Understanding groups in outdoor adventure education through social network analysis

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Abstract

Relationships are a critical component to the experience of an outdoor adventure education (OAE) program, therefore, more fruitful ways of investigating groups is needed. Social network analysis (SNA) is an effective tool to study the relationship structure of small groups. This paper provides an explanation of SNA and shows how it was used by the National Outdoor Leadership School (NOLS) to understand the relationship patterns among different course compositions with students receiving and not receiving scholarships (course compositions included two students, 50% of students, and all students receiving scholarship). Data were collected from three 30-day courses at three different time points throughout the course and were based on two dimensions of cohesion (social and task). The findings suggest that the most homogeneous group (in regard to scholarship recipients) possessed greater social cohesion and the least homogenous group possessed greater task cohesion. Social network analysis should be used more frequently in OAE because it offers a flexible approach to understand groups and group processes.

Keywords: Small groups, relationships, cohesion, NOLS, group structure

Introduction

The small group nature of outdoor adventure education (OAE) plays a critical role in the types of experiences students have during a course. Interpersonal relationships are a critical component to the student experience on OAE courses (Goldenberg, McAvoy, & Klenosky, 2005; McKenzie, 2003). Many students participate in these experiences to develop new relationships and to feel a sense of belonging to a community (D'Amato & Krasny, 2011). Others have suggested that the experiences and the learning that can be achieved is moderated by the relationships students generate with others (Sammet, 2010; Sibthorp, Paisley, Furman, & Gookin, 2008). The quality of relationships between members of a group ultimately affects the social climate which in turn, affects how well the group functions. Furthermore, interpersonal relationships operate at the individual level, but play an important role in producing group level outcomes such as teamwork, cohesion, and communication. Social network analysis (SNA) is a tool that can offer a representation of the interpersonal relationships within a group and show how relationship structures can produce group level outcomes.

The purpose of this paper is to explain the methodological foundations of SNA and show how it can be used in OAE for both research and application. While SNA is not uncommon in other fields such as sociology, education, or economics, it has not been widely used in OAE research. Because small groups and relationships are so central to the OAE experience, SNA can inform applied questions as well as provide researchers in OAE a new and versatile tool to examine group processes. To provide a context for how SNA may be used, we first explain why one OAE organization chose this method to answer an applied problem. Specifically, the National Outdoor Leadership School (NOLS) was interested in how to provide the best experiences for students who received scholarships to attend courses. Second, we present an overview of SNA and show how it differs from traditional survey methods. Third, we return to the NOLS example and show how the data were collected, the results of the data, and how this method provided answers to this problem. Lastly, we consider how SNA can be used for both practitioner and research purposes.

Applied Example of Social Network Analysis

The National Outdoor Leadership School (NOLS) wanted to better understand the social and relationship dynamics experienced by groups on its courses with varying compositions of students receiving scholarships. Social network analysis was used because the interest was in seeing the interpersonal connections between students and to see how these connections produced group level outcomes such as cohesion. In addition, social network analysis also provides a visual component that maps these connections and generates a set of statistics based on mathematical algorithms, which both provide an understanding of individual positioning within the network and group structure. Others have used SNA to understand relationships and group structure among adolescents, such as to understand peer relations among groups with varying compositions of race and ethnicity (Bellmore, Nishina, Witkow, Graham, & Juvonen, 2007), the stability and change of social standing among early adolescents (Lansford, Killeya-Jones, Miller, & Costanzo, 2009), and the social integration and isolation of adolescents based on friendship patterns (Wolfer, Bull, & Scheithauer, 2012).

The National Outdoor Leadership School is an international OAE organization that provides extended, expedition-style wilderness-based courses for students age 14 and older. Though a variety of activity types (sailing, mountaineering, rock climbing, whitewater rafting and kayaking, etc.) and course lengths are offered by the school, the prototypical NOLS course consists of a 30-day wilderness backpacking expedition. Students are expected to learn the technical and leadership skills of wilderness travel that will provide them the necessary skills to plan and execute their own small group expedition at the end of the course. Every year scholarship granting agencies provide students who may otherwise not be able to afford this type of course the opportunity to attend a NOLS course. Typically, students who receive scholarships come from a lower socioeconomic status and live in more urban environments than the "traditional" NOLS student. Students who receive scholarships tend to have less previous experience in wilderness settings or basic camping skills, whereas traditional NOLS students often have some experience with wilderness camping. Because these differences between students on courses may influence their ability to interact with one another or "get along," NOLS wanted to see how different course compositions influenced group structure.

To understand how course composition may influence the relationship patterns within the group, three alternatives were compared. Option 1 represented NOLS' usual approach of including two students receiving scholarships on a standard NOLS course. Option 2 involved intentionally creating a course with 50% of the students receiving scholarships and 50% not receiving scholarship. Option 3 involved running a course for only students who received scholarship. Each course started with 12 students who were 16-17 years old and each was comprised of eight males and four females. The main questions centered on how well each group composition were able to work with one another socially and technically. The National Outdoor Leadership School was also interested in how these relationships changed over time. Specifically, we thought that any initial differences might dissipate over time through more shared experiences. Social network analysis was used to inform this problem because it provides a visual representation and numerical measurement of both individual relationships and group level structure. The ability to see these relationships was of utmost importance to NOLS because they wanted to understand how students who received scholarships integrated into the group and the type of group structure that formed with various group compositions.

In order to better understand how SNA was used in this applied example, it is first necessary to introduce the terms and techniques of SNA. This foundation will provide an understanding of the different types of information that can be collected and how it can be used in different contexts. Thus, we leave the NOLS applied example and offer an overview of SNA before returning to the applied example later in this paper.

An Overview of Social Network Analysis

Social network analysis developed during the 1930s as a few notable scholars, Kurt Lewin, Jacob Moreno, and Fritz Heider, fled Nazi Germany and established a research center that looked at social perception and group structure (Scott, 2013). Moreno's work explicitly focused on interpersonal relations and he believed that a person's psychological well-being was related to the structural features of these relations. His most notable accomplishment was the development of the sociogram, which is a graph that provides a visual representation of the relations between social phenomena such as people, organizations, or communities.

The 1950s brought about further advancements in SNA most notably due to two mathematical achievements that were refined. The first was the development of algebraic models of groups which allowed researchers to model the role of individuals in the network. The second was the development of multi-dimensional scaling, "a technique for translating relationships into social distances and for mapping them in a social space" (Scott, 2013, p. 35). These two developments allowed social network analysts to study many different kinds of social structures. Further advancements in the use and analysis techniques afforded by SNA have been provided by the development of more powerful computer software programs.

