

An Approach for Studying Multiple Learning Outcomes of Undergraduate Engineers

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BACKGROUND

Recent U.S. reports have urged undergraduate engineering programs to develop graduates who will be successful in a competitive future workforce. Similarly, Engineers Australia has identified an array of competency standards that graduates should possess to be prepared to be Professional Engineers. The U.S. National Academy of Engineering (2004) outlined a strategy emphasizing a set of learning outcomes that will prepare engineering graduates for work in a dynamic and global workplace. Engineers still will need to exhibit strong analytical skills, but they also will need to be proficient in an array of other abilities, including professional skills, interdisciplinary competence, and contextual competence. Prior large-scale engineering education research (e.g., Sheppard et al., 2010) has focused on whether and how students develop a particular skill (e.g., fundamental skills *and* teamwork skills *and* design skills) that students will need to meet the expectations of engineering employers.

PURPOSE

This paper develops an outcomes-based typology to: 1) identify empirically distinct groupings of fourth- and fifth-year undergraduate engineers when assessed and categorised on a variety of self-reported learning outcomes, and 2) determine how engineering students' individual characteristics and educational experiences are related to this set of student-reported outcomes.

DESIGN/METHOD

Using a nationally representative sample of 120 U.S. engineering programs from 31 institutions, this study drew on survey data from engineering students who provided information on their pre-university characteristics, curricular and co-curricular experiences in their engineering programs, and self-ratings of engineering-related competencies. This paper used cluster analysis to produce a typology of engineering students based on nine self-reported learning outcomes. Multinomial logistic regression next used student characteristics and university experience variables to predict cluster membership.

RESULTS

Analyses using a multidimensional set of learning outcomes produced a meaningful typology that distinguished between groupings of students. A subset of students reported high skills and abilities on the full array of learning outcomes and are the "model" graduates that programs seek to develop. Though clusters only took into account data related to the outcomes, distinctive curricular and co-curricular experiences distinguished the highly proficient students from other clusters of students. Emphasizing broad and systems perspectives in the curriculum most consistently distinguished these "model" students from other students. Other distinguishing variables differed across clusters, as findings demonstrated great variation in the balance of reported learning outcomes across students.

CONCLUSIONS

The study identifies a technique to create an outcomes-based typology that can be applied to any set of learning outcomes, such as those prioritised by Engineers Australia. Rather than disaggregating knowledge and skills of individual students, this technique allows educators to understand how an individual's skills vary holistically (i.e., which skills are well developed, and which must be strengthened) and links outcomes to students' characteristics and educational experiences. This new approach responds to the needs of academic programs, which seek to cultivate an array of abilities in their graduates rather than just one.

KEYWORDS

Engineering student outcomes; Well-rounded engineers; Data-driven curricular reform

Introduction

Within the United States, both the federal government and industry have renewed calls to improve engineering education so that the nation may remain a leader in innovation (e.g., White House, 2011). Recent U.S. national reports have urged educators to focus on graduating engineers who will be successful in a competitive workforce of the future (e.g., National Academy of Sciences, 2007; U.S. Department of Education, 2006). Looking toward this future, the National Academy of Engineering (NAE) outlined a strategy in its report, The Engineer of 2020: Visions of Engineering in the New Century (2004), which emphasizes a set of learning outcomes that will prepare engineering graduates for work in a dynamic, interdisciplinary, and global workplace. As in the past, these graduates will need to exhibit strong fundamental and analytical skills, but they also will need to be proficient in an array of new abilities, including business management skills, practical ingenuity, creativity, communication, and leadership. Similarly, Engineers Australia (2011) has identified an array of learning outcomes exhibiting much overlap with NAE's outcomes to serve as competency standards for Professional Engineers. The current challenge for undergraduate engineering programs in both national contexts is to identify the organizational conditions, student experiences, and policies that support the development of this array of learning outcomes and thus promote highly proficient, yet well-rounded, graduates.

