An assessment of the adolescent social network and its relationship to program belongingness

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Thesis Proposal

# ABSTRACT

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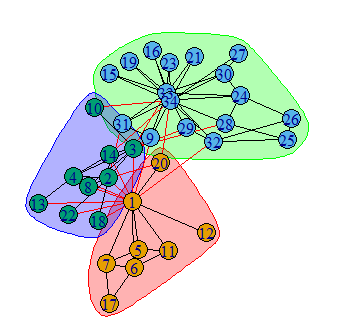
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# CHAPTER I: INTRODUCTION

“One of the most potent ideas in in the social sciences is the notion that individuals are embedded in thick webs of social relations and interactions” (Borgatti, Mehra, Brass, & Labianca, 2009).

In recent years there has been a growing interest in understanding human relationships within the social and behavioral sciences. Studying social networks is one method to help researchers understand these relationships. A social network is defined as a set of relationships between objects and how they can be mapped in a social structure (Kadushin, 2012). In social sciences, the term is most commonly referring to people, but the social networks to any set of related objects. Social network approaches have been used in a diverse set of scientific domains from understand neuronal connections (Bassett & Sporns, 2017) to understanding animal behavior (Brent, 2015).

Every network consists of a set of actors with defining characteristics (a node) and lines to represent the connection between them (known as a tie or edge). A node is an object with defining characteristics to be analyzed within a network of other nodes with similar, or differing, characteristics (Luke, 2015). Social network analysis quantitatively measures the connection of nodes through edges (Kadushin, 2012). Nodes may have several attributes such as, but not limited to, personality characteristics, gender, and age. The connection of these nodes through edges help understand how many connections a node may possess and where those connections come from. Social networks can be viewed from a more ecological standpoint to identify clusters of nodes and the commonalities between them such as family members, friends, and acquaintances (see Leskovec & Mcauley (2012) for an example of clustered networks). A visual display of nodes with attributes, edges, and clustering effects can be seen in *Figure 1*.



*Figure 1.* A social network from the *Zachary’s karate club network* (Gfeller, 2007). This network displays a university karate class’ connections and the clustering between them. The nodes (circles) have differing colors to represent attributes about the actor displayed. The edges (lines) show the connections between these nodes with certain attributes. Furthermore, the edges may be colored to characterize an attribute of the connection. Lastly, the surrounding colors identify how nodes are clustered into groups.

To study the organization of these nodes and edges that make up a social network, we use social network analysis. Social networks analysis (SNA) helps to define and measure the connections among people, organizations, and/or other individual units (T. W. Valente, 2010). More specifically, SNA is the process of understanding social structures quantitatively through network theory and graph theory (Butts, 2008). A wide array of statistics can be derived from social network analysis – often called network statistics. Network statistics allow researchers to quantitatively measure all levels of a social structure (Krause, Croft, & James, 2007). Social network theory, the overall encompassing theory surrounding SNA, can be applied to a wide variety of levels spanning from the simple connection of two people, up to a collection of people and how those people are integrated in a set of systems (Kadushin, 2012).

## **Social Network Analysis in Psychological Research**

Psychological research often relies on self-report surveys to answer research questions. Therefore, social network survey methodologies have been created. Survey research with a social network component consists of questionnaires that ask about relationships among a specified target group (Serrat, 2017). Social network survey questionnaire data is otherwise known as egocentric data, in which the actor is responsible for identifying their own network (Mccarty, Bernard, Killworth, Shelley, & Johnsen, 1997). These questionnaires require careful thought. There are two common approaches to collecting social network data in survey research:

1. *Social Cognitive Mapping/Roster:* Originally developed by Cairns, Perrin, & Cairns (1985), this method shows survey responders a list of names of individuals within the network. Respondents are requested to selected all alters that they have a relationship with. Roster methods require the use of a stem question such as, “To whom do you report to at work?” or “Please select individuals you have a friendship with…”.
2. *Name Generator/Nomination method:* This method allows participants to name any one or several individuals within a network. The name that may be generated are arbitrary and limitless. A common prompt a participant may see is, “Please indicate five individuals that you would seek advice from within your office…”.

