AC 2012-3337: IN SEARCH OF THE ENGINEERS OF 2020: AN OUTCOMES-BASED TYPOLOGY OF ENGINEERING UNDERGRADUATES

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Introduction

Looking toward the globalized future, the National Academy of Engineering outlined a strategy in *The Engineer of 2020: Visions of Engineering in the New Century*[1] that describes the characteristics and skills that will be required for graduating engineering students to be successful in the workforce of 2020. Producing graduates with the attributes of the engineer of 2020 (hereafter referred to as the "E2020 attributes") who are prepared for this dynamic, competitive global workforce is the current challenge for engineering education. Researchers are tasked to empirically identify ways in which undergraduate engineering programs can adjust educational offerings to reach such a goal.

Studies to date have largely focused on ABET criteria and the policies and practices that foster the development of each of these student outcomes. Given the newness and non-mandatory status of the E2020 attributes relative to the ABET accreditation criteria, little research has investigated engineering student outcomes vis-à-vis the Engineer of 2020. This paper examines the suite of knowledge and skills of the engineer of 2020 in combination to develop a typology of E2020 student outcomes. This goal is important because the engineer of 2020 needs a complex skill set to succeed; it is the combination of skills, not the skills in isolation, that must respond to workforce needs of the future. Graduates must have strong fundamental and design skills *and* be able to work in interdisciplinary teams *and* possess leadership, communication, and teamwork skills *and* understand contextual bounds placed on solutions. Rather than explore the development of multidimensional skill sets, most research on engineering students' learning outcomes explores a single skill in isolation, focusing for example on teamwork *or* design skills *or* fundamentals rather than understanding these skills in relation to one another. This paper examines the E2020 suite of knowledge and skills to 1) determine whether there are engineering seniors who score highly on all outcomes, and 2) develop and compare profiles of students within an outcomes-based typology for two engineering disciplines.

E2020 Learning Outcomes

The E2020 outcomes include a variety of learning goals for graduates, including areas such as basic engineering and design, professional skills, contextual competence, and interdisciplinary skills[1]. Assessment of many of these outcomes poses a challenge, as there are no standardized tests available for evaluating student knowledge in many areas, and for some skills, tests of performance would be more useful measures than objective tests. Asking students to design a product is an example of such an assessment, as opposed to asking them to identify steps in the design process (i.e., think-aloud protocols). In the absence of performance measures, think-aloud protocols or self-report surveys have been utilized as a next-best estimate. Given these challenges, this literature review provides a picture of the efforts that have been made toward addressing such outcomes.

Design studies have used verbal protocol analyses to compare first-year abilities to senior abilities in producing creative solutions to problems. These studies find that seniors list more factors that could influence a solution, cover more problem space, and gather more information than first-year students[2,3], suggesting that design education positively influences design learning outcomes. Atman, Kilgore, and McKenna[4] similarly compared design considerations for a playground for first-years, seniors, and experienced practitioners at four institutions. Seniors aligned more closely with experts than with first-years, providing further evidence that design skills are enhanced during college.

Recent research on engineering education has focused on professional skills, including multidisciplinary skills, understanding professional and ethical responsibilities, and communication skills. Advancing research in this area is consistent with an increased emphasis on preparing students for professional practice[5]. Stakeholders' varying definitions of key abilities makes it more difficult to assess professional skills[6] relative to technical outcomes, such as ability to apply theories or formulae[7-9]. Conducting multi-institution studies on these outcomes has been a challenge because professional skill assessments have relied on a variety of measures, including feedback from multiple sources such as faculty, peers, and self-reflections[10], peer evaluations[11], project rubrics[12], and portfolio analyses[13-17].

Lattuca, Terenzini and Volkwein[18] assessed outcomes across multiple institutions in an evaluation of the impact of new ABET accreditation requirements. For each ABET measure, the research team developed survey items grounded in the engineering and higher education literatures, vetted a reduced list of questions with engineering faculty and administrators, and pilot tested the instrument to ensure construct validity. The technical skills traditionally associated with engineering were significantly higher for graduates who completed their educations after the new ABET criteria were implemented, with largest gains in applying an array of engineering skills (net of incoming characteristics). Students who graduated following the implementation of ABET similarly reported higher project skills in other areas, including design and problem solving, communication skills, and group skills. Contextual and professional competence also was higher for the post-ABET graduates, as average competencies of societal and global issues, ethics and professionalization, and life-long learning all increased. Because the implementation of new ABET accreditation criteria resulted in changes in curricula and instruction in engineering programs, these results provide evidence that what happens within engineering programs influences a wide range of student outcomes[18].

Similar research conducted by Besterfield-Sacre et al.[19] created a model linking student experiences to ABET outcomes within a single institution. Though this approach mirrored that of Lattuca et al.[18], the researchers also proposed an index of outcomes that could measure the overall quality of education. This study was unique in how it addressed multiple outcomes as opposed to traditional approaches examining only a single outcome, but it was limited to a single program at a single institution. The authors explained that some students may excel in certain areas, like communication, but may be weaker in other areas, such as basic science and math knowledge[19]. Following this logic, it also stands to reason that a subset of students may excel in a majority of desired areas. Thus, examining the suite of E2020 outcomes in combination rather than separately for a multi-institutional data set is likely to yield a subset of students who report high scores in all areas and who can thus be characterized as the engineers of 2020. Stated formally:

H_1: Within a population of engineering undergraduates, a subset of students demonstrates high skills and competencies on all E2020 outcomes.

Influence of Pre-College Student Characteristics on E2020 Outcomes

The personal and academic characteristics that students bring to college are related to a number of student outcomes[20-23]. In a study of over 36,000 students, high school record and SAT scores were positively related to academic performance in college[20]. Similarly, data on over 1,000 first-year engineers at Penn State University found that high school grade point average and grades in calculus and physics were the best predictors of persistence in the first two years[24]. Precollege student characteristics related to graduation outcomes are generally academic in nature, and certain demographic characteristics are highly correlated to academic achievement. Students of low socioeconomic statuses from impoverished communities who complete rigorous math and science curricula, for example, are as likely to persist as students from a privileged background[25]. Thus, precollege academic characteristics have been shown to predict persistence in engineering.

In college impact studies, precollege student characteristics are generally treated as control variables in order to isolate the actual impact of college on learning[21], but they also directly influence student learning outcomes. An analysis of engineering students' group skills, problem-solving skills, and occupational awareness found that although classroom experiences account for substantially more variance, background and demographic characteristics explain some variance in outcomes[26]. Results from the ABET study[18] indicated that precollege student characteristics accounted for 9% of the variance in students' self-reports of their abilities to apply math and science skills, as well as 5% of experimental skills[27], 7% of design/analytical skills, and 3% of group skills[28]. Evidence also links specific measures of precollege academic abilities to student learning outcomes. In a study of over 1,500 students enrolled in an Introduction to Engineering Design course across 19 campuses in the Penn State system, scores on both the SAT math and verbal tests were negatively correlated with group skills; verbal scores were also negatively related to engineering competence, a scale operationalizing the self-reported likelihood of persistence and motivation in engineering[29]. Using a more recent data set of engineering students' outcomes, even with the inclusion of student experience variables, SAT critical reading scores were strongly and positively related to students' self-reported contextual competence[30] and interdisciplinary skills[31,32].

In summary, precollege student characteristics have a direct effect – although small in some cases – on student learning outcomes. Skills in mathematics have traditionally received the most attention for issues of recruitment and retention because they are necessary fundamental skills for engineering problem solving. The E2020 attributes, however, describe a well-rounded engineer, and critical reading and analogical reasoning skills may be more important for skills such as interdisciplinary thinking or contextual competence. Apart from any experiences in college, students who enter engineering programs with an affinity for both kinds of thinking are more likely to graduate with strong E2020 outcomes. Stated formally:

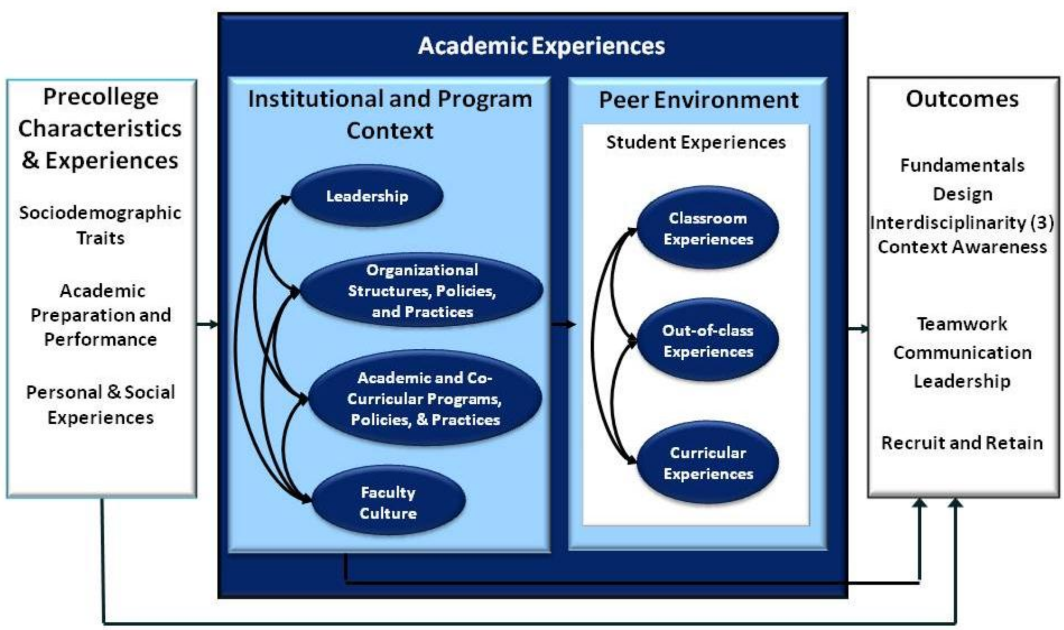
H_2: Students who enter with high SAT scores are more likely than students with lower SAT scores to display high skills and competencies on all E2020 outcomes.

