2021 ASEE ANNUAL CONFERENCE
Virtual Meeting | July 26–29, 2021 | Pacific Daylight Time
Paper ID #33059

Work in Progress: An Investigation of the Influences of Peer Networks on Engineering Undergraduate Performance Outcomes

Mr. Jack Elliott, Utah State University

Jack Elliott is a concurrent M.S. in Engineering (mechanical) and Ph.D. in Engineering Education student at Utah State University. His M.S. research is in experimental fluid dynamics including the application of PIV, and his Ph.D. work examines student collaboration in engineering education.

Dr. Angela Minichiello P.E., Utah State University

Angela Minichiello is an assistant professor in the Department of Engineering Education at Utah State University (USU) and a registered professional mechanical engineer. Her research examines issues of access, diversity, and inclusivity in engineering education. In particular, she is interested in engineering professional formation, problem-solving, and the intersections of online learning and alternative pathways for adult, nontraditional, and veteran undergraduates in engineering.

Dr. Joshua D. Marquit, Penn State Brandywine

Dr. Marquit is an Associate Teaching Professor and Program Liaison of the Psychology Department at Penn State Brandywine in Media, Pennsylvania. He has a doctoral degree in experimental and applied psychological science. He teaches courses in statistics, research methods, environmental psychology, industrial-organizational psychology, and psychology and climate change; and has recently won The Distinguished Teacher/Excellence in Teaching Award in 2019. He has conducted collaborative research in a broad arena of topics in environmental, social, health, sports, organizational, educational, gender, space, and clinical psychology. The results of his research have been presented to government agencies and at professional conferences at the local and international levels and published in peer-reviewed journals.

Work in Progress: An Investigation of the Influences of Peer Networks on Engineering Undergraduate Performance Outcomes

Introduction

The improvement of engineering students' learning through collaboration has theoretical foundations in social learning theory [1]. Further, students' ability to effectively work in a team is a required outcome for all U.S. accredited engineering programs [2]. Research suggests that when collaborative learning (i.e., working with peers) is implemented in undergraduate engineering courses, students show increased engagement with course material [3] and improved academic performance [4].

Despite these promising results, current engineering education research regarding group work and collaborative learning is limited. Existing work has typically employed quasi-experimental approaches and/or collected data using a single class or time sample. There is evidence [5, 6] that student learning networks extend beyond classrooms; these studies suggest that overly bounded approaches may not capture the range of potential effects of student collaboration. Further, existing research has often compared individual student's network traits to a net or aggregate performance (i.e., average course grades or average performance on a test) [7]. These group level performance comparisons have further limited the discovery of individual and contextual group work effects. Today, more research is needed to understand how engineering students form informal learning networks and the impacts these networks have on individual student outcomes (i.e., GPA, attrition).

To this end, this proposed study seeks to expand current understandings of group work effects, including the influences that student peer networks have on each other and student performance outcomes in undergraduate engineering education. Deeper understandings of these relationships will enable engineering educators to make more informed decisions regarding undergraduate pedagogy related to group work and collaboration for improving student retention and performance. Specifically, this proposed research project will investigate relationships that exist between students' formal peer networks, informal peer networks, social peer networks, GPA, and attrition through a two-year dynamic social network analysis of freshmen and sophomore level engineering students at the university of interest. To develop deep understandings of student motivations for their peer interaction preferences and peer network choices, this study will include two series of focus group interviews with engineering students who have participated in the social network analysis.

Literature Review

Within the engineering education literature, student group work has been positively related to student performance overall [4, 8-10]. Studies further indicate that certain types of group work are necessary for the positive effects to appear. For example, Grohs et al. [8] found that the highest performing students spent more time solving problems independently and engaged in small (one to two peer) interactions for only small amounts of time. In the same course, students who increased their performance over time also reported increases in peer collaboration over the same timeframe. Ellis et al. [9] found that those students who reported deep understanding of course material and collaborated with peers had more dense sub-networks than their peers. Zhu and Zhang [10] found that a higher reciprocity of interactions during small group work resulted in better group project performance. Hsiung [4] found instructor led group work resulted in higher quiz performance, but only after the groups were well established (met for several weeks). Taken together, these results suggest that small, densely connected sub-groups relate to general increases in student performance. In addition, groups may need to develop over time for this effective collaboration to occur.

