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# Do People Who Identify as Popular Become Popular in a New Network? A 9-Month Longitudinal Network Analysis

Christopher J. Carpenter

Xun Zhu
*University of North Dakota*, xun.zhu@UND.edu

Rachel A. Smith

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# Do People Who Identify as Popular Become Popular in a New Network? A 9-Month Longitudinal Network Analysis

## Christopher J. Carpenter[a], Xun Zhu[b], and Rachel A. Smith[c]

## Abstract

Although scholars have argued that people actively shape and reshape their social networks (e.g., Parks, 2016), this aspect of relational development has received little attention. This study sought to determine if people's self-perceptions of interpersonal communication skills translated into behavior that led to relationship formation in a new network. A 9-month longitudinal social network analysis (*N* = 94) of the residents of a first-year university residence hall using Facebook tie data was conducted to assess network changes. Results indicate that both self-perceived network centrality in a hypothetical friendship sociogram (Smith & Fink, 2015) and self-reported connector scores (Boster et al., 2011) are good longitudinal predictors of relationship development. Those who began by self-identifying as central, became central.

*Keywords:* relationship development, social network analysis, popularity, sociogram, opinion leaders

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a. Corresponding author: Department of Communication, Western Illinois University, 1 University Circle, Macomb, IL 61455 USA, cj-carpenter2@wiu.edu.
b. Communication Department, University of North Dakota, Columbia Hall Room 2370, 501 N Columbia Road Stop 7169, Grand Forks, ND 58203-7169, xun.zhu@und.edu.
c. Department of Communication, Pennsylvania State University, 216 Sparks Building, University Park, PA 16802, ras57@psu.edu.

# Introduction

Much research has been conducted on the structure of social networks (Monge & Contractor, 2003). People are in networks of friends, networks of coworkers, networks of people who share information, and they are on social networking sites that often involve a combination of these interpersonal relationships and interactions. Yet, although scholars argue that people "act strategically to exploit and even to reshape their networks" (p. 1, Parks, 2016), very little research has been conducted on how social networks emerge from interpersonal communication over time (Brass & Krackhardt, 2012). People often enter into existing networks when they start new jobs, join organizations, or escalate a romantic relationship. New networks can form when a group of strangers find themselves in the same location after a disaster, when they are placed together to cohabit a space, or they are brought together to work on a problem together in a team. A salient example is when a new class of first-year college students is placed together in a single residence hall. In 1961, Newcomb published his book, *the Acquaintance Process*, on his intensive study of 17 college freshmen living in the same dorm, in which he tracked changes in their interaction patterns and group dynamics over time. This study returns to that setting to continue exploring network development over time.

There may be few pre-existing connections among the new residents of a first-year residence hall. Unless they met at summer orientation programs or came from the same geographic area, most of the residents will be strangers to each other. They will have varying expectations about the social network in which they will be embedded, and what place they will have in the network. Some may expect to make many friends, some may expect to make friends strategically, and some may expect to be alone. These expectations are likely to be based on the kind of self-perceptions they have about their place in the social world: popular, influential, powerful, connected, or unique. Parks (2017) notes that maintaining self-perceptions requires a complex self-presentation via multiple media channels and the careful regulation of one's network connections via those channels. Furthermore, these self-perceptions are not entirely under their control to enact: to be a popular friend, for example, a person needs to attempt to become friends with others and those others need to accept him or her as a friend. Someone may start out trying to make many friends, but continued expansion of their network requires reciprocation. The purpose of this investigation is to determine if people's self-perceptions of both their interpersonal behavior and their network centrality, in fact, translate into them attaining network positions consistent with those self-perceptions over the course of their first-year in a first-year residence hall.

Seeking to understand what kind of people engage in networking behavior and who becomes central can make a novel contribution to a variety of important areas of research. Firstly, and despite the value of it, longitudinal network research is fairly rare (Kossets & Watts, 2006). In addition, it is important to understand such networks, because building strong social networks in new environments has a variety of positive benefits for people's health (Sluzki, 2010), their job performance (Thompson, 2005), first-year students' availability of resources to help them succeed (McEwan & Guerrero, 2012), and avoiding a sense of alienation (Parks, 1977). Also, longitudinal research on political communication finds that people tend to adapt their political views to their social network over time (Lazer, Rubineau, Chetkovich, Katz, & Neblo, 2010). Finally, knowing who engages in networking and becomes network central can help identify influential people for interpersonal health communication campaigns (Dearing, 2004; Valente & Pumpuang, 2007).

The questions addressed in the current study are of importance to understanding social influence, because influence is usually social. In 1959, French and Raven brought attention to how influence involved the dyadic relations between an agent and a target, and how power resides in social relationships and social standing. In the past 65 years, much attention has been placed on understanding ideas, like leadership as a characteristic of the person (e.g. Katz & Lazarsfeld, 1955) rather than social positions afforded by others looking to a leader for guidance (e.g. Keller & Berry, 2003). Network analysis provides quantitative means by which to identify the network structures and positions within them that represent leadership, popularity, and more.

What has been missing is an understanding of the extent to which people develop relationships in ways that allow them to reside in the network positions to which they aspire, especially strategically important network positions. Research has improved the means of identifying important network positions (Valente, 2012), but these studies focus on influential agents already in their positions and then consider who is best able to influence others based on the positions they currently hold. And yet, we do not expect people to suddenly appear in important network positions, particularly influential ones, by chance. For example, recent research has focused on identifying influential people based on their personal traits (Boster, Kotowski, Andrews, & Serota, 2011; Boster, Carpenter, Andrews, & Mongeau, 2012), and these traits have been associated with their self-identification with more or less central network positions in a sociogram (Smith & Fink, 2015). In this study, we explore how well alternative individual-qualities explain which people in a new social system construct different kinds of new social networks. This study provides novel insights into relational development, trajectories through which future leaders progress toward influential positions, and potential means of identifying potential future leaders. The following review will first examine who is likely to engage in networking activity over time and then discuss who is likely to become network central.

# Networking Activity

One ongoing area of research attempts to understand who forms ties with whom in a network. For example, people interact and develop relationships with similar others (Newcomb, 1961; Parks & Abelson, 1983). Mayer and Puller (2008) examined a large Facebook dataset of universities and found that demographic similarity was one of the strongest predictors of friendship tie formation. Barnett and Benefield (2017) found that inter-country tie formation on Facebook was more common when people shared a language, among other similarities. That research suggests a process where people of similar backgrounds simply gravitate towards each other.