Dataset and Conceptual Framework

This paper draws on data collected for a study funded by the National Science Foundation, entitled *Prototype to production: Processes and conditions for preparing the Engineer of 2020* (P2P) (NSF-EEC 0550608). The investigation generated five nationally representative data sets on four-year engineering programs, allowing for analyses of the educational experiences and institutional policies, practices, and cultures that may facilitate the development of E2020 outcomes. Surveyed participant groups include students, faculty, program chairs, associate deans, and alumni—this study only makes use of data collected from students. Data collection was organized following a conceptual framework that was originally developed by Terenzini and Reason[22,23] and refined following the P2P investigation and a companion qualitative study (Figure 1).

In reviews of several decades of research on students, Pascarella and Terenzini[21,33] indicated that a student's content acquisition and higher-order thinking skills, among many other outcomes, are enhanced by experiences during their college years. The "college impacts" framework by Terenzini and Reason[22,23] (shown in Figure 1) brings coherence to over 50 years of higher education research and conceptually combines factors that form the "Undergraduate Experience" in an effort to explain student learning outcomes and persistence. It is supported by several research studies in higher[34-36], including ones grounded within an engineering context[18].

Figure 1. Modified framework following two studies of engineering education (originally based on Terenzini and Reason[22,23]).



In general, the model hypothesizes that pre-college characteristics shape students' engagement with various aspects of their institution. That engagement is affected by a variety of curricular (e.g., general education coursework, academic major coursework, socialization to the major), classroom, and out-of-class experiences and conditions, all of which occur within an institutional context that includes an institution's internal organizational characteristics, structures, practices, policies, and faculty and peer cultures and environments. This paper focuses on the combination of nine learning outcomes and the direct influence of precollege characteristics on those outcomes. Future analyses consider the influences of student experiences, institutional practices and policies, and cultures on the combination of outcomes.

A team of education and engineering researchers developed survey-based instruments following a rigorous, two-year process. Literature reviews resulted in a survey bank of over 1,000 items, using sources from the ASEE database, Compendex, and various higher education databases. Further, interviews and focus groups were conducted with administrators, faculty, students, and alumni at the following campuses representing large and small research institutions and community/two-year colleges to vet the items: Penn State-University Park, Penn State-Altoona, City College of New York, Borough of Manhattan Community College, and Hostos Community College. The research team used the results of the literature review and the findings from these site visits to draft surveys designated for each survey group.

Once drafted, these surveys underwent extensive review through pilot testing and focus group discussions. Engineering faculty, administrators, and students at City College of New York, Penn State-University Park, and Penn State-Altoona pilot tested portions of the surveys for four-year students and faculty (survey items with established reliability and validity from other studies were not pilot tested). The research team used factor analysis techniques to explore the pilot results and revised the surveys based on these findings and later met with groups of engineering faculty members and administrators to review surveys one last time for content validity before sampling began.

The American Society for Engineering Education's database was used to develop the P2P sampling frame, using institution- and program-level information for the 2007–08 academic year for enrolled students and faculty. The sampling structure is disproportionate, random, stratified (6 x 3 x 2) using the following strata: six engineering disciplines (biomedical/bioengineering, chemical, civil, electrical, industrial, and mechanical); three levels of highest degree offered (bachelor's, master's, and doctorate); and two levels of institutional control (public and private). As such, the 31 four-year engineering colleges and schools of over 120 engineering programs in the final sample are nationally representative of the population with respect to type, mission, and highest degree offered (Table 1).

The research team "pre-seeded" the sample with six case study institutions that were participants in a companion qualitative study also funded by the National Science Foundation (though one institution failed to produce survey requests). One of these case study institutions only offers a general engineering degree, so three institutions offering general engineering degrees were added to the sample to serve as comparison institutions for a total of seven disciplines. Together, these seven disciplines accounted for 70% of all baccalaureate engineering degrees awarded in 2007. A University Survey Research Center selected 23 additional institutions at random from the population within the sampling framework, including two historically black colleges and universities and three Hispanic serving institutions.

Table 1. P2P final institutional sample

Research Institutions:	**Master's/Special Institutions**:
Arizona State University (Main & Polytechnic)[1]	California Polytechnic State University[3]
Brigham Young University	California State University, Long Beach
Case Western Reserve University	Manhattan College
Colorado School of Mines	Mercer University
Dartmouth College	Rose-Hulman Institute of Technology
Johns Hopkins University	University of South Alabama
Massachusetts Institute of Technology[1]	
Morgan State University[2]	
New Jersey Institute of Technology	**Baccalaureate Institutions**:
North Carolina A&T[2]	Harvey Mudd College[1]
Purdue University	Lafayette College
Stony Brook University	Milwaukee School of Engineering
University of Illinois at Urbana-Champaign	Ohio Northern University
University of Michigan[1]	Penn State Erie, The Behrend College
University of New Mexico[3]	West Virginia University Institute of Technology
University of Texas, El Paso[3]	
University of Toledo	
Virginia Polytechnic Institute and State University[1]	

[1] P360 Institution
[2] Historically Black College or University
[3] Hispanic-Serving Institution

The University Survey Research Center was also responsible for data collection through a web-based questionnaire following procedures supported by Dillman, Smith, and Christian[37]. Though a 16% response rate was lower than what we anticipated, response rates around the country have been declining[38,39], perhaps because of increased use of surveys in general through web-based forms[39-41]. Steps were taken to account for differences between the sample of responses and the overall population. This adjustment weighted cases based on the population and response distributions by gender, discipline, and race/ethnicity within an institution as well as varying response rates of a campus so that the sample reflected the overall population of undergraduate engineers from the sample of institutions.

In addition, missing data were imputed based on procedures recommended by Dempster, Laird and Rubin[42] and Graham[43] using the Expectation-Maximization (EM) algorithm of the Statistical Package for the Social Sciences (SPSS) software (v.18). To reduce data from survey items into scales, a principal axis analysis (Oblimin with Kaiser Normalization rotation) was completed, and items were assigned to a factor based on the magnitude of the loading, the effect of keeping or discarding the item on the scale's internal consistency reliability, and professional judgment. Scales are the average of respondents' scores on component items, as prescribed by Armor[44].

Variables and Methods

The P2P student survey consisted of 51 items that asked respondents to rate their own abilities in engineering-related knowledge and skills (i.e., outcomes). Following data reduction techniques, nine separate outcomes scales related to the E2020 vision emerged, these were incorporated into this investigation as student outcome variables. Table 2 shows the nine outcome scale names, Cronbach's alpha indicating internal consistency, and items included in each scale. Responses were measured on a 5-point Likert-scale, where students responded to statements related to their abilities on different tasks; several items were averaged for each scale to produce continuous variables. The construct validity of several of these scales is enhanced as they also emerged as scales in the ABET study[18], but scales related to interdisciplinarity and contextual awareness were newly created for this project[45,46].

Demographic characteristics include a students' *gender* (male or female), *race/ethnicity* (Asian American, African American, Hispanic/Latino/Latina, White, Other), and *parents' level of education* (highest parent's education level, a proxy for socioeconomic status). Precollege academic characteristics are operationalized by *SAT scores* (critical reading, writing, and math). Because unique relationships have been shown to exist between E2020-related outcomes for each section of the SAT[31,32,47], this analysis explores each section separately. Responses from students in their fourth or fifth years were included in analyses, as it would be inappropriate to compare outcomes with less-advanced students. This paper presents analyses and comparisons for mechanical engineering (n=771) and chemical engineering (n=234)—future work will provide analyses for other engineering disciplines.

Table 2. Student-reported outcomes scales used in this investigation as variables to operationalize E2020 outcomes.