Currently, the group work literature also suggests that not all students believe interactions with peers deepen their understanding of course material [3, 11, 12]. Negative perceptions of group work have been reported in surveys and/or focus groups. Examples of these negative group work perceptions include student behaviors such as freeloading and producing work without contributing [12]. As well, these negative perceptions have been reported by students within both high and low performing groups. Lower performers, however, generally reported disliking the group work, while high performers reported more positive impressions overall. As, these results were limited to a single course, they may reflect participants' grades more than their true perceptions.

There are several limitations to the current student group work and collaboration literature. Most notably, current studies limit data collection to single semesters and/or to single courses, and therefore do not capture the longitudinal effects of collaboration. We identified only one study [6] that extended data collection beyond a single semester. This study reported that student network connectedness continued to develop throughout students' freshmen, sophomore, and junior years; network connectedness later dropped during the students' senior year. This study also noted that living proximity was a common motivator for gaining/losing connections [6]. While these results provide valuable insights, the context of this study, which was a university located on an offshore island in Taiwan with a small sample size (N = 51), may have influenced its findings in ways that do not readily transfer to public university contexts in the United States.

Implications of the Literature Review for the Proposed Study

Quantitative networks developed through convenience volunteer sampling and self-report name generator surveys have been shown to provide a large network data which maximizes student participation. For example, researchers [6] described longitudinal network development through four years of a traditional engineering degree, showing how networks extend beyond a single class in time and proximity [6]. This study, however, was limited in the sense that researchers surveyed students only once per year, and did not capture the changes in student networks that occur during semesters [4, 8]. Others [4, 8, 9, 11, 12] suggest the freshmen and sophomore years of engineering programs of study are critical times in the formation and establishment of their peer networks.

To extend the literature, the proposed study seeks to investigate the varied, time-based effects of student collaboration by generating longitudinal records of student interactions. Longitudinal data generation will be accomplished by querying students about their interactions multiple times during a semester, over several semesters. Moreover, the proposed study will prioritize data generation during the impactful freshmen and sophomore years for network development [6]. Finally, unlike most existing studies, the proposed study will aim to employ inferential statistics to contrast network characteristics of different demographics (e.g., Gender, Race, Ethnicity, Marital Status, etc.).

While the positive potential for group work has been both quasi-experimentally [4] and non-experimentally observed [8-10], data related to student preference has shown that high and low performing students exhibit both positive and negative perspectives of group work [11, 12]. To investigate trends in student success across varying group work strategies, the proposed study will adopt data clustering techniques [8, 9] during analysis to account for student preference and success across study strategies. In addition, based on Li's [6] finding that friendship network effects influenced the study network effects, the proposed study will further distinguish between the multiple peer network types.

Among the papers reviewed, several included qualitative methods to better inform quantitative findings [3, 11, 12]. Focus group discussions allow researchers to concurrently gather topic-specific data through observation of a number of participants simultaneously, which can increase the breadth of data collected while avoiding extreme points of view [13]. As well, the broader, exploratory purpose of this research is more suited to focus groups than more narrowed individual interviews/surveys [13-15]. For these reasons, the proposed study will include qualitative focus group methods. While Chang and Brickman [12] purposefully grouped participants by performance, we will group participants along the clustering dimension of interest (group work preference) to ensure constructive and open conversation regarding each group work level, then by students' GPA.

Research Questions

The purpose of this proposed study is to identify the influences of peer-to-peer interactions on individual engineering student performance (i.e., engineering course GPA and attrition) over time. To accomplish this goal, this study will be guided by the following research questions (RQ):

(1) What relationships exist between the performance outcomes (engineering course-specific GPA and attrition) and peer network characteristics of freshmen and sophomore level engineering students?