Social network analysis is an approach to modeling and measures the relations of social entities within a defined network (Wasserman & Faust, 1994). The main premise of SNA is to understand the "linkages among social entities and the implications of these linkages" (p. 17). Therefore, three assumptions must be presumed when working with network data: structural relations provide a better understanding of data than attribute data; perceptions and beliefs are influenced through the structural mechanisms of social networks; and structural relationships are dynamic processes (Knoke & Yang, 2008). By seeking to understand structural properties, a combination of numerical analytics and graphical displays are used to describe how individuals in the network are connected to each other. One benefit of this approach lies in the constructed visual network diagram that provides an intuitive way to quickly understand both the role of an individual and the larger relationship patterns present within a network. In OAE, the network can be defined as the small group or course, and the individual group members are the social entities (most commonly called actors) within the network. Cliques, social capital, power, and prestige are aspects of the relationships between individuals in the small group that SNA can indicate (Scott, 2013). These would be difficult to expose using traditional survey methods. In the context of this paper, traditional survey methods refer to approaches that sample from the population, which most often use Likert-type scales to measure the mean and variance of a latent construct, and that use inferential statistics to make generalizations back to the population of interest.

There are a few differences between SNA and traditional survey methods. One of the main differences is that the focus is on the *relations* between members of the network and not simply their attributes (Hanneman & Riddle, 2005). Unlike traditional survey methods, SNA is not focused on constructing a sample to estimate relationships in a population. Typically, SNA data are provided from all members of a network so that the underlying relationships can be accurately analyzed and displayed from the entire population under study. While sampling an entire network can be difficult for larger sociological questions, the small group nature of OAE makes SNA a viable option. Second, traditional research methods often use standard statistical procedures such as t-tests or regression. However, due to the assumption of independent observations required for such tests, social network data cannot be analyzed in this way (Hanneman & Riddle, 2005). These differences require the use of a different type of statistical method used for SNA, graph theory. Wasserman and Faust (1994) suggest that graph theory is used in SNA for two primary reasons. First, graph theory provides a specific vocabulary that allows the structural properties of networks to be described. Second, graph theory uses mathematical algorithms and operations to quantify and measure the properties of the networks. Given these differences, asking the right questions to inform a specific question or problem remains central to using SNA.

Types of Questions to Ask

As with traditional survey methods, aligning an appropriate question type with the problem and application is critical. However, the types of questions that are common in SNA are different than traditional survey methods. Rather than asking subjects to respond to Likert-type scale questions, SNA most often asks subjects to identify and describe types of relationships with others. Therefore, the questions that are asked do not need to be derived from a pre-constructed instrument; rather the researcher generates the questions based on the context and the relationships that are of interest. As can be seen and understood by the description of SNA question types below, simple binary questions provide less data, are simpler for participants to answer and are easier to analyze. Using interval level scales, multiple indicators for variables of interest, and inquiring about different relationship dimensions adds complexity to the process, but allows for richer and more nuanced analysis.

The most common type of SNA question uses binary measurement, and seeks to determine whether there is a relationship between actors in a network. For example, a researcher may ask students to identify their "friends" within the small group to detect patterns of friendship relations. This selection is binary because students "nominate" others as either friends or as not friends. This approach is the most straightforward and easiest, but it cannot distinguish levels of friendship (e.g., best friends, more casual friends). Furthermore, within the small group context of OAE, it would not be uncommon for everyone to claim to be "friends." Therefore, the way in which the question is constructed has important implications for how students can and will respond and, thus, what the data mean.

Another SNA measure involves multiple category nominal measures (Hanneman & Riddle, 2005). A question using this type of measure may ask students to select members into appropriate relationship categories such as friend, family, co-worker, or no relationship. These types of data allow the researcher to map the different types of connections between members in a group, which is often important to understanding a group's dynamics (Hanneman & Riddle, 2005). Though these questions specify types of connection individuals have with one another, it may not explain the type of interaction those individuals have with one another.

Grouped ordinal measures may ask members to rate others on an ordinal scale. For example, the question may ask students if they "like," "dislike," or are "neutral" towards other members. This approach generates a rank order of students' feelings toward others, but only within a limited scale (in the example here, 1-3). Full rank ordinal measures, though, allow the members to rate others on a larger scale. In a group of 12 students, the researcher might ask each student to rank the others from "most liked" to "least liked." As such, a member would rank their most liked member "1" and their least liked member "12."

This approach, however, remains challenging as each group member is required to rank all other members of their group, even though some, inevitably, do not differ substantively in their relationships with the respondent.

The last types of measurement that can be used are interval measures of relations. Interval measures have equal distances between their units and, thus, the SNA researcher may not ask questions in regards to particular relationships, but may count the frequency with which people communicate with one another (Hanneman & Riddle, 2005). For example, the researcher may be interested in how many conversations a member of the group had with other members of the group throughout the day. While this could be a fruitful way to understand personal interactions with others, the ability to collect the frequency of interactions is extremely difficult, if not logistically impossible, in the context of OAE.

One advantage of SNA is the ability to construct questions that are of particular interest to the researcher. However, the choice of measurement type should clearly depend on the question that SNA is expected to inform. A different question type will derive different relations between members of a group. Understanding how these relationships are input into a data matrix so they can be recognized by SNA software is another feature that is slightly different than traditional data structures.

Data Structure and Types of Networks

The data structure of SNA is most commonly framed in a member by member matrix (Scott, 2013). If a researcher was interested in a binary type question (whether a relationship existed), the matrix would have members on the far left column (individual cases in traditional data) and members on the top row (individual variables in traditional data). Due to the binary nature of the question, the presence of a relationship between two individuals would result in a "1" in the cell to represent this relationship (See Table 1). The members in the left hand column are the "choosers," while the members in the top row are the "chosen." Therefore, the rows show the "outgoing nominations" and the columns show the "incoming nominations" for each group member. For example, according to the data matrix in Table 1, "A" responded that he or she had an outgoing nomination (relationship) with only "B." The column under "A" indicates that four members in the group (B, C, E, and F) nominated "A."

The data matrix provides a visual summary of the relationships within the group. Simply observing the data matrix can provide a very good representation of the relationships between members in a group because all incoming and outgoing nominations can be seen. However, through the advancement of mathematical algorithms and computer analytic techniques, SNA researchers can now graphically represent the relationships between members in a clearer and more systematic way. Through the use of graph theory, SNA not only maps the relationships between individuals but can formulate their "position" within the network based on these relationships (Scott, 2013). There are a number of common SNA programs that researchers can use to input data, compute statistics, and generate graphs of the networks (called sociograms). Some of the commonly used software packages include C-IKNOW, UCINET, and NodeXL. Whatever software package is used, every sociogram has common components that represent network data. Figure 1 shows an example of a full network sociogram based on the data matrix in Table 1.

