Social Network Analysis of Undergraduate Education Student Interaction in Online Peer Mentoring Settings

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Abstract

This study uses social network analysis to examine the patterns of student interactions in online peer mentoring sites within an undergraduate teacher education program. The peer mentoring sites were developed to provide both newcomers and more experienced peers the opportunity to discuss, share, and learn both from and with one another. The study demonstrated that the online peer mentoring sites supported interaction among first-year and third-year students. In particular, the networks formed by these interactions were sparse; online students did not seek or share course-related advice and information across the sites as a whole, but were selective with those whom they sought out for support, information, or guidance. This study has implications for future research to determine why students chose to use the peer mentoring sites to interact with their peers and what these interactions provided them. Such data could inform the ways the sites helped support students both in their transition and advancement in the program, and could be useful in assisting future development of the peer mentoring sites and similar learning spaces.

Keywords: Online Learning, Peer Mentoring, Social Network Analysis, Undergraduates, UCINET

Introduction

The Internet acts as a forum for the exchange of information, and provides the structure, focus, and communities that support such exchanges (Haythornthwaite & Kendall, 2010; Rainie & Wellman, 2014). The past 10 years has also witnessed the consequent growth of knowledge communities and collectives over the internet. These collectives provide learning spaces that encourage and enable people not only to gain individual knowledge but also to contribute to its distribution (Gee, 2005; Thomas, 2010; Westberry & Franken, 2013). Advances in technology and pedagogical theory allow for the emergence of innovative programs to support student learning (Barab, 2003). One example of this type of programs is peer-to-peer interaction in educational settings or learning spaces many of which are online (Dirckinck-Holmfeld, Hodgson, & McConnell, 2012; Oblinger, 2005; Top, 2012). Online peer mentoring sites can connect students who are separated by time and location, and engage them in the process of social learning. Peer mentoring sites present opportunities for students to connect across academic levels and allow them to discuss their experiences, perspectives, thoughts, and questions with one other to the level at which they are comfortable. Given recent interests by academics and educational practitioners in such programs, it is becoming increasingly important to better understand how students interact in such settings.

Continuing systematic research efforts among online groups will identify, describe, and clarify the specific forms of social life within computer-supported environments and the related benefits, drawbacks, and consequences for participants, culture, and society (Faraj, Jarvenpaa, & Majchrzak, 2011; Feenberg & Bakardjieva, 2004b). Such research can then become the basis for future development of online communication forms toward socially-desired ends (Delwiche & Henderson, 2013; Feenberg & Bakardjieva, 2004a). Consequently, analyzing online peer mentoring site interaction serves to provide a better understanding of student interaction in such settings and the influences that these interactions may have on learning, especially in the specially-crafted student support mechanisms that a mentoring site provides.

Social network analysis (Scott, 2013; Scott & Carrington, 2011) is suited to analyzing online learning spaces and mentoring sites because of its focus on understanding the structure and composition of peer interactions and relationships. Furthermore, the study of the formation of different networks in online settings can assist in understanding the patterns of student behavior in online communal groupings (De Laat, Lally, Lipponen, & Simons, 2007; Renninger & Shumar, 2002; Shen, Nuankhieo, Huang, Amelung, & Laffey, 2008). This study will also serve to uncover the categories and forms that these networks assume, the characteristics of the interactions that contribute to the development of these networks, and the patterns that form as new members mature with the group. Unfortunately, very few studies have utilized social network methodologies in studying these forms of peer interactions in online mentoring sites. Thus, this study examines the ways that undergraduate teacher education students connect and interact in an online peer mentoring setting. Specifically, the study aims to:

1. Describe the structure of the online mentoring site. Is the network dense or sparse – are all students connected to each other, or only to a few others? Does information flow evenly within the network or only controlled by a few students?
2. Examine the role of individual students in disseminating information and advice within the network. Which students are the most (central) connected – the popular opinion leaders?