FUNDAMENTAL SKILLS[1] (alpha = .71); Please rate your ability to:
Applying Math & Science to: The physical sciences to engineering problems
Applying Math & Science to: Math to engineering problems
Applying Math & Science to: Computer tools and applications to engineering problems
DESIGN SKILLS[1] (alpha = .92); Please rate your ability to:
Evaluate design solutions based on a specified set of criteria.
Generate and prioritize criteria for evaluating the quality of a solution.
Producing a product (prototype, program, simulation, etc.).
Apply systems thinking in developing solutions to an engineering problem.
Brainstorm possible engineering solutions
Take into account the design contexts and the constraints they may impose on each possible solution
Define design problems and objectives clearly and precisely.
Ask questions to understand what a client/customer really wants in a "product."
Break down a design project into manageable components or tasks.
Recognize when changes to the original understanding of the problem may be necessary.
Develop pictorial representations of possible designs (sketches, renderings, engineering drawings, etc.).
Undertake a search before beginning team-based brainstorm
CONTEXTUAL AWARENESS[1] (alpha = .91); Please rate your:
Ability to use what you know about different cultures, social values, or political systems in engineering solutions
Ability to recognize how different contexts can change a solution
Knowledge of contexts that might affect the solution to an engineering problem
Knowledge of the connections between technological solutions and their implications for whom it benefits.
INTERDISCIPLINARY SKILLS[2] (alpha = .80); Do you agree or disagree?
I can take ideas from outside engineering and synthesize them in ways to better understand a problem
I can use what I have learned in one field in another setting or to solve a new problem.
I see connections between ideas in engineering and ideas in the humanities and social sciences.
I enjoy thinking about how different fields approach the same problem in different ways.
Given knowledge and ideas from different fields, I can figure out what is appropriate for solving a problem.
Not all engineering problems have purely technical solutions.
In solving engineering problems I often seek information from experts in other academic fields.
I value reading about topics outside of engineering

TABLE 2 CONTINUED ON NEXT PAGE

TABLE 2 CONTINUED

RECOGNIZING DISCIPLINARY PERSPECTIVES[2] (.69); Do you agree or disagree?
I recognize the kinds of evidence that different fields of study rely on.
If asked, I could identify the kinds of knowledge and ideas that are distinctive to different fields of study
I'm good at figuring out what experts in different fields have missed in explaining a problem or proposing a solution
REFLECTIVE BEHAVIOR[2] (alpha = .73); Do you agree or disagree?
I frequently stop to think about where I might be going wrong or right with a problem solution.
I often step back and reflect on what I am thinking to determine whether I might be missing something.
COMMUNICATION SKILLS[1] (alpha = .86); Please rate your ability to:
Make effective audiovisual presentations
Construct tables or graphs to communicate a solution.
Write a well-organized, coherent report.
Communicate effectively with people from different cultures or countries.
Communicate effectively with clients, teammates, and supervisors.
Communicate effectively with non-technical audiences.
TEAMWORK SKILLS[1] (alpha = .86); Please rate your ability to:
Work in teams of people with a variety of skills and backgrounds.
Work with others to accomplish group goals.
Work in teams where knowledge and ideas from multiple engineering fields must be applied.
Work in teams that include people from fields outside engineering.
Put aside differences within a design team to get the work done.
LEADERSHIP SKILLS[1] (alpha = .90); Please rate your ability to:
Develop a plan to accomplish a group or organization's goals.
Help your group or organization work through periods when ideas are too many or too few.
Take responsibility for group's or organization's performance
Motivate people to do the work that needs to be done.
Identify team members' strengths/weaknesses and distribute tasks and workload accordingly.
Monitor the design process to ensure goals are being met.

[1]1: Weak/none; 2: Fair; 3: Good; 4: Very good; 5: Excellent
[2]1: Strongly disagree; 2: Disagree; 3: Neither agree nor disagree; 4: Agree; 5: Strongly agree

Analyses

Cluster analysis is a statistical technique that identifies homogeneous groupings within a sample. It seeks to minimize within-group variance and maximize between-group variance[48,49]. This technique has been used in several studies to classify students[50-55] or programs[56], as well as in research to characterize the curricular and instructional practices of faculty in engineering programs[57]. In this paper, students for each discipline were grouped based on the nine E2020 learning outcomes. Because previous work has shown disciplinary differences across outcomes[47], separate cluster analyses were run for mechanical and chemical engineers.

This research employed a two-stage cluster method, where a hierarchical cluster technique first identified cluster starting points and the potential numbers of clusters to run. This first step informed a nonhierarchical *k*-means method in the second step, which requires the researcher to indicate the number of clusters (*k*) when initializing the procedure[49,58,59]. Selecting the initial centroids, or initial "seeds" of the clusters, can be done in a variety of ways[60,61]. In a review of the procedures of *k*-means clustering, Milligan[62] advises rational starting positions rather than the random start of most statistical programs. SPSS, for example, selects the first *k* observations as seeds in *k*-means clusters, and such a strategy can result in systematic bias of the final clusters if the cases are not sorted randomly[63]. As recommended by Steinley[63], this study first used Ward's method in stage one to identify the numbers of clusters to run (using dendrograms for guidance) and calculated the initial seeds for the *k*-means cluster analysis from these cluster solutions.

Next, an iterative *k*-means method produced the final clusters of students for analysis. This *k*-means method generates centroids based on the pre-set number of clusters, and each case is then assigned to the grouping to which it is closest in Euclidean distance[61,64]. Following an iteration through the data, the centroids are recomputed, and the cases are reevaluated. If a case's multivariate mean is closer in proximity to a different cluster's centroid, it is reassigned. This iterative process continues until no observation changes clusters after the recomputation of the centroid[65]. The *k*-means analysis was completed for each of the *k* numbers of clusters to be explored, as identified in stage 1. Comparisons of the outcomes were made for each set of cluster solutions, and a final solution was determined based on the number of cases falling in each cluster as well as the cluster solution's ability to provide meaningful distinctions between groups of students. For example, a nine-cluster solution with a cluster containing only three students would be a useless typology. In situations like this, a solution producing fewer clusters was examined.

The first hypothesis (H_1) is tested by comparing outcomes scales across the clusters for each discipline independently. Appropriate parametric and nonparametric tests of significant differences across clusters for each discipline were used to compare the top-scoring "E2020" cluster to the other clusters for each of the nine learning outcomes. This same procedure compared learning outcomes of the highest-scoring "E2020 cluster" between chemical and mechanical engineers to determine whether there are disciplinary differences in the E2020 clusters. For each discipline, a precollege characteristic profile is provided for each cluster. The second hypothesis (H_2) is tested by comparing SAT scores between the E2020 cluster to other clusters for each discipline using appropriate parametric and nonparametric tests.

Limitations

Selecting a research design creates several dilemmas for researchers, and each decision is associated with a set of limitations. For sample surveys, generalizability is maximized, but precision of measurement and contextual realism is reduced[66]. During data collection, the research team had access only to participants in a single time setting, so these data are cross-sectional in nature. Though longitudinal data would have been preferable for measuring students' changes in outcomes over time, the project would have required substantially more funding to span a longer time frame and administer multiple surveys. Sample sizes are often reduced in longitudinal formats, however, because of participant attrition.

Another limitation of this study is the reliance on self-report data. To conduct large-scale studies with generalizable results in a timely manner, researchers often turn to self-reports of student learning. Validated self-reports provide a reasonable approach to studying learning in the absence of available direct measures of particular learning outcomes[67-72]. Using self-reports of learning outcomes is not a new practice in higher education, and research shows moderately high correlations between self-reports and abilities as measured by grades and test scores[73], though their use has come under recent criticism[74-77].

In designing survey items, the research team relied on previous surveys with established reliabilities and vetted all new questions with engineering focus groups of students, faculty members, and administrators from multiple campuses. Items also underwent extensive pilot testing to verify construct validity, or the items' abilities to capture the desired construct (e.g., interdisciplinary skills)[78]. Detailed analyses of the psychometric properties and validities of four new scales are presented in other papers[45,46]. The research team is working toward creating a set of direct measures of these outcomes, but self-report data is the best currently available method for a multi-institution study. Future qualitative work could verify perceptions identified in this survey with other measures for a subset of E2020 students.

Results: Mechanical Engineering

Outcomes-Based Clusters

A six-cluster solution based on the nine learning outcomes emerged for mechanical engineering seniors, with the smallest cluster containing 6% of students and the largest containing 26% of students. According to an analysis of variance, this solution significantly differentiates between students for each of the nine outcomes between clusters. Therefore, this clustering solution is deemed successful for the objective differentiating students based on skill levels and competencies. These clusters did not group students according to the institution in which they were enrolled, but rather students from a single institution were found in multiple clusters (e.g., seniors enrolled in the University of Michigan are represented in each cluster).

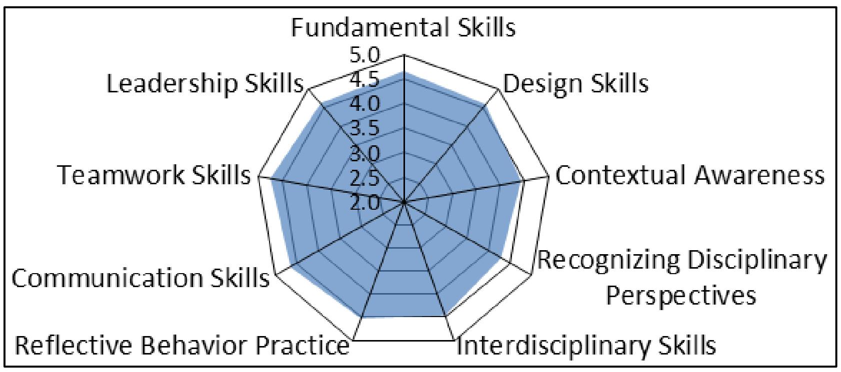
The outcomes measures across clusters are compared to test H_1 (Table 3), and scores for a single cluster of seniors rank highest for every learning outcome. This provides support for the hypothesis that there is a subset of students who report high skills and competencies on all E2020 outcomes. Because industry demands that graduates be highly proficient in all of these areas to be competitive in the future workplace, as outlined by the National Academy of Engineering Reports[1,79], this cluster is referred to as the "E2020 cluster." A radar plot graphically displays these nine outcomes for the E2020 cluster and clearly demonstrates the perceived well-roundedness of these students (Figure 2). Though high on all scales (ranging from 4.29 to 4.74 on a 5-point Likert scale), the plot shows that these students may report especially high proficiencies in professional skills (teamwork, communication, and leadership) on the left relative to the contextual awareness and interdisciplinary competence on the right.