This study examined the extent to which fourth- and fifth-year U.S. engineering undergraduates have attained the knowledge and skill set outlined by the NAE. By examining a students' entire set of outcomes simultaneously, this approach responds to the need to understand how students develop holistically, building a variety of desired abilities as a result of their undergraduate engineering experiences. Although this research specifically assesses how well U.S. engineers have achieved the skills and attributes identified by the NAE's engineer of 2020 report, the approach is readily applicable to the assessment of any set of learning outcomes, such as the competencies outlined by Engineers Australia. This paper first describes the development of a typology of engineering seniors based on their multi-dimensional skill sets (hereafter referred to as the "E2020 outcomes"). It then identifies the personal and tertiary educational experiences related to the development of the engineer of 2020 but also examines how experiences vary for other groups in the typology. To make results accessible for decision-makers, findings consolidate large quantities of educational research into a one-page summary graphic. Specifically, the paper addresses the following:

1. When fourth- and fifth-year undergraduate engineers are assessed and categorized on a variety of self-reported learning outcomes, what groupings emerge?

2. How are engineering students' individual characteristics and educational experiences related to this set of student-reported outcomes?

Conceptual Underpinnings

The "tertiary education impacts" framework by Terenzini and Reason (2005, 2010) brings coherence to over fifty years of higher education research and conceptually combines factors forming the "Undergraduate Experience" in an effort to explain student learning outcomes. Several research studies in higher education (e.g., Reason, et al., 2006, 2007, 2010), including ones grounded within an engineering context (e.g., Lattuca et al., 2006), empirically support the framework. This study used a revised version of this framework, which was modified following two engineering-focused studies funded by the U.S. National Science Foundation (Figure 1). In general, the model hypothesizes that pre-university characteristics shape students' engagement with various aspects of their institutions and also, to a lesser extent, have an influence on outcomes. A variety of curricular, classroom, and out-of-class experiences are ways in which students engage at university. These experiences occur within institutional contexts, which include internal organizational characteristics, practices, policies, and faculty cultures and environments. The revised model specifies learning

outcomes drawn from the NAE's report. This paper focuses on Precollege Characteristics & Experiences, Student Experiences, and E2020 Outcomes portions of the framework.

Only a few engineering education studies (e.g., Lattuca et al., 2006; Sheppard et al., 2010) have taken the comprehensive approach of studying in-class and out-of-class experiences on a range of outcomes. Each of these analyses, however, related student characteristics and experiences to learning outcomes in isolation and not in relation to one another. It is possible, for example, that students reporting high design skills are the same students who report high professional skills. Alternatively, students reporting high design skills may be a different set of students than those reporting high professional skills. By looking at outcomes independently, it is impossible to determine the true scenario. In a notable exception, Besterfield-Sacre, et al. (2002) linked student experiences to multiple accreditation outcomes in a single program and proposed an index measuring the overall quality of an engineering education. This approach conceals how an individual's skills vary (i.e., which skills are well developed, and which are less developed). To improve upon this research, the approach used in the present study considers an array of learning outcomes without masking levels of competency on each outcome. Using the conceptual framework as a guide, identifying differences in pre-college characteristics and educational experiences between highly proficient E2020 students and their peers will provide insight to educators on how to adjust program offerings to cultivate the desired learning outcomes in additional students.

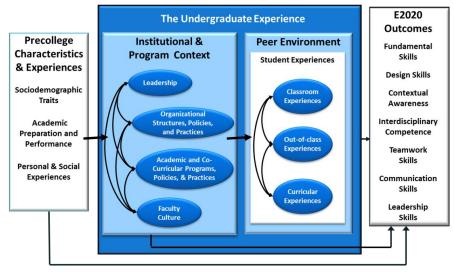


Figure 1: Conceptual framework for the study.