(2) What relationships exist between the formal (course-required) peer study networks, informal (outside of course) peer study networks, and social (i.e., friendship) peer networks of these students over time?

Methods

To answer these research questions, this proposed longitudinal study will apply Social Network Analysis (SNA) to develop qualitative sociograms and quantitative characteristics of freshmen and sophomore engineering students' peer interaction networks from self-report survey responses over a period of two years. This study will use statistical cluster analysis methods to group participants by performance and network characteristics. In addition, we will conduct ANOVA to contrast clusters and individuals' performance, including factorial ANOVAs to investigate possible differences in study outcomes by participant demographics. Finally, these quantitative results will be considered in development of focus group interviews to determine student motivations for their interactions preferences.

To explore the breadth of students' motivations behind the quantitative findings of this study, we will conduct a series of focus group interviews during the second semester of each study year (two in total). Our purposeful and pragmatical sampling (as described by Emmel [16]) will include separating willing participants (identified in the quantitative survey) into nine groups. The groups will first be decided by those who report studying alone (study network out-degree of zero), studying in small groups (study network out-degree between one and four), and studying in larger groups (study network out-degree greater than four). Recognizing the importance of performance on students' responses [12], we will then separate students into groups of high, (80th percentile of GPA) average (20th to 80th percentile of GPA), and low (below 20th percentile of GPA) performance. Within these nested performance groups, we will identify the maximum willing (up to ten) participants per group (nine total combinations or groups each year) to participate in focus group interviews.

Questions for the focus group interviews will be developed from the emerging quantitative results and the research questions. We will conduct focus group interviews with two researchers and up to ten participants. Employing two researchers per focus group will allow one researcher to fully engage with the participants in discussion, while the other researcher manages the audio/video recording, note taking and administrative tasks. After each interview both researchers will conduct immediate memoing [13] and audio/video transcription and verification.

Participants

Population Demographics

The context of the proposed study is a large, public, land grant university located in the western United States. The college of engineering at this university offers ABET accredited undergraduate engineering degree programs in biological, civil, environmental, electrical, computer, and mechanical engineering. Demographics of the undergraduates enrolled in the college of engineering at this university historically include gender: 85% male and 15% female; race/ethnicity: 90% White, 4% Hispanic, 3% two or more races, and 1% Asian (remaining chose not to disclose or account for less than 1%); residency: 84% State resident and 16% non-resident; status: 89% full-time and 11% part time [17]. This research will be conducted using a protocol approved by our university's institutional review board. For ethical reasons, only students over the age of 18 will be invited to participate in this study.

Recruitment Procedures

Clear identification of students who are freshmen (i.e., 1st year) and sophomores (i.e., 2nd year) in the engineering program can be difficult for administrators to accomplish due to the varied credits inside and outside of engineering students prior to enrollment. However, at the university where the proposed study will be conducted, engineering students must be formally accepted into a major-specific professional program prior to enrolling in junior level (i.e., 3rd year) engineering courses. Therefore, we intend to use the student identification numbers of all students working toward entrance into the engineering professional programs as means to identify freshmen and sophomore engineering students to recruit for this study. In this way, we expect the number of participants to reflect the larger freshmen and sophomore engineering student population attending the university.

During the 2019-2020 academic year, there were approximately 1,900 undergraduate students enrolled in the College of Engineering. Approximately 1,200 of these undergraduates met the participant inclusion criteria (i.e., undergraduates who were working toward, but not yet accepted into, an engineering major professional program). Our prior SNA survey work [5] conducted at this university employed volunteer convenience sampling of sophomore engineering students. During this study, we achieved longitudinal response rates between 53% to 78% when participation was incentivized through course extra credit [5].