Literature Review

Learning is done collegially and socially through interactions with others and is mediated by the differences of perspective among co-participants (Lave & Wenger, 1991; Wenger, 2000). Meaning, understanding, and learning are all contained within active contexts, not self-contained structures (Lave & Wenger, 1991; Nemeth, 2014; Sadler, 2014). As Sfard surmises, thinking and interpersonal communication are joint endeavors, which by virtue of their recursivity, “gradually grow in complexity and support incessant, accruing transformations in other human activities” (Sfard, 2008, p. 115). People communicate to express themselves; to transmit information and to learn. But this search for information is often situated in social contexts (Cercone, 2014). In other words, along with these expressions come acculturation, and through this process, “knowledge and culture are perpetuated and transformed as we interact, define new problems, and take on new challenges” (Hoadley & Pea, 2002, p. 323). Oren describes social aspects of internet communication as facilitating the development of unique forms of interpersonal and group interaction (Oren, Mioduser, & Nachmia, 2002). Thus, social relationships with peers in an online setting may be the incubators for learning through collaboration (Hoadley & Pea, 2002). In online environments, acute development of interpersonal relations is necessary to foster the necessary social support needed to sustain a learning community (Domínguez-Flores & Wang, 2011; Haythornthwaite, 2012; Haythornthwaite, de Laat, & Dawson, 2013; Scherer Bassani, 2011).

Interaction and communication are central to the learning process because “ …social learning, process, thought, and knowledge involve the re-imagination of the individual’s identity as well as the re-imagination of the knowledge community” (Renninger & Shumar, 2002, p. 93). Computer-mediated communication offers individuals access to ties that are distant, but enriching, at a minimal cost (Houser, Fleuriet, & Estrada, 2012; Ling & Stald, 2010; Miczo, Mariani, & Donahue, 2011; Rainie & Wellman, 2014). Thus, technology affords participants a unique perspective “not defined by place or by personal characteristics, but by people's potential to learn together" (Wenger, White, & Smith, 2009, p. 11).

Social network analysis provides a vocabulary and set of techniques for understanding interpersonal interactions in communities, offline or online (Stephen P Borgatti, Mehra, Brass, & Labianca, 2009; Scott, 2013). Increasingly, social network approaches have shown how online interaction transforms, extends or augments face-to-face relations and impacts learning (Dimitrova & Koku, 2010; Haythornthwaite & Kendall, 2010; Rainie & Wellman, 2014). Analyzing interactions in fully online settings will broaden the exploration of the way that multiple participants in network settings form ties. From a network perspective, one may see the patterns of interaction through the direction of postings and the person-to-person interactions of all participants by studying the sociograms of the online communication patterns. The interactions can show the support and advising relations that develop among students, the communication patterns that develop as the students engage with their peers, and what results from their dilemma-motivated and practice-centered interactions. By viewing online settings as comprised of networks of relations, analysts can examine the types of interactions, e.g. information, emotional support, material support and companionship that affect online groups (Dimitrova & Koku, 2009; Haythornthwaite et al., 2013; Lee & Lee, 2010; Rainie & Wellman, 2014; Reagans & McEvily, 2003). As a result, this study uses social network analysis in its examination of interactions among peer learners in an online mentoring site.

Methods

Study Site and Participants

The participants of this study were drawn from an online Bachelor of Science Education Program at a medium-sized private university, located in a northeastern city in the United States. This university was founded in the late nineteenth century as a school for men and women to pursue educational opportunities in the arts and sciences. In 1996, this university began offering online degree programs. Currently, the university has approximately 25,000 students and offers undergraduate and graduate degree programs using fully online or hybrid models.

The program administrators of the online Bachelor of Science Education program observed students experiencing difficulty adjusting to this program. To address student questions and concerns, the program administrators developed and implemented an online peer-mentoring site in 2007 to facilitate communication between the instructor-led first-year pedagogy seminar course and those in third-year pedagogy seminar course. The online mentoring sites allow new and more experienced students the opportunity to engage in discussion and problem-solving situations. Study participants consisted of a purposeful sampling of first-year and third-year students enrolled in online mentoring sites on Blackboard™. Six peer mentoring sites were studied:

- Mentoring Site 1 (MS1): Fall 2008-09
- Mentoring Site 2 (MS2): Winter 2008-09
- Mentoring Site 3 (MS3): Fall 2009-10
- Mentoring Site 4 (MS4): Winter 2009-10
- Mentoring Site 5 (MS5): Fall 2010-11
- Mentoring Site 6 (MS6): Winter 2010-11

Studying the selected sites provides the opportunity to view interactions and recurring patterns with different students over the course of several terms. The selected University's Institutional Review Board approved this study.