Methods

This study used data from the *Prototype to production: Processes and conditions for preparing the Engineer of 2020* study ("P2P"), sponsored by the National Science Foundation (NSF EEC-0550608). Engineering students from a nationally representative sample of engineering programs in the United States answered a survey collecting information on their pre-university characteristics, curricular and co-curricular experiences, and self-ratings of engineering-related competencies. The survey was developed by a team of education and engineering researchers who followed a process that included: 1) extensive literature reviews of topics related to the E2020 learning outcomes from within and outside engineering, 2) interviews and focus groups with engineering administrators, academic staff, students, and alumni at five campuses to develop and adjust survey items, and 3) pilot testing with students (sample size=482) at two campuses followed by further adjustment. To maximize generalizability of results, this research relied on voluntary, self-reported data because direct measures of learning for many of these outcomes did not exist or would have required extensive human and financial resources for administration and collection. Extensive preparatory work sought to reduce the effects of limitations associated with self-

report data. Moreover, the validity of the learning outcomes measures used in this paper have been peer reviewed in prior nationally representative studies (Lattuca et al., 2006) as well as for this data set for newly developed items (Lattuca et al., 21012; Ro et al., 2012).

Sampling used institution- and program-level information for the 2007–2008 academic year for enrolled students and faculty and was disproportionate, mixed random/purposeful, 6x3x2 stratified: six disciplines (biomedical/bioengineering, chemical, civil, electrical, industrial, and mechanical); three levels of highest degree offered (bachelor's, master's, and doctorate); two levels of institutional control (public and private). Sample institutions were representative of the population of engineering schools offering these programs with respect to type, mission, and highest degree offered. Schools offering a general engineering degree also were included in the sample following recommendations by the project's advisory board.

	Variables	Cronbach's alpha ¹	Number of items	
E2020 Outcomes Scales	Fundamental Skills	.71	3	
	Design Skills	.92	12	
	Contextual Competence	.91	4	
	Recognizing Disciplinary Perspectives	.68	3	
	Interdisciplinary Skills	.79	8	
	Reflective Behavior	.73	2	
	Communication Skills	.86	6	
	Teamwork Skills	.85	5	
	Leadership Skills	.90	6	
Curriculum Emphases Scales	Core Engineering Thinking	.83	5	
	Professional Values	.82	4	
	Professional Skills	.87	5	
	Broad and Systems Perspectives	.84	4	
Instructional	Student-centered Teaching	.80	5	
Practices Scales	Active/Collaborative learning	.76	4	
Course Taking	Number of courses in humanities Number of courses in social sciences			
Items				
Co-Curriculum Items	Undergraduate research in engineering			
	Engineering internship			
	Engineering cooperative education experience			
	Engineering club			
	Non-engineering club			
	Engineering club for underrepresented students			
	Study abroad/international tour			
	Humanitarian engineering projects			
	Non-engineering community service			
	Student design projects/competitions			
Faculty Interaction Items	Academic/course-related discussions			
	Career/professional advice			
	Informal discussions			
Pre-University	Demographics: Gender, race, highest parent education level			
Characteristics	Academics: Scholastic Aptitude Test ("SAT") scores (math, writing, critical reading)			

Table 1: List of variables used in the study

Characteristics Academics: Scholastic Aptitude Test ("SAT") scores (math, writing, critical reading Measure of a scale's internal consistency or reliability, where > .70 is the generally accepted norm.

A university survey research centre collected data through a web-based questionnaire. Of the 32,737 student surveys sent, 5,249 were returned for a response rate of 16%. Though a higher rate was desired, student response rates have been declining (Baruch, 1999; Porter & Umbach, 2001), perhaps because of increased use of surveys in general through web-based forms (Porter & Umbach, 2006; Van Horn et al., 2009). Differences between the sample and the institutional population were addressed by weighting cases by gender, discipline, class standing, race/ethnicity, and institutional response rate—this allowed the sample to be

generalised to the population of engineers at these institutions. Furthermore, missing data were imputed following social science research norms. Leaving in missing data or omitting cases from data sets results in higher bias (e.g., Cox, McIntosh, Reason, & Terenzini, 2010).

