in **Figure 2**. This interaction illustrates that females and males who intend to major in ME have similar tinkering self-efficacy, but males who intended to major in BME have higher tinkering self-efficacy than females who intend to major in BME.

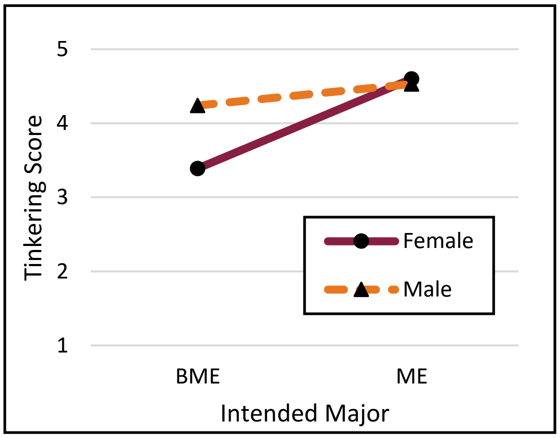

Figure 2. Interaction of intended engineering major and gender on tinkering self-efficacy. The chart illustrates that while males and females in ME have similar tinkering self-efficacy, BME females have a lower tinkering self-efficacy than BME males.

In the two-way ANOVA test with ME and CS students, tinkering self-efficacy is only strongly associated with their intended engineering major [$F(1, 74) = 11.76$, $p < 0.001$]. There is not strong evidence that gender [$F(1, 74) = 1.76$, $p = 0.189$] nor the interaction of gender and intended engineering major are significant [$F(1, 74) = 2.31$, $p = 0.133$]. This result means that we have very strong evidence that there is a difference in tinkering self-efficacy by the intended engineering major of ME and CS students.

Outcome Expectations and Major Selection

Two measures of outcome expectations were also investigated. Group means are shown in **Table 6**. An ANOVA test provided moderately strong evidence of significant differences in professional outcome expectations [$F(9, 261) = 1.67$, $p = 0.098$] between students grouped by their intended engineering major. Tukey's test provides strong evidence that students in Chemical & Biomolecular Engineering (CBE) have significantly higher professional outcome expectations than students in Computer Engineering (CPE) ($p = 0.030$). ANOVA results also provided only weak evidence that lifestyle outcome expectations vary by intended engineering major [$F(9, 268) = 1.59$, $p = 0.117$].

One potential explanation for this difference could also be associated with gender because CBE enrolls the second highest proportion of females in engineering at 39%, while CPE trails at 11%. However, there is not strong evidence of a significant difference between professional outcome expectations when students are grouped by gender [$F(1, 284) = 2.19$, $p = 0.140$]. There is also not strong evidence of a significant difference between lifestyle outcome expectations when students are grouped by gender [$F(1, 288) = 0.42$, $p = 0.518$].

Students were also asked if each of the outcome expectations items were "very important" or "not very important" to them. The average importance of all outcome expectations was 0.90, where "not very important" was coded as 0 and "very important" was coded as 1. There is no difference in importance when dividing the outcome expectations into their respective subscales; professional outcomes have an average importance of 0.90 and lifestyle outcomes have an average importance of 0.91.

Table 6. Average score for each outcome expectation scale by major students are intending to pursue.

	Outcome Expectations, Professional	**Outcome Expectations, Lifestyle**
Aerospace	4.34	3.85
Biomedical	4.16	3.91
Biosystems	3.91	3.13
Chemical	4.46*	3.61
Civil	4.24	4.06
Computer	3.91*	3.47
Computer Science	4.19	4.13
Electrical	4.30	3.88
Industrial & Systems	4.23	3.62
Materials Science	4.54	3.96
Mechanical	4.32	3.90
Nuclear	4.25	4.05

* Students intending to major in Chemical and Biomolecular Engineering have significantly higher professional outcome expectations than students in Computer Engineering.

Conclusions

One of the first major decisions first-year students make is what major they are going to pursue. The students studied here had already matriculated into degree-granting engineering majors but reserve the flexibility to switch engineering majors during their first year of study without delays to graduation. With this flexibility, which is also shared with many institutions that employ a common first-year engineering program, it is helpful to understand what factors may differentiate students who intend to major in the different engineering disciplines. Our work found that tinkering self-efficacy, experimental self-efficacy, and professional outcome expectations are among the factors that differ between students.

Specifically, students in Electrical Engineering have higher experimental self-efficacy than students in both Computer Science and Biomedical Engineering. Students in Mechanical Engineering have higher tinkering self-efficacy than students in both Biomedical Engineering and Computer Science. Male students also report higher general engineering, tinkering, and design self-efficacies than female students. Finally, students in Chemical & Biomolecular Engineering have higher professional outcome expectations than students in Computer Engineering.

While limited, this data could be used to help enhance advising sessions for students who are undecided on their engineering major. Understanding students' self-efficacies and outcome expectations should allow for enhanced advising because students will be able to learn if and to what extent certain desired outcomes are available in common positions obtained by graduates in their intended major. Additionally, misconceptions about potential outcomes or tasks required by the major could be corrected by academic departments so that students can make more informed decisions about their major selection. Finally, future work in this area could be used for enrollment management purposes, especially for institutions with first-year engineering programs.

Limitations

These finding are subject to some limitations. The data was collected from a single institution that utilizes direct matriculation with common coursework (DMa) which may limit generalizability to other institution types. The survey instrument was only distributed one time and therefore asked students about their major at admission retrospectively and about their intended engineering major prospectively, resulting in cross-sectional data. The survey was distributed approximately six weeks into the fall semester. While this time is after the college's primary major exploration event, there could still be changes to students' intended engineering majors. Follow-up studies would ideally include multiple surveys to gauge students' intended majors throughout the first year. Finally, many factors contribute to major selection, the constructs studied here are a subset of them.

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