2018 ASEE Annual Conference & Exposition
June 24–27, 2018, Salt Palace Convention Center, Salt Lake City, UT
Paper ID #21768

Using Social Network Analysis to Study the Social Structures of Inclusion

Mr. Nelson S. Pearson, University of Nevada, Reno

Nelson Pearson is an Ph.D. student at the University of Nevada, Reno. His research interest includes, social networks and the integration of diverse populations, engineering culture as well as engineering pedagogy. His education includes a B.S. and M.S. in Civil Engineering from the University of Nevada, Reno.

Mr. Justin Charles Major, Purdue University, West Lafayette (College of Engineering)

Justin C. Major is a first-year Engineering Education Ph.D student and National Science Foundation Graduate Research Fellow at Purdue University. Justin has two bachelor's degrees in Mechanical Engineering and Secondary Mathematics Education from the University of Nevada, Reno, and during his undergraduate education, he focused on K-12 Engineering Education. Justin's research and service focuses on the experiences and development of low-socioeconomic students as an often understudied population. Justin has served as the ASEE Student Division Co-Program Chair and is a current Director of Special Projects for the Educational Research & Methods Division.

Dr. Allison Godwin, Purdue University, West Lafayette (College of Engineering)

Allison Godwin, Ph.D. is an Assistant Professor of Engineering Education at Purdue University. Her research focuses what factors influence diverse students to choose engineering and stay in engineering through their careers and how different experiences within the practice and culture of engineering foster or hinder belongingness and identity development. Dr. Godwin graduated from Clemson University with a B.S. in Chemical Engineering and Ph.D. in Engineering and Science Education. Her research earned her a National Science Foundation CAREER Award focused on characterizing latent diversity, which includes diverse attitudes, mindsets, and approaches to learning, to understand engineering students' identity development. She is the recipient of a 2014 American Society for Engineering Education (ASEE) Educational Research and Methods Division Apprentice Faculty Grant. She has also been recognized for the synergy of research and teaching as an invited participant of the 2016 National Academy of Engineering Frontiers of Engineering Education Symposium and 2016 New Faculty Fellow for the Frontiers in Engineering Education Annual Conference. She also was an NSF Graduate Research Fellow for her work on female empowerment in engineering which won the National Association for Research in Science Teaching 2015 Outstanding Doctoral Research Award.

Dr. Adam Kirn, University of Nevada, Reno

Adam Kirn is an Assistant Professor of Engineering Education at University of Nevada, Reno. His research focuses on the interactions between engineering cultures, student motivation, and their learning experiences. His projects involve the study of student perceptions, beliefs and attitudes towards becoming engineers, their problem solving processes, and cultural fit. His education includes a B.S. in Biomedical Engineering from Rose-Hulman Institute of Technology, a M.S. in Bioengineering and Ph.D. in Engineering and Science Education from Clemson University.

Using Social Network Analysis to Study Inclusion in the Engineering Classroom

Nelson Pearson, Justin Major, Allison Godwin, Adam Kirn

Introduction

This research paper seeks to examine how race and gender are incorporated into the social structure of a first-year engineering design course at a Western land-grant institution. Of the numerous reasons causing the sluggish demographic shifts in engineering education, one of the most commonly reported is the perception of a "chilly climate" [1]–[3]. Central to understanding the chilly climate of engineering is recognition that social interactions have the potential to foster or hinder the development of an inclusive environment. Therefore, this work focuses on understanding the structure of peer-to-peer interactions within the engineering education environment. Characterizing how and with whom students are interacting with can uncover the hidden social structures that serve to reify the chilly climate. Investigating the social networks within an engineering educational environment may illuminate the social-structural barriers that are working to impede progress towards a more diverse and inclusive engineering workforce. In this paper, we focus on how the social structure within an engineering classroom includes individuals from diverse backgrounds. By addressing the question: How does a first-year, team-based engineering design course integrate diversity into its social structure? Through understanding the social structure of an engineering classrooms and how it includes diversity, we can begin to identify and address the social factors that are thwarting the creation of an inclusive learning experience.

Background

Social Interactions

Antonio (2001) in seeking to understand how diversity affected the dynamics of college friendship groups concluded:

> The strong relationship between friendship group diversity and interracial interaction outside the friendship group suggests that developing interracial friendships encourages students to venture more frequently outside their circle of best friends to socialize across race. In other words, diversity in the friendship group works to define interracial interaction as a norm for expected behavior (p. 83).