Both methodologies are notorious for creating enormous datasets - Datasets that are hard to sift through without a systematic and methodical approach. Both egocentric data collection methodologies have pros and cons. Roster methodology requires high participation to produce valid data (Wasserman & Faust, 1994). Additionally, a roster methodology may only be incorporated when all sets of potential alters in known (Butts, 2008). On the other hand, studies utilizing nomination methods have shown that subjects are likely to produce false negatives due to subjects forgetting or overall fatigue (Butts, 2008). Errors especially occur in instances where the ego (an individual node in the network) has many connections (Brewer, 2000).

These collection methods for social network analysis have been shown to have a useful place in community interventions. For example, Klovdahl (1985) created a social network intervention to identify and prevent HIV outbreaks within a homosexual population. DeLay and colleagues (2016) have used adolescent friendship networks to evaluate the Family Check-up model within adolescent populations. Kornienko, Dishion, & Ha (2018) used social network interventions to reduce antisocial and violent behaviors within adolescent population. Experimental research by Valente (2003) found differences in tobacco intervention programs that identified group leaders in network analysis. In summary measures and analysis of social network can inform and improve interventions directly.

## **Adolescent populations & Mentorship Interventions**

More specifically, providing interventions to adolescents has become a popular area of study in the psychological literature. The adolescent population goes beyond that of being older children or younger adults (Crosnoe & Johnson, 2011). They encompass a unique population that is subject to many biological changes. Furthermore, the transition from adolescence into adulthood can be a difficult one due to mental health issues and environmental influences. Adolescence is when individuals are most at threat to risky health behaviors (Resnick et al., 1997) such as experimentation for use of legal and illegal drugs (Henry, Thornberry, & Huizinga, 2009), unsafe sexual practices and unsafe risk-taking behaviors due to delusions of invulnerability (Steinberg, 2007). These are just a subset of delinquent and problem behaviors that may be elicited by youth (Arthur et al, 2002; Broidy et al, 2003). Other behaviors that have a high risk of being elicited during adolescence include violence and aggressive tendencies (Resnick et al, 1997; Reiss & Roth, 1993). There are many factors that contribute to the likelihood of being vulnerable to these attitudes and risky habits.

Those that have a higher likelihood of generating these risky behaviors are referred to as *at-risk adolescents*. Although at-risk status varies on definition, it generally includes demographic features, home and community factors, and individual skill deficits which can negatively contribute to an individual’s ability to thrive academically, socially, emotionally, and physically (Mcdaniel & Yarbrough, 2016). These behaviors can often escalate into more serious behavior and subsequent consequences such as incarceration (Mcdaniel & Yarbrough, 2016). Given these considerations and outcomes, preventive efforts are needed to reduce levels of emotional stress and minimize behavioral difficulties amongst at risk youth.

Adolescence serves as an important timepoint to intervene and prevent delinquent behaviors. In fact, past research indicates that a strong predictor of adulthood criminal outcomes is childhood delinquency (Makarios, Cullen & Piquero, 2017). The importance of intervening at this critical timepoint during an individual’s life cannot be emphasized enough. Furthermore, serving as the last transition point into adulthood, the adolescent transitioning period is an efficient way to promote better health behaviors as they are more likely to live in a controlled environment with adult influences.

Therefore, it is necessary to provide helpful interventions to troubled youth. One such intervention method is providing youth with a positive mentoring relationship. Mentorship intervention programs provide adolescents with a role model straight from the community they both reside. It is suggested that providing creating a dyadic relationship between an adult mentor and youth mentee can improve outcomes through mechanisms of change (Rhodes et al, 2006). Mentors are encouraged to enhance coping strategies, reduce stressors and create an attachment to the youth mentee (DeWit et al, 2016). Meta-analytic reviews have shown that adolescents in mentorship programs show improvements in behavioral and psycho-social outcomes as compared to the non-mentored counterparts (DuBois, Portillo, Rhodes, Silverhorn, and Valentine 2011; Tolan, Henry, Schoeny, Lovegrove, and Nichols 2014).