Variables included student-reported educational outcomes, pre-university characteristics, and undergraduate experiences (see Table 1) for students in their fourth or fifth year of study (sample size=2,422). This paper presents results for engineering as a field to demonstrate how such an outcomes-based typology can be a useful approach for studying multiple learning outcomes simultaneously. Separate typologies for each engineering discipline were also constructed but are not included in this paper. Analyses were conducted in multiple phases. First, cluster analysis produced a typology (or grouping) of engineering students based on nine self-reported learning outcomes scales (each comprised of highly correlated survey items). After using a two-stage cluster analysis to produce a meaningful typology (i.e., high between-cluster variation and low within-cluster variation), outcomes scales between clusters were compared using analyses of variance. The cluster with consistently high scores on all outcomes was named the "E2020 cluster."

In phase two, multinomial logistic regression models determined which pre-university student characteristics and university experiences predict cluster membership, focusing on the influences of student-level variables on outcomes cluster membership. Institution-level effects not captured by the analytical framework were negligible compared to student-level effects. As such, students did not systematically group into clusters based on their institution of enrolment—rather, students from individual institutions were found across the typology.

Results

Taking into account cluster stability using discriminant function analysis, the balance of cases across clusters, and the size of clusters, a seven-cluster emerged as the optimal typology for this sample of undergraduate engineers. Cluster sizes ranged from 7–19% of the sample. According to a multivariate analysis of variance, there were significant differences (p<.05) for the nine outcomes across the seven clusters. Therefore, the objective of producing unique outcomes-based clusters was met. Because a goal for engineering programs should be to develop additional E2020 students, according to the NAE, identifying a cluster of well-rounded yet highly proficient students benchmarks progress toward that goal. Statistical analyses (i.e. ANOVA for normally distributed outcomes, and a K-W test for nonparametric distributions) indicated that student-reported outcomes for this "E2020 cluster" were significantly higher (p<.05) for all pairwise comparisons with other clusters. Thus, there was abundant support that among engineering undergraduates, a subset of students reported high skills and competencies on all E2020 outcomes.

For assessments to be useful for improving educational conditions and outcomes, academic staff and administrators should be engaged throughout the process, which requires an easily accessible presentation of data (Hutchings, 2010; Mentkowski, 1991). To facilitate sharing of data on student learning outcomes, a graphical representation of the typology is used (Figure In addition, an "F-D-I-P" cluster coding scheme aggregating conceptually similar 2). outcomes and standardizing values across clusters allows for easier comparisons with the E2020 cluster. The fundamental skills scale ("F") stood alone in this scheme. Design skills and contextual awareness scales ("D") were combined since these are closely related competencies (e.g., Adams et al., 2003; Palmer et al., 2011). Recognizing disciplinary perspectives, interdisciplinary skills, and reflective behavior practice scales were aggregated into an interdisciplinary competence dimension ("I") because items forming these three scales were developed to measure this construct. Leadership, teamwork, and communication skills were combined to form a professional skills dimension ("P"), as these skills often are combined by engineering education researchers and practitioners (e.g., Shuman et al., 2005). Summary F-D-I-P codes assigned to each cluster standardized each arouping of students to the E2020 group. For example, the 9-7-9-7 cluster (see Figure 2) indicates that the average values of fundamental skills ("F") and interdisciplinary competence

("I") were approximately 90% of the E2020 cluster's average values for those dimensions. The design/contextual awareness ("D") and professional skills ("P") dimensions were approximately 70% of the E2020 cluster's average values for those dimensions. Thus, this scheme facilitated comparison of outcomes between the E2020 cluster and other clusters.