Antonio's work reveals that students are more likely to seek interactions with diverse peers when diversity is already integrated into their friendship networks. In engineering, this expectation (diversity within a peer network) is often established in first-year courses where diverse teams are created to address the new ABET Criterion 3, Objective 5 (replacement of old Criterion 3, Objective D) of developing students with, "an ability to function effectively on a team whose members together provide leadership, create a **collaborative** and **inclusive environment** (emphasis added by authors), establish goals, plan tasks, and meet objectives." [4] Creating an inclusive engineering and educational environment is critical to engineering's continued success. Antonio's findings demonstrate that if engineering education encourages and provides opportunities for meaningful interactions between diverse engineering students, engineering education can create an expectation for diversity [5]. These diverse ties not only develop improved communication skills [6]–[8] and problem solving [9]–[11], but also from the foundation of an inclusive learning environment [12], a key requirement for ABET accreditation.

Social Network Analysis

Peer interactions are a fundamental aspect of the academic experience and are important for developing an inclusive and collaborative environment. Social network analysis (SNA) provides a method that allows the structures of these interactions to be quantified and visualized [13]–[15]. Through investigating patterns of interactions insight is gained about a range of topics including information flow [8], [16], engagement [17], and inclusiveness of a social environment [18]. For this work, we leverage SNA to explore the inclusiveness of a first-year engineering design environment.

A social network is comprised of students (actors) and their connections (ties) to each other. It is the analysis of the patterns of ties between actors that is at the core of SNA. Using demographic characteristics as actor attributes allows SNA to be used to investigate how diversity (e.g., race/ethnicity and gender) is incorporated into the social structure. The level to which a student is connected to the network is quantified as degree, which is a count of all ties to other network actors. Degree can be decomposed based on the directionality of the tie, determined whether the actor initiated the connections (*out-degree*) or was the recipient of a connection (*in-degree*). In-degree is used as a proxy for student popularity, based in part on the concept that a more popular a student will have a greater number of students seeking them out. In contrast, out-degree reflects a student's sociability, the more social a student is the more they will seek out others to work with others.

Using SNA researchers have been able to demonstrate that increased involvement in a peer network does result in an improved academic experience. Brewe and colleagues [12], [19], [20] working in a physics learning center observed that increased levels of peer interactions are "associated with higher conceptual learning gains [14, p. 377]" Mirroring these findings, Rienties and Tempelaar [21] using a social network approach learned that students "who developed and maintained more learning relations over time (p. 27)" enhanced their academic performance. The benefits of having a robust social network were observed in both short-term (test scores) and long-term (GPA) measures of academic performance. Using SNA to examine engineering design teams Simon and colleagues [9] discovered that when the level of trust and interaction is balanced within a design team, the team's final design was superior to less balanced teams. Given that first-year courses often contain team actives focused on design, these experiences can strongly influence a students' intentions to persist in engineering environments.

Methods

The Open Engineering Lab

The first-year engineering course being investigated uses a semester long team-based design project to introduce students to the engineering design process. Course enrollment represents approximately 80% of all incoming first-year engineering students (total enrollment = 660; 525 identified as first-year students). Other students in the course include upper level students that took the course out of sequence from the traditional plan of study. Due to the volume of students, the course offered two large auditorium style lecture sections and multiple (32) smaller laboratory sections. Each week students would meet in their smaller laboratory classes, maximum of 32 students. Additionally, students were required to attend one of the two larger lectures (~350 students per lecture), each week.

Students were assigned to teams of four to five students during the third week of the 16-week semester, using the Comprehensive Assessment of Team Member Effectiveness (CATME) Team-Maker tool [22]. Team creation attempted to maximize diversity while ensuring that diverse students were not isolated on a team (e.g., avoiding a single female on an otherwise all male team).