Table 3. Average value for the 9 student learning outcomes[1] for each of the 6-cluster solution for mechanical engineering seniors. The shaded column includes the full sample of mechanical engineering seniors. The average value for each outcome is significantly greater for E2020 students relative to every other cluster.

Outcome	Mechanical Engineers (n=771)	E2020 Cluster (n=100)	Cluster 1 (n=60)	Cluster 2 (n=204)	Cluster 3 (n=49)	Cluster 4 (n=179)	Cluster 5 (n=180)
Fundamental Skills	4.01	4.66	3.31	3.70	3.79	3.98	4.33
Design Skills	3.77	4.59	2.64	3.39	3.59	3.99	3.97
Contextual Awareness	3.41	4.42	2.21	2.87	3.25	3.93	3.38
Interdisciplinary Skills	4.01	4.46	3.31	3.87	3.90	4.30	3.90
Recognizing Disciplinary Perspectives	3.63	4.29	2.97	3.52	3.33	4.00	3.34
Reflective Behavior Practice	4.02	4.53	3.39	4.05	2.69	4.23	4.08
Communication Skills	3.78	4.66	2.80	3.31	3.95	3.89	3.99
Teamwork Skills	3.96	4.75	3.06	3.43	4.04	4.18	4.17
Leadership Skills	3.75	4.62	2.54	3.32	3.79	3.89	4.02

[1] Outcomes are sorted to correspond with Figure 2, starting at the top and moving clockwise around the plot.

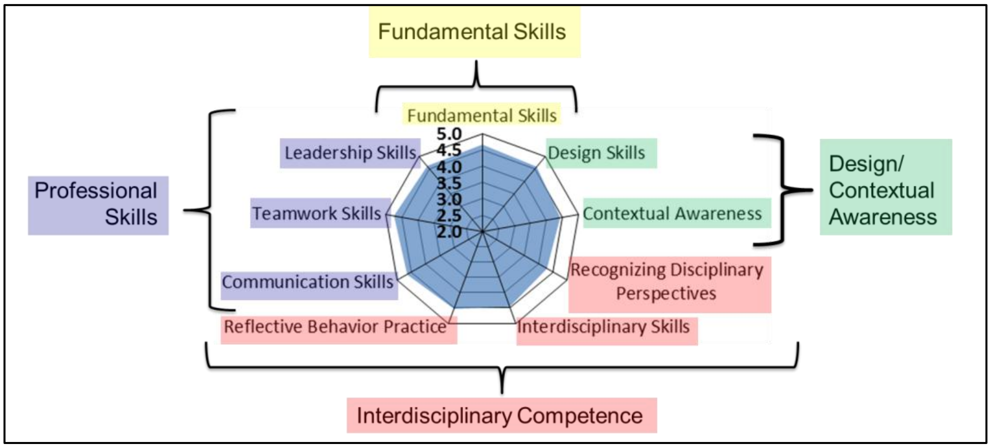
Figure 2. Radar plot depicting the E2020 cluster of mechanical engineering seniors. Each spoke represents the mean of one of the 9 learning outcomes.



Beyond the simple ranking, additional statistical analyses compared the E2020 cluster to every other cluster of mechanical engineering students. Because the distribution of each outcome scale was non-normal for mechanical engineers, appropriate non-parametric analyses were completed. According to a Kruskal-Wallis (K-W) test (the non-parametric analogue to an analysis of variance), the clusters on the whole are significantly different for each outcome. To compare the E2020 cluster to each other cluster, a Mann-Whitney test with a Bonferroni correction was conducted as a post-hoc analysis. For each outcome scale, the mean score for the E2020 cluster was statistically significantly greater than the mean score for every pairwise comparison with other clusters. This provides even stronger statistical support for H_1 that there is indeed a subset of mechanical engineers who report high proficiencies on all E2020 outcomes.

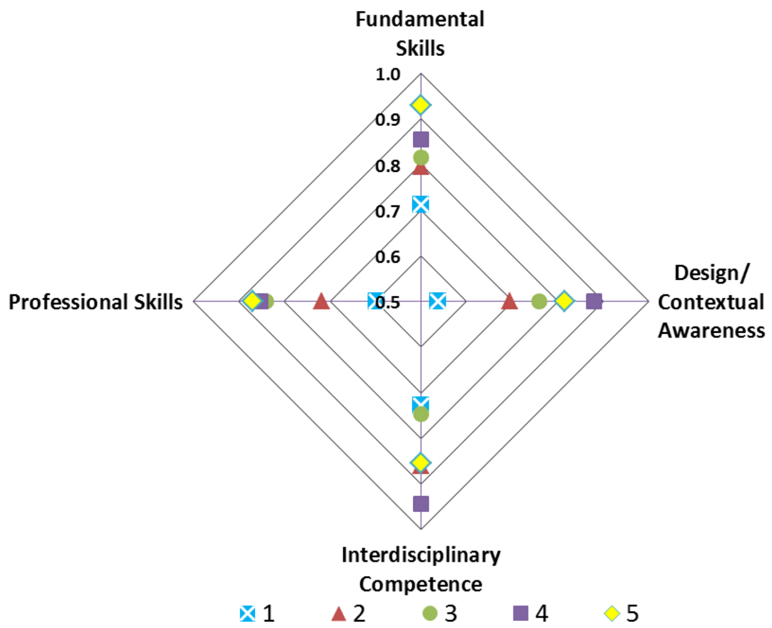
To illustrate these comparisons, averages were taken across some of the scales to reduce the number of dimensions (as shown in Figure 3). Leadership, teamwork, and communication skills combine to form a "Professional Skills" dimension, design skills and contextual awareness combine, and recognizing disciplinary perspectives, interdisciplinary skills, and reflective behavior practice form an "Interdisciplinary Competence" dimension. The cluster analyses to group students still took into account all nine outcomes, but consultations with engineering faculty led to this graphical representation for the sole purpose of simplifying visual interpretation.

Figure 3. Groupings of learning outcomes to ease interpretation of differences between clusters.



Each point on the quadrant radar plot is standardized to the E2020 cluster (Figure 4), so direct comparisons between the E2020 cluster and the other five clusters can be done easily. Students in Cluster 1 have lowest averages on all four dimensions, and future analyses will investigate why these students report different skill levels and competencies than E2020 students. Relative to the E2020 cluster, Cluster 2 students score at approximately 70% for design/contextual awareness and the professional skills, 80% for fundamental skills, and 86% for interdisciplinary competence. Though students in Cluster 3 are similar for fundamental skills, they exhibit a different pattern, scoring higher on professional skills relative to design/contextual awareness and interdisciplinary competence. Clusters 4 and 5 are closest to the E2020 seniors, with Cluster 4 especially excelling in interdisciplinary competence; Cluster 5 students reportedly excel most in fundamental skills. To use a concrete example of how to think about these different types of students, those in Cluster 5 may do well on textbook-style assignments and achieve high grades (high fundamental skills) but would have a harder time designing solutions for open-ended problems that must be placed within a context (relatively lower design/contextual awareness).

Figure 4. Radar plot depicting the clusters of mechanical engineering seniors relative to the E2020 cluster. Each spoke represents the mean of outcome groupings as depicted in Figure 3. The gridline is standardized to the E2020 cluster (i.e., 1.0 is equivalent to the E2020 mean, and .9 is 90% of the E2020 mean).



Cluster	Fund. Skills	Des./ CA	ID Comp.	Prof. Skills
1	0.71	0.54	0.73	0.60
2	0.80	0.70	0.86	0.72
3	0.81	0.76	0.75	0.84
4	0.85	0.88	0.94	0.85
5	0.93	0.82	0.85	0.87

Precollege Characteristic Profiles of Clusters

As anticipated from prior research showing the direct influence of precollege characteristics on outcomes, albeit a relatively small influence, these outcomes-based clusters of seniors exhibit some between-cluster differences in demographic characteristics (see Table 4). Though mechanical engineering as a discipline has a low gender diversity (only 11.4% female for the P2P sample), the E2020 cluster is comprised of even fewer females (8.0%). There is a large body of research suggesting that females tend to lose confidence in their abilities once they enter STEM disciplines because of feelings of isolation[80,81], so this finding may be a reflection of the self-report nature of the data. Female students have nearly double the representation in Cluster 5, whose students report strong fundamental and professional skills but lower design/contextual awareness and interdisciplinary competence. Future analyses will explore whether students in Cluster 5 tend to have different experiences than those in the E2020 cluster (e.g., perhaps they participate on design teams to a different extent). By explaining these differences and targeting such experiences toward female students, for example, programs may be able to further diversify their E2020 student population.

Relative to the full discipline, the E2020 cluster contained a lower percentage of Hispanic/Latino Americans (14.0% compared to 7.9%). These students are overrepresented in Cluster 2 (weakest relative to the E2020 cluster on design/contextual awareness and professional skills). Asian Americans, rather, are overrepresented in Cluster 3 (higher on professional skills relative to design/contextual awareness and interdisciplinary competence). It is not plausible to assume that students from different race/ethnicities develop these outcomes differently. Rather, future analyses that illuminate differences in student experiences between clusters will likely inform engineering educators on how students from different racial backgrounds may engage in their programs differently, which may be associated with differences in learning outcomes.