Yet other research from organizational science suggests that people intentionally engage in networking behavior. Fang, Chi, Chen, and Baron (2015) interviewed business people with varying degrees of networking skill and concluded that people with high networking skills intentionally craft networks of diverse contacts. Burt and Ronchi (2007) found that training programs that focus on teaching skills to build diverse social networks and occupying certain network roles is associated with many metrics of business success. Work by Ellison, Steinfield, and Lampe (2011) found that people engage in a variety of strategies for forming ties online.

This study will look at two methods of identifying people who will be likely to engage in such networking behavior in a new social network. The first method will be to look at what positions people choose to represent themselves in a hypothetical social network represented by a sociogram. This method was developed by Smith and colleagues (Fink, High, & Smith, 2014; Smith & Carpenter, 2018; Smith & Fink, 2010; 2015). Studies showed that people are generally able to identify the social power of nodes in a sociogram that match the nodes' network centrality (Fink et al., 2014; Smith & Fink, 2010). In the Smith and Fink (2015) paper, the participants were asked to imagine that the researchers had gathered real friendship information from the participant and 10 of her friends from an existing social group (e.g., a running group), and then to look at a sociogram and imagine that the nodes (circles) represented the subject and the subject's friends in that subject's network. The lines indicated the connecting nodes representing friendship ties. The subject was asked to identify which node they thought represented him or her in the social network.

However, it remains to be seen how people come to identify with particular network positions. Likely, they are aware of their place in their previous social networks, before the disruption caused by entering a different social environment, such as going away to college. For example, they may have been conscious of being tied to many people, or being tied to a few and existing at the social periphery in their previous networks. This study assumes people strive for consistency: the network position people choose represents how they see themselves in their previous networks. People who self-identify with positions of high network centrality may wish to attempt to actively construct their new network so that their previous position will be reflected in the new network. People who were popular in their old network may actively try to be popular in their new network by forming many new ties in the new network. There are, however, different ways to define popularity, including various types of network centrality.

One basic type of network centrality is called degree centrality (Freeman, 1978/1979). Degree centrality is represented by the number of links to other nodes. In this study of friendship development among strangers, higher degree centrality means more friends. The node in Figure 1 with the highest degree centrality is marked "j." People who choose that node in the hypothetical sociogram shown in Figure 1 are likely to consider themselves to be very popular. When placed in a new network, they would be likely to want to replicate that success in a new network. People who choose positions with few links are likely people who do not tend to make a large number of friends and would thus be less likely to engage in substantial amounts of networking activity to make new friends. Therefore the following hypothesis is proposed:

> H1: People who choose a position with a higher degree centrality in the hypothetical network are more likely to make friends than those who choose a position with lower degree centrality.

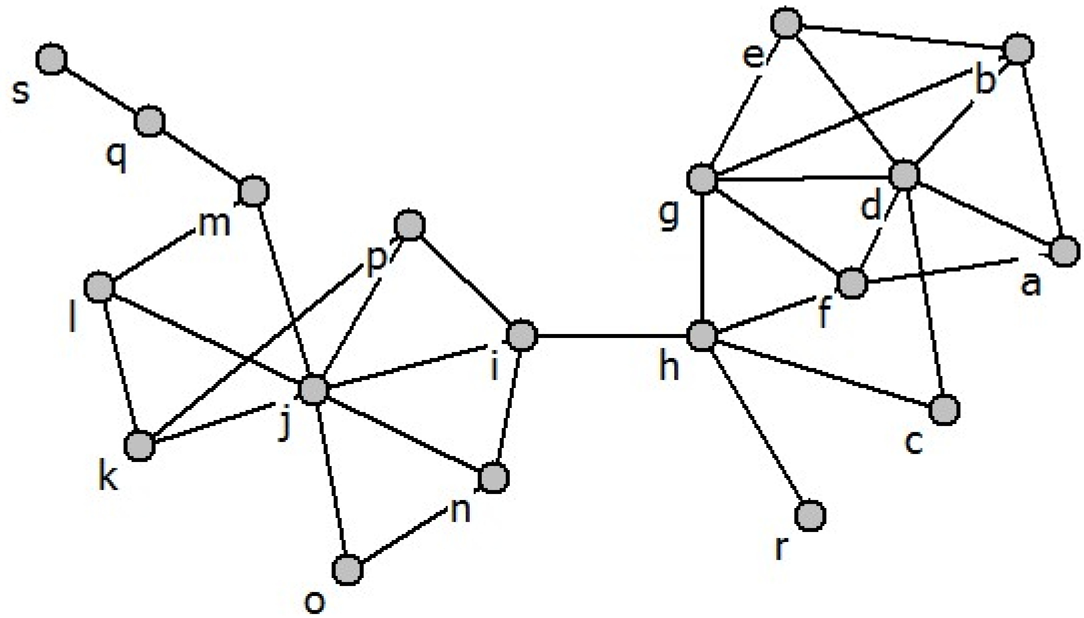



**Figure 1.** The hypothetical sociogram used in the study

Another type of centrality is betweenness centrality (Freeman, 1978/1979), which represents being a common intermediary as other nodes try to reach each other through interpersonal connections. People with high betweenness centrality tend to be bridges between groups. Burt (1992, 2004) identified betweenness centrality as particularly useful for being exposed to new ideas, because opinion and knowledge is often homogenous within a group. Therefore, being able to reach other groups more easily puts someone with high betweenness centrality in a position to learn new information. Such people may also be more likely to be opinion leaders (Burt, 1999).

In studies of sociogram perceptions, people attribute nodes in positions with higher betweenness and degree centrality as having higher social power in the network (Smith & Fink, 2010; 2015). Yet, people who self-identify with a position high in betweenness centrality may not be engaging in a high level of sheer networking volume. They may be more selective and strategic. Burt (1999) argued such behavior is efficient, because forming a few ties between groups gains one access to more information than forming many ties within a group. Forming more ties within a cluster is not consistent with someone who sees themselves as a bridge. In Figure 1, “h” has the highest betweenness centrality. The position of “h” has moderate degree centrality with his/her 4 ties. Yet, “m” has moderately high betweenness with only three friends due to the position of being the only link to reach “q” and “s.” Therefore it remains unclear if people who think of themselves as being in a high betweenness position will be likely to engage in higher networking behavior overall. So the following research question is proposed:

> RQ1: What will the relationship be between betweenness centrality in the hypothetical network and friendship formation over time?

Another method of predicting who will be likely to engage in networking behaviors is to use a self-report measure that attempts to measure people's tendency to be a connector. Boster et al. (2011) proposed that there were three different aspects of a successful opinion leader: being well-connected (connector), possessing high persuasive skill (persuader), and being recognized as an expert on a particular topic in one's network (maven). This study focuses on the connector, people who have a tendency to engage in networking behaviors that bring people together. They are more likely to introduce people and more likely to close triads, a network analysis term for when someone has two friends who do not know each other and then brings them together, such that the result is all three are friends.

