



The Effect of Clusters of Participation in Engineering Co-curricular Activities on Student Outcomes

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Abstract

In this research paper, we identify clusters of participation based on the number of organizations in which students participate and the frequency that they attend activities, and examine their impact on various social, professional, and academic outcomes, including Bonding Social Capital, Bridging Social Capital, Engineering Identity, Intent to Persist, Major Satisfaction, and grade point average (GPA). 4,022 third- and fourth-year undergraduate engineering students at a large public Midwestern R1 university received a survey instrument, and 998 responded. The survey asked several questions regarding student pre-college and on campus experiences, and resulting outcomes. Students were asked whether they participated in engineering-related co-curricular activities, which ones, and how often. We used Agglomerative Clustering Analysis to identify clusters of participation, and found five different clusters: non-participants do not participate in any organizations; occasional participants belong to one or two organizations and are slightly active; regular participants also belong to one or two organizations and attend most activities; selective participants belong to one or two organizations and are leaders of the organizations; and super participants are involved in two to five organizations and are highly active and/or leaders in one or two. T-tests between the 5 cluster types and 5 outcomes show that nonparticipants always have the lowest mean scores on the outcomes, and that these mean scores tend to increase with increasing frequency of participation. Nevertheless, we see no statistically significant differences between the regular, super, and selective groups for most of the outcomes, suggesting that the highly active or officer level involvement isn't related to gains in outcomes compared to more moderate (regular, non-officer). The only outcome for which this is not true is GPA, which is doesn't change significantly between different clusters of participants.

Introduction

It is well established that participation in co-curricular experiences in college has significant impact on student outcomes.[1], [2] It has been shown that co-curricular activities that are related to the academic endeavor are positively related to self-efficacy in that discipline,[3] and that such participation results in the development of a variety of skills related to communication,[4] leadership and ethical development,[5] and design and teamwork.[6] Such increases also have various professional benefits. For example, students who participate in these activities get jobs after graduation at higher rates than those who do not.[7]

But the engineering curriculum is very dense, making participation in out-of-classroom and co-curricular activities challenging. Brint and co-workers [8] found that there are two separate academic cultures of engagement, where the arts, humanities, and social sciences focus on the "interaction, participation, and interest in ideas," and science and engineering disciplines focus on the "improvement of quantitative skills through collaborative study with an eye to rewards in the labor market." As a result, engineering students tend to spend more time preparing for class than other kinds of majors.[9]

Given the tension between the demands of the engineering curriculum and the known benefits of participation in co-curricular activities, it's crucial to understand how students should best spend their time. Simmons and co-workers [10] found that engineering students' most common non-

classroom activities are job, sports, design and competition teams, identity-based groups, and professional experiences such as internships or co-ops. But less is known about how the number of groups and intensity of participation affects various outcomes. The purpose of this paper is to examine whether there are typical clusters of participation with regard to the number of groups in which students participate and the intensity of that participation, and the relationship between those clusters and various social, professional, and academic outcomes.

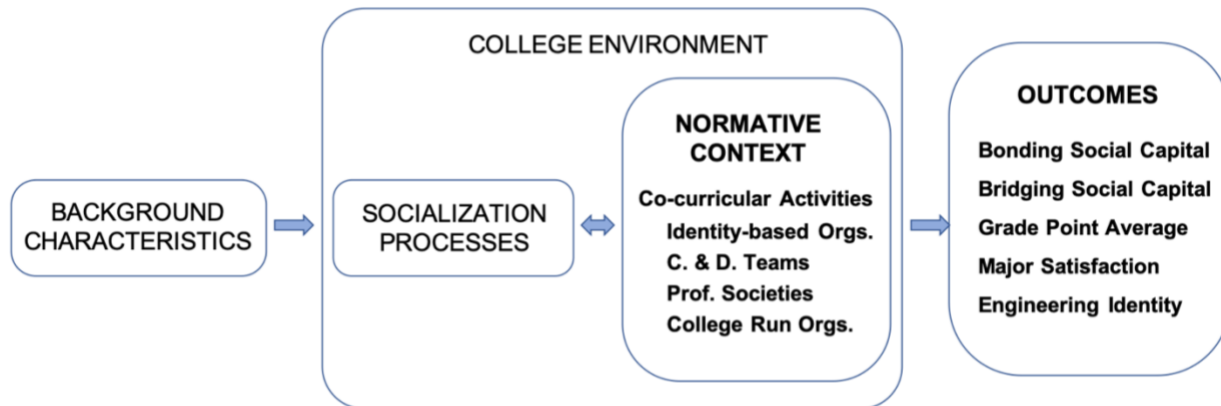


Figure 1: Schematic of the conceptual framework used in this study. Capitalized text indicates the items taken from Astin [11], [12] and Weidman {cite}, while bolded text indicates the items studied in this paper.