Data Collection and Processing:

Social network analysis is based on the premise that social life is created primarily by relations and the patterns formed by these relations (Scott, 2013; Wasserman & Faust, 1994). Relationships combine to form ties and patterns that reveal social networks and sub-networks (Kadushin, 2011; Knoke & Yang, 2007). Information regarding the ties that students are maintaining will show the patterns of interaction, specifically who turns to whom for support, how frequently, and how information travels among the participants.

The data for this study is derived from the threaded discussion boards of the six peer mentoring sites. A total of 1601 discussion threads were collected from 155 participants engaged in the 6 mentoring sites (See Table 1 for a breakdown of participants in each site). All of the collected discussion threads were printed from Blackboard™ and de-identified. The de-identified discussion board data consisted of communications initiated by a site participant and specifically directed at other named site participant(s).

Table 1.

Participants in Peer Mentoring Sites (MS1 - MS6) By Role

Mentoring Site	First-Year Students	Third-Year Students	Facilitators	Totals
MS1	20	17	3	40
MS2	34	12	3	49
MS3	11	4	3	18
MS4	19	5	2	26
MS5	5	2	2	9
MS6	6	5	2	13

Constructing the Communication Networks of Peer Mentoring Sites

In order to conduct the social network analysis, we read each discussion post, and focused on those that have a direct recipient, recording the numerical identifier of the post's author and its recipient. From this information, we created a matrix indicating the communication ties (i.e., who communicates with whom) between the students in each peer mentoring site (see Table 3 for an example of such a matrix). Each cell (*Xij)* of the matrix takes on the value of "1" if student (*i*) directs a communication to student (*j*), and "0" if otherwise. Thus, the cells capture the presence or absence of a communication tie between any pairs of students. The resulting 6 binary asymmetric matrices1 (MS1, MS2, MS3, MS4, MS5, and MS6) became the basis/input for the structural analysis presented in this paper. The social network analysis software, *UCINET* version 6 (Borgatti, Everett, & Freeman, 2002) was used in all data preparation and analysis.

Table 2.

Example of a matrix depicting directed relations between actors in a setting

	Recipient (j)			
Actors (i)	A	B	C	D
A	X	0	1	0
B	1	X	1	0
C	0	1	X	1
D	1	0	1	X

1 The matrices are binary because the cells indicate the presence or absence of a relationship; they are asymmetric because student (i) can direct a communication to student (j) who may not respond. It is also a square matrix because it has the same number of rows and columns (Hanneman & Riddle, 2005).

Note. The table illustrates the communication between senders and recipients. Actor A has a relational tie with actor C. Actor B has a tie with actors A and C. Actor C has relational ties with actors B and D. Actor D has relational ties with actors A and C. Since each actor cannot establish ties with themselves, the letter X is placed in the box where this relationship would be represented.

Measures and Variables:

This study uses three social network analysis measures (i.e, density, centralization and centrality) to describe the communication structure of the peer mentoring network sites (Borgatti & Everett, 2013; Kadushin, 2011).

Density and Centralization: The first set of measures used in this study – *density* and *network centralization* - are intended to characterize the structural properties of the communication network and show its potential for efficient transmission of information and influence. *Network density* describes the general level of cohesion in a graph (Scott, 2000). Density values range from 0 to 1, with 1 being the densest. The centralization score (calculated as a percentage) describes the extent to which this cohesion is organized around particular focal points - in other words, it is an expression of how tightly the graph is organized around its most central point (Borgatti & Everett, 2013; Kadushin, 2011; Scott, 2013). A network with a high centralization score means few actors control the flow of information in the networks, and therefore indicates inequality in accessing resources.

Centrality: Centrality is used in social network analysis to identify important nodes or those that occupy influential positions in a network. Such nodes are usually at an advantage in controlling access to information and other resources. A number of studies have demonstrated the validity of using centrality measures to identify the most connected individuals or powerful nodes (Borgatti, Carley, & Krackhardt, 2006). There are three variations of the centrality measures: degree, indegree and outdegree centrality.