F-D-I-P Cluster	Outcomes Plot	Discriminators from E2020 Cluster	
E2020 (n=261)	Fundamental Skills Leadership Skills Teamwork Skills Communication Skills Reflective Behavior Practice	All Engineers	
9-7-9-7 (n=409)	Fundamental Skills Leadership Skills Teamwork Skills Contextual Awareness Communication Skills Reflective Behavior Practice	 SAT Composite: (1.14) Core Engineering Thinking: (2.25) Broad and Systems Perspectives: (2.14) 	
7-8-9-9 (n=327)	Fundamental Skills Leadership Skills Teamwork Skills Communication Skills Reflective Behavior Practice	 Gender: 2.35 SAT Composite: (1.13) Core Engineering Thinking: (2.07) Student-Centered Teaching: (2.50) Student design projects: (1.03) 	
7-7-8-7 (n=340)	Fundamental Skills Leadership Skills Teamwork Skills Communication Skills Reflective Behavior Practice Interdisciplinary Skills	 Gender: 2.34; SAT Composite: (1.15) Core Engineering Thinking: (2.32) Professional Skills: (2.05) Broad and Systems Perspectives: (2.70) Student-Centered Teaching: (2.63) Other clubs or activities: (1.24) Student design projects: (1.04) 	
8-7-7-8 (n=161)	Fundamental Skills Leadership Skills Teamwork Skills Communication Skills Reflective Behavior Practice Reflective Behavior Practice	 SAT Composite: (1.07) Broad and Systems Perspectives: (3.84) Student-Centered Teaching (2.24) Undergraduate Research: (1.08) 	
7-5-7-5 (n=233)	Fundamental Skills Leadership Skills Tearnwork Skills Communication Skills Reflective Behavior Practice	ord and systems respectives. (2.00)	
9-8-8-9 (n=380)	Fundamental Skills Leadership Skills Teamwork Skills Communication Skills Reflective Behavior Practice	 SAT Composite: (1.12) Broad and Systems Perspectives: (2.47) 	

Figure 2: Graphical representation of the outcomes-based typology, with each concentric circle indicating the average value for the cluster. F-D-I-P codes consolidate outcomes to ease interpretability and standardize values to the E2020 cluster to ease comparability.¹ Discriminating variables resulted from multinomial logistic regression models.²

- ¹ F=fundamental skills, D=design skills/contextual awareness, I=interdisciplinary competence (recognizing disciplinary perspectives, interdisciplinary skills, reflective behavior practice), P=professional skills (communication, teamwork, leadership skills). Values are standardized to the E2020 cluster (e.g., 10 is equivalent to the E2020 mean, 9 is 90% of the E2020 mean).
- ² Values represent odds ratios of cluster membership relative to the E2020 cluster (parentheses indicate inverse odds ratios; i.e., a greater likelihood of E2020 membership for an increase in the variable). An inverse odds ratio of (1.14), for example, indicates that students were 14% more likely to be in the E2020 cluster than the comparison cluster for increases in the discriminating variable.

Clusters demonstrated variation in the balance of reported learning outcomes, as shown in the radar plots (Figure 2). For example, 7-5-7-5 students appeared to be weakest overall compared to the E2020 cluster, as design skills/contextual awareness and professional skills outcomes were approximately 50% of the E2020 values. Students in cluster 7-7-8-7, rather, excelled on interdisciplinary competence relative to other outcomes, and students in the 8-7-7-8 cluster excelled on fundamental skills and professional skills relative to other outcomes. Prior approaches for researching engineering student learning outcomes have been limited in their abilities to reveal such variation across different outcomes within individual students.

In addition, though clusters only took into account information related to the E2020 outcomes, distinctive pre-university, curricular, and co-curricular experiences distinguished E2020 students from other groupings of students. These findings coincide with previous research on specific skill development in engineering (e.g., Atman et al., 2010; Lattuca et al., 2006; Sheppard et al., 2010). The Scholastic Aptitude Test (SAT) score was the only variable that significantly discriminated between the E2020 cluster and every other cluster. For every 50-point increase, students were 7–15% more likely to be in the E2020 cluster, suggesting that students' academic preparation for university has an influence on their self-reported, final-year outcomes. Relative to student experience variables, however, these inverse odds ratios are fairly low. A curricular emphasis on broad and systems perspectives consistently distinguished between E2020 students and those in other clusters, with significant inverse odds ratios ranging from 2.14 to 3.84.