Students in the course had access to an open engineering laboratory (OEL), a large workspace where they could work on their projects. On average, 50 students worked in the OEL at any one time. However, it was observed that at times up to150 students could be in the OEL working. Located in the OEL were, several tables, computers, supplies, and materials to be used for the project, and a computer classroom in the back. The classroom in the back of the OEL was used by the individual lab sessions (n = 32) and, during regular course activities, students were required to complete assignments in the OEL. A previous SNA study [18], on student interactions in the OEL, discovered that approximately 20% all peer-to-peer interactions occurred between students in different lab sections. These inter-class interactions have not only been found to improve academic success [21], but can also foster a course-wide sense of community. Social ties that bridge beyond formal classroom boundaries allow for a more equitable distribution of information. The improved dissemination of knowledge is a direct result of information from small isolated clusters of students (i.e., a classroom) being shared with the larger community. In this manner, not only are more students getting access to the information, but there is greater continuity in the information that the students are receiving. A sense of community may also be fostered through the exchange of information across these boundaries, transitioning the focus from the classroom to the class of engineers.

Data collection

Social networking data was collected using an online self-report survey (n = 502, 74% response rate), developed explicitly for this the study population (see Pearson et. al 2017 for a detailed description of the instrument development). The survey asked students to indicate with whom they had interacted with for course-related engineering task using a lab specific roster and three task specific free responses questions. Student names were imported using the official course (lab) roster. Additionally, the three free response questions allowed students the opportunity to identify other students with whom they had interacted with but we not part of their lab section (i.e., not on the prepopulated list). The social networking survey was given during week five, two weeks after the students had been assigned to their teams. The institutional IRB office approved all data collection procedures.

Due to the nature of self-reported social network ties, there exist some potential pitfalls and advantages [21]. One potential issue with social network data collection is an increased opportunity for positive response basis. That is, students may be enticed to respond that they interacted with all their class peers, rather than indicating that they only interacted with a few. Of the numerous advantages that SNA provides, one of the most substantial is the ability include all individuals of an environment, with less than full survey participation. Students who did complete the survey could indicate peers registered in the course who did not respond to the survey, increasing the representation of the network connections. It is this advantage that affords us the ability to draw inferences about the inclusiveness of the entire course.

Demographics

The CATME survey used in this study collected student demographic data and schedules, this information was used to assign students to design teams and was mandatory for the course. The CATME data allowed for actor attributes (e.g., demographics) to be assigned to students that choose not to complete the voluntary SNA survey. CATME uses traditional gender identification (i.e., male, female, and other) and racial categories (i.e., Asian, Black, Hispanic, Native American, Other, Declined, and White). We used this information along with student self-reported demographics to construct the social network for the first-year engineering course and to understand the diversity within the social structure.

Data analysis

Social networking data is discrete, positively skewed, and leptokurtic; therefore, SNA data typically does not meet normality requirements, thus nonparametric methods are required. Kruskal-Wallis (KW) nonparametric hypothesis testing seeks to identify if two or more samples originated from the same distribution. KW testing is the nonparametric equivalent of one-way analysis of variance (ANOVA). Unlike Mann-Whitney nonparametric testing, KW testing allows multiple group comparisons. The key assumption of KW testing is that all samples have equivalent distributions. If it is assumed that the distributions are similar, except median values, then the null hypothesis is that the median values of all groups are equal versus the alternative hypothesis that at least one groups' median value is different. KW testing does not identify which median(s) are different and requires *post hoc* analysis for identification. Dunn's testing was used *post hoc* to determine which, if any, groups had significant differences in median values. When doing multiple comparisons there is an inflated chance for Type 1 errors; to account for this, Benjamini-Hochberg (BH) false discovery rate (FDR) correction was used. FDR procedures are designed to reduce false discoveries by limiting the number that can occur during multiple hypotheses testing. FDR methods are less stringent than controlling for family-wise error rates (FWER), which allows the method to retain statistical power [23], [24]. The use of a FDR correction provides for greater confidence that any differences discovered are representative of the student behavior and not an artifact of the statistical testing procedures.

Results

Gender

To begin the investigation of how diversity is incorporated into the social structure of the first-year engineering course, we examined if and how student social behavior (in- and out-degree) was influenced by students' gender. In this study, "unknown" gender is a composite category comprised of students that did not provide their gender information on the CATME survey (NA, n = 21) and those that did participate in the survey (no response, n = 22). Descriptive statistics are provided in Table 1, for both in- and out-degree based on student's self-reported gender.

Table 1: Social interaction descriptive statistics based on gender.