Table 1: Member by Member Data Matrix of a Binary Type Question

	A	B	C	D	E	F
A	0	1	0	0	0	0
B	1	0	0	0	0	1
C	1	1	0	1	0	0
D	0	1	0	0	1	0
E	1	0	0	1	0	0
F	1	0	1	0	0	0

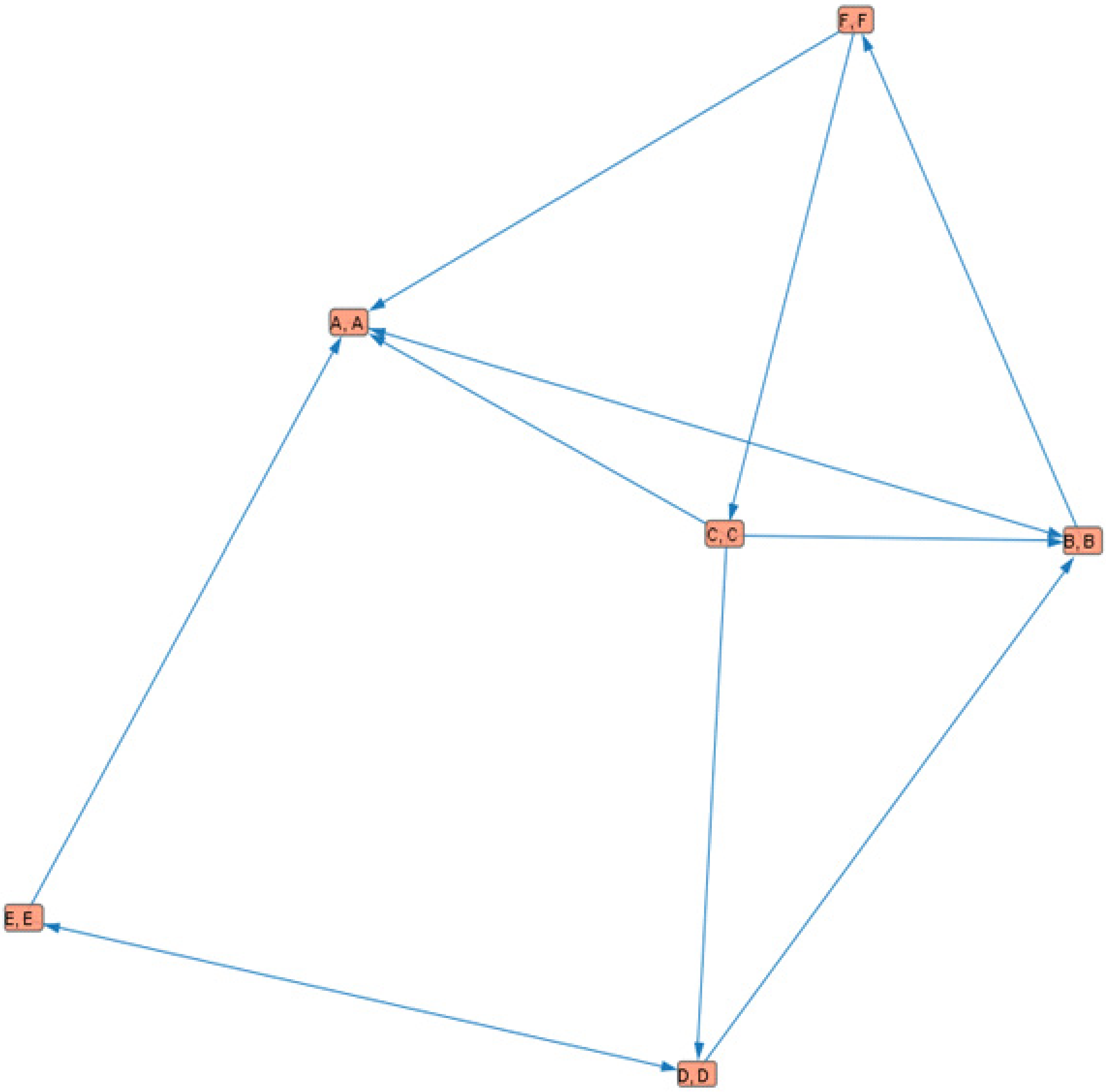

Figure 1: Example of a Full Network Sociogram

Components of a Social Network

In every social network, four fundamental components will always be present: the actor (node), relational ties (edges), the type of relational tie, and the boundary of the network (Wasserman & Faust, 1994). The actors in every network represent these social entities. Actors may also be organizations or goods being exchanged if researching networks other than social networks, but in terms of a small group in OAE, the actors are the students in each group. The actors in every network are represented by some type of shape, name, or object. It can also be possible to represent different attribute data about each actor by generating different shapes or using different colors. For example, a circle may be used to represent actors who have been on an OAE course before and a triangle for those who have not and, simultaneously, the color blue may be used to represent males and orange for females. These attribute data do not specify the relationships, but provide a richer visualization of the relationships within the sociogram. In addition, SNA can also place each actor in the network based upon the relational ties he or she has with other members.

Relational ties are the links connecting different actors in a network (Wasserman & Faust, 1994). These are represented by a line (also called an edge) from one actor to another. The two types of edges most used are undirected and directed. An undirected edge indicates a connection between two actors, but does not specify the direction of that relationship. This edge type, represented by a line without any arrows, may be useful if the user was only concerned about the existence of a connection between actors. Directed edges, represented by lines that have arrows on the ends of them, specify the direction of the relationship. For ease of interpretation, reciprocated relationships (two actors who choose one another) are represented by lines with arrows on both ends (Figure 1 is a directional graph). While the relational ties represent the extent to which each actor is connected, knowing what the connections are based upon is critical and represents the type of relational tie.

The type of relational tie is what the connections between actors represent. Most often, this is guided by the question being asked or the topic of interest. The ties between actors can represent a variety of relationships such as friendships or business interactions.

Finally, every network must have a defined boundary, which is a predetermined parameter of the study (Wasserman & Faust, 1994). As noted earlier, for OAE, this is usually the entire group of interest. If a researcher is trying to understand the interpersonal relationships in OAE, the defined boundary would be the entire student group, but may also include any staff or instructors who are taking part in the experience. They share the same experience and all have relations that connect them to one another.

Full group level sociograms are typically constructed when interested in the overall group dynamics and relationships. However, an ego network can be modeled if a researcher is interested in the specific relationships an individual student has within a group. Ego networks show the relations between a particular individual and other members of the network. Most ego networks are concerned with the particular "neighborhood" of the actor: the members of the network that are directly connected to the actor by either incoming or outdoing relationships (Hanneman & Riddle, 2005). Figure 2 shows an example of an ego network for "D" derived from the data in Table 1. Although D is connected to "B," "C," and "E," we see that "B" and "C" are connected with one another but not with "E." In addition to the sociograms, a general set of centrality measures can be computed through mathematical algorithms by SNA.