Carpenter, Boster, Kotowski, & Day (2015) conducted a pair of studies establishing that connectors tend to be popular. The first study showed subjects a list of random last names and asked how many names from this were the same as people they knew. The subjects' connector scores were positively associated with how many people the subjects reported knowing. The second study found that when the names of students at a medium-sized university with previously measured connector scores were shown to a sample, the connectors were substantially more likely to be recognized by other students from that university. These studies indicate that connectors are well-known people. But it remains to be seen whether or not they will engage in networking behavior in a new environment. It is also unclear what strategy they would use. They might engage in a high amount of friendship formation early on or they might steadily expand their network across time. The Carpenter et al. study suggests that at least they will become well-known so the following hypothesis is offered:

H2: Connector scores will be positively related to making friends in a new network.

## Becoming Network Central

As mentioned earlier, attempting to form friendship ties is likely to be something that people can control, but becoming central in a friendship network may not be. Relational networks, such as friendship networks, are highly interdependent, such that a person's relational activities may pose opportunities and constraints on the behavior of those who are directly or indirectly connected. Thus, network centralities (e.g., degree and betweenness) are a function of not just one's own behaviors, but also of the networking behaviors of the rest of the network (Wasserman and Faust, 1994). Popularity, based on degree centrality, is essentially relative to the rest of the network. If Frank has five ties in a network of mostly isolated people, his degree centrality and popularity is high. If Ed has five ties in a very large and very dense network, his popularity may not be that high. Kossinets and Watts (2006) claimed that people are unlikely to be able to manipulate their network to intentionally become highly central. They argued that "it appears that individual-level decisions tend to "average out," yielding regularities that are simple functions of physical and social proximity" (p. 90). Klein, Lim, Saltz, and Mayer (2004) looked at the longitudinal impact of personality on network ties in small workgroups and found that extraversion had no substantial impact on network centrality, but that neuroticism was negatively associated with degree centrality in particular. They concluded that rather than choosing to become central in a network, one's network chooses you, because you are easier to work with. A similar finding was reported by Niven, Garcia, Lowe, Holman, and Mansell (2015), who conducted a longitudinal network analysis of new M.A. students in a particular degree program over the course of their first semester. They found that a trait called "interpersonal emotion regulation" (i.e., the inclination to help other people experience positive emotions) predicted degree centrality. Emotion regulators may attract friends rather than set out to make more friends.

On the other hand, other research suggests that people can engage in successful networking if they are so motivated. Fang, Landis, Zhang, Anderson, Shaw, and Kilduff (2015) conducted a meta-analysis of the studies examining cross-sectional links between network centrality and personality. They found that the strongest predictor of degree centrality was high self-monitoring. This trait is associated with active attempts to please and be liked by others. Similarly, Selden and Goodie's (2018) meta-analysis of big 5 traits and networking found that people who are high in extroversion tend to initiate ties more frequently. People who want to be liked may succeed.

It is unclear whether or not people who self-identify with a high degree centrality position in the hypothetical network will then become highly degree central when placed in a new network of people who are largely unknown to each other. The research is divided on the extent to which degree centrality can be created by a person or conferred by the social system. People may think of themselves as highly degree central, but they may never have had high degree centrality in their previous network or be able to attain such a position in a new network. Therefore, the following research question is advanced:

> RQ2: Will the degree centrality of the subjects' chosen position in a hypothetical network position be associated with higher degree centrality over time?

Similar to the degree centrality findings, the Fang et al. (2015) meta-analysis found that self-monitoring is positively associated with higher betweenness centrality scores. Yet, just as it is unclear if people can engineer degree centrality, it is also unclear if people can intentionally become bridges, even if they were bridges in a previous network. Like degree centrality, betweenness centrality depends on the rest of the network. To remain a bridge between two groups, other members of those two groups would have to fail to forge other ties between the groups. Burt and Ronchi (2007) focused some of their training on the value of betweenness centrality and found that the training produced positive business outcomes like promotions, especially among those who participated more frequency during the training. But it is unclear if those people attained those outcomes via changes in betweenness centrality. Therefore, an additional research question will be advanced:

> RQ3: Will the betweenness centrality of the subjects' hypothetical network position be associated with higher betweenness centrality over time?

Finally, the network centrality outcomes associated with high self-reported connector scores are also uncertain. Previous research on the popularity of connectors (e.g., Carpenter et al., 2015 reviewed above) suggests that they do tend to become well-known. Their habit of connecting people together is likely to make them known to many people. Research by Totterdell, Holman, and Hulkin (2008) also supports this supposition. They found that a similar measure of connection, called “propensity to connect” was positively associated with higher degree centrality of the friendship network at work. The following hypothesis will be tested:

H3: Connector scores will be associated with higher degree centrality over time.

As originally conceived by Boster et al. (2011), the connector is someone who is likely to have high betweenness centrality, such that they occupy the structural holes identified by Burt (1992). The items in the self-report measure are about the kind of outcomes associated with occupying such positions, like introducing new people to each other and people knowing each other due to being introduced by the connector. However, in a new network, such people may not end up in a position of high betweenness centrality. If they truly close triads by introducing people across the various groups they span, those groups will not stay separate. They will have historically been a bridge, but when people are introduced through their connection skills, they will not remain so and then the connector would no longer be a bridge. Though the Totterdell et al. (2008) study did find a small association between propensity to connect and betweenness centrality, no research has been conducted on the betweenness centrality associated with scores on Boster et al.’s connector measure. Therefore, the following research question will be advanced:

RQ4: Will connector scores be associated with higher betweenness centrality over time?

# Method

## *Overview*

The members of a first-year residence hall at a medium-sized Midwestern university were the social network studied herein. The hall holds about 600 residents. Although some first-year students might choose not to make friends in their residence hall, they would certainly have the opportunity to do so given the frequent possibility for interaction due to co-habiting a single structure (Festinger, Schachter, & Back, 1950). The self-report measures were collected by recruiting subjects with posted advertisements in the hall during the first week of classes. Participants completed the surveys on the spot using laptop computers and an online survey.

The network graphs were obtained via examination of participants’ Facebook.com profiles. The lead author created a new Facebook account and every research participant created a “friend” tie with that account. That enabled the collection of monthly network data by recording which friends were linked via examination of their Facebook.com “friend page” list. Facebook friend links is not a perfect map of the actual social relations of the subjects. However, the uncertain validity is offset by the ability to collect the longitudinal data without the difficulty of, and attrition from, re-contacting every member of the study once a month.