Table 4. Precollege characteristic profiles of each cluster for mechanical engineering seniors. Percentages are calculated within a cluster for each precollege characteristic (e.g., 8% of students in the E2020 Cluster were women mechanical engineers). The shaded column includes the full sample of mechanical engineering seniors.

Precollege Characteristic		Mechanical Engineers (n=771)	E2020 Cluster (n=100)	Cluster 1 (n=60)	Cluster 2 (n=204)	Cluster 3 (n=49)	Cluster 4 (n=179)	Cluster 5 (n=180)
Gender	Female	11.4%	8.0%	10.0%	11.3%	12.2%	10.6%	14.4%
Race	African American	5.2%	4.0%		6.9%		7.3%	5.0%
	Asian American	12.1%	11.9%	13.8%	11.8%	24.5%	12.8%	7.8%
	Hispanic/ Latino American	14.0%	7.9%	13.8%	17.6%	2.0%	16.2%	14.4%
	White	51.1%	54.5%	53.4%	48.5%	44.9%	48.0%	56.1%
Parent Education Level	Less than HS	2.3%	7.1%	5.1%	2.5%		1.7%	
	HS or GED	6.8%	4.0%	20.3%	5.9%	12.2%	4.4%	5.6%
	Some College	6.5%	7.1%	1.7%	4.4%		11.1%	7.3%
	Certificate	2.7%	3.0%	1.7%	2.9%		3.3%	2.8%
	Associate	10.3%	6.1%	5.1%	14.7%	6.1%	6.1%	14.5%
	Bachelors	32.3%	26.3%	28.8%	32.8%	42.9%	28.3%	37.4%
	Masters	26.2%	35.4%	30.5%	24.0%	24.5%	25.6%	23.5%
	Doctorate	12.9%	11.1%	6.8%	12.7%	14.3%	19.4%	8.9%
SAT Scores	Crit. Read	579	595	558	546*	628	578	599
	Writing	583	591	577	554*	632	579	604
	Math	657	673	646	630*	680	667	668

* Statistically significant difference (comparison group: E2020 cluster)

The highest educational level of students' parents also varied across clusters. Seniors in the E2020 cluster had a similar percentage of parents who earned at least a bachelor's degree as students in other clusters (approximately 70%). The E2020 cluster, however, had a higher percentage of its students with parents who earned at least a master's degree (46% compared to 38% for the full discipline). Parents' educational level may serve as a proxy for socioeconomic status, which is highly correlated to precollege academic ability. To test this relationship, comparisons of SAT component scores were made across the clusters. According to an analysis of variance, seniors in the E2020 cluster had significantly higher scores on all SAT sections than students in Cluster 2, but there were no significant differences with other clusters. This provides counterevidence to H_2, as students who enter with higher SAT scores do not appear to be more likely to fall within the E2020 cluster. Had the hypothesis been true, students in the "weakest" Cluster 1 would have the lowest scores, which is also not the case. Thus, this finding supports the notion that experiences in college are likely more important in determining students' educational outcomes than their entering academic abilities (at least as measured by the SAT). Undergraduate engineering programs either help less-prepared students "catch up" to their peers academically during their four years, or the seniors in this sample are fairly homogeneous in their entering academic abilities as their less-prepared peers may not have persisted over four years. In addition, the SAT does not provide measurement of many of the E2020 outcomes other than fundamental skills, so the non-discriminating ability between clusters may be unsurprising.

Results: Chemical Engineering

Outcomes-Based Clusters

A six-cluster solution also emerged for chemical engineering seniors, with the smallest cluster containing 9% of students and the largest containing 29% of students. As with mechanical engineering, this solution significantly differentiates between students for each of the nine outcomes between clusters. Scores for a single E2020 cluster of seniors ranks highest for nearly every learning outcome, with the exception of fundamental skills (Table 5). This result points toward sufficient support for the hypothesis that there is a subset of students who report high skills and competencies on all E2020 outcomes. The graphical representation of these nine outcomes for the E2020 cluster illustrates these students' well-roundedness (Figure 5). Though high on all scales (ranging from 4.35 to 4.63 on a 5-point Likert scale), the plot shows that these students reported especially high proficiencies in the professional skills (teamwork, communication, and leadership) on the left relative to contextual awareness, recognizing disciplinary perspectives, and fundamental skills scales.

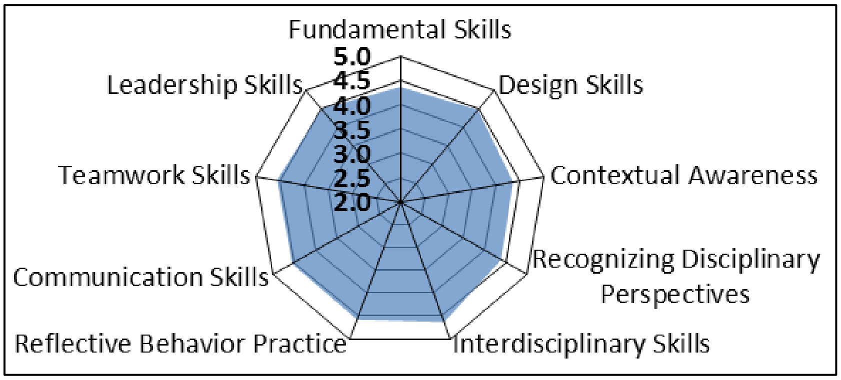
Table 5. Average value for the 9 student learning outcomes for each of the 6-cluster solution for chemical engineering seniors[1]. The shaded column is the full sample of chemical engineers. The average value for each outcome is significantly greater for E2020 students relative to every other cluster unless otherwise noted.

Outcome	Chemical Engineers (n=234)	E2020 Cluster (n=29)	Cluster 1 (n=35)	Cluster 2 (n=69)	Cluster 3 (n=34)	Cluster 4 (n=45)	Cluster 5 (n=22)
Fundamental Skills	3.90	4.36	4.38*	3.74	4.65*	3.23	3.29
Design Skills	3.69	4.47	3.65	3.85	4.22	3.16	2.51
Contextual Awareness	3.41	4.35	3.06	3.45	4.17*	3.10	2.07
Interdisciplinary Skills	3.95	4.63	4.02	3.94	4.02	3.81	3.19
Recognizing Disciplinary Perspectives	3.56	4.39	3.68	3.41	3.66	3.41	2.95
Reflective Behavior Practice	3.99	4.59	4.42	4.09	3.56	3.68	3.51
Communication Skills	3.92	4.56	3.79	4.19	4.27	3.34	3.04
Teamwork Skills	3.92	4.57	3.37	4.25	4.29	3.68	2.78
Leadership Skills	3.85	4.50	3.62	4.26	4.17	3.33	2.62

* Relative to the average value for the E2020 cluster, this average value is not significantly different.

[1] Outcomes are sorted to correspond with Figure 2, starting at the top and moving clockwise around the plot.

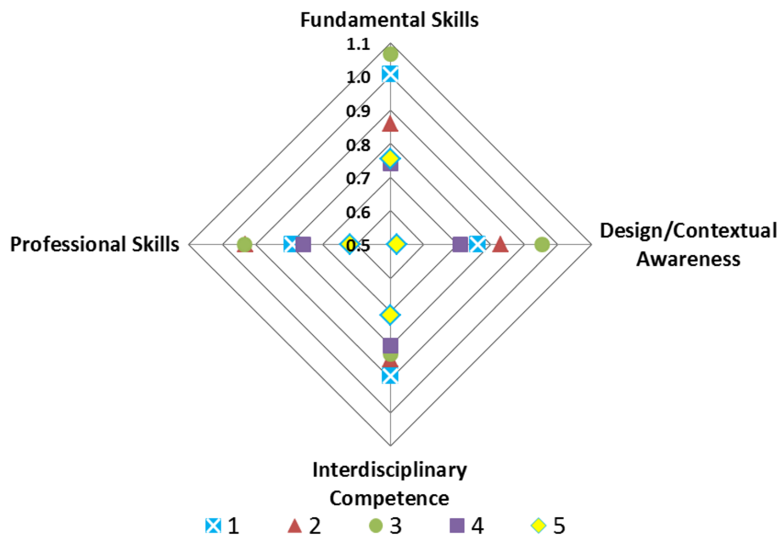
Figure 5. Radar plot depicting the E2020 cluster of chemical engineering seniors. Each spoke represents the mean of one of the 9 learning outcomes.



As with mechanical engineering students, additional statistical analyses compared the E2020 cluster to every other cluster of chemical engineering students. The contextual awareness and leadership skills scales are normally distributed, and analyses of variance indicate significant differences in these outcomes across clusters. According to post-hoc analyses, the mean of the E2020 cluster is significantly greater than the mean of every other cluster for these two scales with the exception of Cluster 3. All other learning outcome scales are not normally distributed for chemical engineers, so appropriate non-parametric tests were completed. The K-W test indicates that the remaining seven outcomes scales exhibit significant differences across the clusters, and that the E2020 cluster average value is significantly greater than the value for the other clusters with the exception of fundamental skills. Clusters 1 and 3 are not significantly different than the E2020 cluster for fundamental skills. Taking all of this comparative evidence into account, however, there is strong support for H_1 that there is a group of chemical engineers that report high proficiencies on all E2020 learning outcomes.