While these previously attained response rates (i.e., 53% to 78%) can be considered high for survey research generally, SNA is sensitive to network completion and, thus, student participation [18]. Therefore, to maximize student participation and participant retention in this proposed study, we will employ the following specialized procedures that are based on our previous experiences researching with engineering undergraduates at this university:

- Integrate invitations to participate and survey informed consent and into a familiar platform (i.e., a Canvas course) that is easily accessible and already a part of students' everyday course workflow.
- Introduce the research project and its motivation through a short, informational video at the beginning of each semester in common foundational level engineering courses.
- Employ support from engineering student government, ambassadors, etc. and include survey reminders in weekly engineering announcements, video presentations at engineering events, and flyers hung in university engineering buildings.
- Incentivize survey participation through random drawings for one $100 dollar gift card and two $50 gift cards per survey iteration.
- Incentivize survey participation though course extra credit.

To invite all freshmen and sophomores in the college of engineering to participate in the study, we will automatically enroll students identified by college administrators as working toward entrance to the professional program in the LMS "course". This "course" will describe the study, data collection methods, motivations, and methods for opting out. We will use this platform to obtain informed consent, as well as to encourage ongoing participation in the study through course announcements sent to all students enrolled in this "course" as a reminder before for each survey iteration.

Study Variables

Independent variables for the quantitative (survey) portion of this study will consist of SNA *measures* (quantitative descriptive values calculated for individuals or networks in SNA), time, interaction type (i.e., face-to-face or online) and participant demographics. In SNA, *nodes* describe an individual or group of interest, and *ties* represent their weighted, directed interaction. The SNA individual (node-specific) measures of interest include *in-degree* (the number of connections toward a node), *out-degree* (the number of connections leaving a node), *total-degree* (the combined number of connections leaving or entering a node) interactions, and *eigenvector centrality* (a weighted measurement of a node's total influence on a network). Sub-network measures of interest include *reciprocity* (the likelihood of interactions being shared across members in a network), *density* (the number of ties in a network relative to the maximum possible connections), *clique size* (the number of nodes in a network of fully interconnected nodes), and *sub-group size* (the size of a clique which has an allowed count of missing ties). Participant demographics will include age, race, gender, ethnicity, veteran status, and marital status.

Dependent variables will consist of participants' course performance outcomes (i.e., an engineering course specific GPA calculated to avoid potential bias incurred from including outcomes from general education courses), retention (i.e., continuation in the engineering program to the following semester), and cluster(s). K-plex sub-group identification will provide clusters of student sub-groups (well-connected groups of students) and modularity clustering will provide clusters of participant performance paths.

Survey Data Collection Procedures

In addition to gathering informed consent and participant information, Qualtrics surveys will be used to identify participants' informal (A), formal (B), and social (C) peer network connections as shown in survey excerpt provided in Figure 1.

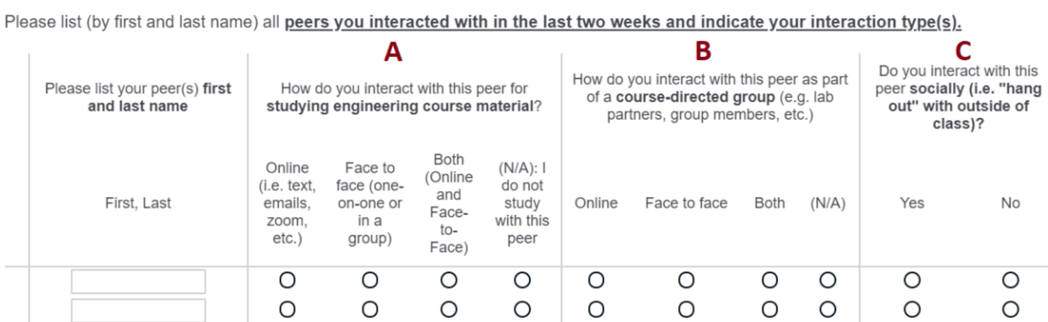

Figure 1. Qualtrics survey question(s) to query students about their peer interactions.

Peer network development surveys will be sent out in Canvas for a week at a time, every three weeks, for a total of five iterations per semester. After each semester, the university registrar's office will provide researchers with the participants' engineering specific GPA, retention across semesters, and demographics (i.e., age, race, gender, ethnicity, veteran status, and marital status). In addition, first and second year course instructors will provide lists of any formal peer groups they facilitate in their courses at the end of each semester (this timing will help to account for students' course attrition and changes in groups throughout the semester). We will implement these data collection procedures during the Fall 2021, Spring 2022, Fall 2022, and Spring 2023 semesters over a total of four consecutive semesters.