## *Sample*

There were 94 participants who completed the survey and were found to have valid Facebook accounts that were linked to the study account. Of these, there were 61 female subjects and 33 male with an average age of 18.11 (*SD* = .37). All were residents of the selected residence hall. Subjects were given $10 at the time of the survey completion for their participation.

## *Procedure*

Participants were recruited by placing posters advertising the study and the compensation in the windows of the main doors of the residence hall. Two laptop computers were set up on a table in the lobby of the hall. Participants responded to the survey items using the laptops in an online survey. They were then asked to open their Facebook account and "friend" the account created for the study. They were then paid and thanked. After three days of data collection, a network graph was recorded by loading each Facebook page and noting which of the other 93 subjects each subject was connected to on Facebook. Then another graph was recorded on the first of every month and at the end of finals week. Once the data collection was concluded, the Facebook account created for the study was deleted.

## *Measures*

In the survey, the subjects were first shown the sociogram (created by Ortiz-Arroyo, 2010, to highlight nodes with varying forms of centrality; see Figure 1), which was described as a friendship network. The sociogram was displayed in a group layout (i.e., nodes in the same group are closer together, and different groups are visually separated) with minimum edge-crossing (i.e., minimizing the number of lines between nodes that bisect each other, such as the lines connecting *g* to *b* and *e* to *d*). Viewers process sociograms displayed with group layouts and minimum edge-crossing more quickly and accurately than sociograms in other layouts (e.g., Huang, Hong, & Eades, 2005). The network size (19 members) and number of interpersonal connections (from 1 to 6) was consistent with studies of self-reported friendship networks (Brewer & Webster, 1999). Research using this hypothetical sociogram found that participants tended to rate it as believable (Smith, Zhu, & Fink, 2017).

Then they were asked, "Please imagine that this sociogram represents the friends in your life. You and your 18 friends would be the circles, and the lines represent friendships. Imagine we had gathered that information, and one of those circles is you: which letter do you think represents you?" These instructions were based on the Smith and Fink (2015) methodology. The degree centralities and the betweenness centralities for each position were calculated and the centralities for the positions chosen by each subject were recorded based on that analysis. The position picked most frequently as participants' chosen position in a friendship network was S (20.2%), followed by J (12.8%), H (12.8%), D (9.6%), I (8.5%), R (6.4%), M (5.3%), A (4.3%), Q (4.3%), F (3.2%), K (3.2%), B (2.1%), C (2.1%), and O (2.1%); the least popular positions were G, L, and N (1.1%). If all positions were equally likely, each would be selected about 5.3% of the time. The average standardized degree centrality for the hypothetical chosen positions was .25 (*SD* = .10) with range [.06, .39] and the average standardized betweenness centrality was .24 (*SD* = .22) with range [.00, .58].

They then completed the 15-item superdiffuser scale (Boster et al., 2011). Each of the three constructs, connector, persuader, and health maven were measured with five items using 7-point

Likert response scales. The connector scale was distributed with a moderate negative skew (*M* = 4.83, *SD* = 1.32, α = .90). The persuader scale had a somewhat larger negative skew (*M* = 5.26, *SD* = 1.18, α = .89). The health maven scale was approximately normally distributed (*M* = 4.47, *SD* = 1.32, α = .88). The persuader scale and the health maven scale did not affect any of the study outcomes.

# Results

## *Analysis Method*

To assess longitudinal tie formation, this study used the Simulation Investigation for Empirical Network Analysis (SIENA; Snijders, van de Bunt, & Steglich, 2010) to analyze the longitudinal friendship network data with nine observations. SIENA uses stochastic actor-based models (SABMs) to estimate and simulate the emergence of networks where people develop, maintain, or terminate relationships that are constrained by individual, dyadic, and structural factors. SIENA estimates the probabilities of change in the network using the objective function, and produces a distribution of networks with Markov-chain Monte Carlo (MCMC) simulation given specified effects of the objective function (Snijders et al., 2010). The statistical model allows for the specification of effects depending on standard ways networks change (i.e., endogenous effects) and effects depending on external attributes of the members of the network (i.e., exogenous effects). A well-fit model is obtained when the simulated networks with the specified effects reasonably approximate the observed networks (Snijders et al., 2010).

SIENA was originally developed to assess the evolution of networks with directed ties (Snijders, 2001). Additional work, however, has extended it to deal with undirected tie relationships (Ripley et al., 2015), such as those found on Facebook. We used the unilateral initiative and reciprocal confirmation (UIRC) model to estimate the parameter values of the objective function. The UIRC model assumes that a relationship between two participants in the network forms when one person proposes a new relationship and the other person confirms it. In the case of relationship dissolution, a person takes the initiative, but the confirmation is not required (Snijders, 2007). Thus, the UIRC model has a natural parallel with how people friend or unfriend others on Facebook.

SIENA is a useful technique to test the hypotheses in the current study. First, the model simultaneously estimates both endogenous and exogenous processes in friendship formation (Osgood, Feinberg, & Ragan, 2015), thereby testing the effects of one variable, such as connector scores, *above* and *beyond* other competing explanations (e.g., transitivity). Second, SIENA treats network outcome as a Markov process, such that at any time point, the current state of network probabilistically determines its immediate future evolution, thereby taking the complex dependencies across time into consideration (Snijders, 2005; Snijders et al., 2010). SIENA has been applied to the evolution of a variety of networks, such as HIV/AIDS non-governmental organization networks (Shumate, 2012), intra-organizational communication networks (Whitbred, Fonti, Steglich, & Contractor, 2011), and online health networks (Meng, 2016). We contributed to the growing literature by modeling the dynamic influence of variables representing networking motivations on friendship tie formation.

Based on Ripley, Snijders, Boba, Vörös, and Preciado's (2016) recommendations, we first estimated a model with structural control variables (e.g., density). After obtaining a converged model, we built a nested model with all the hypothesized exogenous individual covariates (e.g., connector score).[1] A parameter was considered significant when the estimate was at least 1.96 times greater than the standard error (Snijders et al., 2010). Network composition change was modeled using Huisman and Snijders' (2003) method of joiners and leavers. Compared to using structural zeros, the method of joiners and leavers presents a more efficient way of addressing missingness by using "additional information on relations between joiners and other actors in the network before joining, or leavers and other actors after leaving" (Ripley et al., 2016, p. 34). In this study, one participant left the network (de-activated their Facebook account) at each of three time points. One participant left the network at time 2, and re-joined the network at time 4. The analyses used SEINA version 4.0 within the R statistical system (Ripley et al., 2016).