Degree centrality scores measure the ties that each actor receives and directs in the network. *In-degree* centrality measures the ties an actor receives from others, while the *out-degree* centrality measures the ties an actor directs to others. According to Hanneman & Riddle (2005), if an actor receives many ties (i.e, have high in-degree centrality), he or she is considered prominent or prestigious. On the other hand, if an actor directs information to many others or makes others aware of his/her views, this actor would have a high out-degree score (Borgatti & Everett, 2013; Hanneman & Riddle, 2005).

Results

Research Question 1: *What is the nature of interpersonal interactions among the students? Is the network dense or sparse – are all students connected to each other or only to a few others? Does information flow evenly within the network or only controlled by a few students?*

Density and Centralization

Figure 1 shows the density and centralization scores of the communication network in all the six peer mentoring sites. Both sets of scores reveal two insights about the structure of the communication network in the mentoring sites.

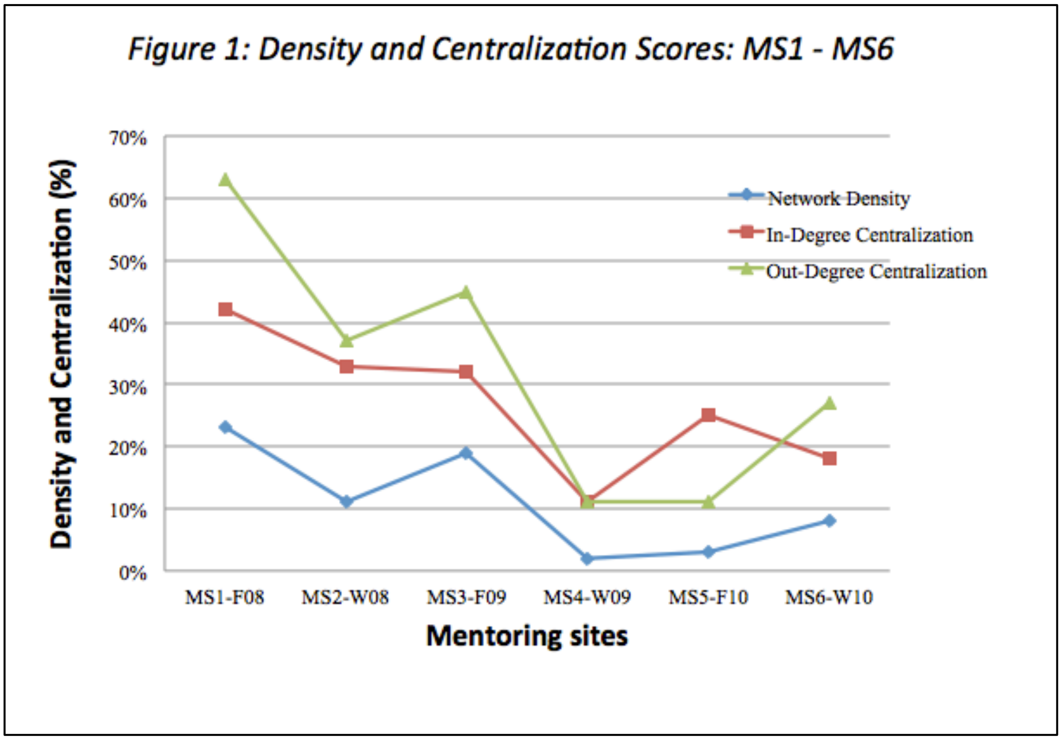

Figure 1. Density and Centralization Scores

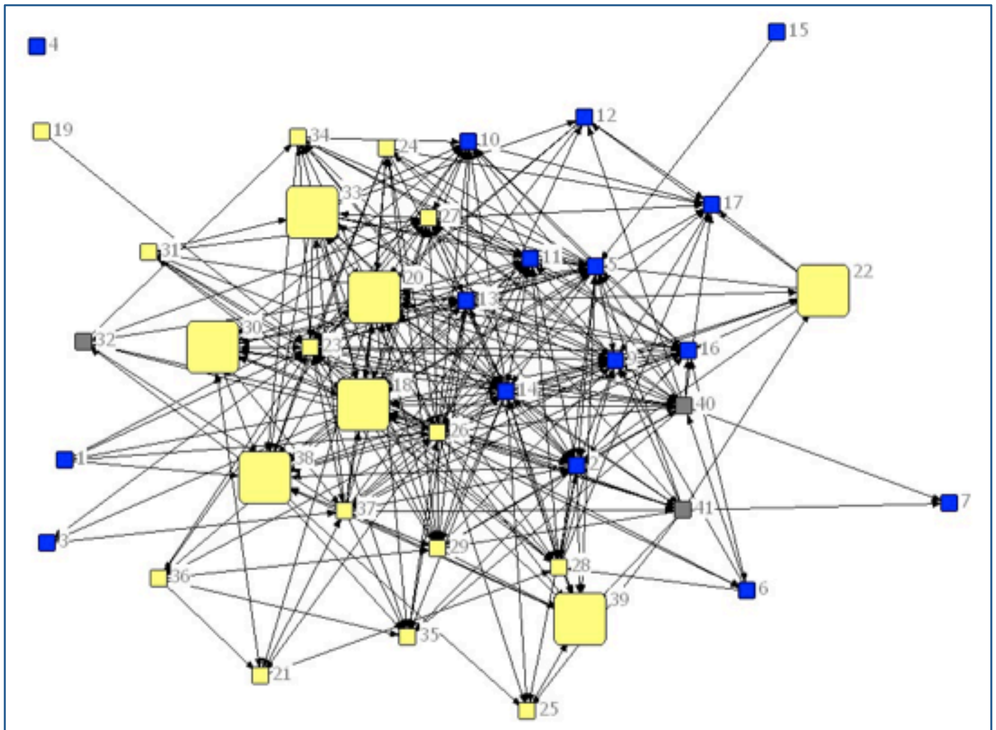

Figure 2. Sociogram of MS1 indicating participants' program level and participation in more than one peer mentoring setting. Blue represents third-year students. Yellow represents first-year students. Grey represents facilitators. The black lines indicate established ties between actors in this network. Larger nodes indicate that a student has participated in more than one peer mentoring

Figure 2. Sociogram of MS_1

First, the communication network in each of the mentoring sites exhibits its own distinctive structure – namely varying levels of connectivity and centralization. MS1 and MS3 networks are characterized by high density and centralization. For example, the density score for the Fall 2008-9 peer-mentoring site (MS1) shows that 23.1% of all possible participant ties are present. Compared to the other 5 mentoring sites, MS1 was the most active with 360 ties established out of a possible 1560. Figure 2, a sociogram of communication ties for MS1 illustrates the extent of connectivity and cohesion in the network.

The network centralization scores for MS1 is 63.116% for outgoing communication (out-degree) and 42.078% for incoming communication (in-degree). Similarly, the communication network in MS3 is also relatively dense (density = 19%), and moderately centralized (indegree centralization = 33%; outdegree centralization = 45%). The density scores indicate a moderately active network, with close to a fifth (20%) of all possible ties active in the network.