Survey Data Analysis

Research Question 1

To identify relationships between the performance outcomes and peer network characteristics of freshmen and sophomore level engineering students qualitatively, we will develop sociograms that describe each SNA measure of interest using Gephi [19], (a software package designed to perform SNA). To help visualize differences within the SNA measures, sociogram node sizes will be increased according to the SNA measure of interest (e.g., when viewing eigenvector centrality (EC), the node with the highest EC will be largest, and the node with the lowest EC will be smallest). Nodes will be filled with color scales corresponding to their engineering GPA, (i.e., red indicating the lowest value GPA across all networks [to be identified post hoc], and blue will indicate a 4.0, with a linear gradient between these values, black indicating attrition from the program). These color and size scales will be constant across all sociograms to allow consistent comparisons across iterations. Force Atlas spacing applied at the iteration with the largest network (by node count, to be identified post hoc) will provide sociograms which have minimal overlapping ties and node positions across all sociograms will be constant across all SNA measure inquiries according to these positions identified at the largest network.

When viewing clusters, spacing will be determined first by the cluster each node belongs to, and second by the Force Atlas 2 spacing algorithm. Node outline colors will indicate cluster belonging. Nodes' performance value and SNA measures of interest in cluster visualization will continue to be indicated by node fill color and size, respectively.

To identify relationships between the performance outcomes and peer network characteristics of freshmen and sophomore level engineering students quantitatively, we will identify correlations of individual and sub-network SNA measures to performance. Anticipating cluster analysis as a requirement for statistically significant relationships [8, 9], we will conduct cluster analysis of participants into interaction sub-networks (small groups of well-connected participants) using k-plex clustering. Correlations of clusters' SNA measures to performance and review of underlying distributions will provide relationships between SNA measures (sub-network and actor level) and performance. Modularity cluster analysis, to be accomplished in Gephi [19], will provide mixed performance and SNA measure clusters. These performance paths will be contrasted using one-way ANOVA to identify significant differences across group work strategies. To explore any network differences across gender race, etc., we will also complete a factorial ANOVA (specific F-test depending on underlying distributions) to contrast demographic variables against performance and SNA measures of interest.

Research Question 2

To identify relationships between the formal, informal, and social peer networks over time quantitatively, we will create a dynamic network composed of the discrete networks from each survey iteration. Network changes across each peer sub-network will be compared to the precursor peer networks of the other two types (e.g., a new informal network edge will be searched for in the prior iterations' formal, and social networks). Cluster analysis will compare changes in GPA per participant to changes in each peer network, similar to the performance path clustering performed by Grohs, Knight, and Soledad [8].

To identify relationships between the formal, informal, and social peer networks over time qualitatively, we will overlay the formal, informal, and social peer networks for each iteration, continuing with performance indicated by color and using network *edge* (the graphical representation of a tie) colors to indicate the nature of the tie (e.g., green edges indicate formal ties, orange edges indicate informal ties, and purple edges indicate social ties). Multiple ties across the same node pairs will be indicated on the sociogram (e.g., if two nodes share formal and social ties, both edges will appear). To identify the potential influence of interaction type (i.e., online or face-to-face), we will also compare the sociograms with each interaction type isolated.

To provide a scale of responses and overall network traits through time, we will identify network-wide SNA measures (total edge count, overall density, etc.) at each survey iteration and compare these raw values to those normalized by iteration node count to account for increases/decreases in survey participation over the data collection period.