## *Descriptive statistics*

Descriptive statistics across 9 waves of friendship networks appear in Table 1, and changes of friendship ties between two successively observed networks appear in Table 2. SIENA assumes that the changes in network occur gradually across time periods (Snijders et al., 2010). To assess quantitatively whether the observed networks have sufficient changes across waves, the Jaccard index between the successive waves was calculated (Snijders et al., 2010, p. 49). Gradual changes in network were indicated by Jaccard indices greater than 0.6. Jaccard indices in the current study ranged from 0.82 to 0.94, thereby meeting the assumption of the statistical model. An average of 14.6 ties were created per observational wave, with an average of 4.5 ties being terminated. On average, participants had about 2 friends in the initial period, and had about 4 friends at the conclusion of the observation. The sociograms of friendship networks at time 1 and time 9 appear in Figure 2.

**Table 1.** Descriptive statistics across nine observational periods

| Observation time | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| Density | 0.025 | 0.029 | 0.032 | 0.037 | 0.039 | 0.041 | 0.042 | 0.045 | 0.043 |
| Average degree | 2.319 | 2.681 | 3.021 | 3.404 | 3.66 | 3.787 | 3.894 | 4.17 | 4.043 |
| Number of ties | 109 | 126 | 142 | 160 | 172 | 178 | 183 | 196 | 190 |
| Missing fraction | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Average degree: 3.442

[1] Model convergence was indicated by *t*-ratios equal to or less than 0.1. All model parameters were less than 0.1 in the reported models, except that the parameter of transitivity triads in the hypothesized model has a *t*-ratio of 0.13.

**Table 2.** Changes in network relationships across nine observational periods

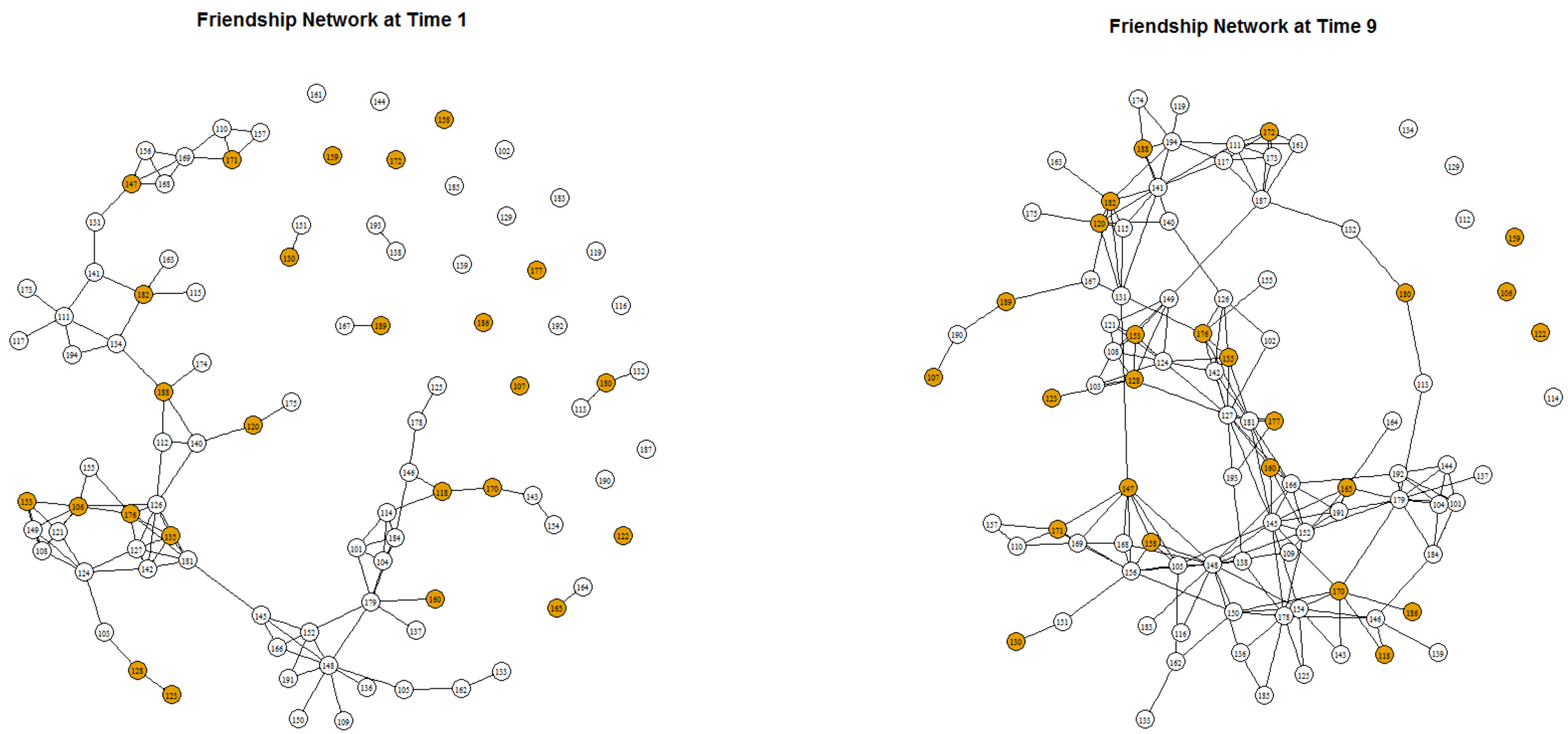
| Periods | 0 =>0 | 0 =>1 | 1 =>0 | 1 =>1 | Jaccard |
|---|---|---|---|---|---|
| 1 ==>2 | 4242 | 20 | 3 | 106 | 0.822 |
| 2 ==>3 | 4226 | 19 | 3 | 123 | 0.848 |
| 3 ==>4 | 4208 | 21 | 3 | 139 | 0.853 |
| 4 ==>5 | 4198 | 13 | 1 | 159 | 0.919 |
| 5 ==>6 | 4187 | 12 | 6 | 166 | 0.902 |
| 6 ==>7 | 4179 | 14 | 9 | 169 | 0.88 |
| 7 ==>8 | 4173 | 15 | 2 | 181 | 0.914 |
| 8 ==>9 | 4172 | 3 | 9 | 187 | 0.94 |

## *Research questions and hypotheses testing*

To test H1, H2, and RQ1, the variables, including density, triads, and popularity, were first entered into the model to control for the influence of these network endogenous mechanisms in friendship formation (e.g., transitivity: people with mutual friends tend to become friends). The model parameters appear in Table 3. The results showed that density had a significant, negative coefficient (estimate = -0.85, *SE* = 0.27), suggesting that participants did not make friends on Facebook randomly, but instead network structure had an influence on who they befriended (Parks, 1977). Triads had a significant, positive coefficient (estimate = 0.81, *exp*[0.81] = 2.25, *SE* = 0.07), indicating that participants were 2.25 times more likely to befriend a friend of a friend rather than with those who they did not share a common friend. The likelihood of making friends with people who themselves had many friends (i.e., the popularity effect; e.g., Snijder, 2001) was not statistically significant (estimate = -0.10, *SE* = 0.13).