Conceptual Framework

We developed a survey based on the theories of Astin [11], [12] and Weidman [13], [14] to investigate how various pre-college characteristics and the college environment influence a number of student outcomes (Fig. 1).[15]–[19] In this paper, we are interested in how participation in co-curricular activities are related to specific outcomes. Therefore, we chose to examine social, professional, and academic outcomes that we believed to be related to participation in co-curricular activities. For social outcomes, we chose to measure social capital, or the productive benefits derived from an individual’s social network [20]. We also wanted to know how academic outcomes, such as performance, i.e.: grade point average (GPA), and major satisfaction [21] would be affected by such participation. Finally, we wished to understand whether participation in co-curricular activities influenced professional outcomes, specifically engineering identity [22].

Research Questions

In this paper, we identify the clusters of participation in co-curricular activities, such as the types of organizations, number of organizations joined, and the frequency of participation, and show how they are related to social (bridging social capital, and bonding social capital), academic (major satisfaction), and professional outcomes (engineering identity). The specific research questions we address are:

RQ1; Are there clusters of participation with regard to frequency of participation and number of organizations?

RQ2: Are there differences between the clusters in observed social, professional, and academic outcomes?

Survey Sample

4,022 third- and fourth-year undergraduate engineering students at a large public Midwestern R1 university received an invitation to complete our survey, and 870 returned responses. The demographics and socioeconomic status of the survey sample, the sampling frame, and estimates of the national population of engineering students at Carnegie-classified research institutions obtained from the National Center for Education Statistics (NCES) are shown in Table 1. The survey sample is approximately representative of the sampling frame, except that females are overrepresented, and URM and international students are under represented. The institution under study has a higher proportion of Asian and international students compared to the national average, but a lower proportion of low income and first-generation students.

Table 1: Distribution of the demographics and socioeconomic status within the survey sample, sample frame, and national engineering R1 institutions.

	Survey Sample (%) N = 870	Sampling Frame (%) N = 4022	National Sample ^a (%)
Female	362 (41.6)	1033 (25.7)	(24.0)
URM	81 (9.3)	711 (17.7)	(20.0)
White	459 (52.8)	2202 (54.7)	(63.4)
Asian/American Asian	250 (28.7)	1109 (27.6)	(15.7)
International	58 (6.7)	540 (13.4)	(8.8)
Low Income	116 (13.3) ^b	458 (11.4) ^b	(25.3) ^c
First Gen	106 (12.2)	578 (14.4)	(31.1)

^a National data from U.S. Department of Education, National Center for Education Statistics, 2015 – 16 National Postsecondary Student Aid Study (NPSAS:16) for graduating seniors from a bachelor's degree program in 2015 – 16 with a major field of study in engineering or engineering technology.

^b Percentage of students with a family income less than \$65,000 based on the survey.

^c Estimate represents percentage of students with a family income less than \$63,000 based on the NCES.

Types and Frequency of Participation

The survey asked students whether they were currently involved or had ever been involved in an engineering-related organization. Students who indicated that they had participated in such an organization were then asked to submit the names of no more than five of which they were most involved. We classified each of these organizations post hoc by type (Authors, submitted). Table 2 lists each type of organization, a definition, and the top 3 organizations in that type. On average, participants report participating in 1.9 ± 1.0 organizations, with the most common (61%) being a competition or design team.

Table 2: Types of organizations, definitions, and examples of the top 3 organizations lists for each type.