## **Social Network Analysis in Mentorship Research**

Mentorship on Adolescents are often a population of interest in social network research. Years of research have promoted the influence of peer networks towards cigarette smoking (Ennett et al., 1993; Ennet et al., 2008) and other health behaviors. Additionally, recent studies have shown that adolescent alcohol consumption is directly mediated by the peer groups they associate with (Quiroga et al., 2018).

More specifically, the dyadic nature of the mentor-mentee relationship allows for a heavy emphasis in social network approach to in mentorship research.

## **Belongingness**

Related to an adolescent’s social network is their feeling of belongingness. The positive impact of feeling a sense of belonging has been studied for decades and is related to many positive outcomes (Allen & Bowles, 2012). Furthermore, targeting school students’ sense of belonging is often a form of intervention strategy to improve academic outcomes (Walton, 2014). Therefore, measuring belonging in an intervention program serves as an important feat to understand the true effect of the program.

## **Proposal**

The purpose of this study is to combine the understanding of adolescent belongingness and social network principles. Based on the similarities between social networks and belongingness, I hypothesize that a youth’s social network and score on a belongingness will grow at a similar trajectory. The collection, analysis and interpretation of social network data is complex and burdensome. Therefore, if we can determine that a youth’s belongingness in the program, an easy measure, is a good proxy for a youth’s friendships in the program.

# CHAPTER II: METHODS

## **Data**

Data for this project will be collected from youth who participated in the Campus Connections (CC) mentoring intervention at Colorado State University (CSU). Campus Connections at CSU is a mentoring program for youth at heightened risk for poor developmental outcomes, such as behavior and emotional problems. It is flexibly designed to respond to the needs of a heterogeneous group of youth with varying risk levels. The program is grounded in theoretical and empirical research on positive youth development settings (Eccles & Appleton Gootman, 2002; Kelly, Ryan, Altman, & Stelzner, 2000; Tseng & Seidman, 2007) and Rhodes’ model of youth mentoring (Rhodes, 2005). See Haddock et al. (2013) and Weiler et al. (2015) for complete information on the program model.

Data were collected as part of a three-year grant funded by the William T. Grant (WTG) foundation to study two versions of a youth mentoring program. The first involved traditional dyadic mentoring, in which one mentor was assigned to one mentee to experience the 12-week program together. The second involved nesting 4 mentor-mentee pairs within mentor families. As a result, mentees were exposed to both a mentor of their own, as well as to 3 other mentor-mentee pairs in their mentor family over the course of the 12-week program. More information of the youth mentor family approach may be read in Haddock et al. (2013).

Campus Connections typically occurs four nights a week (Monday – Thursday) during a regular academic semester, with each mentee assigned to one night. Twenty-eight mentees are assigned to each night. Mentees were randomly assigned to either the experimental mentor family condition or the treatment-as-usual dyadic pairing mentorship condition. Study inclusion criteria include: Youth be aged 11-18 years of age, experience at-least one risk factor from the risk screening tool (Herrera, Dubois, & Grossman, 2013), and available to participate during the CC operating hours. Participants could not have participated in previous CC sessions to be eligible for this study.

Youth (the mentee) were referred to the CC program through several community agencies including the local school district, juvenile justice system, Department Human Services, and various youth and family agencies. Upon receipt of the referral, trained CC staff contacted potential participants and conducted an intake appointment to determine program eligibility and obtain assent and parental consent.

## **Measures**

In the proposed investigation, data will be drawn from multiple time-points. If eligible and willing to participate in the CC program, mentees were provided 5 surveys during their time at CC. surveys were provided at week 1 (Baseline; wave 1), week 3 (wave 2), week 6 (wave 3), week 9 (wave 4), and week 11 (wave 5) of the 12-week program. Surveys were completed using Qualtrics, a web-based survey. The Institutional Review Board at Colorado State University approved all the described procedures.

### *Belongingness*

Campus Connection mentees responded to a five-item scale that inquired about their belongingness at CC via an adaption of the belonginess measure created by Youth Development strategies, Inc. This measure was distributed at all five waves. At wave 1, youth participants were asked about their expectations to belong (i.e. “I feel like I will belong at Campus Connections”). For all other weeks, youth were asked about their present feelings of belongingness in the program (i.e. “I belong at Campus Connections”). All five time points showed stable and great internal consistency (α = .88 - .92).