After controlling for endogenous processes, we then added hypothesized variables including connector scores, and normalized degree and betweenness centrality of the self-perceived hypothetical network position (chosen from those available in Figure 1) into the model 2. H1 predicted that people who perceived themselves in a position with a higher degree centrality in the hypothetical network are more likely to make friends than those who chose a position with a lower degree centrality. The results showed that an increase in the degree centrality of the position people perceived themselves to occupy was associated with being 7.92 times more likely to make friends across time (estimate = 2.07, *exp*[2.07] = 7.92, *SE* = 0.81). Therefore, H1 was supported. RQ1 investigated if people who chose a higher betweenness centrality position in hypothetical networks are more or less likely to make friends across time. The results showed that an increase in the betweenness centrality of the position participants perceived themselves to occupy was associated with being 0.27 times as likely to make friends (estimate = -1.30, *exp*[-1.30] = 0.27, *SE* = 0.46).

**Figure 2**. Sociograms of friendship networks at time 1 and 9




***Note***: Colored dots represent the participants with connector scores above the 75th percentile of the scale (Boster, Kotowski, Andrews, & Serota, 2011)

**Table 3**. Results of stochastic actor-based models with tests of time heterogeneity

| | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| | *Est.* | *S.E.* | *Est.* | *S.E.* | *Est.* | *S.E.* |
| **Rate Parameters** | | | | | | |
| 1. Rate parameter period 1 | 0.74* | 0.17 | 0.74* | 0.18 | 0.80* | 0.17 |
| 2. Rate parameter period 2 | 0.69* | 0.16 | 0.72* | 0.16 | 0.68* | 0.14 |
| 3. Rate parameter period 3 | 0.76* | 0.15 | 0.76* | 0.16 | 0.74* | 0.16 |
| 4. Rate parameter period 4 | 0.41* | 0.11 | 0.41* | 0.11 | 0.42* | 0.11 |
| 5. Rate parameter period 5 | 0.52* | 0.13 | 0.54* | 0.13 | 0.50* | 0.13 |
| 6. Rate parameter period 6 | 0.65* | 0.14 | 0.62* | 0.13 | 0.65* | 0.14 |
| 7. Rate parameter period 7 | 0.47* | 0.12 | 0.49* | 0.12 | 0.45* | 0.10 |
| 8. Rate parameter period 8 | 0.33* | 0.09 | 0.33* | 0.10 | 0.31* | 0.09 |
| **Structural Effects** | | | | | | |
| 9. Density | -0.85* | 0.27 | -0.76* | 0.26 | -0.80* | 0.27 |
| 10. Triads | 0.81* | 0.07 | 0.85* | 0.08 | 0.85* | 0.08 |
| 11. Popularity (sqrt) | -0.10 | 0.13 | -0.17 | 0.13 | -0.15 | 0.13 |
| **Hypothesized Effects** | | | | | | |
| 12. Connector Score | | | 0.00 | 0.06 | 0.01 | 0.07 |
| 13. S-ndegree | | | 2.07* | 0.81 | 2.21* | 0.85 |
| 14. S-betweenness | | | -1.30* | 0.46 | -1.33* | 0.47 |
| **Time-Varying Effects of Connector Score** | | | | | | |
| Period 2: Connector Score | | | | | 0.70* | 0.24 |
| Period 3: Connector Score | | | | | 0.19 | 0.22 |
| Period 4: Connector Score | | | | | 0.10 | 0.24 |
| Period 5: Connector Score | | | | | -0.05 | 0.23 |
| Period 6: Connector Score | | | | | -0.12 | 0.23 |
| Period 7: Connector Score | | | | | -0.15 | 0.24 |
| Period 8: Connector Score | | | | | 0.48 | 0.28 |

*Notes*: $t$ refers to the convergence t ratio; $t$ scores equal to or less than |.10| suggest good convergence. Mathematical definitions of parameters included in the model are: density $[S_{i1}^{net}(x) = \sum_j x_{ij}]$; Transitive triads $[S_{i1}^{net}(x) = \sum_{j,h} x_{ij}x_{jh}x_{hi}]$; Popularity (sqrt) $[S_{i1}^{net}(x) = \sum_j x_{ij}\sqrt{\sum_h x_{hj}}]$; Monadic covariate effects $[S_{i1}^{net}(x) = \sum_j x_{ij}v_j]$ where $v_j$ represents composite scores of a variable (e.g., connector score) for a given actor.

$^*p < .05$;

H2 predicted that connector scores would be positively associated with friendship formation. The results failed to reject the null hypothesis that connector scores were associated with friendship formations over time (estimate = .00, *SE* = .06). We further explored whether connector scores had a time varying effect on friendship formation. Following Lospinoso, Schweinberger, Snijders, and Ripley (2012), we added interaction terms between time and connector scores to model 3. Similar to the model 2, connector scores were not significantly associated with friendship formations across time (estimate = 0.01, *SE* = 0.07). However, the test of time heterogeneity showed a significant variation in connector scores across time periods, $\chi^2$ ($df = 7$) = 21.11, $p < .01$. To further explore time heterogeneity and connector scores, one-step estimates for each time period were performed, together with other endogenous and exogenous specifications. The results of one-step estimates suggested that connector scores had a positive, significant coefficient in the initial period, estimate = 0.70, $exp(0.70) = 2.01$, *SE* = 0.24, suggesting that people with high connector scores were about 2 times more likely to make friends than those with low connector scores in the initial period. However, the influence of connector scores on the likelihood of forming friendship ties disappeared in later periods.

We also explored if the association between centrality scores of self-selected positions in the hypothetical network and the probability of friendship formations varied significantly across time. The results showed that neither the association between degree centrality in hypothetical network and friendship formation ($\chi^2$ [$df = 7$] = 5.91, $p = .55$) nor that between betweenness centrality and friendship formation ($\chi^2$ [$df = 7$] = 6.47, $p = 0.49$) was heterogeneous across time.