	Definition	Top 3 Organizations
Identity-based	Student-run organizations that cater to specific identities held by students	Society of Women Engineers, National Society of Black Engineers, Society of Hispanic Professional Engineers
Competition	Engineering design student-run organizations, either for the social good or in competition	Bluelab, Health Engineered for All Lives, Hybrid Racing
Professional	Student-run professional societies associated with engineering practice	Tau Beta Pi, American Institute of Chemical, Theta Tau Professional Engineering Fraternity Engineers
College-run	College-run activities in engineering	Engineering Student Government, Peer Mentoring Program, Engineering Honors Program

We also asked additional questions about how active participants were in each organization. Students were asked how active they were in each organization in the past year. The possible responses were: not active, attend occasionally, attend regularly, participate in most activities, held a leadership post. Figure 2 shows that the distributions of responses is somewhat bimodal, with the “occasional participation” and “holding a leadership position” as the most common responses.

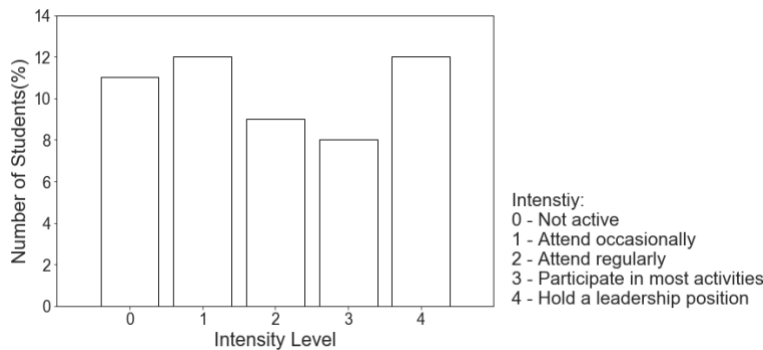


Figure 2: Histogram of the responses regarding how active participants were in each of their organizations.

This data is somewhat difficult to interpret because most students participate in more than one organization, and likely participate differently across depending on the type of organization and how many other organizations in which they participate. For instance, some students only participate in one organization but participate in most activities, while others participate in multiple organizations and are barely active.

Outcomes

The survey adapted several scales related to social, academic, and professional outcomes. We asked a series of questions for each outcome, and each of them were measure using a 7-point Likert scale, where 0 representing Strongly Disagree and 6 indicating Strongly Agree. We validated the scales using Confirmatory Factor Analysis and kept 5 outcomes (Bonding Social Capital, Bridging Social Capital, Engineering Identity, Intent to Persist, Major Satisfaction) with good construct validity (Authors, submitted). We define students who had never participated in any of the four types of organizations as *non-participants*, while *participants* had involved in at

least one type of organization. Table 3 defines each of the outcomes, and shows the average score and standard deviation on a 7-point (0-6) Likert scale for non-participants and participants. The two social outcomes scales measure the amount of social capital held by individual students, either within their social circle (Bonding Social Capital) or between social circles (Bridging Social Capital) [20]; the academic outcome scale measures the degree to which students are satisfied with their academic major (Major Satisfaction) [21]; the professional outcomes scale measures the degree to which respondents identify as engineers (Engineering Identity) [22]. We also study an additional academic variable, the GPAs of individual students, which were taken from the institutional database.

Table 3: Average scores and standard deviations for outcomes (on a 7-point Likert scale) for non-participants and all participants.

Outcomes	Description	Non-participants	Participants
		N = 253	N = 620
Social Bridging	The amount of social capital held by individual students between social circles.	3.7 ±1.1	4.3 ±1.0 ***
Social Bonding	The amount of social capital held by individual students within their social circle.	3.2 ±1.3	3.8 ±1.1 ***
Engineering Identity	The degree to which they identify as engineers.	4.3 ±1.1	4.8 ±0.9 ***
Major Satisfaction	The degree to which students are satisfied with their academic major.	4.3 ±1.3	4.6 ±1.2 **
GPA	Cumulative GPA of the semester when they took the survey.	3.34 ±0.41	3.42 ±0.41 *

* indicates p-value < 0.05, ** indicates p-value < 0.01, and *** indicates p-value < 0.001

The data in Table 3 shows that participation in co-curricular activities is beneficial across all outcomes, in agreement with the literature [1], [2]. T-tests between non-participants and participants show that participating is correlated with significantly higher levels of the outcome scales. Participants also have significantly higher GPAs than non-participants, in agreement with prior reports on the relationships between participation and academic performance. [2]