Qualitative Focus Group Interview Analysis

Once the recordings are transcribed and the transcriptions are verified, the research team will open code the transcripts using first cycle in vivo coding strategy. As Saldana [20] points out, in vivo coding is a practical method for introducing novice coders to qualitative analysis. The use of in vivo coding will also help to retain the participants' voice [20] throughout the separate (axial and versus) first to second cycles. The second cycle of coding will be axial coding. Axial coding seeks to understand the properties and dimensions of categories: "Properties (i.e., characteristics or attributes) and dimensions (the location and property along a continuum or range) of a category refer to such components as the conditions, causes and consequences of a process" [20]. We will apply axial coding to explore the categories identified through focused coding and identify emerging themes in each group.

The final coding stage will be axial coding to find themes which are common across groups. Upon completion, in vivo codes not aligned with axial codes will be analyzed on a group-by-group basis through a second stage of versus coding. "Versus codes identify in binary terms the individuals, groups, social systems, organizations, phenomena, processes, concepts, etc. in direct conflict with each other" [20]. Given the inherent contrasts of groups' study preferences (with or without peers) this final versus coding stage of unique codes will allow the researchers to identify contrasts which exist against the axial codes and responses given by each group work preference. Each coding stage will include measures of interrater reliability to ensure coding quality.

Pilot Study Findings

To refine our study methods in preparation for data collection starting in the Fall 2021 semester, we are currently (Spring 2021) piloting the full recruitment and survey data collection procedures among current freshman/sophomore engineering students. Issues we are uncovering include low survey response rates and the potential skewing of results due to COVID-19 complications. Casquero, Ovelar, Romo, and Benito [21] observed (in a face-to-face context) that the traits of group work vary between face-to-face and online educational contexts [22]. As all courses for engineering students at our university are currently online, we recognize that the ongoing pilot recruitment results are likely to be different from the main recruitment study (anticipating that courses will return to primarily traditional format in the fall 2021 semester). Current low survey response rates may also result from campus and course restrictions due to COVID-19. Although we anticipate an increase in survey responses as traditional format returns, we also intend to include additional incentives in the form targeted course extra credit to ensure we maximize participation.

To further inform refinements of the study survey, we included an open response request for feedback on the survey. Early observation of these open-ended responses show COVID-19 as the most frequent issue referenced in survey responses. Pilot study participant responses include:

- "Covid has made it really difficult to network with engineers in person. So while I do have several people I work with very frequently, I only know the real names of a select few of them."
- "I'm not much help on these. The one name is my lab partner. I just transferred from ____ so this is my first semester here at University and in all honesty I don't have many friends let alone study buddies due to the pandemic and not being able to go anywhere."
- "Whereas we have been online, it's been hard to really meet people so I don't have many which makes this survey a little hard."

Other pilot study survey responses also included valuable feedback, such as recommendations to use QR codes on survey flyers, support for distributing study information and surveys via the Canvas LMS, and appreciation for the generous gift cards as a major incentives. Another important observation was made that course incentivized and/or orchestrated groups would have a positive impact on some students by helping them overcoming social barriers (aligning with previous findings [5]):

> "It would actually be way cool if you took this opportunity to help make groups for people like me. I don't know where to go to search for friends, so it would be a good thing to have people make groups. I really don't know where to go to search for friends, so it would be a good thing to have people make groups."

Along with implementing the survey feedback, we plan to develop and implement a smaller scale longitudinal study in parallel with the main study described here to help us identify the motivations of students who chose not to participate in the surveys. The longitudinal nature of this parallel study will also help us to understand how these motivations change during the transition back to traditional formats.

Conclusions

This study will provide educators with a more complete understanding of how undergraduate peer-interaction networks form and evolve during the pivotal freshmen and sophomore years at a large public university. In addition, this study will identify relationships between network types and performance in engineering, while developing understandings of students' motivations behind their group work preferences. These understandings will better equip engineering educators and institutional leaders to design collaborative learning activities into their curricula in ways that are effective, lasting, and responsive to authentic student learning practices in engineering.

Acknowledgments

This material is based upon work supported by the National Science Foundation Graduate Research Fellowship Program under Grant No. DGE1745048. Any opinion, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

References

[1] A. Kozulin, *Vygotsky's Psychology: A biography of ideas*. Cambridge, MA: Harvard University Press, 1990.