As with mechanical engineers, easy comparisons can be made between the E2020 cluster and other clusters using a quadrant radar plot (Figure 6). Cluster 1 seniors report as high values in fundamental skills but slightly lower (89%) in interdisciplinary competence and even lower relative to the E2020 students in design/contextual awareness and professional skills. Students in Cluster 2 report slightly lower scores on professional skills (93%) but are in the mid-80% range for the remaining outcomes. Cluster 3 students are most similar to E2020 students, with the main difference being lower reported scores on interdisciplinary competence. Clusters 4 and 5 comprise the weakest students relative to the E2020 cluster, with Cluster 5 especially low on design/contextual awareness (52%) and professional skills (62%).

Figure 6. Radar plot depicting the clusters of chemical engineering seniors relative to the E2020 cluster. Each spoke represents the mean of outcome groupings as depicted in Figure 3. The gridline is standardized to the E2020 cluster (i.e., 1.0 is equivalent to the E2020 mean, and .9 is 90% of the E2020 mean).



Cluster	Fund. Skills	Des./ CA	ID Comp.	Prof. Skills
1	1.00	0.76	0.89	0.79
2	0.86	0.83	0.84	0.93
3	1.07	0.95	0.83	0.93
4	0.74	0.71	0.80	0.76
5	0.75	0.52	0.71	0.62

Precollege Characteristic Profiles of Clusters

Comparisons of the demographic profiles of chemical engineering student clusters exhibit differences (Table 6). The E2020 cluster for chemical engineering contains a lower percentage of females (20.7%) than the overall discipline (27.8%). Females are overrepresented in Cluster 2, which is higher on professional skills than the other outcomes relative to the E2020 cluster (as was the case for mechanical engineering, as well). For race/ethnicity demographic variables, African Americans are not represented in the E2020 cluster, and Asian Americans' representation is slightly lower than that for the overall discipline. Both Asian Americans and Hispanic/Latino Americans are overrepresented in the "weakest" Cluster 5. Forthcoming analyses seek to determine why students in these demographic groups in particular reside within this cluster. E2020 chemical engineering students, like mechanical engineers, tend to have a parent with a higher education level than the average for the discipline. Only 6.8% of E2020 students' parents had a GED or less compared to 10.6% for the discipline, and 83% had at least a bachelor's degree compared to 76% for the discipline.

Analyses of variance indicate that students in the E2020 cluster score significantly higher on the critical reading and math portions of the SAT than students in Clusters 4 and 5. For the writing portion of the test, E2020 students scored significantly higher than students in Cluster 5. Relative to the E2020 cluster, these students report lower abilities on the E2020 learning outcomes, as depicted in Figure 6. Because prior research suggests that incoming student characteristics have some influence on learning outcomes, these clusters of students would be expected to exhibit slightly lower levels of academic preparation than other clusters of students. Despite participating in their programs for at least three full academic years, students in these clusters still have not "caught up" to their colleagues. Subsequent analyses may identify undergraduate experiences in which these students can participate to more closely resemble their

E2020 peers. Because the SAT test scores do not differentiate students in the E2020 cluster from every other cluster of students, however, H_2 is not supported.

Table 6. Precollege characteristic profiles of each cluster for chemical engineering seniors. Percentages are calculated within a cluster for each precollege characteristic (e.g., 20.7% of students in the E2020 Cluster were women mechanical engineers). The shaded column includes the full sample of chemical engineering seniors.

Precollege Characteristic		Chemical Engineers (n=234)	E2020 Cluster (n=29)	Cluster 1 (n=35)	Cluster 2 (n=69)	Cluster 3 (n=34)	Cluster 4 (n=45)	Cluster 5 (n=22)
Gender	Female	27.8%	20.7%	11.4%	42.0%	23.5%	24.4%	31.8%
Race	African American	3.0%			2.9%	5.9%	6.5%	
	Asian American	17.9%	13.8%	14.3%	27.5%	11.8%	8.7%	27.3%
	Hispanic/ Latino American	6.8%	6.9%		5.8%	2.9%	6.5%	27.3%
	White	50.6%	58.6%	34.3%	49.3%	61.8%	56.5%	40.9%
Parent Education	Less than HS	3.8%	3.4%	2.9%	1.4%	2.9%		23.8%
	HS or GED	6.8%	3.4%	5.7%	7.2%	5.7%	11.1%	4.8%
	Some College	4.7%	6.9%	2.9%	7.2%	2.9%	4.4%	
	Certificate	3.0%		11.4%	1.4%	2.9%	2.2%	
	Associate	5.6%	3.4%	2.9%	4.3%	5.7%	11.1%	4.8%
	Bachelors	32.1%	44.8%	31.4%	30.4%	25.7%	35.6%	23.8%
	Masters	35.0%	27.6%	34.3%	34.8%	45.7%	31.1%	38.1%
	Doctorate	9.0%	10.3%	8.6%	13.0%	8.6%	4.4%	4.8%
SAT Scores	Crit. Read	611	643	647	601	630	588*	565*
	Writing	619	650	647	616	628	607	560*
	Math	692	714	726	685	722	668*	652*

* Statistically significant difference (comparison group: E2020 cluster)

Results: Disciplinary Comparisons

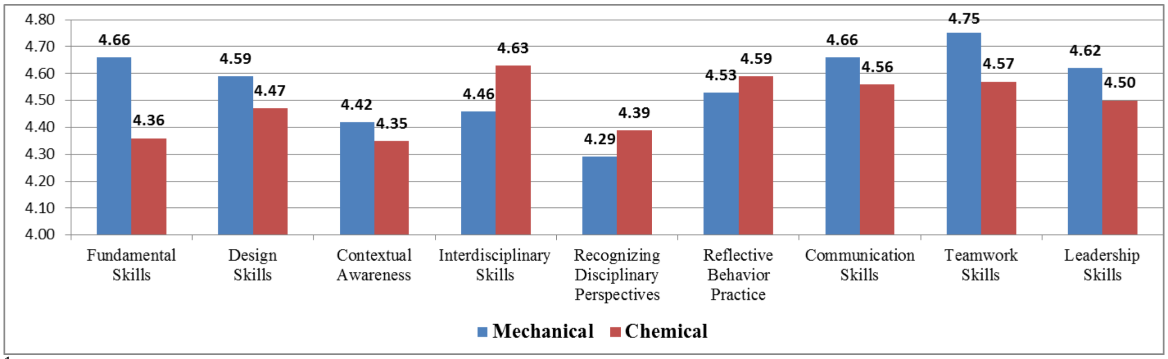
Approximately 12% of students in each discipline were categorized in the E2020 cluster, though multiple other clusters of chemical engineers were “closer” to the E2020 chemical engineering cluster on the fundamental skills outcome. In comparing these clusters, however, there were a few differences in the magnitude of outcomes variables. Mechanical engineering E2020 students reported significantly higher levels of fundamental skills and teamwork skills, and chemical engineering E2020 students reported significantly higher levels of interdisciplinary skills (according to an independent samples *t*-test). Though both of these E2020 clusters are well-rounded in general (as shown in Figures 2 and 5), the reported average magnitude of these three dimensions varies between these subsets of students. The extent to which certain skills are emphasized and valued may vary across disciplines.

Previous work using the P2P data set showed that program chairs in chemical engineering indicated a greater degree of emphasis on interdisciplinarity throughout the curriculum than mechanical engineering program chairs[47], thereby corroborating these findings. In addition, students in mechanical engineering on average spend more time working on design teams than chemical engineers[47], which may explain why the E2020 cluster of mechanical engineers report higher teamwork skills. Borrego and Newswander[82] claim that interdisciplinarity in science and engineering occurs in team activities, so it is interesting that the disciplines were significantly different (in opposite directions) on these two measures in particular. The interdisciplinary skills scale is comprised of items related to an individual's perceived ability to synthesize information across multiple perspectives. Perhaps the process of weighing and synthesizing different perspectives through team-based activities was not captured by these survey items.

Chemical engineering has greater gender diversity than mechanical engineering (27.8% versus 11.4% for the P2P sample). The E2020 cluster for both chemical and mechanical engineering, however, contains a lower percentage of females than the overall percentage for each discipline. Clusters with an overrepresentation of females tended to report higher professional skills than the other outcomes relative to the E2020 cluster. This raises future research questions with regard to this apparent pattern: 1) might females have a different affinity for certain skills than males; 2) do females engage in different experiences leading to different outcomes than males; 3) do females perceive and/or report certain learning outcomes differently than males? Answering these important questions is beyond the scope of the current paper, but this analysis illustrates how males and females appear to be consistently and differentially represented among outcomes-based clusters. Similar questions and future analyses can address other patterns across the disciplines for race/ethnicity and parents' educational level.

According to an independent samples *t*-test, there are statistically significant differences between the E2020 clusters for SAT scores. The E2020 chemical engineers have significantly higher average scores on each subcomponent. Despite entering their programs with lower academic abilities (as measured by the SAT), E2020 mechanical engineers perceive higher abilities than their E2020 chemical engineering peers on each outcome, with the exception of interdisciplinary skills. Prior research indicates that the analogical reasoning that is measured by the SAT critical reading section may be the foundational knowledge required for a student to be able to think in interdisciplinary ways[31,32,47]. The 48-point difference in means on this section between disciplines may partially explain the difference in the interdisciplinary skills outcome. Comparisons of the educational experiences between disciplinary clusters of E2020 students might also illuminate why mechanical engineers are reportedly able to "catch up" to their chemical engineering peers on learning outcomes. Perhaps the disciplines have different standards of skills/competencies against which students rate their own abilities, different programmatic objectives (i.e., may value different kind of outcomes), or different interpretations of each outcome based on different kinds of problem solving topics and processes.