However, this level of connectivity is not evenly distributed within the network, indicating variations in the level of activity of individual network members. The network centralization score for outgoing communication in both MS1 and MS3 show a more centralized network, where a few participants are at the center of information exchanges, actively reaching out to their peers for advice and exchange of information. In this type of setting, information often passes through the central figures before reaching others.

By contrast, the communication networks in MS2 and MS4 are not as dense and centralized as those in MS1 and MS3. The low density of MS2 (10%) and MS4 (3%) indicate little cohesion in the network. The lower centralization scores for the two sites means interpersonal communication is not centralized and controlled by a few actors. Put differently, the sparseness of the network and the fact that it is not so centralized implies students are likely to reach out to a varied number of participants and not focus on establishing relations with a few set of their peers.

The second structural feature is the gradual decline in both network cohesion, density, and centralization after Fall 2009-2010 (i.e., in MS4, MS5, and MS6). Despite slight variations, both network density and centralizations were much lower in these mentoring sites, compared to the others, probably due to fewer students participating in the sites.

Research Question 2: *Which students are the most connected (central)– the popular opinion leaders? Are there isolates in the network?*

Degree centrality scores measure the ties that each actor receives and directs in a network. Degree centrality scores were determined for each actor in the peer mentoring sites for MS1-MS6 using UCINET software. As indicated earlier, there are two variations of what degree centrality measures. In-degree centrality measures the ties an actor receives, while the out-degree centrality calculation measures the ties an actor directs. If an actor receives many ties (i.e., has a high indegree score) he/she is considered prominent or has a high level of prestige. If an actor directs information to many others or makes others aware of their views, he/she would have a high out-degree score and be considered influential (Borgatti & Everett, 2013; Hanneman & Riddle, 2005). Table 2 shows a break down of centrality scores of students in each of the peer mentoring sites (MS1 to MS6).