Analytical Methods

The primary analytical method in this study is clustering analysis, a common method in statistical analysis to categorize data into clusters having similar features [23] that has been applied to developing typologies in engineering education research.[24] The algorithm groups objects based on their features, such that objects in the same cluster are more like each other than those in other clusters.[23] In this work, we grouped students (the objects) into clusters based on several features: how many organizations in which they participated, the activity level for each, and the minimum, maximum, mean, and standard deviation for each activity level. The cluster

analysis algorithms were implemented using the Python programming language using the Scikit-learn library.[25] We first ran K-Means Clustering, a method that minimizes the sum of the squared distance of data within the same group.[26] One of the most difficult parts of this kind of analysis is determining the correct number of clusters. In K-Means Clustering, the optimal number of clusters is when the within-cluster sum of squared distance versus the number of clusters changes slope. Using this criteria, Fig. 3a indicates that 4 clusters is the optimal number. K-Means Clustering assumes that the population of objects can be split into equally -sized clusters. However, we observed that the clusters vary in size by approximately a factor of 2. Therefore, we also considered Agglomerative Clustering,[27] which assumes that there is a hierarchical structure between possibly variably-sized clusters. In this analysis the silhouette score, a graphical representation of how similar an object is to other objects within its cluster, should be maximized for the optimal number of clusters.[28] Figure 3b shows that the optimal number of clusters is between 3 and 4, in agreement with the results of the K-Means Clustering method. Manual inspection of the resulting clusters suggests that four clusters are reasonable. Therefore, we find that including non-participants, there are five clusters of participation.

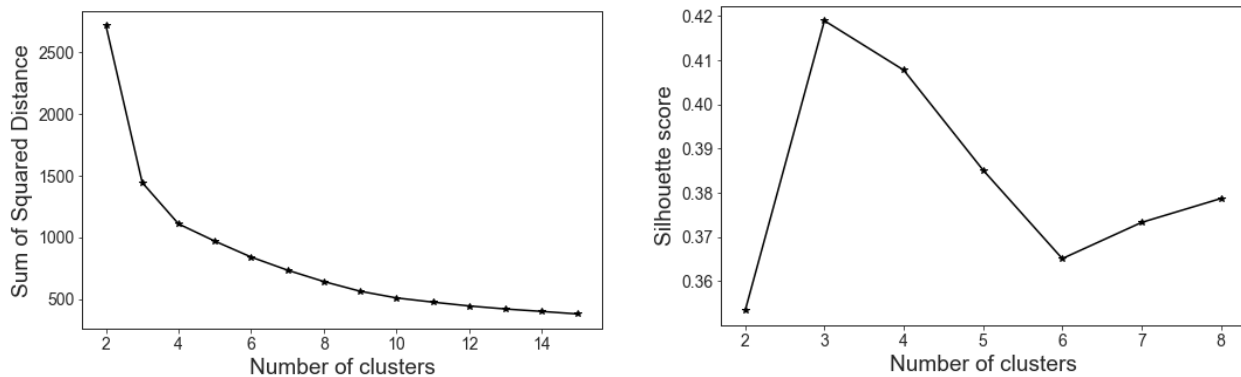


Figure 3. (a) Sum of squared distance of different number of clusters for determining the number of clusters in the K-Means Clustering algorithm, and (b) the silhouette score used for determining the number of clusters in the Agglomerative Clustering method.

Limitations

There are several limitations of this work that reduce its generalizability. This is a single institution study, and the institution itself is not a typical national engineering school. The number of low income and first-generation students is lower at our institution than overall in the nation, but the proportion of Asian and international students is higher. Therefore, the clusters of participation reported here may be specific to highly-selective research-intensive institutions. Second, the way in which the organizations were categorized into types may lead to ambiguity. Organizations such as the National Society of Black Engineers, for example, are both identity-based and professional societies; but we categorized them only into the identity-based type. This is because in prior work (Authors, submitted), we found that they behaved more like the identity-based type than like the professional society type. The college-run type may also have some ambiguity within it, because it consists of a heterogeneous collection of activities. Finally, the evaluation metrics for the cluster analyses (Fig. 3), do not definitively indicate the optimal number of clusters. In other words, similar results could have been found for a total of 4 or 6 clusters of participation.