Figure 7. Comparisons between the E2020 clusters for mechanical and chemical engineering[1].



[1] Statistically significant differences: Fundamental skills, Interdisciplinary skills, Teamwork skills

Conclusions and Future Work

The main objective of this work was to develop an outcomes-based typology of students in two engineering disciplines. Using nine learning outcomes related to the attributes that will be required for students to be successful in the workforce of 2020, as outlined by the National Academy of Engineering[1,79], the cluster analysis described in this paper successfully places students in separate groups according to these outcomes. Though industry demands that engineering graduates possess competencies in several areas, no other institution-spanning research considers the combination of skills as an outcome variable but rather treats each skill in isolation. As such, this approach to studying learning in undergraduate engineering is a contribution to education research.

The first hypothesis assumed that a subset of students would emerge from the cluster analysis and demonstrate high skills and competencies on all nine learning outcomes. Results supported this hypothesis for both mechanical and chemical engineering, as a single cluster of students reported significantly higher scores than students from every other cluster on nearly every learning outcome. These are the students that industry demands: high-achieving on all learning outcomes. Future research can compare their undergraduate experiences to those in other clusters to determine whether there are programmatic changes that can be made to produce more of these E2020 students. In addition, future analyses can determine whether students from certain clusters tend to obtain a job in industry, continue to graduate school, or leave the engineering field entirely. Perhaps certain skills are more important than others for certain career tracks.

This paper also produced profiles of precollege characteristics for clusters in these disciplines and demonstrated some variation in demographic representation. Women in particular tended to be underrepresented in the E2020 cluster and overrepresented in clusters skewed toward higher professional skill levels relative to design/contextual awareness and interdisciplinary competence. As previously indicated, future work will seek to determine why this is the case. The second hypothesis received little empirical support: students in the E2020 cluster did not arrive to school with higher SAT scores than students in other clusters. This finding suggests that what happens within engineering programs may largely determine students' outcomes-based cluster membership. Finally, differences were observed between the E2020 clusters of chemical and mechanical engineers. This supports previous findings that the disciplines should be treated separately in education research[31,32,47], as considering the engineering field as a homogeneous whole may not be appropriate. Future work using these clusters will treat the disciplines independently, as unique educational experiences specific to certain disciplines may lead to students' placement in the clusters.

References

[1]National Academy of Engineering (2004). *The engineer of 2020: Visions of engineering in the new century*. Washington, D.C.: National Academies Press.

[2]Adams, R. S., Turns, J., & Atman, C. J. (2003). Educating effective engineering designers: The role of reflective practice. *Design Studies*, *24*(3), 275-294.

[3]Atman, C. J., & Bursic, K. M. (1996). Teaching engineering design: Can reading a textbook make a difference? *Research in Engineering Design*, *8*(4), 240-250.

[4]Atman, C., Kilgore, D., & McKenna, A. (2008). Characterizing design learning: A mixed-methods study of engineering designers' use of language. *Journal of Engineering Education*, *97*(3), 309-326.

[5]Sheppard, S. D., Macatangay, K., Colby, A., & Sullivan, W. (2009). *Educating Engineers.* San Francisco: Jossy-Bass.

[6]Lattuca, L.R. & Knight, D.B. (2010). In the eye of the beholder: Defining and studying interdisciplinarity in engineering education. *Proceedings of the 117th Annual Conference of the American Society for Engineering Education***,** Louisville, KY.

[7]Evans, D., Gray, G. L., Krause, S., Martin, J., Midkiff, C., Notaros, B. M., et al. (2003). Progress on concept inventory assessment tools. *Proceedings of the 33rd Annual Frontiers in Education Conference*, Westminster, CO.

[8]Olds, B.M., Streveler, R.A., & Miller, R.L. (2004). Preliminary results from the development of a concept inventory in thermal and transport science. *Proceedings of the Annual Conference of the American Society for Engineering Education Conference*, Salt Lake City, UT.

[9]Shuman, L. J., Besterfield-Sacre, M., & McGourty, J. (2005). The ABET 'Professional Skills'—Can They Be Taught? Can they Be Assessed? *Journal of Engineering Education*, *94*(1), 41–55.

[10]McGourty, J. (2000). Assessing and enhancing student learning through multi-source feedback. *IEEE Transactions on Education*, *43*(2), 120-124.

[11]Kaufman, D.B., Felder, R.M., & Fuller, H. (2000). Accounting for individual effort in cooperative learning teams. *Journal of Engineering Education, 89*(2), 133–140.

[12]Besterfield-Sacre, M., Lovell, M., McGourty, J., Shuman, L., & Wolfe, H. (2002). An interdisciplinary certificate in product realization: Meeting the challenges of industry and engineering criteria. *Proceedings of the Annual Frontiers in Education Conference*, Boston, MA.

[13]Moskal, B., Knecht, R., & Pavelich, M. (2001). The design report rubric: Assessing the impact of program design on the learning process. *Journal for the Art of Teaching: Assessment of Learning, 8*(1), 18-33.

[14]Miller, R. & Olds, B.M. (1997). Using portfolios to assess student writing. *Proceedings of the Annual Meeting of the American Society for Engineering Education*, Washington, D.C.

[15]Olds, B.M. (1997). Using portfolios to assess student writing. *Proceedings of the Annual Meeting of the American Society for Engineering Education*, Washington, D.C.

[16]Olds, B.M. (1998). How are we doing? Assessing a writing-intensive introductory humanities and social sciences course. *Proceedings of the Annual Meeting of the American Society for Engineering Education,* Seattle, Washington.

[17]Popham, W.J. (1997). What's wrong—and what's right—with rubrics. *Educational Leadership,* Oct., 72-75.

[18]Lattuca, L.R., Terenzini, P.T., & Volkwein, J.F. (2006).*Engineering change: A study of the impact of EC2000.* Baltimore, MD: ABET.

[19]Besterfield-Sacre, M., Shuman, L. J., & Wolfe, H. (2002).Modeling undergraduate engineering outcomes. *International Journal of Engineering Education*, *18*(2), 128-139.

[20]Astin, A.W. (1993). *What matters in college? Four critical years revisited*. San Francisco: Jossey-Bass.

[21]Pascarella, E.T, & Terenzini, P.T. (2005). *How college affects students*. *Vol. 2: A third decade of research*. San Francisco, CA: Jossey-Bass.

[22]Terenzini, P. T., & Reason, R. D. (2005, November). *Parsing the first-year of college: A conceptual framework for studying college impacts.* Paper presented at the Annual Conference of the Association for the Study of Higher Education. Philadelphia, PA.

[23]Terenzini, P. T., & Reason, R. D. (2010, June).*Toward a more comprehensive understanding of college effects on student learning*. Paper presented at the Annual Conference of the Consortium of Higher Education Researchers (CHER), Oslo, Norway.

[24]Levin, J., & Wyckoff, J. (1990). Identification of student characteristics that predict persistence and success in an engineering college at the end of the sophomore year: Informing the practice of academic advising. Division of Undergraduate Studies Report No. 1990.1, Pennsylvania State University.

[25]Campbell, P.B., Jolly, E., Hoey, L., & Perlman, L.K. (2002). Upping the numbers: Using research based decision making to increase diversity in the quantitative disciplines. GE Foundation Report.

[26]Terenzini, P.T., Cabrera, A.F., & Colbeck, C.L. (1999, November). *Assessing classroom activities and outcomes*. 29th ASEE/IEEE Frontiers in Education Conference, San Juan, Puerto Rico.

[27]Harper, B.J., Lambert, A.D., & Lattuca, L.R. (2006, November). *The interaction of student race and experience: Critical influences on learning outcomes in engineering*. Paper presented at the meeting of the Association for the Study of Higher Education, Anaheim, CA.

[28]Strauss, L. C., & Terenzini, P. T. (2007). The Effects of Students' In-and Out-of-Class Experiences on their Analytical and Group Skills: A Study of Engineering Education. *Research in Higher Education, 48*(8), 967-992.

[29]Bjorklund, S. A., Parente, J. M., & Sathianathan, D. (2004).Effects of faculty interaction and feedback on gains in student skills. *Journal of Engineering Education, 93* (2), 153-160.

[30]Palmer, E., Terenzini, P. T., Harper, B.J., McKenna, A., & Merson, D. S. (2011). Design in context: Where do the engineers of 2020 learn this skill? *Proceedings of the 118th Annual Conference of the American Society for Engineering Education*, Vancouver, Canada.

[31]Knight, D.B. (2011a, April). *Engineering broad thinkers: The effects of curricular emphases and instructional practices on undergraduate interdisciplinary skills*. Paper presented at the Annual Meeting of the American Educational Research Association, New Orleans, LA.

[32]Knight, D.B. (2011b). Educating broad thinkers: A quantitative analysis of curricular and pedagogical techniques used to promote interdisciplinary skills. *Proceedings of the 118th Annual Conference of the American Association for Engineering Education*, Vancouver Canada.

[33]Pascarella, E.T., & Terenzini, P.T. (1991). *How college affects students: Findings and insights from twenty years of research*. San Francisco, CA: Jossey-Bass.