		Female	Male	Unknown	Other/ Prefer not to answer
In-degree	*n*	136	491	43	5
	Mean	4.25	4	2.91	4
	Std. Deviation	1.82	1.85	1.82	1.41
	Median	4	4	3	5
	Minimum	1	0	0	2
	Maximum	11	10	6	5
	Skewness	1.22	0.62	-0.23	-0.42
	Kurtosis	2.21	0.36	-1.05	-2
Out-degree	*n*	110	325	16	2
	Mean	6.15	5.81	7.19	4.5
	Std. Deviation	3.21	3.15	7.38	0.72
	Median	5	5	4.5	4.5
	Minimum	3	2	4	4
	Maximum	29	31	27	5
	Skewness	4.11	4.38	2.04	0
	Kurtosis	23.52	28.72	2.39	-2.75

In-degree

The initial indication, based on Table 1, is that students of both genders were sought out (as measured by in-degree) by their peers equally. To confirm the observation that in-degree values were equivalent for both genders, KW testing was conducted. The results of the KW testing ($H(3) = 11.89$, $p = .01$) suggests that gender does have a significant influence on in-degree. The KW results indicate that gender influences in-degree values; however, it does not indicate between which pair(s) of observations the difference(s) exist. To determine where the difference(s) occur, *post hoc* Dunn's testing was carried out using BH FDR correction. The results presented in Table 2 indicate that difference between male or female and those with an unknown gender are statistically significant ($p^* = .0018$ and .0042, respectively [p^* adjusted *p*-values based on BH correction]).

The results suggest that students who choose to provide a gender identification (even if it was to indicate that they did not want to identify themselves) experienced a greater level of connection to the social environment than their peers that opted not to participate (median value of 4 and 3, respectively). A possible explanation of this phenomenon could be that choice to identify reflects the student's willingness to participate and belong to their engineering education community; therefore, they may make themselves more socially available than their peers that opted not to respond to the surveys.

Out-degree

Out-degree represents the sociability of the students. From the results in Table 1, we observe students have a greater number of outgoing ties than incoming. This results from the nature of SNA data and the survey response rate. Out-degree descriptives are based on only students that completed the SNA survey while in-degree descriptives are based on all students represented in the network. In this study, the social network represents all students enrolled in the class. If all students were to complete the SNA survey the total number of ties would be equal for both in- and out-degree. The descriptive statistics illustrate variability in student responses. The descriptive statistics also reveal that most students listed relatively few outward ties (data is highly leptokurtic and positively skewed), while a small percentage indicated many outward connections. KW testing was performed to determine if there were gender differences in out-degree. Results ($H(3) = 5.2661$, $p = .1533$) demonstrate that gender does not influence out-degree. The results of the KW test reveal that all genders of students seek social interactions equivalently.

Table 2: Post Hoc Dunn's testing results for in-degree and gender

	Female	Male	Other/ Prefer not to answer
Male	1.2916		
	0.1965		
Other/ Prefer not to answer	0.0531	-0.2246	
	0.4788	0.4934	
Unknown	3.4343	2.9910	1.2204
	0.0018*	0.0042*	0.1667

Notes Upper number is the pairwise z test statistic.

Lower number is the adjusted p-value based on the Benjamini- Hochberg correction (* indicates significance)

Race

Continuing the investigation into how the social structure of this first-year engineering design course includes diverse personnel, both in- and out-degree were tested for differences by race or ethnicity. Prior to analysis, composite groupings were created due to limited representation, this allows statistical power to be maintained while helping ensure parsimony. Groups included "unknown," which is comprised of students that either chose not to provide their racial identification (NA, $n = 21$) or chose not to participate in the data collection (NR, $n = 22$), as well as an "non-quorum" (NQ) which is comprised of students that identified as either Black ($n = 16$), Native American ($n = 7$), or that that actively declined ($n = 25$) to identify by marking the decline to participate option. The authors treated students that chose decline on CATME survey's race identification questions as being different from students where there is no racial identification response (NA or NR). This choice attempts to be respectful of the student's choice to not provide information yet still complete the survey. The remaining groups were White, Asian, and Hispanic. Descriptive statistics for both in- and out-degree are presented in Table 3**.**

In-degree

Examining in-degree (Table 3) it appears that Asian students (*M* = 4.57) were sought out slightly more than their peers, however, the difference is minimal. Initial observations suggest that in-degree is not influenced by race/ethnicity. KW testing was conducted to determine if race was a significant factor for in-degree. Results ($H(5) = 17.152$, $p = .00422$) provides evidence that race/ ethnicity has a significant influence on in-degree. To determine which racial groups, have different behavior *post hoc* Dunn's testing was conducted with BH FDR correction (Table 4). Dunn's testing revealed a statistically significant difference in median values between Asian and Unknown ($p^* = .0008$), Hispanic and Unknown ($p^* = .0049$) and White and Unknown ($p^* = .0118$). These results suggest that the overall network is inclusive of race/ethnicity. However, there is clearly an issue surrounding students that have an Unknown racial identification and those that identified as Asian, Hispanic or White. As stated previously this may reflect the students' willingness to participate in engineering's culture, although at this time no conclusive evidence, and presents a clear arena for future work.