Results and Discussion

Research question one asks whether there are clusters of participation regarding frequency of participation and number of organizations. Agglomerative Clustering Analysis showed that there are five different clusters of participation (including nonparticipation) based on the number of joined organizations and how active they are in each. *Non-participants* do not participate in any organizations. Figure 4 shows a series of histograms of the number of organizations each student joined, and their average level of participation for each of the remaining clusters. *Occasional participants* belong to a few organizations and are somewhat active in each; *regular participants* also belong to one or two organizations and attend most activities; *selective participants* belong to one or two organizations and are leaders in the organization; and *super participants* are involved in two to five organizations and are highly active and/or leaders in one or two. The largest of these groups is non-participants (N=237), followed by super participants (N=211), occasional participant (N=202), regular participants (N=125), and selective participants (N=95).

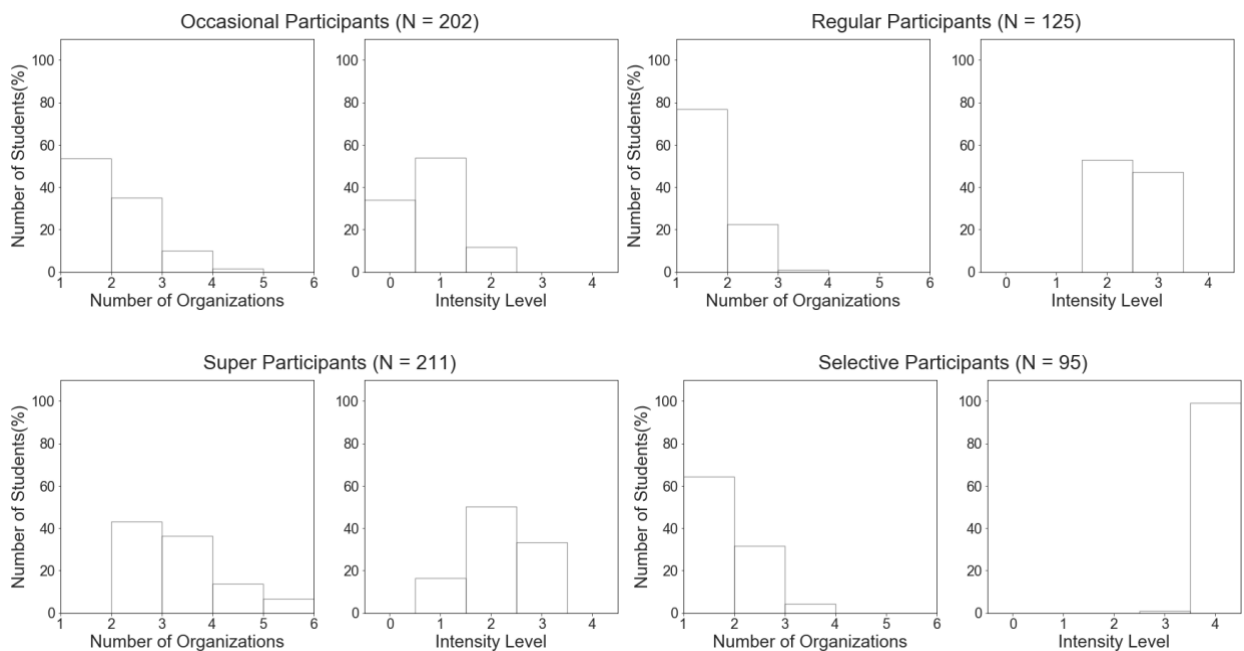


Figure 4: Histograms shows the number of organizations joined by each student, and their average level of activity for each of the identified clusters.

We also examined which types of organizations are most common for each of these clusters of participation. Figure 5 shows a series of Venn diagrams that shows the distribution of participation for each combination of types of organizations. Occasional participants are most likely to belong to one organization, such as competition and design teams (35%), professional societies (15%), or identity-based organizations (12%). Smaller fractions (6-8%) are pairwise combinations of those three. Regular participants are most likely to be members only one of the 4 types: competition and design teams (41%), professional societies (20%), college-run organizations (12%), or identity-based organizations (10%). A small number (6%) tend to be members of both competition and design teams and professional societies. Super participants tend to be members of competition and design teams plus some combination of the remaining types of groups, with the most common combination being competition and design teams and professional societies (25%). Selective participants tend to only be involved in either competition

and design teams (39%) or professional societies (32%), with a smaller group (12%) participating in both. Each of the clusters show that competition and design teams are the organizations in which students are most likely to participate, but super participants also tend to participate in professional societies. Participants in identity-based organizations tend to fall into one of two clusters, occasional or super participant; participants in professional societies or college-run activities tend to be either super or selective participants.