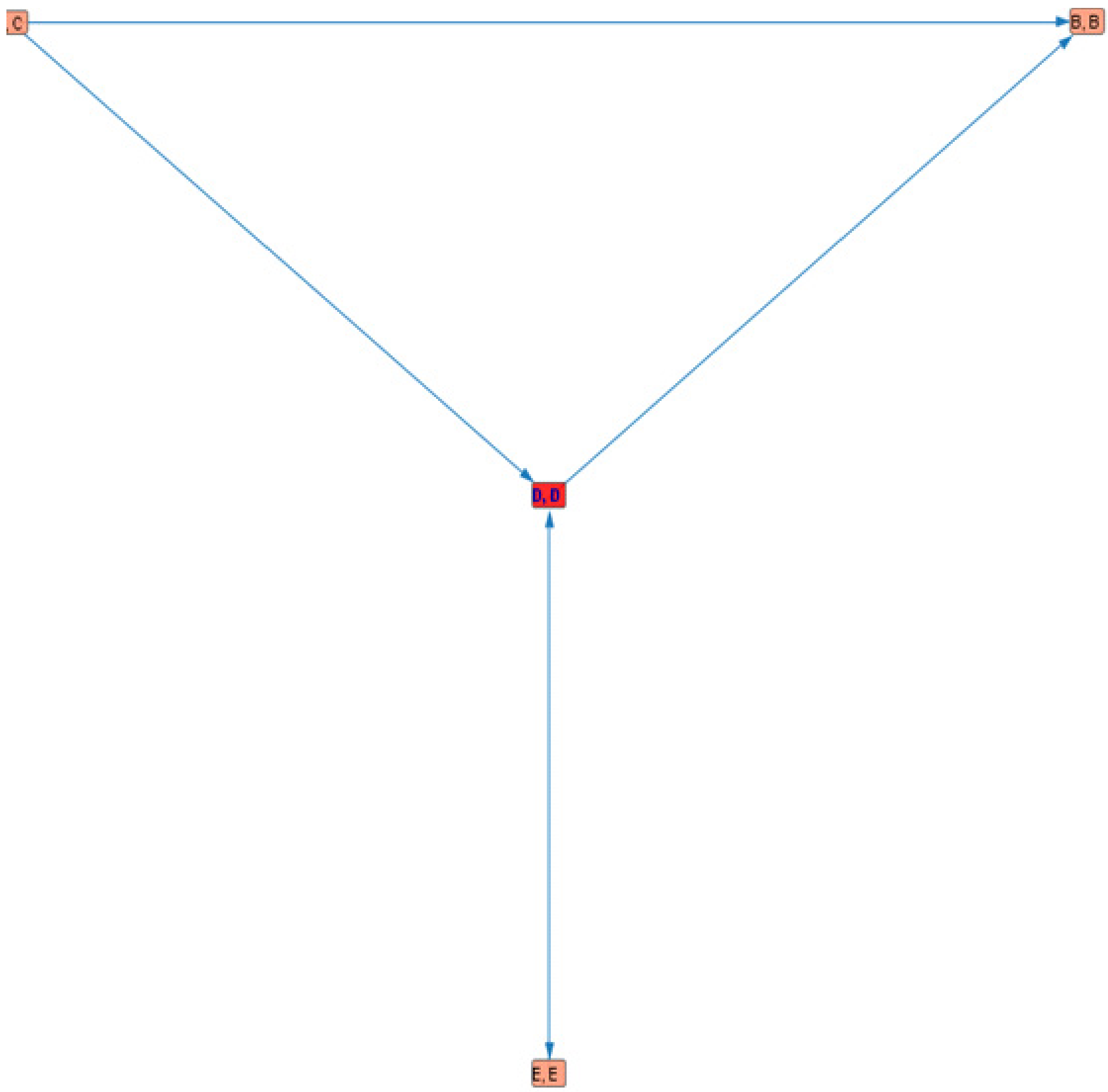

Figure 2: Example of an Ego-Network for "D"

Measures of Centrality

The centrality measures generated by SNA provide a statistical descriptor of actors in the network. Along with the sociograms that are generated, useful statistics are also computed through algorithms to summarize the relationships between actors. Centrality is an important concept in SNA because it represents where an actor is located in the sociogram, which has implications on his or her ability to influence others (Hanneman & Riddle, 2005). The more central an actor is in the network, the more opportunity they have to influence the surrounding members and control or access information from other members (Hanneman & Riddle, 2005; Haythornthwaite, 1996). Three types of centrality are degree centrality, in-closeness centrality, and betweenness centrality.

Degree centrality.

The concept of degree centrality refers to the in-degree and out-degree of each actor and influences their position within the sociogram (Wasserman & Faust, 1994). In-degree is the number of nominations an actor of the network receives, whereas out-degree is the number of nominations an actor gives to others (Wasserman & Faust, 1994). The more nominations an actor receives and gives, the more central they are in the network. The total number of actors in any network will determine how many possible relationships can exist. As networks become bigger, the chances of connectivity between all actors decrease. For example, in the small group setting of OAE, the chances of connectivity are much higher than in a camp setting, where the number of actors within the network of the camp is larger. Two concepts related to degree centrality that are important are *density* and *prestige*.

The density of a network is a statistic that provides a numerical score of the connectivity between all members of the network by computing the ratio of all connections present in a network to all possible connections (Wasserman & Faust, 1994). Density can range from 0 (no connections in the network) to 1(all possible connections are present) and be useful if the researcher is interested in how quickly information diffuses among actors (Wasserman & Faust, 1994).

Prestige (also termed page rank) is an individual statistic based on the number of in-degree nominations for an individual compared to others (Hanneman & Riddle, 2005). Reported on a scale of 0-1, those who have a higher prestige ranking are more central in the sociogram and theoretically have a higher ability to influence others. The members of a group who are high in prestige are those who receive the most nominations from other actors. A measure of centrality that is helpful in understanding group level phenomena is in-closeness.

In-Closeness centrality.

In-closeness centrality is a composite measure of the distance between an actor and other actors (Wasserman & Faust, 1994). The more central an actor is to the network, the easier it is for them to interact with other members. The relational tie between two members in a network is known as a geodesic distance. In-closeness is concerned with the number of geodesics required for one actor to reach all other actors (Wasserman & Faust, 1994). Therefore, as the number of geodesics increase, the in-closeness centrality will decrease. This statistic can also be used to understand group level conditions such as cohesion and communication.

Betweenness centrality.

Betweenness represents the ability of an actor to mediate the relationship of two other actors (Wasserman & Faust, 1994). If two actors in a network are not directly connected, they must use other actors to complete the connection. The actors who are able to complete these connections have higher levels of betweenness. Individuals who have high betweenness values "often act as the 'go between' or 'gate keeper', linking people who could otherwise not contact one another" (Forsyth, 2010, p.160).

In the following section we return to our NOLS example. We show how NOLS constructed their questions and how in-closeness was used to understand group cohesion. Specifically, recall that NOLS wanted to better understand the social and relationship dynamics experienced by groups on its courses with varying compositions of students receiving scholarships.