### *Social Network*

Youth were asked to indicate their relationships with other youth, mentors, and staff in the program during wave 1-5 of the program. Youth were shown pictures of other youth, mentors, and program staff within the program. The youth were asked to select all that they had a relationship with. Youth were then asked to rate the relationship on a scale of 1-10 with the other youth in the program.

## **Analysis Plan**

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**Background**

Historically, attempts to understand social networks have been around since the time of Socrates, whom theorized about the influences of social classes on people (Borgatti et al., 2009). However, the quantitative approach to understanding them is relatively new. It was not until the 1960’s that researchers began to theorize how the connections between people may impact the human experience. Travers & Milgram (1969) used social network methodology to determine everyone connected via six degrees of separation. Traverse & Milgram’s (1969) study represents the concept of the *small-world effect*, indicating that all individuals are in some way connected. These empirical studies have determined that the mean number of number of connections, despite the size of the network is relatively short (Newman, 2018).

Analyzing large scale social networks and performing the complex analyses associated with network theory in early scientific studies was nearly impossible. The scarcity of social network research in past decades is due to the overall complexity of social network data collection and analysis. However, the number of studies with network analysis methodologies have increased since the turn of the century. Advances in statistical programming have provided social science researchers an avenue to include strong social network components within their research studies (Luke, 2015). Several cutting-edge social network analysis methodologies require intensive processing power to be performed. Advanced Bayesian modeling techniques such as Exponential Random Graphing Models (ERGM) and *S*imulation Investigation for Empirical Network Analysis (SIENA) models (Ripley, Snijders, Boda, Vörös, & Preciado, 2019; Snijders, 2005) are examples of modeling techniques that require heavy processing power. These techniques are now feasible thanks to advances social computing that increase processing speeds and allow for large datasets (Parameswaran & Whinston, 2007); which social network data is notorious for producing.

Beyond analyses, social network data collection has also become more feasible over time. Social network sites such as Facebook and Twitter have provided a path for large quantities of social network data for analysis. Online social networks (OSN) are often collected via an application programing interface (API) provided by OSN providers. These OSN websites automatically collect a wealth of data from their users (Abdesslem, Parris, & Henderson, 2012). Modern utilization of SNA goes well beyond the of social networking websites. Research implementing social network methods include identifying characteristics of terrorist networks (Ressler, 2006), obesity (Cohen-Cole & Fletcher, 2008) and adolescent drug use (T. Valente, 2003).

Psychometric scales rely solely on self-report data and social network survey research utilize the same self-report methodology.

Despite these concerns, there are no standardized checks to test for data quality, accuracy, or trustworthiness.

Because social science relies heavily on self-report measures it is a necessary component of the literature. Measurements of reliability is among the most emphasized subjects in the social science domain. As with social network survey methodology, many psychological measures depend on self-report. These self-report questionnaires need to be assessed for their reliability through many statistical methods.

There is light research concerning this issue of social network data reliability and validity.

Other social science fields place a strong emphasis on ensuring construct measures are both reliable and valid.

Research on testing in employment processes has shown that anywhere from 15% to 40% of provide fake responses (Arthur, Glaze, Villado, & Taylor, 2010; Griffith, Chmielowski & Yoshita, 2007). Novel fake response detection methods such as unlikely response patterns detection (Holden et al., 2017) and social desirability scales (Crowne & Marlowe, 1960; Paulhaus 1999) have been utilized in order to retain scale validity and trustworthiness.

Social network research has no excuse to pursue similar practices to ensure the field is taken seriously.

Pat methodological approaches focused

Fields with an emphasis on testing and measurement incorporate a numerous number of methods to ensure validity and reliability exist within the measures they use. Social network data is a measure of relationships and bonds and there is no excuse to ensure the quality. This thesis project proclaims the assumption that social network data needs to be validated via standardized methods.