The 40 students in MS1 are in advice exchange relationships with 9 of their peers on the average. The most central students are approached by 19 to 20 of their peers for advice and to exchange information. These central students are also active, contacting between 20 to 33 of their peers for advice. Actor 18 is a typical example. She contacted 26 of her 40 peers for advice, and in turn was contacted by 20 others, indicating the extent to which she is vital to the communication processes in the network. Interestingly, most of the central and prominent students in MS1 are female first year students. Their in-degree and out-degree scores show their prominence and influence in this site.

Table 3.

Degree Centrality Scores of Students in Six Mentoring Sites (Top 3 Scores Only)

Mentoring Site Indegree and Outdegree Scores	Rank	Actor	Score	Program Level	Gender
MS1 [Mean = 9.0 / N = 40]					
In-Degree	1	23	25	First year	Female
	2	18	20	First year	Female
	3	14	19	Third year	Female
Out-degree	1	26	33	First year	Male
	2	18	26	First year	Female
	3	14	20	Third year	Female
	3	20	20	First year	Female
MS2 [Mean = 5.09 / N=49]					
In-Degree	1	7	21	Third Year	Female
	2	46	18	First Year	Female
	3	8	16	Third Year	Female
Out-Degree	1	7	23	Third Year	Female
	2	46	18	First Year	Female
	3	2	17	Third Year	Female
	3	6	17	Third Year	Female
	3	8	17	Third Year	Female
MS3 [Mean = 2.83 / N = 18]					
In-Degree	1	1	8	Third Year	Female
	2	3	7	Third Year	Female
	3	14	6	First Year	Female
Out-Degree	1	1	10	Third Year	Female
	2	3	8	Third Year	Female
	3	9	5	First Year	Female
	3	16	5	First Year	Female
	3	14	5	First Year	Female
MS4 [Mean = 0.42 / N = 26]					
In-Degree	1	4	3	Third Year	Female
	1	6	3	First Year	Female

Mentoring Site Indegree and Outdegree Scores	Rank	Actor	Score	Program Level	Gender
	2	5	2	Third Year	Female
	3	2	1	Third Year	Female
	3	8	1	First Year	Female
	3	24	1	Facilitator	Female
Out-Degree	1	4	3	Third Year	Female
	1	2	3	Third Year	Female
	1	5	3	Third Year	Female
	2	3	1	Third Year	Female
	2	8	1	First Year	Female
	3	n/a	n/a	n/a	
MS5 [Mean = 0.22 / N = 9]					
In-Degree	1	2	2	Third Year	Female
	2	n/a	n/a	n/a	
	3	n/a	n/a	n/a	
Out-Degree	1	3	1	Third Year	Female
	1	8	1	Facilitator	Female
	2	n/a	n/a	n/a	
	3	n/a	n/a	n/a	
MS6 [Mean = 1.0 / N = 13)					
In-Degree	1	7	3	First Year	Female
	1	8	3	First Year	Female
	2	5	2	Third Year	Female
	2	4	2	Third Year	Female
	2	2	2	Third Year	Female
	3	3	1	Third Year	Female
Out-Degree	1	4	4	Third Year	Female
	2	2	2	Third Year	Female
	2	7	2	First Year	Female
	2	8	2	First Year	Female
	3	3	1	Third Year	Female
	3	5	1	Third Year	Female
	3	12	1	First Year	Female

The density scores discussed earlier indicate little cohesion in MS2 network. This is partly reflected in the centrality scores. These scores show that on average students in MS2 reach out to 5 of their 49 peers for advice. The most central students contact up to 23 other students for advice. Typical students are Actors 7, 46 and 8. Actor 7, a third-year female student, and actor 46, a first-year female student, have the highest in-degree scores, 21 and 18 respectively, showing these students are very prominent. Actors 7 and 46 also have the highest out-degree scores, 23 and 18 respectively, indicating their influence in the network. All the central students are female, most of whom are in their junior (3rd) year.