Out-degree

Having established that social structure was receptive to diverse interactions, we tested to see if a particular racial group was more socially active than their peers. The descriptive statistics (Table 3) suggest that out-degree behavior is highly volatile (large standard deviations and range), positively skewed and extremely leptokurtic. KW testing ($H(5) = 5.6179$, $p = .3452$) concludes that out-degree values are not dependent on the students' racial/ ethnicity identification.

Table 3: Descriptive statistics for in- and out-degree based on race/ ethnicity identification.

		Asian	NQ	Declined	Hispanic	Unknown	White
In-degree	*n*	77	68	25	128	43	334
	Mean	4.57	3.87	3.8	4.12	2.91	3.97
	Std. Deviation	2.04	1.69	1.71	1.8	1.82	1.85
	Median	4	4	3	4	3	4
	Min	1	1	1	0	0	0
	Max	10	10	9	9	6	11
	Skew	0.83	0.97	1.17	0.4	-0.23	0.72
	Kurtosis	0.35	1.45	1.52	0.13	-1.05	0.84
Out-degree	*n*	60	44	13	86	16	234
	Mean	5.98	6.07	5.77	5.65	7.19	5.93
	Std. Deviation	2.18	4.51	2.2	3.34	7.38	3.07
	Median	6	5	5	5	4.5	5
	Min	3	3	2	3	4	3
	Max	12	29	11	31	27	29
	Skew	0.85	3.54	0.66	5.27	2.04	4.13
	Kurtosis	0.16	13.92	0.26	36.26	2.39	26.03

Table 4: Post Hoc Dunn's testing for in-degree by race/ethnicity identification.

	Asian	Declined	Hispanic	NQ	Unknown
Declined	1.7422				
	0.0873				
Hispanic	1.2043	-1.0937			
	0.1904	0.1865			
NQ	2.0510	-0.2553	1.1170		
	0.0604	0.3992	0.1980		
Unknown	3.8902	1.3501	3.2169	2.0493	
	0.0008*	0.1659	0.0049*	0.0505	
White	2.3644	-0.5706	1.4089	-0.4403	-2.8260
	0.0475	0.3279	0.2006	0.3534	0.0118*

Notes: Upper number is the pairwise z test statistic.
Lower number is the adjusted p-value based on the Benjamini-Hochberg correction (* indicates significance)

Discussion

Our study has shown that this first-year first-semester engineering design class's social structure has integrated all students in terms of race and gender. Having shown that there are no significant structural discrepancies in terms of either incoming or outgoing social ties. Therefore, the social environment of the OEL appears to be inclusive for diverse students based on network measures of student interactions. While we cannot speak to what occurred during the student interactions, the pattern of the interactions suggests that all students interacted equally in the social network within the OEL.

Recent literature [25] discussing the changing attitudes of students about diversity has highlighted that students are pushing the definition of diversity away from traditional physical characteristics (e.g., gender, race/ethnicity) and are instead viewing diversity through the lens of cognitive diversity (i.e., diverse mindsets) [26]–[28]. Millennials and younger generations are approaching the topic of diversity from the point-of-view that everyone has different experiences and insights [29]. This changing focus on how diversity is defined and operationalized by students entering engineering may explain some of these results. Our study shows that students seek out and are sought out by their peers equally in terms of race/ethnicity and gender. The findings suggest that students work with people they value as peer and collaborator regardless of their demographic characteristics.

While we are not able to state how interpersonal interactions shape students' perceptions of engineering climate from this analysis, these findings are encouraging. The data suggest that students are developing robust and diverse social networks. Several studies have shown that academic success is positively correlated with participation in the social network [10], [30]–[33]. The creation of a heterogenous social network means that students have opportunities to interact with a broad range of students. Previous work in the OEL [18] revealed that approximately 20% of all social ties are between students in different lab classes within the main course, combining this result with the current study indicates that the social environment is open and receptive to collaboration across a wide range of personal characteristics.