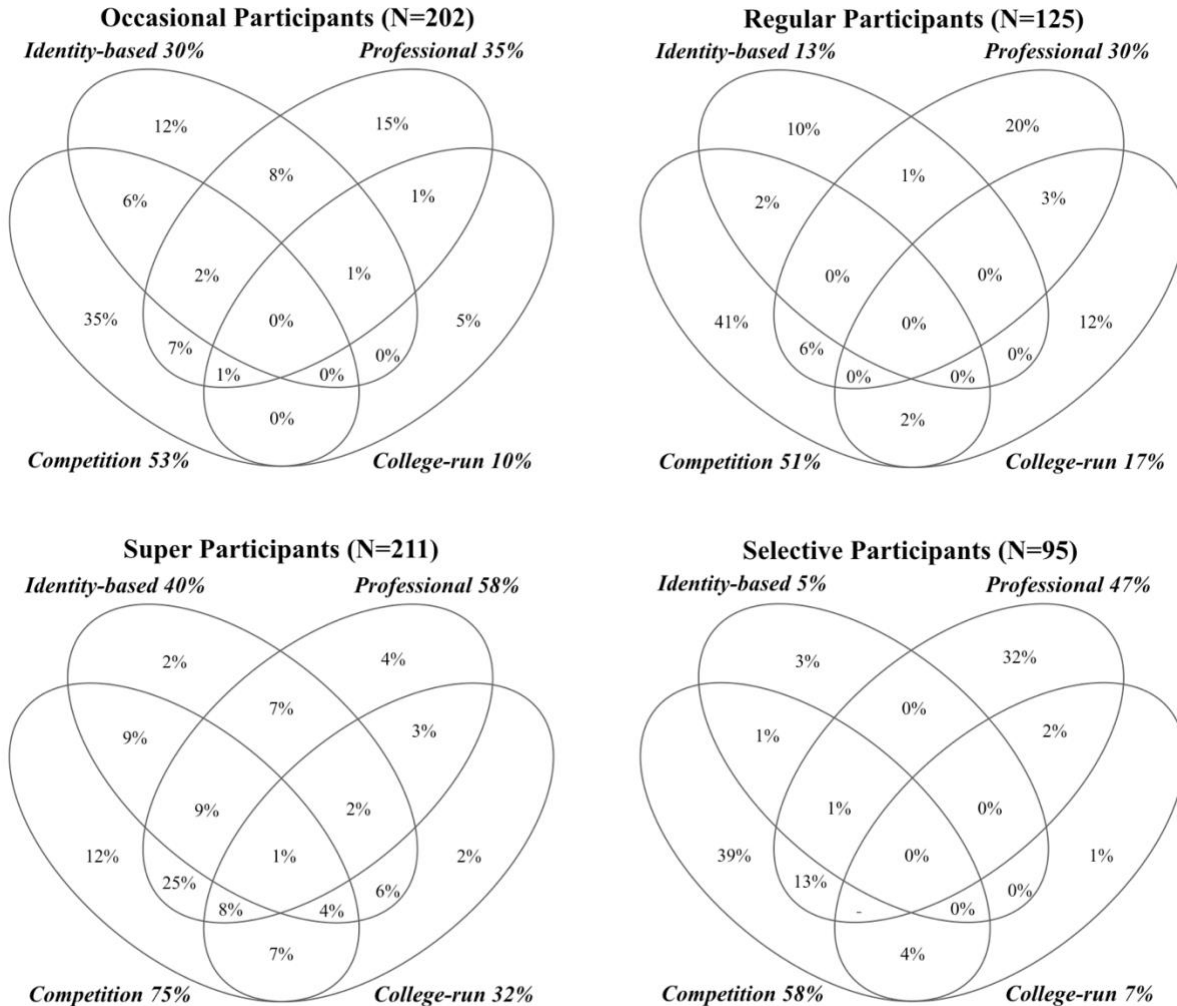


Figure 5: Venn diagrams of the different clusters of participation observed in the data, with percentage of the specific cluster of participation in each grouping of activities.