[34]Reason, R. D., Cox, B. E., Lutovsky-Quaye, B. R., & Terenzini, P. T. (2010). Individual and institutional factors that encourage faculty to promote student encounters with difference in first-year courses. *Review of Higher Education, 33*(3), 391-414.

[35]Reason, R. D., Terenzini, P. T., & Domingo, R. J. (2006). First things first: Developing academic competence in the first year of college. *Research in Higher Education, 47,* 149-175.

[36]Reason, R. D., Terenzini, P. T., & Domingo, R. J. (2007). Developing social and personal competence in the first year of college. *The Review of Higher Education, 30,* 271-299.

[37]Dillman, D. A., Smyth, J. D., & Christian, L. M. (2009). *Internet, mail, and mixed-mode surveys: The tailored design method* (3rd ed.). Hoboken, NJ: Wiley.

[38]Baruch, Y. (1999). Response rate in academic studies—A comparative analysis. *Human Relations, 52*, 421-438.

[39]Porter, S.R., & Umbach, P.D. (2001, June). What works best? Collecting alumni data with multiple technologies. Paper presented at the annual meeting of the Association for Institutional Research, Long Beach, CA.

[40]Porter, S.R., & Umbach, P.D. (2006). Student survey response rates across institutions: Why do they vary? *Research in Higher Education, 47*(2), 229-247.

[41]Van Horn, P.S., Green, K.E., & Martinussen, M. (2009). Survey response rates and survey administration in counseling and clinical psychology: A meta-analysis. *Educational and Psychological Measurement, 69,* 389-403.

[42]Dempster, A.P., Laird, N.M., & Rubin, D.B. (1977).Maximum likelihood from incomplete data via the EM algorithm.*Journal of the Royal Statistical Society,* Series B, 39, 1–38.

[43]Graham, J.W. (2009). Missing data: Making it work in the real world. Annual Review of Psychology, 60, 549-576.

[44]Armor, D. J. (1974).Theta reliability and factor scaling. In H. Costner (Ed.). *Sociological methodology: 1973-1974.* San Francisco: Jossey-Bass, pp. 17-50.

[45]Lattuca, L.R., Knight, D.B. & Bergom, I. (2012, June). *Developing a measure of interdisciplinary competence for engineers*. Paper forthcoming at the 119th Annual Meeting of the American Society for Engineering Education, San Antonio, TX.

[46]Ro, H.K., Merson, D., Lattuca, L.R. & Terenzini, P.T. (2012, June). *The development of a scale that measures engineering students' contextual competence*. Paper forthcoming at the 119th Annual Meeting of the American Society for Engineering Education, San Antonio, TX.

[47]Lattuca, L.R., Trautvetter, L., Codd, S., & Knight, D.B. (2011). Working as a team: Enhancing interdisciplinarity for the Engineer of 2020. *Proceedings of the 118th Annual Conference of the American Society of Engineering Education***,** Vancouver, Canada.

[48]Borden, V. M. H. (2005). Identifying and analyzing group differences. In M. A. Coughlin (Ed.), *Intermediate/advanced statistics in institutional research* (pp. 132–168). Tallahassee, FL: Association for Institutional Research.

[49]Everitt, B., Landau, S., Leese, M., & Stahl, D. (2011). *Cluster analysis, 5th edition*. Hoboken, New Jersey: Wiley

[50]Ammon, B. V., Bowman, J., & Mourad, R. (2008). Who are our students?: Cluster analysis as a tool for understanding community college student populations. *Journal of Applied Research in the Community College*, *16*, 32-44.

[51]Bahr, P. R. (2010). The bird's eye view of community colleges: A behavioral typology of first-time students based on cluster analytic classification. *Research in Higher Education*, *51*, 724-749.

[52]Boughan, K. (2000). The role of academic process in student achievement: An application of structural equations modeling and cluster analysis to community college longitudinal data. *AIR Professional File*, *74*, 1-18.

[53]Hagedorn, L. S., & Prather, G. (2005). *The community college solar system: If university students are from Venus community college students must be from Mars*. Paper presented at the 2005 Annual Forum of the Association for Institutional Research, San Diego, California.

[54]Kuh, G., Hu, S., & Vesper, N. (2000). They shall be known by what they do: An activities based typology of college students. *Journal of College Student Development*, *41*(2), 228-244.

[55]VanDerLinden, K. (2002). *Credit student analysis: 1999 and 2000*. Annapolis Junction, Maryland: Community College Press, American Association of Community Colleges.

[56]Knight, D.B., Lattuca, L.R., Kimball, E.W. & Reason, R.D. (2011, November). *Understanding interdisciplinarity: Curricular and organizational features of undergraduate interdisciplinary programs*. Paper presented at the Annual Meeting of the Association for the Study of Higher Education, Charlotte, NC.

[57]Lattuca, L. R., Terenzini, P. T., Harper, B. J., & Yin, A. C. (2010). Academic environments in detail: Holland's theory at the subdiscipline level. *Research in Higher Education, 51*(1), 21-39.

[58]Hunt, L., & Jorgensen, M. (2011). Clustering mixed data. *Wiley Interdisciplinary Reviews: Data Mining & Knowledge Discovery*, *1*, 352-361.

[59]Rapkin, B. D., & Luke, D. A. (1993). Cluster analysis in community research: Epistemology and practice. *American Journal of Community Psychology*, *21*, 247–277.

[60]Punj, G.N., & Stewart, D.W. (1983). Cluster analysis in marketing research: Review and suggestions for application. *Journal of Marketing Research, 20*, 134-148.

[61]Steinley, D. (2006). K-means clustering: A half-century synthesis. *British Journal of Mathematical and Statistical Psychology, 59*, 1-34.

[62]Milligan, G. W. (1980). An examination of the effect of six types of error perturbation on fifteen clustering algorithms. *Psychometrika*, *45*, 325-342.

[63]Steinley, D. (2007). Initializing *K*-means batch clustering: A critical evaluation of several techniques. *Journal of Classification, 24*, 99-121.

[64]Wilks, D.S. (2006). *Statistical methods in the atmospheric sciences, Second edition*. Burlington, MA: Academic Press.

[65]Bahr, P.R., Bielby, R., & House, E. (2011). The use of cluster analysis on typological research on community college students. *New Directions for Institutional Research*, S1, 67-81.

[66]McGrath, J.E., Martin, J., & Kulka, R.A. (1982). *Judgment calls in research.* Beverly Hills, CA: Sage.

[67]Anaya, G. (1999). College impact on student learning: Comparing the use of self-reported gains, standardized test scores, and college grades. *Research in Higher Education*, *40*, 499-526.

[68]Kuh, G. D., Kinzie, J., Schuh, J. H., Whitt, E. J., & Associates. (2005). *Student success in college: Creating conditions that matter*. San Francisco: Jossey-Bass.

[69]Laing, J., Swayer, R., & Noble, J. (1989). Accuracy of self-reported activities and accomplishments of college-bound seniors. *Journal of College Student Development, 29*(4), 362-368.

[70]Pace, C. R. (1985). *The credibility of student self-reports*. Los Angeles: The Center for the Study of Evaluation, Graduate School of Education, University of California at Los Angeles.

[71]Pike, G. R. (1995). The relationship between self-reports of college experiences and achievement test scores. *Research in Higher Education, 36*(1), 1-22.

[72]Shavelson, R.J. (2010). *Measuring college learning responsibility: accountability in a new era*. Palo Alto, CA: Stanford University Press.

[73]Volkwein, J.F., Lattuca, L.R., Harper, B.J., & Domingo, R.J. (2007). Measuring the impact of professional accreditation on student experiences and learning outcomes. *Research in Higher Education, 48*(2), 251-282.

[74]Campbell, C.M. & Cabrera, A.F. (2011). How sound is NSEE? Investigating the psychometric properties of NSEE at a public, research-extensive institution. *The Review of Higher Education*, *35*(1), 77-104.

[75]Dowd, A.C., Sawatzky, M. & Korn, R. (2011). Theoretical foundations and a research agenda to validate measures of intercultural effort. *The Review of Higher Education*, *35*(1), 17-44.

[76]Nora, A., Crisp, G. & Matthews, C. (2011). A reconceptualization of CCSSE’s benchmarks of student engagement. *The Review of Higher Education*, *35*(1), 105-130.

[77]Porter, S.R. (2011). Do college student surveys have any validity?. *The Review of Higher Education*, *35*(1), 45-76.

[78]Shadish, W. R., Cook, T. D., & Campbell, D. T. (2002). *Experimental and quasi-experimental designs for generalized causal inference*: Houghton, Mifflin and Company.

[79]National Academy of Engineering (2005). *Educating the engineer of 2020: Adapting engineering education to the new century*. Washington, D.C.: National Academies Press.

[80]Seymour, E. (2001). Tracking the processes of change in US undergraduate education in science, mathematics, engineering, and technology. *Science Education, 86*, 79-105.

[81]Whitt, E.J., Pascarella, E.T., Elkins, B.S., Neisheim & Martin, B.P. (2003). Differences between women and men in objectively measured outcomes, and the factors that influence those outcomes, in the first three years of college. *Journal of College Student Development*, *44*(5), 587-610.

[82]Borrego, M., & Newswander, L.K. (2010). Definitions of interdisciplinary research: Toward graduate-level interdisciplinary learning outcomes. *The Review of Higher Education*, *34*, 1, 61-84.