Paralleling the results of this study, Rodriguez and colleagues (2017) in a qualitative study looking at how diversity effects engineering teaming experiences, concluded that students are willing to work with a diverse group of peers. Simultaneously, while open to working with diverse students and in diverse teams it was discovered that engineering students often prioritize task completion over developing interpersonal connections and skills. Combing these recent studies suggest that engineering is primed and willing to become more inclusive of its diverse members but may be missing the interpersonal skills required to shift the climate to become more inclusive [34]. While making the case for increased diversity and inclusion from a social justice and equality stance is important for helping shift attitudes, engineering's cultural influence may be muddling this message [35]. Utilizing the task-driven nature of engineering, the case for diversity may be better received through explicitly linking the cognitive benefits of diversity to improved engineering outcomes. That is shifting the conversation to better align with unique cultural influences of engineering. The OEL has created a social environment that is demonstrating structural signs of cultural warming for diverse students, while we cannot pinpoint the exact cause, the literature suggests that all students and engineering will benefit from an inclusive social network.

Implications

The social structure of this first-year first-semester engineering course shows that students are receptive to interacting with diverse peers. Understanding the nature of these interactions and how they influence a student's psychological state (e.g., belongingness, diversity sensitivity) and their position within the social network, will further develop an understanding of the complex social settings that are present in a university setting. Additionally, the results of an SNA study could provide insight into how instructional practices may or may not support students in the development of inclusive teaming practices. While it is unclear if the inclusive environment described here is a result of a changing student body or the concentrated efforts of the institution; we have shown that encouraging and supporting opportunities to work with diverse students has resulted in an inclusive social structure.

Limitations and Future Work

The data presented here does not directly address what occurred during the student interactions, although we do assume that the interactions were productive. This assumption is based in part due to the nature of the questions asked, "With whom did you have a meaningful interaction

with?” Future work will scrutinize the nature of the interactions through both more advance SNA techniques (e.g., homophily, dyadic and triadic nature of interactions) and triangulation with qualitative interviews. Future work will also examine how a student’s position within the network influences their feelings of belongingness in engineering. The addition of affective traits (e.g., belongingness, cultural sensitivity) as nodal attributes will provide insight into how the social structure self-organizes around these traits. As well as offer awareness of how a student’s position within the social network acts to support or hinder an inclusive environment.
While we have demonstrated that this first-year engineering course’s social structure is inclusive of both race and gender, there are opportunities to develop a more robust understanding of how diversity is included in the social structure. The current study examined both in- and out-degree in terms of the overall social network. Other SNA metrics are available that can shed light on how information is disseminated and can identify the students that work to bridge otherwise isolated groups. These individuals may act as gatekeepers or allies in the support of developing a more diverse and demographically representative engineering population. Understanding who these central students are and how they are positioned in the social structure may lead to improving and understanding the overall social structure.

It is important to note that data presented here is from a single time point early into the students’ engineering experience. The social structure of an environment is dynamic living thing evolving as students come and go. Future work should include a longitudinal study of how the social structure changes as students become more indoctrinated into engineering culture.

The continued investigation using SNA should examine the homophily of ties, while it has been shown that neither race nor gender significantly impacts in- or out-degree we do not know if the observed behavior results from multiracial interactions or between different genders. Following this line of reasoning future analysis should shift away from traditional broad demographic categories and utilize the more inclusive terms as suggested by [36]. To better understand the experiences of a broad range of students, we need to explore inclusivity based on markers that students identify with rather than broad bins that may not represent their identities. Building on students shifting perceptions of diversity, further exploration is needed is to understand how the social structure supports cognitive and affective diversity. SNA provides a unique opportunity to map and understand how differing affective profiles come together or repeal each other to help solve engineering problems.

Conclusions

The examination of the social structure of this first-year engineering design course has revealed that it is receptive to social interactions (both incoming and outgoing) in terms of gender and race/ethnicity. The results indicate that neither race nor gender is a significant factor for in-degree (popularity). That data also suggest that race/ethnicity may play a role in out-degree (sociability). Analysis of out-degree revealed that the median values of Asian, Hispanic and White students are significantly different than the students where racial identification was unavailable. The SNA investigation of this first-year first-semester engineering design class suggests that social structure of the OEL is inclusive of both race and gender. This study has revealed that first-year engineering students when encouraged and afforded the opportunity to work in an OEL with a diverse group of students, create inclusive social networks.