Applied Example of Social Network Analysis

To better understand how to serve students receiving scholarships, data were collected from three 30-day NOLS courses in the summer of 2012. The students in this study were selected from a single scholarship granting program, which used socioeconomic status as a main criterion to evaluate students for scholarship acceptance. Data were collected during the first two re-ration periods and at the end of the course, which would have been approximately the 10, 20, and 30-day (end) points of the course. The first two administrations were conducted by the instructors in the field; these data were placed into an envelope and taken out of the field by those who brought in the re-ration. The third administration was completed the day students returned from the field. Students were informed that all responses would be confidential and instructors were asked not to look at the responses from students.

Because NOLS was interested in how the group functioned both socially and when focused on completing some technical aspect of the course, we termed the main outcome variables *social* and *task cohesion*. For purposes of this study, social cohesion refers to the degree to which members of a group like each other, whereas task cohesion is the degree to which members of a group can work together to achieve common goals. These definitions are consistent with the extant literate on the multidimensional nature of group cohesion (Forsyth, 2010).

The SNA data were collected by asking each student to choose three members of the group he or she would prefer to be with based on each of the two different scenarios developed to represent the social and task dimensions of the group. The two scenarios were developed by the authors and NOLS staff in order to represent "typical" situations students may experience during their course. The choice to ask a binary type question and create a context that is common to all NOLS courses was intentional. Students were asked to respond to the following two scenarios:

> 1. You are preparing to do an easy day of travel without instructors. The route is only a few miles on-trail and the weather will be excellent. You will be camping near a lake and should have plenty of time to hang out and enjoy each other's company. Name up to three students you would want in your group. (Social Dimension)
>
> 2. Your small group is doing a peak ascent without instructors. The off-trail travel is difficult and it has been raining all day. Everyone will need to use their skills to make sure the group makes it to camp safely. Name up to three students you would want in your group.(Task Dimension)

The questions were designed to generate an equal number of "outgoing" relationships for each student to provide equal weighting for the in-closeness values. If students were able to select as many other members as they wanted, they would artificially centralize themselves based on their out-degree. We wanted the out-degree to be as close to equal as possible for each student so we could see the effects of incoming relations.

These data were collected at three times for each course and were entered and uploaded into the software package C-IKNOW (Huang, Contractor, & Yao, 2008). Sociograms were generated for each course and questionnaire administration on both the social and task dimensions. In addition, the group statistic of "in-closeness" for each course and questionnaire administration were computed and used as a centrality indicator of both social and task cohesion because of its measure of "distance" between actors in the network. As discussed above, in-closeness measures the distance it takes each actor to reach all other actors in the network. Therefore, we can view this statistic as a measure of "accessibility" to others in the group. The individuals in groups with high levels of in-closeness are able to access the knowledge, skills, and abilities much easier than individuals in groups with lower in-closeness scores and thus possess higher levels of cohesion. Therefore, the in-closeness score provides a measurement of the structure of the group, which has been used to assess the social cohesion of other groups (Moody & White, 2003).

Results and Discussion

Social dimension.

The results for each composition (2, 50%, or all students receiving scholarship) on the three administrations for the social dimension of cohesion can be seen in Table 2. Each composition of students receiving scholarships has a different pattern of in-closeness scores across the three administrations. The group with two students receiving scholarships shows a slight increase in social cohesion from time one to time two, but then a drop from time two to time three. The group with 50% of students receiving scholarships shows a small but steady increase across the three administrations, but shows on average the lowest social cohesion of the three compositions. The group with all students receiving scholarships has the highest score at administration one, but shows small decreases thereafter. There are not current studies in the OAE field that have looked at varying compositions of "different" students. However, Breunig, O'Connell, Todd, Anderson and Young (2010) found that cohesion significantly increased due to increased physical challenges and communal type group activities. Glass and Benshoff (2002) also found social cohesion to increase due to a one-day challenge course experience. While the in-closeness scores can provide a quantitative interpretation of the level of social cohesion, the sociograms show the structure of the relationships within the group.

Table 2: Social Cohesion Scores for the Three Course Compositions over Time

Composition	Time 1	Time 2	Time 3
2 students receiving scholarship	.65	1.04	.40
Half students receiving scholarship	.35	.37	.49
All students receiving scholarship	.91	.69	.63

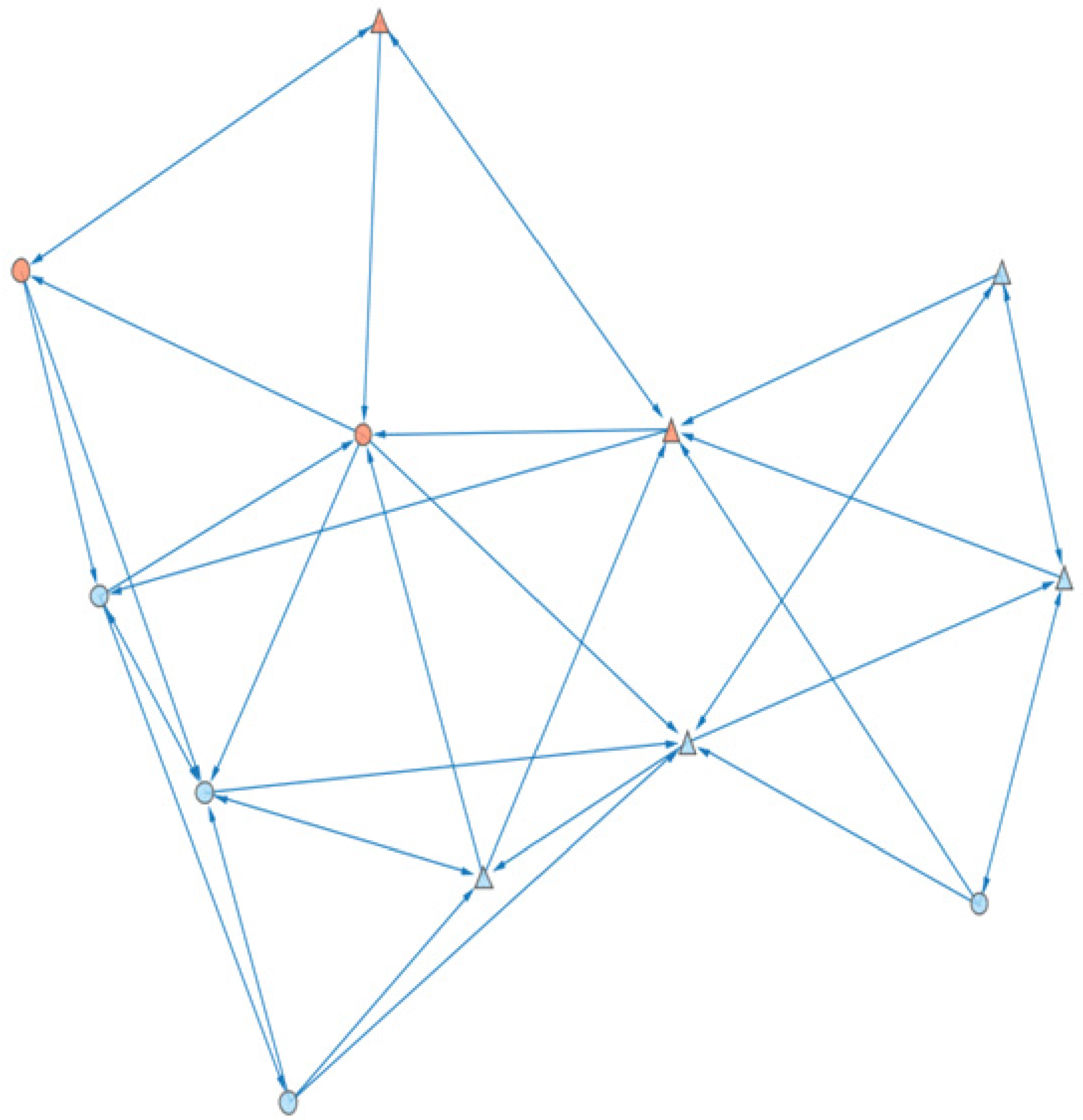

Figure 3: Sociogram of Lowest Social In-closeness Score (.35) From Group with Half Students on Scholarship