RQ2 and RQ3 considered whether the degree and betweenness centrality of self-perceived positions in a hypothetical friendship network would predict the observed degree and betweenness centrality in the new residence hall friendship network over time. H3 and RQ4 considered whether connector scores would predict observed centrality (degree and betweenness) in the new residence hall friendship network over time. To test the hypothesis and investigate these research questions, intercepts and linear slopes for each participant were estimated with two growth curve models (Hox, 2010) using the obtained nine observations: one model for normalized degree centralities and the another model for normalized betweenness centralities.[2] For each regression model, connector scores, degree and betweenness centrality of hypothetical network positions were entered as predicting variables. Zero-order correlations among the variables appear in Table 4. Regression analyses were conducted using UCINET 6 (Borgatti, Everett, & Freeman, 2002) with 10,000 permutations. Regression coefficients were produced with ordinary least squares (OLS), and permutations were used to construct standard errors for significance testing in order to address interdependence in the data across time points (Borgatti, Everett, & Johnson, 2013).

The results showed that the intercepts of observed degree centralities in the residence hall network were positively associated with normalized degree centrality of chosen positions in the hypothetical network (estimate = 0.01, *SE* = 0.004, $p = .06$), and were negatively associated with normalized betweenness centrality of the chosen position in the hypothetical network (estimate =

[2] Intercepts represented an estimated average of centrality scores for each individual across time, and slopes represented the ratio of change of the centrality scores for each individual across time. These intercepts and slopes were treated as dependent variables in separate regression models.

**Table 4.** Zero-order correlations among the variables (*N* = 94)

| | connector | sndegree | sbet | ndeg_int | ndeg_slope | nbet_int | nbet_slope |
|---|---|---|---|---|---|---|---|
| connector | | | | | | | |
| sndegree | .07 | | | | | | |
| sbet | .22$^{*}$ | .63$^{**}$ | | | | | |
| ndeg_int | .01 | -.10 | -.03 | | | | |
| ndeg_slope | -.03 | .10 | -.08 | -.36$^{**}$ | | | |
| nbet_int | -.03 | -.05 | -.13 | .59$^{**}$ | .16 | | |
| nbet_slope | .01 | .01 | .09 | -.40$^{**}$ | .31$^{**}$ | -.62$^{**}$ | |

*Notes:* sndegree= normalized degree centrality in the hypothetical network; sbet= normalized betweenness centrality in the hypothetical network. ndeg_int= individual intercepts estimated with normalized degree centrality across 9 time points; ndeg_slop= individual linear slopes estimated with normalized degree centrality across 9 time points; nbet_int= individual intercepts estimated with normalized betweenness centrality across 9 time points; nbet_slope= individual linear slopes estimated with normalized betweenness centrality across 9 time points;
$^{*}p$<.05; $^{**}p$<.01

-0.004, *SE* = 0.002, *p* = .08). The answer to RQ2, then, was that people who chose higher degree centrality positions in hypothetical networks reached the position with higher degree centralities in real friendship networks, while people who chose higher betweenness centrality positions in hypothetical networks reached the positions with lower degree centralities in real friendship networks. No other significant associations were found in the regression models. Therefore, RQ3 and RQ4 were answered negative and the data was not consistent with H3.

# Discussion

## *Hypothetical Sociogram Position Choice*

This study proposed that the kind of position people perceived themselves to hold within the hypothetical sociogram shown in Figure 1 (Smith & Fink, 2015) would predict their observed friendship behavior and the evolution of their centrality in a new friendship network over time. The data showed that those who perceived themselves to occupy positions higher in degree centrality in a hypothetical friendship network tended to be more likely to form friendship ties in a new network. In contrast, those which perceived themselves to occupy positions higher in betweenness centrality formed fewer ties.

There are several potential explanations for these findings. First, one possibility is that people’s choices on hypothetical sociograms represent an accurate picture of the social network of friends they had before they came to the university. Whatever traits they possess that caused their previous centrality in a friendship network also caused them to engage in friendship behavior to reach that position again. It seems that people who are accustomed to a central position among friends make continuous efforts to reach it, as the associations between degree centralities in a hypothetical network and friendship formation did not significantly vary across time.

Alternatively, their sociogram choices may represent their identity, such that they think of themselves in more or less central network positions and are motivated to reach a network position in a new friendship network consistent with that identity. Future work is needed to understand why people self-identify with particular positions in hypothetical sociograms. As Parks (2017) noted, people's self-presentation occurs not just one-on-one but within a larger network and this study helps understand what kinds of identities are translated into what kind of networked self-presentations.

The findings concerning betweenness scores in the hypothetical networks merit further examination. Those who saw themselves as occupying high betweenness positions in the hypothetical network tended to form fewer friends in the residence hall. It may be that developing a diverse set of friendship ties in the hall causes them to find a few friends in the first-year residence hall before branching out to make friends outside that limited social space. One possibility is that people who desire a high-betweenness position in a network may strategically form ties with those who are embedded in multiple subgroups of a larger community network. This possibility is consistent with Parks's observation that people "act strategically to exploit and even reshape their networks" (2016, p. 1): Making friends with people who belong to several subgroups may afford a way to become an intermediary in a disconnected system. Future research would profit from examining the interaction effects between one's betweenness centrality in a hypothetical network and the network positions of their friends.

The null finding for the impact of hypothetical network betweenness centrality on betweenness centrality in the residence hall network suggested that within this network, perceiving yourself to occupy a high betweenness centrality position is not enough to ensure that you will occupy one in a new network. While degree centrality is locally dependent upon the number of people a person can reach within his or her relational proximity, betweenness centrality is more globally constrained. Whether people manage to ascend to the intermediary position is constrained by how the rest of networked individuals are connected. It may be that people who find themselves as bridging groups in one network may not end up in the same position in a new network (Kossinets & Watts, 2006).

## *Connector Scores*

This study also sought to understand the networking behavior of people who reported high scores on the Boster et al. (2011) connector measure. This data suggests that connectors attempt to engage in quick networking behavior when they first join a new network, but then slow down their efforts in that network after a short time. It may be that after they have made all the friends they wish from that initial network they move on to other networks of people in student organizations and other residence halls. They may continue to form ties as they meet people in their residence hall throughout the year, but they seem to engage in their local networking activity quickly.

Another possibility is that the connector trait influences a person's friendship formation when a network is sparse rather than dense. Connectors' ability to bridge different groups together may in part depend on the ease of which they can identify disconnected subgroups. Identifying groups that can be connected may be easier in initial stages of friendship formation, when opportunities of doing so are abundant. As a network becomes denser, which was shown in decreasing rate parameters in Table 3 (see Steglich, Sinclair, Holliday, & Moore, 2012 for an illustration), it becomes increasingly difficult for connectors to navigate through the system and create linkages, thereby leveling out the influence of connector abilities on friendship formation. It would be helpful to see if they continue this trend in a variety of new networks by longitudinally measuring their friendship formation across groups.