All the past research takes a focus on understanding data validity by use of the structural components of the network. However, the assumption that actors in a social network study can properly assess their own network is not nearly as researched. Often it is merely assumed that an actor assessing their own network through survey questions may accurately report. Ideally there needs to be systematic checks to determine the quality and trustworthiness of the data that has been collected. However, a standardized process to validate collected social network data remains unclear.

Using these methods to collect data requires a large assumption: *That respondents can properly assess their own networks*. This assumption is especially important depending on the population being assessed. For example, are adolescents able to properly assess their friendships with their peers? This overarching question is important and scarce in the literature.

The social ecological model is arguably the most heavily utilized model in public health and social science. The social ecological model emphasizes the integration of the social environment and an individual predicting determinant of health. We can approach the social ecological model’s integration of social systems and the individual via the social networks of these system.

The validation of network data comes with its challenges. When social network data is collected, it

There are a variety of methods for collecting friendships and bonds.

Despite these differing methods, the way social network data is processed is quite similar. Social network data may be represented in terms of an edge list or adjacency table. However, despite the standardized way of representing social network data, there is no standard process in existence to ensure the quality of social network data.

At the end of the project, a series of “checks” will be created to create an understanding of the validity of social network data. This is an essential step to determine the true effects of the network on health outcomes.

Due to the quantitative properties of SNA, a series of quantitative terms are used to represent relationships between people and systems. When these terms are used, we are establishing a mathematical representation of the network as a whole or the individual components of the network. Individual units in the network are referred to as nodes. In SNA, we study the connection and relationships between nodes (Marin & Wellman, 2008). The connecting points representing edges within a network are known as edges.

**Data Collection**

**Implications of Social Network Analysis**

The dissemination of SNA information has real world implications that may influence communities. Therefore, researchers need to be held accountable that the data they collect are valid and trustworthy. When reviewing the social network literature, a check on data quality is never mentioned. Social science’s dependability on reporting of standardized validity, reliability measures and checks for data trustworthiness helps to ensure the credentials of the field. Social network analysis research, an expanding part of the social science field, does not follow these same rules. It is naïve to assume that the network data collected by researchers is valid and appropriate for analyses. Even more so, populations of interest may differ in the validity of network data collected. Therefore, because there is no standardized methodology to evaluating social network data, the legitimacy of the field is at risk.

Without assessing the trustworthiness of collected data, there is no understanding how valid our conclusions are. Cole et al. (2018) have proposed latent variable approaches to validating social network data. Sociometric reliability has also been a topic of discussion for some time now. Pepinsky (1949), mentions that there is that there is no guarantee of consistency regarding sociometric data. Contrarily, Harmon (1949) made the exact opposite argument, stating that reliability in sociometric data collection is not necessary because it serves as a description of the real world itself. Terry (2000) later indicated the validity of sociometric methods are of concern because the there is no consistency in question stems (i.e. “Who are your best friends” vs. “Name your friends”). In either instance, the participant is expected to recall their network, which is may be prone error.

Newman (2018) has expressed concern over the omission of reliability measurements in social network analysis. Social network measurement error is especially prevalent in social science research due to the subjective nature of the network by both the subject and the experimenter assessing the network (Bernard & Killworth, 1977; Killworth & Brenard 1976; Marsden, 1990). Furthermore, previous research shows that these subjective errors may have large impacts on results (CITE).

**A Psychometric approach to Social Network Validation**

The aforementioned concepts are analogously related to classical test theory in the psychometric testing and measurement literature. Past research has noted this concern with validity as the observance of the true structure of the network as compared to the observed structure of the network (Wasserman & Faust, 1994).

These concerns are no different than the concerns in psychometric testing and measurement. Testing and measurement practices emphasize extreme precautions to ensure their measures are both reliable and valid. Quantitative measures for reliability and validity such as, internal consistency (Cronbach, 1951), interrater reliability, construct validity, and criterion validity among many others are essential components to the psychometric literature (DeVellis, 2016). It is common practice to report these quantitative statistics whenever possible. However, measures such as these do not exist in the social network literature.

**Current literature on Network Statistics and Measurement Error**

I Just finished a chapter about this in textbook called *Networks*  by Newman (2019), and will begin incorporating everything from that soon – Neil

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