Circles = students receiving scholarship; triangles = "traditional" students; blue = males; orange = females

The sociograms show the actors who are more centralized and the direction of the nominations between all actors of the group. Figures 3 and 4 show the sociograms for the lowest and highest socially cohesive groups. Figure 3 shows the sociogram for the group with 50% of the students receiving scholarships at time 1. This sociogram illustrates the clear division in the group between the traditional students and the students receiving scholarships. There are two key students in this network who link the two sides of the group; thus they possess high betweenness centrality. There is a large cluster of students receiving scholarships to the left of the sociogram, and only one student receiving scholarship on the right side of the sociogram. This division between the students also corresponds to the lowest level of in-closeness (cohesion). Figure 4 shows the highest level of social cohesion and is from the group with two students receiving scholarships at time 2. When there are more actors central to the sociogram, the group in-closeness scores increase because they provide the links to nodes on the opposite side of the network. Figure 4 shows three actors who are central, with one receiving the majority of nominations. As a whole, this group shows strong connectivity and a high in-closeness and thus, a higher level of social cohesion. While cohesion may be high, the sociogram shows the two students receiving scholarships on the periphery of the network, which demonstrates that, although the group as a whole may be cohesive, these two students are not central socially in this group.

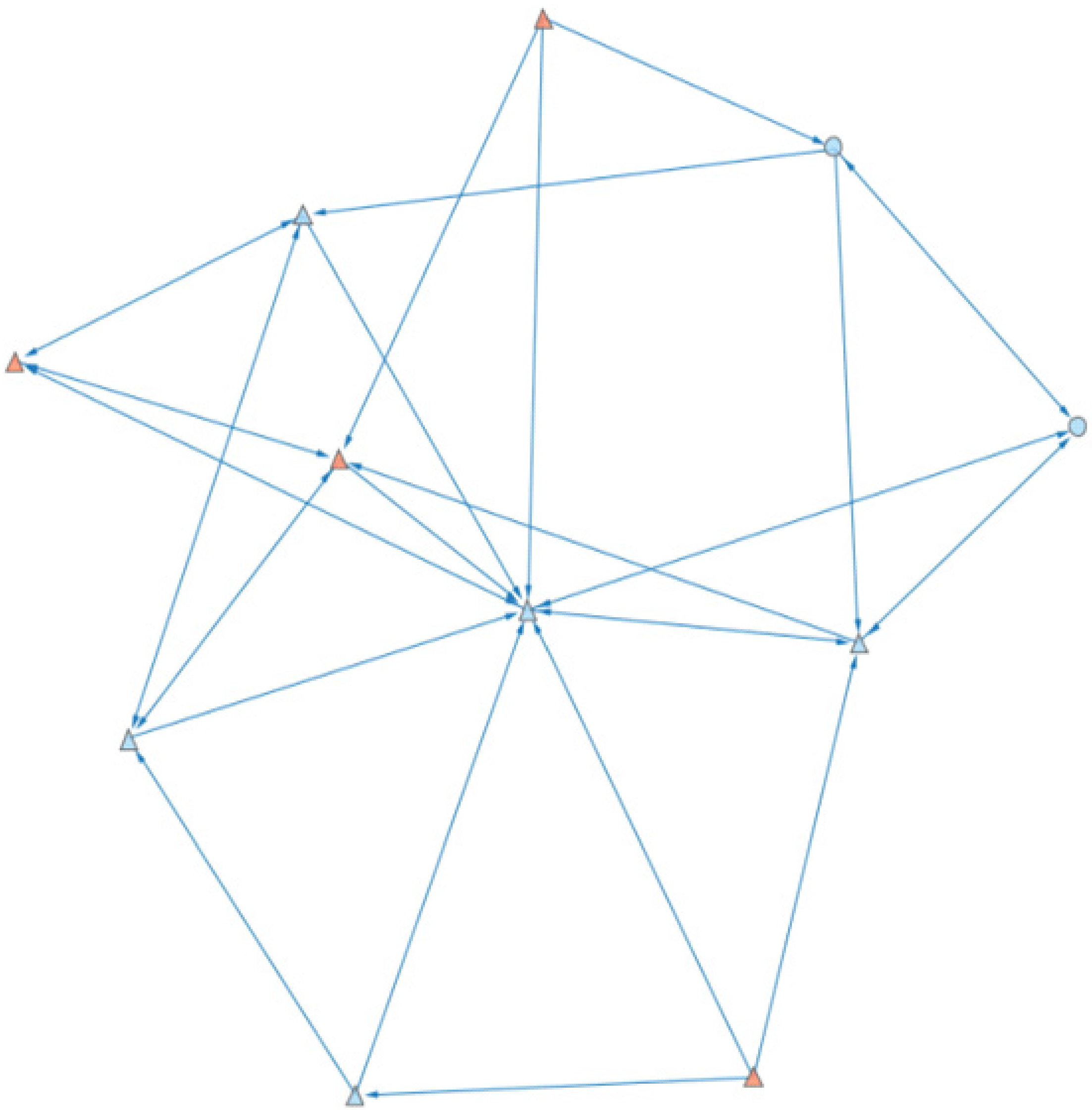

Figure 4: Sociogram of Highest Social In-closeness Score (1.04) From Group with Two Students on Scholarship

Circles = students receiving scholarship; triangles = “traditional” students; blue = males; orange = females

If we consider actor centrality as a measure of power or influence, (Hanneman & Riddleman, 2005; Scott, 2013; Wasserman & Faust, 1994), then we see that the "traditional" NOLS student is often the most influential in the social setting (this would only apply to compositions 1 and 2). Ideally students who both receive and do not receive scholarship should hold these positions of influence.

Task dimension.