While these initial relationships have given insight into how students work together in a collaborative engineering class, at the beginning of a semester, these trends may or may not persist over the course of the semester. Future work includes examining the network dynamically over three points throughout the semester. Overall, our work indicates that students have regular opportunities to interact with people who are diverse in their first-year engineering course. Fostering productive interactions, similar to those found within this network, may provide ways to make engineering environments become an educational environment that is inclusive of a more demographically representative population.

Acknowledgments

This work was supported by the U.S. National Science Foundation through grants EEC-1531586 and EEC-1531174. The opinions expressed are those of the authors and do not necessarily represent those of the NSF. The authors wish to thank the participants of the study and the PriDE and STRidE research groups. We also wish to thank Mr. Justin Major for assistance with data collection.

References

[1] G. M. Walton, C. Logel, J. M. Peach, S. J. Spencer, and M. P. Zanna, “Two Brief Interventions to Mitigate a ‘chilly climate’ Transform Women’s Experience, Relationships, and Achievement in Engineering.,” *J. Educ. Psychol.*, vol. 107, no. 2, pp. 468–485, 2015.

[2] D. Collins, A. E. Bayer, and D. A. Hirschfield, “Engineering Education For Women : A Chilly Climate,” *Women in Engineering Conference : Capitalizing on Today’s Challenges - 1996 WEPAN National Conference*. pp. 323–328, 1996.

[3] C. E. Foor, S. E. Walden, and D. a. Trytten, “‘I wish that I belonged more in this whole engineering group:’ Achieving individual diversity,” *J. Eng. Educ.*, no. April, pp. 103–115, 2007.

[4] “ABET.org,” 2018. [Online]. Available: www.abet.org. [Accessed: 20-Aug-2002].

[5] A. L. Antonio, “Diversity and the Influence of Friendship Groups in College,” *Rev. High. Educ.*, vol. 25, no. 1, pp. 63–89, 2001.

[6] M. E. Riedlinger, C. Gallois, S. Mckay, J. Pittman, and J. Pittam, “Impact of social group processes and functional diversity on communication in networked organizations,” *J. Appl. Commun. Res.*, vol. 32, no. 1, pp. 55–79, 2004.

[7] J. Gilleard and J. D. Gilleard, “Developing Cross-Cultural Communication Skills,” *J. Prof. Issues Eng. Educ. Pract.*, vol. 128, no. October, pp. 187–200, 2002.

[8] C. Patterns, “Communication Patterns in Task-Oriented Groups,” *J. Acoust. Soc. Am.*, vol. 22, no. 6, pp. 725–730, 1950.

[9] P. A. Simon, S. Finger, D. Krackhardt, D. P. Siewiorek, and A. Smailagic, “Levels of Social Network Analysis and Small Team Problem Solving in the Classroom,” *ASEE Annu. Conf. Expo. Conf. Proc.*, 2015.

[10] J. Y. Tsai, D. A. Kotys-Schwartz, and D. Knight, “Introducing Actor-Network Theory Via

the Engineering Sophomore Year," in *American Society for Engineering Education Annual Conference & Exposition*, 2015.

[11] M. Kenny Feister *et al.*, "Exploring the Social Processes of Ethics in Student Engineering Design Teams," in *ASEE Annual Conference and Exposition, Conference Proceedings*, 2015, p. ID# 13322.

[12] E. Brewe, V. Sawtelle, L. H. Kramer, G. E. O'Brien, I. Rodriguez, and P. Pamela, "Toward equity through participation in Modeling Instruction in introductory university physics," *Phys. Rev. Spec. Top. - Phys. Educ. Res.*, vol. 6, no. 1, 2010.

[13] S. Wasserman and K. Faust, *Social network analysis : methods and applications*, vol. 24. 1994.

[14] D. Z. Grunspan, B. L. Wiggins, and S. M. Goodreau, "Understanding classrooms through social network analysis: A primer for social network analysis in education research," *CBE Life Sci. Educ.*, vol. 13, no. 2, pp. 167–178, 2014.