Research question two asks whether there are differences between the clusters and observed social, professional, and academic outcomes. Table 4 shows t-tests between the 5 cluster types and 5 outcomes for each participation cluster. Nonparticipants have the lowest scores for all the outcomes, and the mean outcomes increase with increasing number of organizations and frequency of participation. We see statistically significant differences between the occasional, regular, super, and selective groups for the bonding social capital outcome. Regular, super, and selective participants have statistically significantly higher bridging social capital than non-participants and occasional participants. We see no statistically significant differences between

the regular, super, and selective groups for the engineering identity and major satisfaction outcomes, suggesting that highly active or officer level involvement isn't required to see significant relationships with these outcomes compared to more moderate (regular, non-officer) participants. A statistically significant difference in GPA was only found between super participants and nonparticipants, with the super participants having a higher GPA.

Table 4: Difference (column minus row) between mean outcome values and significance for each pair of clusters.

	Social Bridging				Social Bonding			
	Occ	Reg	Sup	Sel	Occ	Reg	Sup	Sel
Non	0.43 ***	0.65 ***	0.65 ***	0.69 ***	0.30 **	0.43 ***	0.81 ***	0.84 ***
Occ	-	0.21 *	0.21 *	0.26 *	-	0.12	0.50 ***	0.54 ***
Reg	-	-	0	0.04	-	-	0.38 **	0.42 **
Sup	-	-	-	0.04	-	-	-	0.04

	Engineering Identity				Major Satisfaction			
	Occ	Reg	Sup	Sel	Occ	Reg	Sup	Sel
Non	0.37 ***	0.44 ***	0.53 ***	0.55 ***	0.19	0.29 *	0.40 ***	0.34 *
Occ	-	0.07	0.16	0.18	-	0.1	0.21	0.15
Reg	-	-	0.1	0.11	-	-	0.1	0.05
Sup	-	-	-	0.01	-	-	-	-0.06

	GPA			
	Occ	Reg	Sup	Sel
Non	0.05	0.04	0.12 **	0.05
Occ	-	-0.01	0.07	0.00
Reg	-	-	0.08	0.01
Sup	-	-	-	-0.07

* indicates p-value < 0.05, ** indicates p-value < 0.01, and *** indicates p-value < 0.001

Conclusions and Future Work

Our results show that there are specific clusters of participation regarding the number of joined organizations and frequency of participating, including nonparticipants, occasional participants, regular participants, selective participants, and super participants. While cluster analysis has been used to categorize various aspects of the engineering education, including faculty beliefs and practices,[29] student epistemic beliefs and motivation,[30] and student outcomes as a result of various educational experiences,[24], [31] this study is the first to our knowledge to categorize the intensity of student participation and relate the resulting clusters to outcomes.

We also find that any participation, even occasionally, is correlated with a higher mean value in the four out of the five social, professional, and academic outcomes studied here. The fifth outcome, GPA, was largely unaffected. This is good news for students who may feel that they

don't have enough time to participate at a level that would see benefit. Additional studies are needed to understand the root cause. For example, focus groups are needed that dig deeper into the ways that co-curricular activities build outcomes for even occasional participants. Alternatively, examining these findings through an expectancy-values lens [32] may provide additional insights.

We see statistically significant differences between the different clusters for the both social capital outcomes. Both results make intuitive sense, as the number and strength of friendships within and between social circles, should increase as the number of organizations and frequency of participation increases.

Perhaps the most surprising result is that there appears to be a statistically significant difference in GPA only between super participants and nonparticipants, and the super participants have a higher GPA. Intuition might suggest that student who have a lot of co-curricular activities may have less time for coursework, and thus perform less well. Indeed, students often report that a reason for not participating in these activities is because they are concerned about their effects on their academic performance. It isn't known whether super participants are simply stronger students overall, or being a super participant somehow leads to better academic performance by creating the expectation for academic excellence.

The outcomes examined here are merely a subset of possibilities. It is likely that other outcomes such as leadership skills, communication skills, systems thinking, risk management may depend more strongly on the intensity of participation.

Acknowledgements

The authors gratefully acknowledge the support of the National Science Foundation under Grant No. EEC-1640417.

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