Examining each cluster of students independently produces nuanced understandings of how clusters of students are different from one another. For example, the 9-7-9-7 cluster is distinguished from the E2020 cluster by lower curricular emphases on core engineering thinking—increases in one unit on this scale make students over twice as likely to be in the E2020 cluster than the 9-7-9-7 cluster. Program emphases on design (encompassed in the core engineering scale) intuitively appear to be related to design and contextual awareness outcomes—the curriculum is more important than the co-curriculum in distinguishing these students from E2020 students. Students in cluster 7-8-9-9, who are more likely to be female than the E2020 cluster, report relatively weaker fundamentals and design outcomes. Higher reports of program emphases on core engineering thinking (inverse odds ratio=2.07) as well as increased participation in out-of-class design projects (inverse odds ratio=1.03) increase the likelihood of students to be in the E2020 group than this cluster, with the curriculum having a larger impact in distinguishing students. Both of these experiences presumably positively influence these outcomes in particular, so the significant relationship is intuitive.

Finally, an array of student experiences separates the weakest 7-5-7-5 students from those in the E2020 cluster. These students' outcomes are skewed toward interdisciplinary competence, which raises questions about the direction of their career aspirations. For some of these students, professional and design skills may be less important than the development of interdisciplinary skills. This observation may explain why students are 48% more likely to be in the E2020 cluster if they participate in additional humanitarian engineering projects. The 7-5-7-5 students may not engage in such activities if they are not training for a future in engineering, despite the fact that demonstrations of the social relevance of engineering may be the persuasion that these students need to remain in the field. Alternatively, because these students reportedly are less proficient than their colleagues, they may not be in a strong position to decide whether or not to remain in engineering post-graduation.

Conclusions and Implications

This paper shows how using cluster analysis of multiple learning outcomes results in a typology that demonstrates variations in the relative balance of learning outcomes. A single E2020 group of students reports high skills and abilities on all outcomes—these are the "model" students which engineering programs seek to develop. Comparisons between the E2020 students and other groupings of students identify differences in their characteristics and university experiences, despite only taking into account outcomes to produce the

groupings. Such differences illuminate opportunities for engineering programs to implement interventions for helping promote highly proficient and well-rounded graduates. If an institution sought a single way to expand its E2020 population, increasing curricular emphases on broad and systems perspectives would be the "silver bullet" recommendation.

The study contributes to research and practice by identifying a technique to create an outcomes-based typology that can be applied to any set of learning outcomes, such as those identified as important by Engineers Australia. Rather than disaggregating knowledge and skills of individual students, this technique allows educators to understand how an individual's skills vary holistically (i.e., which skills are well developed, and which must be strengthened). This new approach responds to the needs of academic programs, which seek to cultivate an array of abilities in their graduates rather than just one. The investigation also operationalized the conceptual model proposed by Terenzini and Reason (2005, 2010) in a new manner by considering multiple outcomes as a single dependent variable. Findings provide empirical support for the conceptual framework, showing that a variety of student experiences and characteristics influence this array of outcomes.

This paper's purpose was to demonstrate the overall approach using undergraduates from the full engineering field. Because prior research suggests disciplinary differences in student outcomes and experiences (e.g., Lattuca et al., 2011), separate typologies were developed for each discipline to uncover such nuances (not presented because of space limitations). Specific programmatic changes should be based on research tailored to individual disciplines within engineering rather than considering the engineering field as a homogeneous whole. Future research will operationalize organizational components to study the full conceptual framework. Another important area of research emerging from this analysis involves comparisons of the projected career trajectories of students populating different outcomes clusters. This analysis will test whether or not the NAE's vision for the engineers of 2020 may be more applicable to certain industries, job trajectories, or disciplines than others.

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