[15] B. B. Potts, "Book Review: Social Network Analysis," *Acta Sociolgica*, vol. 37, no. 4, pp. 419–423, 2015.

[16] Army, *FM 3-24 MCWP 3-33.5 Insurgencies and Countering Insurgencies*, 1st ed. Washington .D.C.: Department of the Army, 2014.

[17] E. Williams, E. Brewe, J. P. Zwolak, and R. Dou, "Understanding Centrality: Investigating Student Outcomes within a Classroom Social Network," in *2015 Physics Education Research Conference Proceeding*, 2015, pp. 375–378.

[18] N. Pearson, A. Godwin, and A. Kirn, "Developing an Instrument to Understand the Social-Structural Integration of Developing an Instrument to Understand the Social-Structural Integration of Diverse Students," *ASEE Annu. Conf. Expo.*, 2016.

[19] E. Brewe, L. Kramer, and G. O'Brien, "Investigating student communities with network analysis of interactions in a Physics Learning Center," *AIP Conf. Proc.*, vol. 1179, pp. 105–108, 2009.

[20] V. Sawtelle, E. Brewe, and L. H. Kramer, "Exploring the Relationship Between Self-Efficacy and Retention in Introductory Physics," *J. Res. Sci. Teach.*, vol. 49, no. 9, pp. 1096–1121, 2012.

[21] B. Rienties and D. Tempelaar, "Turning Groups Inside Out: A Socail Network Perspective," no. November, 2017.

[22] M. L. Loughry, M. W. Ohland, and D. J. Woehr, "Assessing Teamwork Skills for Assurance of Learning Using CATME Team Tools," 2014.

[23] Y. Benjamini and Y. Hochberg, "Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing," *J. R. Stat. Soc.*, vol. 57, no. 1, pp. 289–300, 1995.

[24] A. Dinno, "Nonparametric Pairwise Multiple Comparisons in Independent Groups Using Dunn ' s Test," *Stata J.*, vol. 15, no. 1, pp. 292–300, 2015.

[25] C. Smith and S. Turner, “The Radical Transformation of Diversity and Inclusion The Millennial Influence.” 2015.

[26] A. Taylor, R. Waters, S. Bhaduri, B. Lutz, and W. Lee, “Student Attitudes about Diversity : ‘ If the field of engineering were more diverse , what would that mean for you ?,’” 2017.

[27] S. A. Williams, B. Lutz, C. Hampton, H. M. Matusovich, and W. C. Lee, “Exploring Student Motivation towards Diversity Education in Engineering,” 2016.

[28] B. Benedict, D. Verdín, A. Godwin, and T. Milton, “Social and Latent Identities that Contribute to Diverse Students ’ Belongingness in Engineering,” no. 1554057, 2017.

[29] H. Rodriguez-Simmonds, N. Pearson, J. Rohde, K. Vealey, A. Kirn, and A. Godwin, “Forget Diversity, Our Project is Due,” *ASEE Annu. Conf. Expo.*, 2016.

[30] N. M. Tichy, M. L. Tushman, and C. Fombrum, “Social network analysis for organizations,” *Acad. Manag. Rev.*, vol. 4, no. 4, pp. 507–519, 1979.

[31] R. Reagans, E. W. Zuckerman, R. Reagans, and E. W. Zuckerman, “Networks , Diversity , and Productivity : The Social Capital of Corporate R & D Teams,” vol. 12, no. 4, pp. 502–517, 2018.

[32] M. W. Ohland and R. Andrew Long, “The Impact of Social Integration on Engineering Students’ Persistence, Lon- gitudinal, Interinstitutional Database Analysis. The Impact of Social Integration on Engineering Students’ Persistence, Analysis of a Longitudinal and Multi-institution Database.”

[33] J. A. Middleton *et al.*, “Examining the Relationship between Faculty Teaching Practice and Interconnectivity in a Social Network,” 2015.

[34] A. Godwin, A. Kirn, and J. Rohde, “Awareness without action: Student attitudes after engeineering teaming experiences.,” *Int. J. Eng. Educ.*, 2017.

[35] S. E. Page, *The Diversity Bonus: How Great Teams Pay Off in the Knowledge Exonomy*. 2017.

[36] T. Fernandez, A. Godwin, J. Doyle, A. Kirn, L. Benson, and G. Potvin, “More Comprehensive and Inclusive Approaches to Demographic Data,” 2016.