In OAE, groups are formed to pursue and complete a particular objective or task. One of the tasks for individuals at NOLS is to be able to lead others and travel in difficult wilderness terrain. The task cohesion scores for each composition are shown in Table 3. The task scores for all of the course compositions are, on average, higher than on the social dimension. The group with two students receiving scholarships noted an increase from time one to time two, followed by a decrease at time three. The group with 50% of the students receiving scholarships realized a consistent increase across the three times and has the highest overall average in-closeness score of the three compositions. The group with all students receiving scholarships showed an increase from time one to time two, and a slight decrease from time two to time three.

Table 3: Task Cohesion Scores for the Three Course Compositions over Time

Composition	Time 1	Time 2	Time 3
2 students receiving scholarship	.69	1.17	.64
Half students receiving scholarship	.94	.93	1.21
All students receiving scholarship	.87	.99	.91

The sociograms for the lowest and highest scores of the task dimension are shown in Figures 5 and 6. Figure 5 shows a sociogram from the group with two students receiving scholarships at time 3. In this sociogram, two students receive the majority of the nominations and provide the link to others. Figure 6 shows the most cohesive group for the task dimension from the group with 50% of the students receiving scholarships at time 3. This network has three main actors who connect all of the students within the network. All of the students receiving scholarships, except for one, are on the outside of the network. Females also tend to be on the outside of the sociograms for the task dimension; however, Figure 6 does show a female as a central actor.

The social network data presented in this example illustrate how SNA and sociograms provide an additional rich layer of data that cannot be easily captured by more traditional survey methods. Network data provide visual depictions of group level structures as well as quantified centralization statistics. They also allowed us to see, specifically, how the students receiving scholarships were positioned in the network irrespective of group statistics.

The question NOLS was seeking to answer was how to provide the most beneficial experiences for students who received scholarships for their courses. Because the small group is such an influential component of the experience and learning, three different group compositions were created. Given the idiosyncratic nature of this data, social network analysis was used as one tool to help inform NOLS of the group structures that existed among the three different compositions. The three courses used in this study are not sufficient to suggest that all groups, given these same compositions, will generate the same results. Other qualitative data were collected from the participants, the course instructors, the program administrators, and the agency providing the scholarships, but are not presented in this paper. Through these combined data, and given the complexities in the nature of the program, it was determined that the course of two students receiving scholarships and all students receiving scholarships would be offered the following year. This decision was best aligned with the programmatic goals and prioritized the collective student experience.

The use of SNA provided valuable information for NOLS that helped answer a complex problem. Without being overly intrusive, the data provided a "picture" of the relationships within the group and thus, produce group level properties. This information allowed NOLS to make an informed decision which will help their admissions department place students in groups that should provide better experiences.

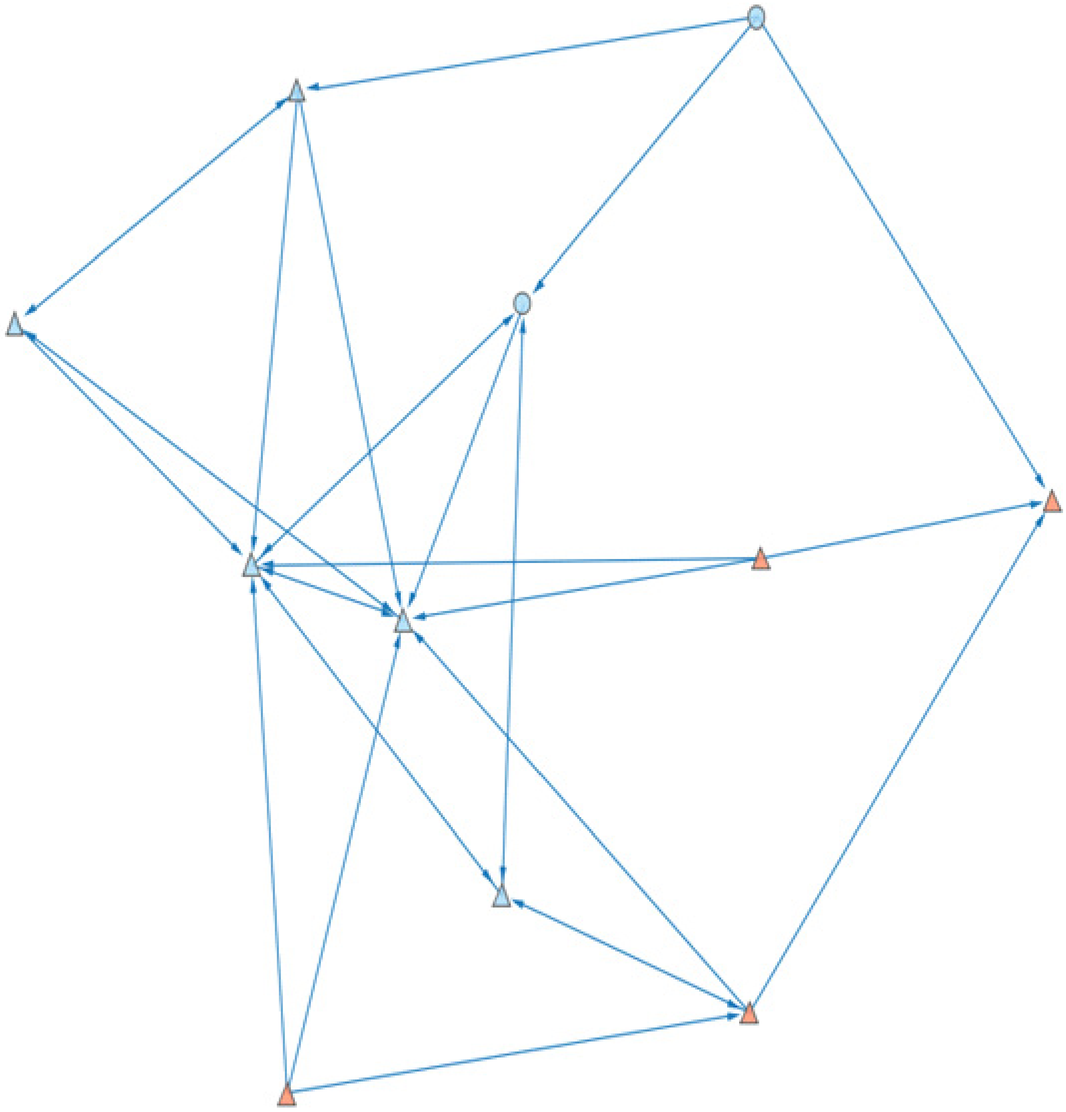

Figure 5: Sociogram of the Lowest Task In-closeness Score (.64) From Group with Two Students on Scholarship

Circles = students receiving scholarship; triangles = “traditional” students; blue = males; orange = females