Following connector behavior across multiple networks might also account for the surprising finding that connector scores were not associated with either degree or betweenness centrality over time. The Carpenter et al. (2015) study found that on a college campus, high connector scores were associated with being known by more people. That finding would have suggested at least high degree centrality in their residence hall network. Yet, becoming known by a variety of students across campus would likely require networking outside of the residence hall and to multiple groups. One might see high connector scores predicting degree and betweenness centrality across a wider sample than just a first-year residence hall. It is also possible that connectors form many in-degree ties (people see them as a friend), but form fewer out-degree ties (they do not remember all the people that know them). The use of undirected Facebook ties in a single residence hall prevented us from testing these ideas; these hypotheses await future research.

Another possibility is raised by Obstfeld's (2005) research on the tertius iungens approach to network development. Burt (1992) argued that a person who exists in a structural hole, such that one brokers information between two groups, can produce positive outcomes for the person occupying that hole. The tertius iungens approach suggests that people who occupy that position who then try to close that triad by bringing their connections together may also be in a powerful position. Obstfeld's conceptualization and measure of that approach bears a conceptual similarity with the Boster et al. (2011) connector conceptualization and measure. It may be that connectors operate similarly and thus reduce their betweenness centrality by introducing people in different social groups. Although there was no evidence from the current study of the connectors varying in their betweenness centrality, such that it increased and then decreased over time, that may be an artifact of only focusing on one potential part of their overall university network. Additional work is needed to determine if the connector measure and the Obstfeld tertius iungens measure are indeed correlated, as well as if they both predict similar kinds of behavior.

## *Implications for Theoretical Development in Social Network Analysis*

A variety of researchers have examined the impacts of knowing the structure of one's social network (Krackhardt, 1990; Obstfeld, 2005; Stephanone, Iacobucci, & Svetieva, 2016). These varying approaches converge on the idea that people vary in the extent to which they are aware of the varying connections and types of connections that make up their social network. This knowledge may confer more power (Krackhardt), involve one in innovations in a corporation more often (Obstfeldt), and allow one to perceive complex social situations more accurately

(Stefanone et al.). This study extends that perspective by exploring the extent to which people are aware of their own ability to actively engage in network structuring**.** The hypothetical sociogram approach to predicting network centrality was particularly effective, such that people who self-identified with degree central positions became degree central in a new network.

It may be possible to begin to build a broader model combining these approaches. People may vary in both their ability to accurately perceive their network, as well as their ability to accurately perceive their place in it. It is currently unknown if the two abilities tend to positively covary, but one might expect that they would. The two types of knowledge, though distinct, are likely similar and rely on similar social perception abilities. Such a theoretical development would require additional psychometric and sociometric advances that may be profitable for scholars to pursue.

## *Limitations*

As the foregoing analysis suggests, one of the limitations of this study is that the network was not strongly bounded. People may have engaged in networking and become network central in other networks or in the larger university student network. The first-year residence hall context was a better choice than a residence hall composed of a variety of classes because those students would not be as strongly motivated to make friends given their pre-existing networks on and off campus. Studying a first-year hall on a medium-sized university does still offer only a partial network, especially over time.

The study was also limited by its sample in that there were only 94 participants, which represent a subset of the residents of the residence hall, an even smaller subset of all of the first year students, and a smaller subset of all of the students of the university. Without a complete network, it may be that some participants with high connector scores were more network central, but the part of the network in which they were central was not represented. Several researchers have attempted to estimate the effects of various types of missing social network data in the form of missing nodes and missing edges. Borgatti, Carley, and Krackhardt (2006) found that node removal tended to uniformly reduce the extent to which centrality indices accurately predicted node centrality scores relative to the full network. They also found that this effect was smaller when the network was less dense, as is the case here. In general, they concluded that centrality measures were somewhat robust to such deletions. Follow up work by Wang, Shi, McFarland, and Leskovec (2012) confirmed that although there was a linear, negative effect on accuracy from edge and node deletions, centrality indices did tend to remain fairly robust despite the loss of data. On the other hand, simulation work by J. Smith and Moody (2013) found that such missing data has a larger impact on betweenness centrality estimates than on degree centrality. So it remains to be seen if the null findings concerning betweenness centrality will replicate or if a larger network sample would show different effects.

Given that such a small portion of the overall network was represented, these results must be interpreted with caution. This study serves as a strong pilot test of this method and may serve as an endorsement of further research rather than strong evidence in favor of the particular findings. Finally, like other analytic methods using passive observational data, SABMs does not produce definitive causal inferences.

## *Future research*

These results suggest many fruitful possibilities. One possibility is to measure networking behavior frequency to assess what mediators may exist between the predictor variables and the networking outcomes. Do people seek introductions from existing friends? Do they intentionally go to places in which they are likely to meet new people like social events? Assessing what kinds of communication behavior forms the link between the predictors in this study and network outcomes is essential to developing a better understanding of network centrality (Brass & Krackhardt, 2012). Such advances can then be applied to opinion leader campaigns (e.g. Boster et al., 2012).

Another possibility for studying networking interactions would be to examine speed networking events. These events provide an opportunity to interact with a variety of new people and form mutually beneficial ties. Although the current study sought to explain networking behavior over a period of months, similar factors may operate in a shorter timeframe. The predictor measures studied here could be administered at the outset and the interactions could be recorded. The extent to which certain traits lead to particular types of networking communication could be tested, which, in turn, could be associated with network centrality measures as outcomes.

Although this study has largely focused on the popular people, it is important to consider the implications of these findings for those at network's periphery. Some participants reported positions in the hypothetical sociogram with few ties and ended up forming fewer ties in the residence hall. Research by Segrin and Kinney (1995) found that social anxiety tended to be associated with loneliness, but that relationship was only weakly explained by actual social skill deficits. The results from the residence hall suggest that self-identification with lonely positions may predict being lonely in a new network. Perhaps if people joining a new network can learn to think of themselves as someone who could be network central, they would form new relationships more easily. Park's (1977) research on networks suggests that moving to a new place can enhance feelings of alienation, but that feelings of similarity to one's social network can reduce those feelings. Additional work on the effects of combinations of personal and network attributes on integrating people socially could be used to design interventions for when people enter new networks, like a university or a new job.

# Conclusion

Although there have been advances in people's understandings of their social worlds through network analysis, there is much to be done to connect it to fundamental questions in relational development. This study explored how people form relationships as they transition to new social contexts. It appears that the kind of social position one perceived oneself to occupy in a hypothetical network had an impact on networking behavior and reaching a central position in a new social context. The connector trait that forms part of the Boster et al. (2011) superdiffuser construct was only associated with early networking behavior. This study represents the first step in a new direction for network research on relational development.

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