On average, the 18 students in MS3 contact about 3 of their peers for advice and course-related information. The most central are the two female, third year students, Actors #1 and #3. Actors 1 and 3 have the highest in-degree scores, 8 and 7 respectively, showing their prominence. These same actors have the highest out-degree scores, 10 and 8, respectively. Actor #1 approached 10 of her 19 peers for advice, while Actor 3 contacted 8 for advice. These interactions indicate their relative influence in driving advice exchanges in their mentoring site. Overall, however, it is the first year students who are most central in this network. The first-year students are particularly active in reaching out to their peers for advice.

As indicated earlier, the level of connectivity among students is low in MS4, MS5 and MS6. For example, the typical student in MS4 is in contact with about 1 out of his/her 26 peers. Similarly, the 13 students in MS 6 are involved in advice relations with only 1 of their peers on the average. The most central students in this site seek or receive advice from 3-4 of their peers. Most of the central students in MS4, MS5 and MS6 are third year, female students.

Summary of Findings

The social network analysis provided a way of examining the relationships that developed among the students in the six (6) peer mentoring settings. This data provided insight into the social structures that developed among the actors in each site. Specifically, the social network analysis allowed for aggregate study of the interpersonal relationships among the participants.

The centralization levels for the six (6) peer mentoring sites ranged from 10.72% to 63.116% for out-degree centrality and from 10.72% to 42.078% for in-degree centrality. These scores, especially the lower end of the scores, show decentralized patterns, where students are not directing communications to particular members of the mentoring sites but to others. This observation is consistent with the cohesion levels of all six (6) peer-mentoring sites. Cohesion (measured by network density) ranged from 1.7% to 23.1%. Lower cohesion often results in a sparse network. One implication of such a network is a wider disparity in communication patterns within each of the mentoring sites, where students are more likely to reach out to some of the other students in the sites to exchange information and learn from one another.

The centrality analysis shows that third-year, female students were the most central, prominent, and influential in the six (6) mentoring sites. MS1 was the exception, where the first year students were the most central. As the third-year students have taken more courses in the degree program and have begun their pre-student teaching experience, these students will likely have much information to share with the first-year students.

Overall, the social network analysis shows that students' level in the program and the population of the sites impacted the participation patterns in these sites. We found that higher participation rates occurred in the sites with population totals of twenty (20) or more. While the social network analysis shows the first-year students participated frequently in the peer mentoring sites, the scores indicate that the third-year students had higher levels of influence and prominence. Therefore, the activities of the third-year students had more impact in the relationship development and information sharing in these sites.

Conclusion

Online learning technologies offer educators opportunities to create learning spaces that allow students to communicate and collaborate with their peers in informal ways asynchronously. These types of spaces are especially beneficial for online students who do not have the chance to chat with peers before or following a face-to-face course. As online program and course development in higher education and online student populations continue to grow, supporting online students is becoming increasingly important (Allen & Seaman, 2013). Online peer mentoring sites can offer students opportunities to interact, collaborate, and engage with peers in new and enhanced ways.

The results of this study demonstrate that the online peer mentoring sites supported interaction among first-year and third-year students. The results showed that the student interaction was more sparse than dense, indicating that the students were less active in their outreach and information sharing. This finding suggests that the online students did not seek the support of others to both ask questions and share information across the sites as a whole, but were selective with those whom they sought out for support, information, or guidance. Specifically, third-year students had more impact in the relationship development in the peer-mentoring sites, although first-year students strategically controlled the flow of communication in the MS1. Having both first-year and third-year students in central roles in these sites shows that student of both levels assumed powerful positions in the sites, forging relations with students both at the same and across levels. Better engaging first-year students in the peer mentoring settings could aid in increased student interaction in future peer mentoring settings and also strengthen the first-year student transition to their online degree programs.

This study provides a foundation for future research regarding student experiences in peer mentoring sites and the ways that such settings may support their learning experiences. This study has implications for future research to determine why students chose to use the peer mentoring sites to interact with their peers and what these interactions provided them. Such data could inform the ways that the sites helped support the students both in their transition and advancement in the program, and could be useful in assisting future development of the peer mentoring sites and similar learning spaces. Finally, insight into the student experience would provide additional data to determine if such sites are useful to students and worthwhile endeavors for colleges and universities to provide their online student populations.

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