[2] ABET. (2021, Jan 6 2021). *Criteria for accrediting engineering programs, 2020 - 2021*. Available: https://www.abet.org/accreditation/accreditation-criteria/criteria-for-accrediting-engineering-programs-2020-2021/

[3] W. Boles and K. Whelan, "Barriers to student success in engineering education," *European Journal of Engineering Education*, vol. 42, p. 368, July 01, 2017 2017.

[4] C. M. Hsiung, "The effectiveness of cooperative learning," *Journal of Engineering Education*, vol. 101, 01/01 2012.

[5] J. Elliott, A. Minichiello, and J. Ellsworth, "Examining relationships between student interactions with peers and resources and performance in a large engineering course using social network analysis," presented at the American Society for Engineering Education Annual Conference, Virtual Conference, 22-24 June, 2020.

[6] S. C. Lin, "Evolution of civil engineering students' friendship and learning networks," (in English), *Journal of Professional Issues in Engineering Education and Practice*, Article vol. 144, no. 4, 10 / 01 / 2018.

[7] S. A. Kalaian, R. M. Kasim, and J. K. Nims, "Effectiveness of small-group learning pedagogies in engineering and technology education: a meta-analysis," *Journal of Technology Education*, vol. 29, no. 2, p. 16, Spring 2018.

[8] J. Grohs, D. Knight, G. Young, and M. Soledad, "Exploring academic performance paths and student learning strategies in a large foundational engineering course," *International Journal of Education in Mathematics, Science and Technology*, vol. 6, p. 13, 2018.

[9] R. Ellis, F. Han, and A. Pardo, "When does collaboration lead to deeper learning? Renewed definitions of collaboration for engineering students," *IEEE Transactions on Learning Technologies*, vol. 12, no. 1, pp. 123-132, 01/01/ 2019.

[10] M. Zhu and M. Zhang, "Network analysis of conversation data for engineering professional skills assessment. Research Report. ETS RR-17-59," *ETS Research Report Series*, 12/01/ 2017.

[11] C. Damsa and M. Nerland, "Student learning through participation in inquiry activities: two case studies in teacher and computer engineering education," *Vocations and Learning,* vol. 9, 03/01 2016.

[12] Y. Chang and P. Brickman, "When group work doesn't work: insights from students," (in eng), *CBE Life Sciences Education,* vol. 17, no. 3, pp. ar42-ar42, 2018.

[13] J. W. Creswell and C. N. Poth, *Qualitative Inquiry and Research Design: Choosing Among Five Approaches*, 4 ed. Thousand Oaks, CA: SAGE Publications, Inc, 2018, p. 459.

[14] C. Glesne, *Becoming qualitative researchers: An introduction*, 5 ed. Boston, MA: Pearson, 2016.

[15] M. Patton, *Qualitative research and evaluation methods*, 3 ed. Thousand Oaks, CA: Sage Publications, 2002.

[16] N. Emmel, *Sampling and Choosing Cases in Qualitative Research: A Realist Approach*. London, United Kingdom: SAGE Publications, Ltd., 2013.

[17] USU. Utah State University: Enrollment [Online].

[18] S. P. Borgatti, M. G. Everett, and J. C. Johnson, *Analyzing Social Networks*. SAGE Publications, 2013.

[19] M. Bastian, S. Heymann, and M. Jacomy, "Gephi: an open source software for exploring and manipulating networks," presented at the International AAAI Conference on Weblogs and Social Media, 2009.

[20] J. Saldana, *Coding Manual for Qualitative Researchers*. SAGE Publications, 2009.

[21] O. Casquero, R. Ovelar, J. Romo, and M. Benito, "Reviewing the differences in size, composition and structure between the personal networks of high- and low-performing students," *British Journal of Educational Technology,* Article vol. 46, no. 1, pp. 16-31, 01// 2015.

[22] S. Dawson, ""Seeing' the learning community: An exploration of the development of a resource for monitoring online student networking," *British Journal of Educational Technology,* vol. 41, no. 5, p. 17, 2010.