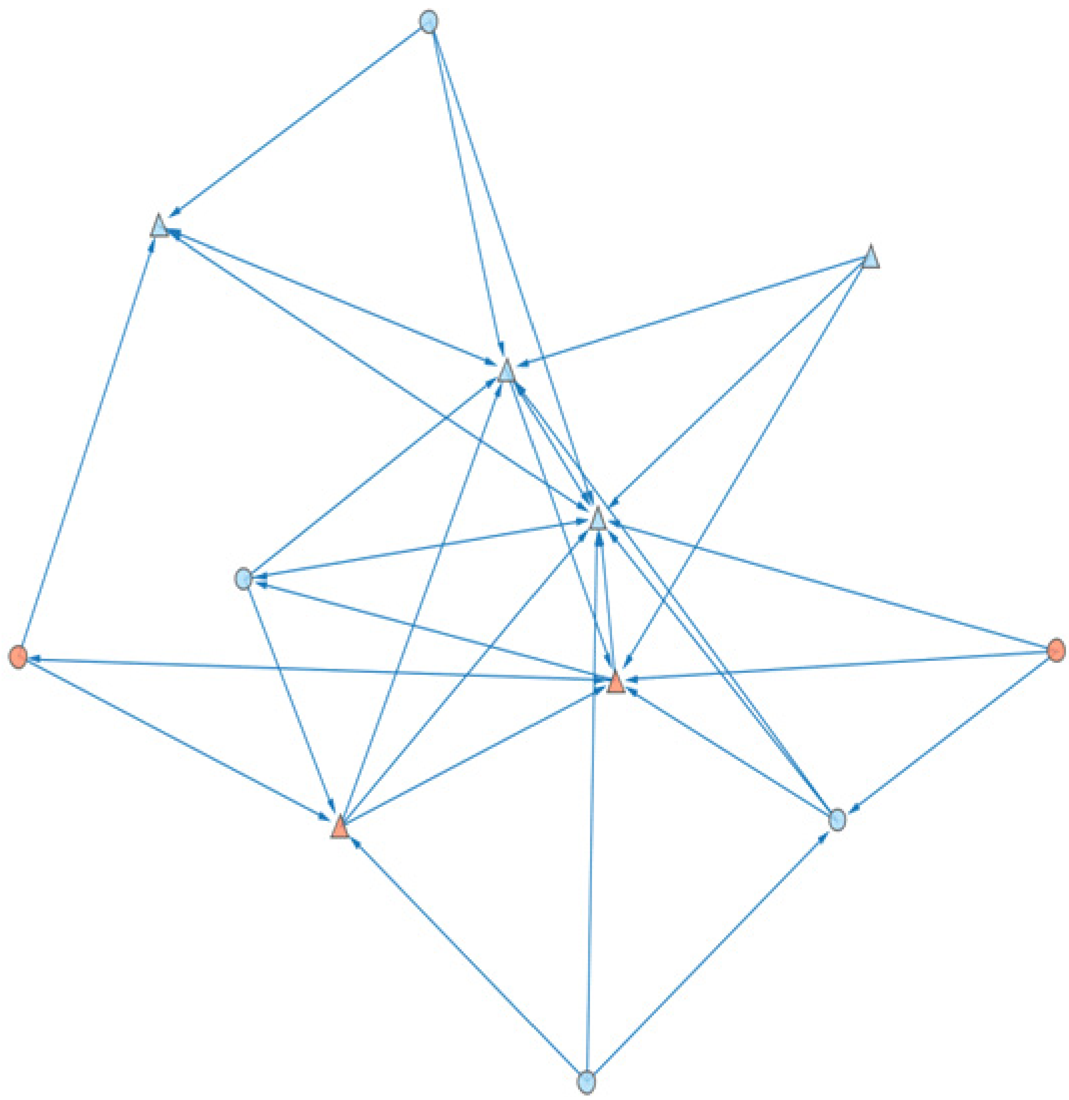

Figure 6: Sociogram of the Highest Task In-closeness Score(1.21) From Group with Half Students on Scholarship

Circles = students receiving scholarship; triangles = "traditional" students; blue = males; orange = females

Research and Practitioner Implications

As seen through the example above, SNA can provide valuable information to OAE programs interested in program evaluation or research. The findings from these data show that SNA can provide results similar to traditional survey methods since these data align with what others studying group cohesion and individual differences have found (Knouse, 2006; Hackman & Katz, 2010; Mannix & Neale, 2005). However, SNA offers additional tools that compile both group and individual level survey data and graphically display the data in a manner that facilitates interpretation beyond conventional descriptive statistics.

The types of questions that can be asked and the relations that can be represented by sociograms should further our understanding of small groups. While the example presented in this article uses very basic techniques, more advanced analyses and ways of presenting the data exist. As technology continues to expand, more resources to explore networks will become available. We also believe the use of rigorous statistical analyses can produce more robust findings from network data. Because of the interdependent nature of SNA data, traditional statistical models (e.g. general linear models) should not be used (Wasserman & Faust, 1994). However multilevel modeling techniques can provide both individual and group level analyses that acknowledge the nested data structure inherent in network data.

Perhaps the biggest appeal of SNA is the intuitive nature of the sociograms. Practitioners can easily see the relationships between the social entities they are interested in without having to understand the statistical nature of most studies. Furthermore, practitioners often know the actors in the network they are studying and the sociogram can provide a visual representation of relationships that may show why a group may be performing or acting in a particular manner. For example, before the current study, the SNA method was bench-tested with a small group of students who were already collectively working together with the authors. After analyzing the sociograms of the group, the behavior between individuals in the group was more understandable by the relationships that were represented in the sociograms. Knowing the students in this group beforehand helped to make sense of these relationships. Furthermore, many individuals within small groups take on a different personality when “authoritative” figures are present. Thus, how a group acts in front of “authority” may be different than how they would act if by themselves. The use of SNA provides an “inside” look at the dynamics of the group without an “authoritarian” figure being present.

Lastly, an elementary form of SNA can be utilized in the field and would be able to help leaders and instructors have an idea of who people prefer to be with. For example, instructors can simply ask students who they would prefer to share a tent with. This question is not as specific as the scenarios we presented, but eludes to the idea of who individuals would want to be around in social situations. By using a member by member matrix, instructors could easily plug in indicators for the nominations and be able to see how students nominated others and who received nominations. This understanding may be able to help instructors tailor the social dynamic of their course more effectively.

Conclusion

Groups are dynamic entities that are co-created through interactions of participants. They are not linear, not easily quantified, and are not socially just. Regardless of these complexities, a better understanding of small group processes in OAE is needed (Ewert & McAvoy, 2000; Sibthorp, Paisley, & Gookin, 2007) and, in order to achieve this task, a wider array of tools and methods should be understood and applied. The purpose of this paper was to introduce the method of SNA to OAE. The basic components of SNA were introduced along with an example that illustrated how SNA can be used to understand the interpersonal relationships between members in small groups.

Social network analysis provides a nuanced look into a complex topic in a way that traditional survey methods cannot. The possibilities afforded by SNA offer a distinct tool for both researchers and practitioners to further understand small groups in OAE. A better understanding of the nature, structure, and properties of small group processes is critical to a variety of practical and conceptual issues in OAE. Social network analysis provides an innovative, intuitive, and helpful option toward this goal.

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